Is Imputing Poverty Efficient? An example from refugee data in Chad

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Abstract

Collecting household survey data on refugees remains a challenge, at least in the foreseeable future, for various logistical and technical reasons. We address this challenge by applying cross-survey imputation methods to a combined survey and UNHCR census-type dataset to predict the welfare of refugees in Chad. Our proposed cross-survey imputation method offers poverty estimates that fall within a 95% margin of the true rate. This result is robust to different poverty lines, sets of regressors, and modelling assumptions of the error term. The method also outperforms widely used methods such as Proxy Means Tests (PMT) and the targeting method currently used by humanitarian organizations in Chad, although the latter performs surprisingly well given its simplicity.

JEL classifications: C15, F22, I32, O15, O20.

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I. Introduction

The UN General Assembly Sustainable Development Goal 1 – *End poverty in all its forms* – by 2030 explicitly pledges that 'no one will be left behind'. To achieve this goal, the availability of high-quality household consumption surveys is essential, and it is equally important for these surveys to be inclusive and cover marginal populations such as refugees. Unfortunately, there are a number of reasons that high quality consumption surveys for forcibly displaced people will remain in limited supply in the foreseeable future. Household consumption surveys are costly and time-consuming to implement for most developing countries, even for the regular population. As such, these surveys rarely include forcibly displaced populations such as refugees or Internally Displaced Persons (IDPs). It is perhaps a paradox that while forcibly displaced persons form the most vulnerable population group (i.e., they lack fundamental rights such as freedom of movement and right to work, have eroded human and physical capital and can face more frequent shocks than surrounding host communities), we typically have much less welfare data for this group.

This is a significant and growing challenge, particularly in Sub-Saharan Africa. During the last decade, the number of forcibly displaced persons grew from 43.3 million in 2009 to 70.8 million in 2018. Among them, 25.9 million are refugees, 3.5 million asylum seekers, and 40.3 million Internally Displaced Persons (IDPs). Almost 4 out of 5 refugees live in a country neighboring their home country and some 84% of them live in developing countries. Sub-Saharan Africa hosts around one-third of the world's refugee population and has witnessed an annual increase of 1.1 million refugees in 2017, which represents a 22% increase from 2016. In 2018, Sub-Saharan countries represented half of the ten countries with the highest refugee population relative to the national population and six of the ten countries with the highest numbers of IDPs. This is also the region with the highest poverty rates in the world and where data are typically scarce or of low quality. Measuring poverty for displaced populations in Sub-Saharan Africa is, therefore, a particularly important task that is severely hampered by missing household consumption data.

Missing data is not, of course, a problem limited to displaced populations. There is an established literature in statistics that have developed numerous methods to impute for the missing data (see, e.g., Little and Rubin (2002)). Similarly in economics, survey-to-survey imputation methods have been widely employed to estimate household welfare trends across time periods (see, e.g., Dang and Lanjouw (2018) for cross-survey imputation between the same survey administered in different years), geographical areas (see, e.g., Elbers et al. (2003) for cross-survey imputation between survey and census data, commonly known as poverty mapping), or types of surveys (see, e.g., Douidich et al. (2016) cross-survey imputations across different types of surveys administered in the same year). Newhouse et al. (2014) and Dang, Jolliffe, and Carletto (2019) offer recent summaries of previous imputation studies that highlight the main advantages, debate different approaches, and provide useful insights about practices of welfare imputation. Recent evidence suggests that imputation is quite promising for measuring welfare among the Syrian refugees in Jordan (Dang and Verme, 2019).

This paper is among the first to provide an application of cross-survey imputation methods to the context of refugees using survey and administrative data from Chad.[2] We build a prediction model based on survey data conducted in refugee camps, and subsequently apply it to the United Nations High Commissioner for Refugees (UNHCR) global registration system data (proGres) to estimate poverty for refugees. We investigate how the set of variables available in the registration data can predict the welfare status of households. We also evaluate the current methodology for targeting cash-based assistance programs employed by the UNHCR, the World Food Programme (WFP) and the National Commission on the Welcoming and Resettlement of Refugees and Returnees (CNARR) of the Government of Chad (hereafter the UNHCR/WFP/CNARR targeting strategy) put in place in 2015.

Estimation results indicate that the limited set of variables available in the UNHCR registration data predict household welfare reasonably well (consumption in this case). Estimates from the three sets of data available for the analysis produce similar welfare figures.[3] While the current

[2] To our knowledge, the only exception is the paper by Dang and Verme (2019). But we make several new contributions in this paper that distinguish itself from that paper. These include analysis of richer datasets (i.e., the household consumption survey, the targeting survey, and the UNHCR registration data) and more detailed comparison of various targeting methods. Furthermore, we study Chad, a much poorer host country (than Jordan) in a different region.

