Improving Targeting and Welfare of the Syrian Refugees

World Bank and United Nations High Commission for Refugees[1]

Abstract

The United Nations High Commission for Refugees (UNHCR) has the mandate to protect and assist refugees worldwide. In the context of the Syrian humanitarian crisis, this mandate is financially constrained by the size of the crisis, a fact that forced the UNHCR to target its cash assistance program. The objective of this paper is to apply welfare modelling and cross-survey imputation techniques to measure the impact of the UNHCR cash assistance program on the welfare of Syrian refugees and provide recommendations to improve its targeting. For the first time in UNHCR history, the universal registry of refugees is disclosed and used in conjunction with household data to measure and predict refugees' welfare. The application of welfare modelling and targeting evaluation methods on UNHCR refugees' data is also a novelty for the World Bank. This paper documents the first pilot experiment conducted in March-April 2014. Results of the entire study will be published by June 2015.

Keywords: Refugees, Syrian crisis, Cash assistance, Targeting, Poverty.

JEL: I3; H2; O1; O2; P4

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1 The paper has been prepared by a joint UNHCR-World Bank team. The team included Paolo Verme (Team Leader) and Utz Pape for the World Bank and Hashim Sharief, Shadi Mhethawi, Nisreen Abo Sammour (DAG), Koen Van Rossum, Edouard Legoupil (IM), Karen Whiting (Protection), Hassan Bahjat Mohammed (Community Services), Volker Schimmel, Rasha Bartaseh (Field), Susanne Butscher (Registration) for the UNHCR.

Introduction

In the context of the Syrian humanitarian crisis, the UNHCR has the mandate to register and protect refugees. For this purpose, the UNHCR collects information at the individual and household level during the first contact with asylum seekers when they enter the host country and during follow-up contacts that enable the organization to update and expand information on refugees. This information includes socio-economic characteristics of the refugees as well as other indicators relevant to the UNHCR work. At the time of this study, the UNHCR had over two millions records of Syrian refugees collected into one large database called the profile Global registration system (proGres).

The UNHCR Jordan has also been collecting starting from 2012 more detailed information on Syrian refugees via a home visits questionnaire that is expected to be administered to all refugees' cases in Jordan[2]. The objective of this data collection exercise is multi-fold but its main objective is to collect information on welfare and vulnerability necessary for targeting the monthly cash assistance program provided by the UNHCR. These data are currently available only in Jordan and, to date, have covered approximately 80% of the estimated 585,000 Syrian refugees registered in the country. More recently, in October 2013, the questionnaire has been revised and improved and the latest dataset covers already over 16,000 cases[3] or over 65,000 individuals.

This wealth of data collected by the UNHCR in Jordan is unique and largely unexploited in terms of analysis. The UNHCR regularly publishes statistics on refugees and has recently produced a statistical report based on the home visits data (UNHCR, 2014a). However, these same data can be used for more advanced analysis including econometric analysis that can produce useful information on targeting and welfare of refugees. In particular, by matching the information contained in the proGres data with the information contained in the home visits data in Jordan, it is possible to assemble a rather rich data set for further analysis of the whole refugees' population.

The objective of this paper is to apply standard welfare modelling and cross-survey imputation techniques to data covering the Syrian refugee population in Jordan in order to measure the impact of the UNHCR cash assistance program and improve its targeting. The paper will outline the data and the methodologies adopted as well as providing a set of results that can be readily used by the UNHCR to improve its targeting approach and, by consequence, be more effective in improving the wellbeing of refugees. It should be noted that the UNHCR has the mandate to protect refugees and that this protection includes but is not exhausted by welfare criteria. Therefore, assessing the welfare reduction capacity of the UNHCR cash assistance program only assesses one part of the UNHCR's mandate to assist refugees.

The paper is organized as follows. The next section describes the data used. Section 3 reports the main welfare models, section 4 discusses the results and section 5 concludes.

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[2] The home visit system started in the context of the IRQ refugee response in 2008, but was scaled and adapted during the response to the SYR refugee crisis from 2012.

[3] In the UNHCR jargon a "case" corresponds to a family unit at the time of registration. See Annex 1 for more details.

Data

This paper uses two data sets prepared by the UNHCR. The first data set is an extraction of the profile **Global registration system (proGres)**. This is the main global database held by the UNHCR and the data provided include all registered refugees in Jordan as of March 2014. This covers all the 585,000 refugees currently registered in Jordan. The value of this database is its size and the inclusion of key socio-economic characteristics of refugees. Its shortcoming is that this database contains only a few variables and no variables measuring welfare. We call this data set "PG" in the remainder of the paper.

Registration of new arrivals takes place in two urban UNHCR registration centres based in Amman (Khalda) and Irbid, at the Raba Sarhan joint GoJ/UNHCR registration centre close to the border. This last registration center is where refugees crossing informal border points are registered. The UNHCR also organizes mobile registration missions to remote areas and registers refugees in the two existing camps, Zaatari camp and the Emirates Jordanian camp. Refugees belonging to the same family are registered jointly as a case. A case is a processing unit, which is headed by a principle applicant and includes its dependents.

At registration, personal information for each individual is gathered as well as information relevant for the case. The data set collected as part of UNHCR Jordan's enhanced registration practice includes all relevant personal data such as names, date of birth, place of birth, sex, date of flight, arrival date in Jordan, registration date, ethnicity, religion, specific needs and vulnerabilities. It also includes a very short summary of the refugee claim, the whereabouts of close relatives whether in country of origin, country of asylum or other countries, educational details, professional skills, occupation in country of origin and asylum, if any, the addresses in country of origin and the country of asylum including key movement within the country of origin and reasons of flight categories among others. If refugees have relatives who are registered refugees in Jordan the cases are linked.

As a result of registration, UNHCR issues an Asylum Seeker Certificate with 12 months' validity – increased from six months as of 1 April – to registered persons of concern in the urban centers. Every person of concern comes once a year to a UNHCR registration center for renewal of the asylum seeker certificate, and is then re-verified once a year as part of this process. The Asylum Seeker Certificate is used as a continuous registration mechanism, whereby the information collected is re-verified, validated and updated as appropriate, so as to maintain an updated profile of the refugees' population. UNHCR Jordan also uses quality control and audit reports. The systematic and comprehensive use of audit reports at the registration stage is crucial to achieving and ensuring high data quality and preventing fraud.

The second data set is an extraction of the **Home Visits database** as of March 2014. This is a survey that aims at capturing the socio-economic situation and vulnerability of refugees for the purpose of targeting. It uses an extended questionnaire which results in over 185 variables that can be used for analysis. The questionnaire used for the Home Visits survey was revised in October 2013. As a consequence, this paper uses only the most recent data collected with the revised questionnaire amounting to 16,000 cases interviewed between November 2013 and March 2014. We call the Home Visits Data HV data in the remainder of the paper.

The definitions of case, household and family adopted by the UNHCR are provided in Annex 1. Occasionally, the text will refer to households as it is common in welfare analyses. However, throughout the paper, the unit of analysis is the case as defined by the UNHCR. We will also use a poverty line for the purpose of identifying the poor. This is the same poverty line used by the UNHCR for its cash assistance program, which is 50 JD per person per month.

Models

Central to the various objectives set in this paper it is the estimation of a welfare model that exploits at best the HV and PG data available. The general welfare model is described as follows:

$$W_i = \alpha + \beta_1 HP_i + \beta_2 H_i + \beta_3 P_i + \varepsilon_i \tag{1}$$

Where *W*=welfare measure (income or expenditure); *HP*=vector of case characteristics present in both the PG and HV databases; *H*=vector of case characteristics present in the HV data but not in the PG data; *P*=vector of case characteristics present in the PG data but not in the HV data; ε_i= normally distributed error term with zero means; *i*=household (case number in UNHCR data). The model described in (1) is then reduced following a systematic analysis of all independent variables available (HP, H and P, see description below).

The welfare model described in (1) can also be used for cross-survey imputation between the PG data and the HV data. This implies a two-steps procedure where the first step consists of estimating a welfare model with HV data using only variables that are common to HV and PG data:

$$W_i = \alpha + \beta HP_i + \varepsilon_i \tag{2}$$

The estimated Betas coefficients can then be used in the PG data to estimate welfare for all cases available in PG data:

$$\widehat{W}_i = \widehat{\beta} HP_i + \varepsilon_i, \tag{3}$$

where the "hats" represent estimated values. In this way, one can estimate welfare and poverty for all refugees registered by the UNHCR.

Also, from the welfare model in (1) one can learn what variables could be added in PG data to improve the capacity of PG data to predict welfare and poverty. By adding these variables to the data collected at registration, equation (3) becomes more powerful in predicting welfare and poverty without having to resort to the measurement of welfare aggregates for all refugees registered in PG.

For both models (1) and (2), a similar approach was used to select the variables HP, H and P. First, variables at the individual level (e.g., level of education) were aggregated at the household (case) level by choosing the values from the household head (principal applicant). Second, variables representing counts per household like children in school were transformed to per-capita variables by dividing for the case size. Third, aggregates were created by counting the "Yes" to responses for housing conditions, sanitary conditions, food security, coping strategies, health, etc. This set of modified variables with the remaining unaltered variables was used for the model selection process.

In the first model selection step, each variable was individually regressed on the main log-transformed per-capita welfare aggregate. Variables were selected if they were able to explain more than 1% of the variance of the welfare aggregate ($R^2 > 0.01$) and were not missing in most cases.[4] The selected variables were used to build a full model explaining about 60% of the variance of the welfare aggregate in model (1) and 50% in model (2). In subsequent steps, variables were individually tested for collinearity, substitution by similar/aggregated variables and loss of explanatory power if removed. Based on the refined model, all the remaining variables were added one-by-one. As none of the variables increased the R^2 by at least one percentage point, the refined model was not altered. In a final step, indices were substituted one-by-one for all individual variables included in the corresponding index. However, the substitution did not contribute to additional explanatory power; therefore, indices were not added to the models.

Following a similar approach to the identification of the optimal welfare model, we tested a number of composite indexes designed to measure welfare or vulnerability. Humanitarian agencies routinely use composite indexes for the measurement of welfare or vulnerability status. For example, the World Food Program (WFP) uses indexes to measure food scarcity and household coping strategies. The UNHCR does not use indexes for targeting the cash assistance program but eligibility includes vulnerability criteria that function *de facto* as binary indexes for the selection of beneficiaries. Therefore, it is instructive to test the correlation between welfare and various types of composite indexes and see how effective indexes are in meeting the stated objectives.

Results

Welfare aggregates

The first problem to address given the available data was the construction of the main welfare aggregate to be used for the welfare model. The HV data contain three questions on welfare, one question on incomes structured in seven items, and two questions on expenditure, the first structured in six items and the second structured in ten items. Questions on income and expenditure both refer to a recall period of one month prior to the interview.

As it is typical in poor countries, we found that income in HV data is clearly underreported given two simple observations. The first is that average expenditure was twice as high as average income. In the case of a refugees' population, we should expect income to be lower than expenditure as most refugees cannot work but may be selling out assets or spend savings. But the difference between income and expenditure is very large and the refugees' population considered lives in urban areas and mostly in rented accommodation. The second is that 49% of cases reported no income at all. We should expect many refugee cases to report zero income but the share of these zero incomes is very high, especially if compared with answers on expenditure, which are largely net of donations.

The two expenditure aggregates found in the data are more comprehensive but also not ideal for a welfare analysis. We found a significant difference between the two questions with an average difference of 72 JD per case per month. On the assumption that expenditure is also underreported, we constructed a third indicator of expenditure based on the other two. This was done by taking the highest reported value for each of the items common to both expenditure questions and the highest value of the rest of the items

[4] An arbitrary threshold of 15,000 cases was used to determine whether variables were present in a sufficient number of cases.

combined together. This new expenditure aggregate resulted in an average increase of 10 JD per case per month as compared with the higher of the two other expenditure measures (See table below).

Next, on the assumption that expenditure includes expenditure made with UNHCR cash assistance, we created a fourth expenditure item by subtracting UNHCR cash assistance from all cases that were receiving this assistance at the time of the survey. This assumption was checked by comparing expenditure of those receiving UNHCR cash assistance with the expenditure of those not eligible and also with exchanges with UNHCR and WFP staff. This last expenditure aggregate was then selected as the main welfare aggregate for the analysis.