[3] The welfare figures used in this paper are not official and are not representative of the entire population of refugees in Chad. That is because the subsample of refugees covered by the three sets of data used by the paper excludes some of the refugees and because all data sets have been collected by humanitarian organizations working with refugees rather than the national statistical agency. However, the national statistical office of Chad, in collaboration with the World Bank and the UNHCR, will be conducting a nationally representative household survey that will include

targeting strategy in Chad used jointly by CNARR, UNHCR, and WFP is accurate in predicting welfare, our results suggest that this targeting strategy could be further improved by reducing both the inclusion and exclusion errors. If these encouraging results are replicated in other contexts, poverty predictions for refugees can be expanded at scale with good prospects for the improvement of targeted programs.

The paper is organized as follows. Section II outlines the country context. Section III presents the data and the analytical framework. The estimation results are presented in section IV whereas section V evaluates the current UNHCR/WFP/CNARR targeting strategy and simulates poverty-alleviation policies. Section VI discusses the limitations of the study, and Section VII concludes.

II. Country Context

Chad is one of the poorest countries in the world. According to the latest national consumption survey administered in 2011, 29% of the population falls below the food poverty line and 47% falls below the national poverty line (World Bank, 2018). The last decade has also been a decade of instability for Chad with negative consequences on household well-being. Per capita GDP decreased by 15% between 2015 and 2017- from an average of US$963 in 2015 (PPP 2010) to US$823 (PPP 2010) in 2017. In terms of overall development, Chad is ranked 187 out of 189 countries on the Human Development Index (World Bank, 2019). Due to these challenges, Chad struggled to meet numerous of the Millennium Development Goals in 2015, and barring an unforeseen economic growth, or great increases in ODA, the country will likely not meet many of the SDG objectives set for 2030.

Despite the current negative economic downturn, Chad continues to host a high number of refugees and is among those countries that top the world's list in this respect (Table A1). Chad is the tenth largest host country of refugees in the world and the fifth largest host in the Africa region after Ethiopia, Kenya, Uganda and the Demographic Republic of Congo, and the refugee population

refugee populations. Results are expected to be ready by the end of 2020 and should provide further insights into the methodology proposed in this paper.

represents a significant portion of the national population - about 3%. The number of forcibly displaced persons increased from 474,478 in 2015 to 667,586 as of March 2019, of which about 69% were refugees or asylum seekers.[4] Of the 459,809 current refugees and asylum seekers, the majority are Sudanese refugees (74%) living in the Eastern part of Chad and 21% are Central African Republic Refugees living in Southern Chad, with a much smaller number of Nigerian refugee (about 2%) living in the Lake Chad Basin. The situation is further complicated by a large population of Internally Displaced Persons in the Lake Chad region estimated at 165,313 at end of 2018 (UNHCR, 2018). Figure 3 provides a map of the refugee camps in Chad.

III. Methodology and Data

Methodology

The methodology used in this paper relies on the cross-survey imputation framework first introduced by Elbers et al. (2003).[5] Most recently, Dang et al. (2017) built on this literature to propose a model that imposes fewer restrictive assumptions and offers an explicit formula for estimating the poverty rate and its variance. Three advantages of the modifications introduced by Dang et al. (2017) are: a) the variance formula, which is simple and in line with the recent statistical literature; b) it can accommodate complex design sampling, and c) the framework remains applicable to two surveys with different designs. Finally, the approach allows for different modelling methods including the standard linear regression model, its variant with a flexible specification of the empirical distribution of error terms, a Logit Model and/or a Probit Model.

Let x_j be a vector of characteristics that are commonly observed between the two surveys, where j indicates survey type with 1 the base survey and 2 the target survey. Let us assume the welfare indicator is a function of household and individual characteristics (x_j):

$$y_j = \beta_j x_j + \mu_{cj} + \varepsilon_j$$

[4] UNHCR uses the term people of concern to describe those forcibly uprooted from their home including asylum-seekers, refugees, stateless persons, the internally displaced and returnees.

[5] See also Tarozzi (2007) and Mathiassen (2009) for further improvements and adaptation of this approach (e.g., by estimating the standard errors in a different way).

where y_j is the welfare indicator (consumption per capita per month), β_j a vector of parameters, μ_{cj} is a cluster random effects and ε_j is the idiosyncratic error term.

The framework proposed by Dang et al. (2017) is based on two assumptions. The first assumption (Assumption 1), which is critical for poverty imputation, states that measurement of household characteristics in each sample of data is a consistent measure of the characteristics of the whole population. In other words, it stipulates that the two surveys are representative of the same target population. In our context, the two surveys represent the same population of refugees and they were conducted approximatively at the same time. We do not expect, therefore, major issues with this first assumption. However, we will conduct means difference tests on the observed overlapping variables between the target data and base data to ensure that this is the case. The second assumption states that changes in x_j between the data collection periods of the two data sets can capture the change in welfare over the period (Assumption 2). As data collection for the two data sets we use refer to the same year, there is no need to test Assumption 2. Under these two assumptions, the imputed welfare is