Table 1 – Summary statistics of the main welfare aggregates

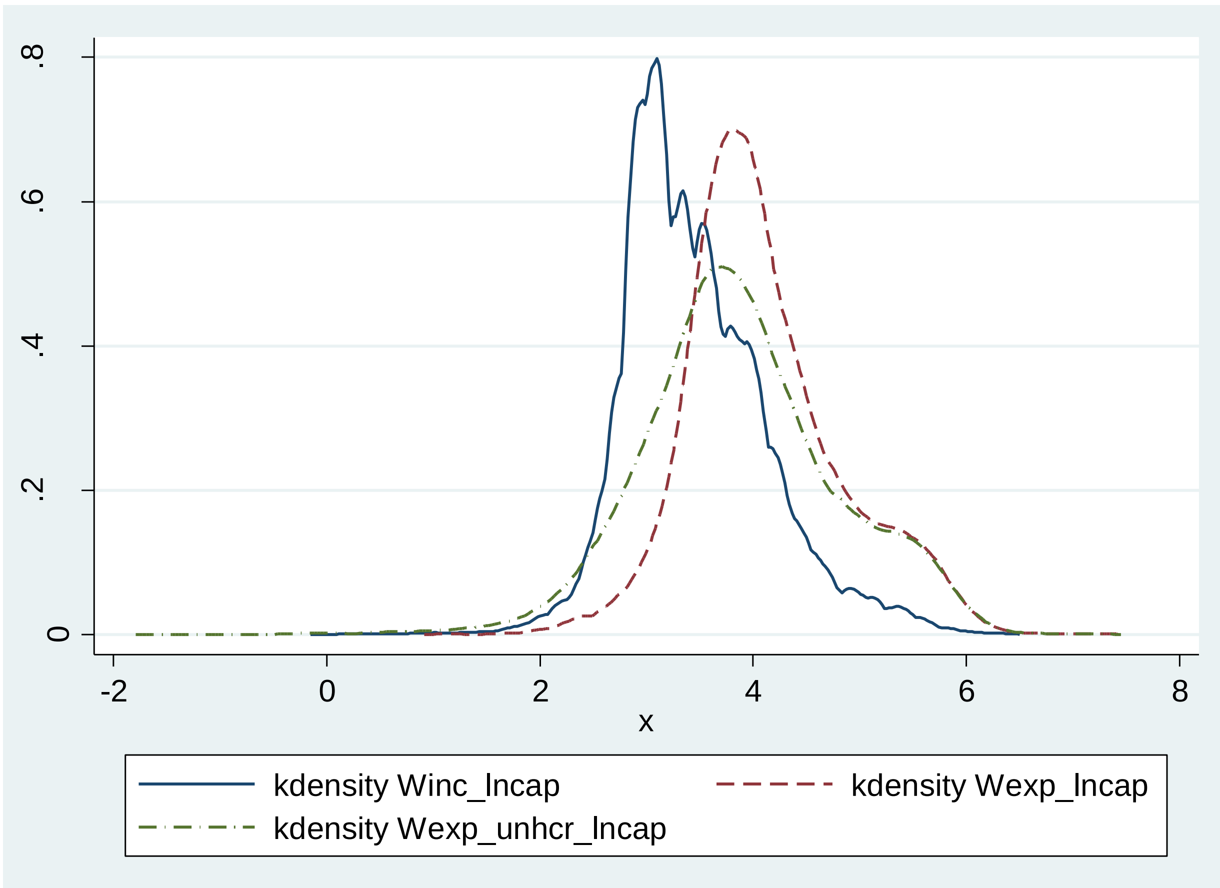
	Obs	Mean	Std. Dev.	Min	Max
Income for quest.	15975	82.1	111.1	0	2800
Expenditure 1 from quest.	15975	161.0	123.1	0	2582
Expenditure 2 from quest.	15975	232.9	120.3	0	2260
Expenditure from 1 and 2	15975	242.4	121.3	5	2592
Expenditure from 1 and 2 net of UNHCR	15975	202.8	126.5	0	2492
Income per capita	15975	21.0	36.3	0	667
Expenditure0 per capita	15975	82.0	84.1	2.5	1725
Expenditure1 per capita	15975	73.7	86.3	0	1725
Poverty (income)	15975	0.9	0.3	0	1
Poverty (expenditure0)	15975	0.4	0.5	0	1
Poverty (expenditure1)	15975	0.5	0.5	0	1

To test the various welfare aggregates in terms of conformity with theory and empirics, we plotted the distributions of the natural logarithm functions of income (lninc) and expenditure with (lnexp) and without (lnexp_unhcr) UNHCR cash assistance. The Figure below illustrates the results. As a rule of thumb and according to theory, a distribution of income or expenditure should have a regular “bell” shape with few observations on the two tails of the income or expenditure range and more observations as one approaches its central moments (mean and median). This theoretical statement is based on probabilistic theory and is also consistent with empirics. For example, if one plots income or expenditure distributions using the 1,800 plus surveys available at the World Bank, the greatest majority of these distributions would appear as bell-shaped, even if the distributions may not be perfectly bell-shaped.

This is also what we find with the expenditure aggregates constructed from the HV data. The aggregates with and without UNHCR assistance are clearly bell-shaped with a saddle point around a value of 5.5 (ln JD). This is much less the case for income, the distribution of which is extremely irregular. We can also observe that the expenditure aggregate net of UNHCR cash assistance is more regular and a less narrow distribution as compared to the expenditure aggregate that contains UNHCR cash assistance. This visual exploration of the income and expenditure distributions confirms that the constructed measure of expenditure net of UNHCR cash assistance is the best choice given the available data.

One should also keep in mind that welfare models typically utilize Ordinary Least Square (OLS) regression as estimators. These estimators perform particularly well if the continuous variables contained such as income or expenditure have a bell-shaped distribution. In fact, this is one of the requirements of OLS models. Therefore, a bell-shaped distribution serves both the purpose of confirming what we should expect in a welfare distribution and the purpose of satisfying the basic requirements of an OLS model.

Figure 1 – Income and Expenditure Distributions



Source: Home Visits Data

There are reasons why the welfare measure selected may be under or over estimated. As already discussed, it may be under-estimated because some of the expenditure is not reported. But it may also be over-estimated because some of the expenditure may include expenditure financed by donations. In addition to UNHCR cash assistance, refugees receive WFP food vouchers and occasional assistance in-kind or in cash by many different local and international organizations. The UNHCR tries to keep track of these donations but does not have a full record for each case to an extent that we could not use this information for the analysis. This means that, for some cases, the expenditure measure could include WFP or other donations, particularly those in cash. Donations increase welfare of course but our aim was to capture expenditure net of donations because we wanted to measure the real capacity of households to provide for themselves in the absence of donations and for the purpose of the UNHCR cash assistance. Following consultations with UNHCR and WFP staff, we believe this phenomenon to be small. It would also "compensate" the under reporting of actual expenditure, which is a further element that provided some degree of confidence in the final welfare measure selected. Nonetheless and as a further test, regressions will also be applied to income and the other expenditure measures constructed.

Welfare regressions

Based on the model selection procedure already described, two models (1 and 2) were constructed to explain the main welfare aggregate. The constructed models were applied to the three constructed welfare aggregates. The welfare aggregates reflect – if not noted otherwise – welfare before receiving any assistance like UNHCR cash assistance and WFP food vouchers. However, assistance from other sources cannot be excluded if it was not reported by the respondent.

Welfare Model (1) based on HV and PG variables

We setup model (1) using the described model selection algorithm but excluding the variable for monthly cash assistance from UNHCR as explanatory variable. The same variable was used to construct the main welfare aggregate (as it was used to subtract assistance if received). We assessed the validity of the model by testing its predictive power to classify households as poor and non-poor based on the independent variables without using the observed welfare aggregate.[5,6] The validity is confirmed by a very low inclusion error of 18% indicating that 18% of predicted poor households are in fact non-poor. This is further corroborated by an equally low exclusion error of 17% implying that only 17% of the poor are predicted as non-poor. Hence, the model can predict with surprising accuracy whether households are poor.[7]

The variables for model (1) were selected using the welfare aggregate after subtracting UNHCR assistance. This model achieves an R^2 of 0.592. Applying the same model to the welfare aggregate including UNHCR cash assistance obtains an even higher R^2 of 0.605. Using the income welfare aggregate, the R2 is substantially lowers at 0.404 while the number of observations is reduced from around 14,000 to around 7,000 due to the high frequency of zero entries for income. This is a strong indication that the welfare aggregates based on expenditure more systematically capture welfare.[8] The results are mirrored if applying the model to a poverty indicator based on the different welfare aggregates (Table 2).[9]

The most important explanatory variable for welfare is the number of individuals in the case as well as the proportion of children. Households with higher number of individuals or children have lower welfare. Living conditions like having a concrete house, improved sanitation and ventilation are related to wealthier households. Less wealthy households often do not pay rent (free housing) or share the costs with a host family while wealthier households more often live together with a host family. Interestingly, a higher proportion of children in school age are related to wealthier households while the proportion of children in school is associated with less wealthy households.

Note that the coefficients in the table measure the elasticity of welfare (income or expenditure) with respect to changes in the listed variables. For example, -0.191 means that for each additional case member, the welfare of the case per capita is reduced by 19.1%. The sign depends on how households share costs. For example, if most of expenditure is rent as in our data, the larger the household the lower is rent per capita. We consider this result as lower welfare. That is because, expenditure per case being equal, we assume that a person living alone and spending 100 JD in rent has double utility (welfare) of two persons living together and paying 100 JD.

[5] The classification for poor / non-poor was conducted by predicting the welfare aggregate based on the model variables and subsequently applying the poverty line.
[6] Note that ‘poor’ indicates poverty based on the poverty line used by the UNHCR but is assessed for refugees before receiving any known assistance from organizations like UNHCR or WFP.
[7] Proxy Mean Tests to predict welfare based on proxy variables often have inclusion and exclusion errors around 40%; see AusAID 2011.
[8] Selecting variables using the income welfare aggregate does not improve the R^2 considerably.
[9] Note that the direction of the coefficients is inverted as the poverty indicator is 1 if the household is poor and 0 otherwise.

Table 2: Welfare Model (1) including HV and PG variables

	Ln of Expenditure per Capita		Ln of Expenditure per capita net of UNHCR assistance		Ln of Income per capita	
	coef	**t**	**Coef**	**t**	**coef**	**t**
Individuals in case (HV)	-0.191***	-85.361	-0.212***	-69.811	-0.149***	-45.036
Proportion of children	-0.452***	-25.326	-0.611***	-25.245	-0.563***	-17.581
Concrete House	0.249***	13.940	0.195***	8.017	0.087***	2.796
Santitation average or above	0.100***	9.011	0.109***	7.244	0.091***	5.321
Ventilation average or above	0.064***	5.327	0.100***	6.194	0.050***	2.675
Free Housing	-0.681***	-32.000	-0.705***	-24.419	-0.134***	-3.352
Proportion school-aged children	0.146***	15.688	0.113***	8.919	0.016	0.862
Proportion of children in school	-0.033***	-3.253	-0.207***	-15.267	-0.068***	-4.560
Sharing costs with host family	-0.063***	-5.987	-0.095***	-6.628	-0.055***	-3.153
Living together with host family	0.085***	9.088	0.114***	8.987	0.087***	5.635
IsCertificateValid	-0.007	-0.754	0.124***	9.190	0.044***	3.091
_cons	4.796***	224.612	4.715***	162.779	4.315***	115.328
Number of observations	14,150		14,150		7,244	
R2	0.605		0.555		0.404	
Adjusted/Pseudo R2	0.605		0.554		0.403	

Source: Home Visits data. Note: The model excludes endogenous variable for monthly financial cash assistance from UNHCR. *, ** and *** indicate significance levels at 10%, 5% and 1%.

These findings suggest that the selected variables are associated with welfare. Hence, poor and non-poor households should differ significantly in the corresponding variables. Testing for differences in means shows that indeed all selected variables sharply distinguish between poor and non-poor households (

Table 3). The average number of individuals per household is 3.1 for non-poor households compared to 5.9 individuals in poor households. The proportion of children is almost twice as high with 63% for poor households than for non-poor households. The fact that most households (89% for poor and 98% for non-poor) live in concrete houses is due to the fact that HV were exclusively conducted outside camps.

Table 3: Difference in means for model (1) variables, by poor and non-poor households.

Description	Non-poor	Poor	p-value
Individuals in case (HV)	3.1	5.9	<0.01
Proportion of children	39%	63%	<0.01
Concrete House	96%	89%	<0.01
Sanitation average or above	78%	65%	<0.01
Ventilation average or above	83%	73%	<0.01
Free Housing	2%	8%	<0.01
Proportion school-aged children	28%	38%	<0.01
Proportion of children in school	30%	54%	<0.01
UNHCR Monthly Financial Assistance	24%	36%	<0.01
Sharing costs with host family	24%	15%	<0.01
Living together with host family	35%	22%	<0.01
Valid work/residence certificate	82%	80%	<0.01

Source: Home Visits Data

Welfare Model (2) based on PG variables only

Model (2) was constructed in a similar fashion to model (1) but the set of independent variables was constrained to PG variables. This allows using this model to predict welfare for all PG households;[10] but one would expect a smaller explanatory power given the lower number of available variables. This is confirmed with a R^2 of 0.52 based on only five independent variables (Table 4).[11] Testing the validity of the model on the set of households with HV data reveals an inclusion error of 20% and an exclusion error of 17%. Thus, the model is still a surprisingly good predictor of poverty.

Similar to model (1), the number of individuals in the household (case) and the proportion of children are important predictors for welfare in model (2). A higher number of individuals or children are associated with lower welfare. Interestingly, female headed households (principal applicant is female) are associated with higher welfare. The same holds for households where the household head has a higher occupation or higher education sophisticated. As for model (1), applying model (2) to the income welfare aggregate obtains a considerably lower R^2, which does not improve by selecting additional variables. In addition, some of the coefficients even point to the opposite direction than for the two expenditure aggregates. While this is generally worrying, it is likely that consistent under-reporting of income dilutes and changes the characteristics of 'poor' households.

Table 4: Model (2) only including PG variables

	Ln of Expenditure per Capita		**Ln of Expenditure per capita net of UNHCR assistance**		**Ln of Income per capita**	
	coef	**t**	**coef**	**t**	**coef**	**t**
Case Size from ProGres	-0.192***	-71.416	-0.208***	-59.520	-0.164***	-42.507
Female Principal Applicant	0.085***	9.101	0.141***	11.527	-0.104***	-6.888
Proportion of children	-0.424***	-21.099	-0.720***	-27.452	-0.465***	-13.333
Higher Occupation of PA	0.022***	7.420	-0.048***	-12.599	-0.028***	-6.113
Highest Education of PA	0.043***	11.479	0.070***	14.516	0.032***	5.467
_cons	4.971***	363.268	4.971***	278.698	4.530***	194.903
Number of observations	15,342		15,342		7,864	
R2	0.517		0.498		0.380	
Adjusted/Pseudo R2	0.516		0.498		0.379	

Source: Home Visits Data. Note: *, ** and *** indicates significance levels at 10%, 5% and 1%.

The selected PG variables distinguish between the poor and non-poor (Table 5). The average household (case) size for poor households is 5.8 compared to 3.1 for non-poor households. More than 1 in 3 non-poor households are headed by a woman while this is true for only 1 in 4 poor households. Usually female-headed households suffer from lower rather than higher welfare. This result might indicate that aid programs successfully and preferentially target female-headed households over-compensating for their monetary disadvantage.[12] Poor and non-poor households also differ significantly in terms of education and occupation of the household head (principal applicant). Both are measured on a scale with higher values indicating higher occupation (managerial vs. unskilled, e.g.) and higher education.

[10] The model selection retrieves a coefficient for all selected variables. The coefficient indicates the direction and size of influence of the selected variable on welfare. The complete relationship is described by all coefficients together. Thus, the variables from households without welfare aggregates can be used to sum up the coefficients resulting in a predicted welfare aggregate for this household.

[11] The model is also applied to poverty indicators in **Error! Reference source not found.**.

[12] While the welfare indicators are constructed by subtracting known assistance, it is unlikely that all assistance including in-kind assistance is covered. Therefore, the welfare aggregates are likely to reflect some aid contributions.

Table 5: Difference in means for model (2) variables, by poor and non-poor households.

Description	Non-poor	Poor	p-value
Case Size from ProGres	3.1	5.8	<0.01
Female Principal Applicant	36%	25%	<0.01
Proportion of children	39%	63%	<0.01
Broad Occupation of PA	1.47	1.65	<0.01
Highest Education of PA	2.48	2.35	<0.01

Source: Home Visits Data.

Indexes performance

One of the frequently debated questions in Jordan is the use of composite indexes for the assessment of welfare and vulnerability of refugees. As a by-product of this work, we followed a similar approach to the welfare model to test the capacity of various composite indexes to capture welfare. It should be clarified that not all indexes are designed to capture welfare or welfare vulnerability. One may want to design indexes to capture sanitation, health or disability that may or may not be related to monetary welfare. Therefore, testing indexes in their capacity to capture monetary welfare is not a test of these same indexes in terms of other specific needs that refugees may have such as mental of physical disability.

As for the welfare model, we first constructed in binary form (0/1) all variables that we wanted to use to construct composite indexes. As a first test, we run these binary indicators in a welfare regression one at the time where the dependent variable is expenditure net of UNHCR cash assistance (natural log). We then listed these variables in order of R squared, a measure of the explanatory capacity of the individual variables' models to explain welfare. The full results are shown in Table A1 in Annex while the table below reports the top ten variables in terms of R squared. The top variable is rent which alone explains 1.74% of the variation in welfare. This is followed by the presence of a latrine and by the interviewer's judgment about good living conditions of the case. As it can be seen, taken alone, these binary indicators explain a small percentage of welfare.

Table 6 – Top binary indicators in terms of capacity to predict welfare (R2)

Variable	Obs	Mean	Std. Dev.	Min	Max	R2	%
i_rent	15975	0.91518	0.278622	0	1	0.017427	1.742672
i_latrine	15975	0.773083	0.418852	0	1	0.014387	1.438695
i_good_liv~d	15975	0.476557	0.499466	0	1	0.013578	1.357762
i_housecon~n	15975	0.86723	0.339337	0	1	0.007125	0.712506
i_pipewater	15975	0.878685	0.326503	0	1	0.007003	0.700316
i_good_san~y	15975	0.138717	0.345662	0	1	0.006762	0.676154
i_good_ven~n	15975	0.28626	0.452026	0	1	0.006047	0.604679
i_waste	15975	0.746792	0.434863	0	1	0.005852	0.585157
i_water	15975	0.797684	0.401739	0	1	0.005125	0.512468
i_good_ele~y	15975	0.281189	0.449594	0	1	0.005017	0.501678

Next, we simply aggregated these indicators by group in an effort to capture different aspects of wellbeing. In this exercise, we attempted to create composite indicators that are used or at least considered by humanitarian organizations for different purposes. The list of composite indexes and their construction is the following:

- ind_house_crowd= number of case members/number of rooms
- ind_house_crowd1= number of household members/number of rooms
- ind_wash_water=wash_source + wash_available + wash_waste + wash_latrine
- ind_nfi=counts the number of aid donors the case benefits from
- ind_house_subjective=good house quality + good living conditions
- ind_house_assets=house_heating+house_ventilation+house_electricity+house_kitchen+house_sanitary
- ind_cope_index=sums number of items from a list of coping actions taken by households
- ind_wash_hygiene=sums toiletry items
- ind_cope_wfp=WFP cope index
- ind_food_wfp=WFP Food Consumption Score (FCS)
- ind_house_quality=house kind + house condition
- ind_food_score=sums the number of food items consumed
- ind_food_variety=counts the variety of food items consumed

The indicators selected were then regressed on our welfare indicator one by one as we did for the binary indicators. The table below reports the main statistics of each indicator and the R squared of the univariate regression of the indicator against the welfare aggregate. Results show that the house crowd indicators are the most powerful in explaining welfare. In particular, the first indicator using the size of the case divided by the number of rooms in the household explains alone 26.7% of the variation in welfare. Interestingly, the second indicator in order of importance is house_crowd1 which uses the size of the household in place of the size of the case. The explanatory power of this second indicator is less than one tenth of the first (2.2%). All the other indicators follow with a much lower explanatory power.

What should be noted in the table below is that, if we exclude the first composite indicator, all the other indicators have not much more explanatory power in terms of welfare than their single components. This is an important finding to keep in mind for analysts engaged in the construction of composite indicators. The sum of the R squared of the binary components of the composite indicators is not equivalent to the R squared of the composite indicator. That is because there are statistical associations between the components of the composite indicators that can work in opposite directions and can reduce the capacity of a composite indicator to explain welfare vis-à-vis its components.

Table 7 – Statistics and R squared of composite indicators

Variable	Obs	Mean	Std. Dev.	Min	Max	R2
ind_house_crowd	15975	1.781887	1.364509	0	16	0.267
ind_house_crowd1	15975	2.551506	1.697571	0	58	0.022
ind_wash_water	15975	3.196244	1.168634	0	4	0.014
ind_nfi	15975	0.16169	0.381374	0	7	0.011
ind_house_subjective	15975	1.736588	1.619757	0	6	0.009
ind_house_assets	15975	8.3682	3.006631	0	13	0.008
ind_cope_index	15975	2.448013	1.727429	0	5	0.007
ind_wash_hygiene	15975	4.192363	1.150333	0	5	0.007
ind_cope_wfp	15975	1.665477	1.481963	0	8	0.006
ind_food_wfp	15975	42.55236	16.63382	0	112	0.003
ind_house_quality	15975	1.685383	0.57311	0	2	0.003

ind_food_score	15975	22.13459	8.49884	0	56	0.002
ind_food_variety	15975	7.101659	1.576538	0	8	0.001

These same composite indicators were used in Model (1) in place of the variables that compose the indicators. None of the composite indicators was retained for the final welfare model as the additional explanatory power of these indicators were found to be inferior to their components.

Targeting tests

The UNHCR in Jordan provides cash assistance to selected households using welfare and vulnerability criteria for eligibility. Cash assistance is provided to cases that are found below a poverty line of 50 JD per person per month and that meet at least one of 11 vulnerability criteria. Targeting also includes a list of exclusion criteria that can "switch off" each of the inclusion vulnerability criteria. The inclusion and exclusion criteria are listed in UNHCR (2013).[13]

Using both welfare and vulnerability criteria for targeting cash assistance is justified from a UNHCR perspective from the very nature of the refugees' population. Displacement due to armed conflict affects all parts of society, but often has a greater impact upon vulnerable groups of people and their equitable access to assistance and protection, both in terms of immediate effects and upon their ability to cope and remain resilient over the longer term. Individuals or groups can be vulnerable due to their age, gender, religion, ethnicity, their social, family or legal status, their marginalization from society, or from disabilities. Due to their difficulties in accessing protection and assistance (including income generating activities), vulnerable refugees are more likely to revert to negative or harmful coping strategies such as removing children from school, engaging in child labour, selling off family assets, working in dangerous conditions, survival sex and other harmful practices, such as early marriage. One of the primary purposes of humanitarian assistance should therefore be to prevent vulnerable refugees from engaging in negative coping mechanisms. This justifies prioritizing categories of vulnerable refugees when it comes to targeting cash assistance.

As a first test, we reproduced the UNHCR's decision for assistance from the data, which is based on income rather expenditure. Using HV data, we were able to reproduce the UNHCR decision for cash assistance rather accurately, despite the fact that not all inclusion and exclusion variables are present in the HV data. The table below shows our estimation of those who should receive cash assistance according to our simulation of the UNHCR criteria against the actual decision taken by the UNHCR. It can be seen that in only about five percent of cases we are not able to reproduce the UNHCR decision, which may be explained by the fact that not all inclusion and exclusion indicators were available. This also implies that the UNHCR applies its cash decision rules rather accurately.

Table 9 – Reproduction of UNHCR cash assistance decision based on HV income data

	Simulated Decision (Income)		
UNHCR decision (income)	No	Yes	Total
No	64.8	1.0	65.8
Yes	4.7	29.5	34.2

[13] UNHCR Cash Assistance Standard Operating Procedures (2013)

Total	69.5	30.5	100.0

Source: Home Visits Data

Next we tested how income and expenditure compare for targeting. As a measure of welfare, the UNHCR uses the income instead of expenditure, which is a shortcoming in the light of the analysis presented above. It is therefore instructive to test how the targeting capacity of the UNHCR would change if expenditure instead of income would be used. As a first observation, selecting the poor using income or expenditure results in a very different welfare assessment. The table below crosses the poor and non-poor using income or expenditure criteria and it shows that the income criteria finds 37.1 percent of cases (5,927 cases) of poor cases that result as non-poor according to expenditure criteria. There are also 4.6 percent of cases (736 cases) that are poor according to expenditure but not to income. Therefore, income and expenditure provide two very different snapshots of who is poor.

Table 8 – Poor according to income and expenditure criteria

	Income		
Expenditure	Non poor	Poor	Total
Non poor	8.5	37.2	45.6
Poor	4.6	49.8	54.4
Total	13.1	86.9	100.0

Source: Home Visits Data.

If we test further the cash assistance decision against the targeting that would have resulted if our expenditure welfare aggregate was used in place of income, we find that those who should be targeted and that are not targeted are a very small share (0.65%), slightly smaller than those excluded using income. Instead, we find that the cash assistance decision has included about 10 percent more cases than it should have included if expenditure instead of income was used as welfare criteria. This can be explained by the fact that - income being lower than expenditure on average - targeting based on income is more "inclusive" than targeting based on expenditure. Therefore, while expenditure is a better measure of welfare for welfare modelling and for targeting purposes, it can result in a higher percentage of cases excluded because of non-eligibility. In other words, the fact that expenditure is higher than income on average reduces the number of eligible cases. The expenditure measure remains a better measure of welfare than income and, for this reason, is more likely to exclude non-eligible cases.

Table 10 – Reproduction of UNHCR cash assistance decision based on HV expenditure data

	Simulated Decision (Expenditure)		
UNHCR decision (Income)	No	Yes	Total
No	65.1	0.6	65.8
Yes	13.6	20.6	34.2
Total	78.7	21.3	100.0

We now measure the coverage and leakage rates of the UNHCR cash assistance decision based on income and expenditure criteria. The coverage rate is defined as the percentage of poor cases that are targeted. The leakage rate is defined as the percentage of the non-poor cases that are targeted. Of course, one should consider that these rates take into account two factors. One is the “error” made by using income instead of expenditure. This can be assessed by comparing coverage and leakage rates between income and expenditure criteria. And the second is the “error” made due to the fact that vulnerability inclusion and exclusion criteria are used in addition to poverty criteria. This can be checked by looking at the coverage and leakage criteria of the income decision if true welfare is income in the table below.

Technically, none of these are “errors”. These simply reflect decisions taken by the UNHCR in the targeting methodology. If the UNHCR wished to change the methodology and use only poverty criteria and expenditure in place of income, then these errors would be largely reduced. As it can be seen from the table below, if expenditure is the real measure of household welfare but income is used for targeting, then the leakage rate would be quite high while coverage would be around 42%. If, vice-versa, income was the real measure of welfare and also the measure used for targeting, then leakage would be much lower and coverage marginally lower. However, this paper has shown that expenditure as we constructed is the best option to measure welfare with available data. This means that, as it stands, the UNHCR decision based on income leads to a rather large leakage. If the UNHCR shifted to expenditure for the purpose of targeting, this would make some savings that could be used to expand coverage of beneficiaries.

Table 11- Coverage and Leakage of UNHCR cash decisions according to Income and Expenditure Criteria

	Coverage	Leakage
Income Decision if true welfare is income	38.2	3.1
Income Decision If true welfare is expenditure	42.1	33.2

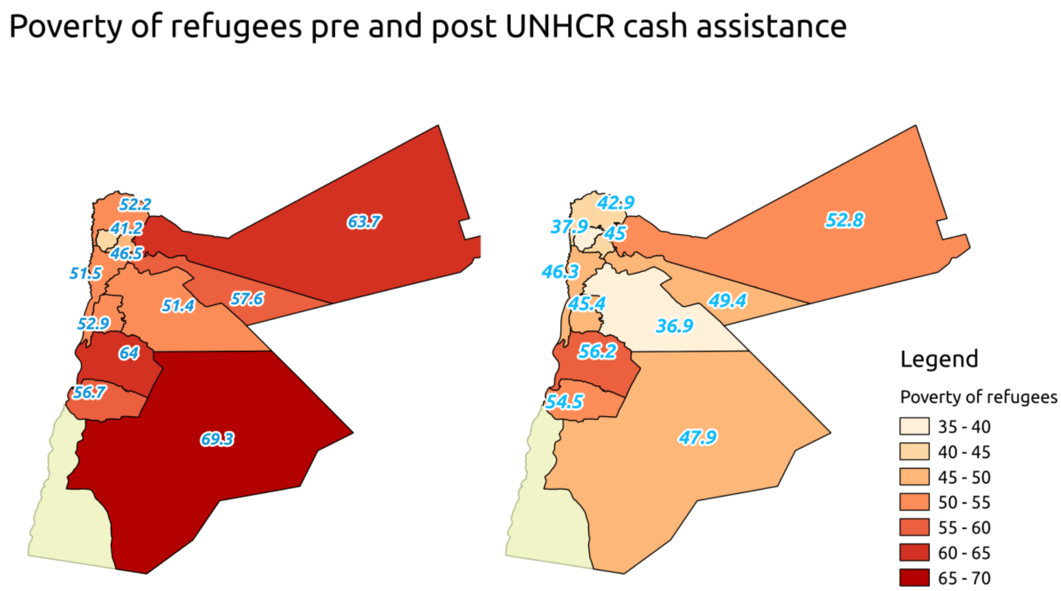
Source: Home Visits Data

Finally, we can measure the impact of UNHCR cash assistance and also WFP food voucher on poverty. This is reported in the Table below where we can see that the pre-transfer poverty rate of 54.4 is reduced to 44 percent with UNHCR cash transfer alone, to 23.9 percent with WFP food voucher alone, and to 8 percent with both UNHCR cash assistance and WFP food voucher. Considering that this last table does not include other forms of assistance that refugees may receive from other organizations, we can conclude that aid to refugees is able to eliminate poverty altogether if we consider as poor cases with expenditure per capita inferior to 50 JD per person per month. The figure below illustrates the poverty reduction capacity of the UNHCR cash assistance program at the governorate level. As it can be seen, the program is effective in reducing poverty of the refugees in all governorates of Jordan.

Table 12 – Poverty Rates Pre and Post UNHCR and WFP Transfers

	%
Pre-transfers	54.4
With HCR cash assistance	44.0
With WFP food voucher	23.9
With HCR cash and WFP voucher	8.0

Source: Home Visits Data



Conclusions

The analysis revealed that the welfare aggregates based on expenditure are better suited to predict poverty than the welfare aggregates based on income. Consistently, the models have higher predictive power if applied to the expenditure aggregates. Possibly, expenditure is more accurately reported as it requires more sophistication to leave out specific items; while households might under-report income by concealing specific income sources completely. Thus, welfare modelling and decision making should be based on expenditures rather than income. This is also consistent with the welfare approach followed in low income countries where consumption or expenditure are typically taken as a proxy of income given that income is under reported and also a more volatile measure than expenditure.

The best welfare model that the paper could find explains just below 60 percent of the variation in welfare (expenditure) with just 11 variables. This particular combination of 11 variables has a better explanatory power than using all the 185 variables available in the HV and PG data combined. Reducing further the model to those of the 11 variables that are present in both HV and PG data, it reduces the number of variables to five. However, these five variables alone still explain almost 52 percent of the variation in welfare. The additional six variables present in HV data but not in PG could be included into the PG database to improve on the welfare prediction capacity of the database.

It is the quality of variables that one seeks in welfare modelling rather than the quantity. This was one lesson learned from the analysis of composite indexes. With no prior knowledge of the correlation structure of the individual components, composite indexes may have an explanatory capacity in terms of welfare inferior to that of their single components. Therefore, the construction of composite indexes designed to measure welfare can be improved by the use of welfare modelling as shown by this paper.

While the paper uses a poverty line of 50 JD per capita, it is important to note that the welfare aggregate among refugees cannot be compared directly to welfare aggregates of the Jordan population measured. The disaggregated items of the welfare measure used in this paper are still considerably more aggregated than in standard living standard surveys. Literature suggests that reporting aggregated items instead of disaggregated items can reduce measured welfare by more than 30% (Beegle et al, 2012). Therefore, it is likely that the welfare of the refugees is under-estimated while poverty is over-estimated using the same 50 JD per capita threshold.

The paper has also shown that UNHCR applies its targeting rules accurately and that cash assistance is a powerful tool to reduce poverty. This assistance reduces poverty very significantly. This tool can also be further improved in terms of leakage (the share of non-poor individuals who receive cash assistance) if targeting was based on expenditure rather than income.

References

AusAID (2011) Targeting the Poorest: An assessment of the proxy means test methodology, 2011.

Beegle, K.; De Weerdt, J.; Friedman, J. and Gibson, J. (2012) Methods of household consumption measurement through surveys: Experimental results from Tanzania. Journal of Development Economics 98 (2012) 3 – 18.

UNHCR (2014) Chapter 3 Criteria for Monthly Financial Assistance, mimeo

UNHCR (2014a) Syrian Refugees Living Outside Camps in Jordan. Home Visits Data Findings, 2013

Table A1 – Summary Statistics for indicators used for composite indicators

Variable	Obs	Mean	Std. Dev.	Min	Max	R2	%
i_rent	15975	0.91518	0.278622	0	1	0.017427	1.742672
i_latrine	15975	0.773083	0.418852	0	1	0.014387	1.438695
i_good_liv~d	15975	0.476557	0.499466	0	1	0.013578	1.357762
i_housecon~n	15975	0.86723	0.339337	0	1	0.007125	0.712506
i_pipewater	15975	0.878685	0.326503	0	1	0.007003	0.700316
i_good_san~y	15975	0.138717	0.345662	0	1	0.006762	0.676154
i_good_ven~n	15975	0.28626	0.452026	0	1	0.006047	0.604679
i_waste	15975	0.746792	0.434863	0	1	0.005852	0.585157
i_water	15975	0.797684	0.401739	0	1	0.005125	0.512468
i_good_ele~y	15975	0.281189	0.449594	0	1	0.005017	0.501678
i_good_fur~e	15975	0.035618	0.185342	0	1	0.004297	0.429655
i_storage	15975	0.744413	0.436204	0	1	0.003275	0.32748
i_liquid	15975	0.153427	0.36041	0	1	0.002135	0.213523
i_shampoo	15975	0.770642	0.420433	0	1	0.001556	0.155561
i_basin	15975	0.51687	0.499731	0	1	0.001371	0.137066
i_car	15975	0.006135	0.078085	0	1	0.00125	0.125025
i_tpaste	15975	0.512426	0.499861	0	1	0.001128	0.112812
i_cream	15975	0.375587	0.484289	0	1	0.000689	0.06892
i_diaper	15975	0.062973	0.242923	0	1	0.00065	0.06495
i_good_kit~n	15975	0.518247	0.499683	0	1	0.000448	0.044821
i_razor	15975	0.317434	0.465492	0	1	0.000415	0.041542
i_soap	15975	0.904664	0.293688	0	1	0.000137	0.01374
i_bin	15975	0.329891	0.470188	0	1	0.000136	0.013615
i_housekind	15975	0.818153	0.38573	0	1	8.87E-05	0.008868
i_powder	15975	0.04964	0.217207	0	1	1.42E-05	0.00142
i_tbrush	15975	0.165008	0.371199	0	1	6.19E-06	0.000619
i_heating	15975	0.327887	0.469458	0	1	1.20E-06	0.00012
i_napkin	15975	0.033803	0.180727	0	1	8.64E-07	8.64E-05

Table A2: Model (1) including HV and PG variables to explain poverty. *, ** and * indicate significance levels at 10%, 5% and 1%.**

	poor_Wexp		poor_Wexp_unhcr		poor_Winc	
	coef	t	Coef	t	coef	t
Individuals in case (HV)	0.493***	49.418	0.451***	46.109	0.174***	18.211
Proportion of children	0.412***	5.746	0.705***	10.732	-0.226***	-3.706
Concrete House	-0.652***	-10.279	-0.480***	-7.354	0.004	0.057
Sanitation average or above	-0.287***	-7.686	-0.241***	-6.237	-0.146***	-3.511
Ventilation average or above	-0.135***	-3.330	-0.112***	-2.659	-0.099**	-2.172
Free Housing	1.255***	16.724	1.132***	14.605	0.156*	1.888
Proportion school-aged children	-0.251***	-4.597	-0.021	-0.492	-0.006	-0.197
Proportion of children in school	0.017	0.494	0.258***	7.779	-0.123***	-3.299
Sharing costs with host family	-0.121***	-3.714	-0.152***	-4.699	-0.108***	-3.337
Living together with host family	0.064*	1.960	-0.247***	-7.297	0.096***	2.721
IsCertificateValid	-1.667***	-22.148	-1.348***	-17.668	0.738***	9.251
_cons	0.493***	49.418	0.451***	46.109	0.174***	18.211
Number of observations	14,150		14,150		14,150	
R2						
Adjusted/Pseudo R2	0.369		0.394		0.053	

Table A3: Model (2) only including PG variables to explain poverty. *, ** and * indicates significance levels at 10%, 5% and 1%.**

	Wexp_lncap		Wexp_unhcr_lncap		Winc_lncap	
	coef	t	coef	t	coef	t
Case Size from ProGres	0.453***	49.103	0.431***	46.460	0.219***	23.162
Female Principal Applicant	-0.031	-1.110	-0.116***	-4.054	0.449***	14.037
Proportion of children	0.255***	3.888	0.759***	12.272	-0.537***	-8.766
Higher Occupation of PA	-0.072***	-8.172	0.073***	8.339	-0.046***	-4.765
Highest Education of PA	-0.107***	-9.425	-0.144***	-12.497	-0.004	-0.315
_cons	-1.902***	-43.435	-1.792***	-40.819	0.469***	10.704
Number of observations	15,342		15,342		15,342	
R2						
Adjusted/Pseudo R2	0.317		0.359		0.063	

Annex 1 – UNHCR Definitions of Case, Family and Household

Case

A case is a processing unit, similar to a nuclear family headed by a Principal Applicant (Principal Representative). It comprises (biological and non-biological sons and daughters up to the age 18 (or 21) years, but also includes first degree family members emotionally and/or economically dependent and for whom a living on their own and whose ability to function independently in society/in the community and/or to pursue an occupation is not granted, and/or who require assistance from a caregiver.

Household

A group of persons (one or more) living together who pool their resources, make common provisions for food or other essentials for living/ surviving and where the members are dependent on each other and all trying to meet their combined set of needs..

Family

Members of a household who are related to a specific degree through blood, adoption or marriage. The degree of relationship used in determining the limits of the family is dependent on the uses (common in the area of intervention and/or UNHCR) and cannot be defined on a worldwide basis.