$$y_2^1 = \beta_1' x_2 + \upsilon_1 + \varepsilon_1. \qquad (1)$$

Dang et al. (2017) propose different imputation methods for parameters' estimation. The first method relies on the assumption of normal distribution for the two error terms (μ_{cj} and ε_j are uncorrelated and $\mu_{cj} \,/\, x_j \sim \mathcal{N}(0, \sigma_{\mu_{cj}})$ and $\varepsilon_j \,/\, x_j \sim \mathcal{N}(0, \sigma_{\varepsilon_j})$). This method is, hereafter, referred to as Normal Linear Regression Model. An alternative method proposed is the Empirical Error Method that assumes no functional form for these error terms and uses instead the empirical distribution to estimate the parameters. Dang et al. (2017) also propose two other alternative methods - the Probit Model and the Logit Model - which are more restrictive, and model poverty status (poor and non-poor) instead of consumption expenditure.

Once the parameters are estimated, the welfare indicator, which is the household consumption per capita is obtained as follows:

$$\hat{y}_{2,s}^{1} = \hat{\beta}_1' x_2 + \tilde{\tilde{\upsilon}}_{1,s} + \tilde{\tilde{\varepsilon}}_{1,s}. \quad (2)$$

The imputed poverty rate and its variance are then estimated as:

$$\text{i) } \hat{P}_2 = \frac{1}{S}\sum_{s=1}^{S} P(\hat{y}_{2,s}^{1} \leq z_1) \quad (3)$$

$$\text{ii) } V(\hat{P}_2) = \frac{1}{S}\sum_{s=1}^{S} V(\hat{P}_{2,s}|x_2) + V\left(\frac{1}{S}\sum_{s=1}^{S} \hat{P}_{2,s}|x_2\right). \quad (4)$$

These poverty estimates are unbiased estimates of the parameters of interest (Dang et al., 2017) and outperform in terms of prediction accuracy those proposed by the Proxy Means Testing literature that typically omit the error terms $\upsilon_1 + \varepsilon_1$, leading to biased estimates of the welfare indicator.

Data

In its mandate of protection of displaced persons in host countries, the UNHCR collects data to track refugees and other populations of interest, better monitor these populations and deliver assistance and services. In the framework of this study, we use three sets of data collected by the UNHCR (Table A2). The first one is the *ProGres* dataset, which is the UNHCR's registration system covering all refugees or asylum seekers requiring assistance. The *ProGres* dataset is a live instrument continuously updated as new refugees/asylum seekers arrive or existing refugees contact the UNHCR. The data we use were extracted at the end of December 2017. This set of data contains socio-economic variables (such as household size, marital status, gender, age, country of origin, region of residence) but no consumption or expenditure data. This data set can be considered as the "census" of refugees.

The second set of data, the *Targeting* dataset, is also a census-like data set for refugees living in Chad. The main aims of this census are to fill knowledge gaps regarding refugee livelihoods, the level and the differences of vulnerability in refugee households, and to categorize refugees into wealth groups for cash, food and livelihoods assistance. In addition to categorize refugees, the *Targeting* dataset aims to identify factors that can enable self-reliance. This dataset is based on a mixed methods approach including both qualitative and quantitative methods. The first step is the use of focus groups with refugee leaders, female organizations, and youth associations in order to identify wealth characteristics and key challenges specific to age and gender. Next, a sample survey is carried out across camps to confirm wealth characteristics identified by refugees in the first step. Based on the outcomes of the first two steps, a quantitative survey designed to capture wealth characteristics is administered to all refugee households. The *Targeting* dataset includes all Sudanese, Central African and Nigerian refugees living in Chad. The data was collected between 17 June 2017 and 15 July 2017 and covers 19 refugee sites and refugees living in nine host villages**.** After the data collection, a statistical model which takes into account household welfare is used to classify households into four socioeconomic groups (*'very poor'*, *'poo*r', *'average'*, *'better off'*). In terms of variables relevant to this study, this data contains demographics variables (household size, gender, age, country of origin, region of residence), variables related to asset and animal ownership, and to coping strategies. As for the *proGres* dataset, the *targeting* dataset does not contain information on consumption or expenditure. It does, however, contain information on wealth.

The last set of data is the Post Distribution Monitoring (*PDM)* dataset, a sample survey which covers similar themes when compared to the *Targeting* dataset. This data, collected in 2017 by WFP, aims to better understand how refugees use food assistance and contains data on consumption and expenditure. The sampling design is a two-stage stratified random sample where the first stage includes the selection of camps and the second stage the selection of households. Beforehand, the different camps are stratified in three zones: (i) North East *(Ourecassoni, Amnaback, Iridimi Touloum),* (ii) Centre-East *(Goz Amir, Djabal, Gaga, Teguine, Bredjing, Farchana)* and (iii) South *(Amboko, Dossey, Gondjé, Belom, Moyo)* (Figure 3). In addition, the sampling takes into account the kind of humanitarian assistance provided to refugees (in-kind, food voucher, cash). The survey includes two consumption aggregates measuring monthly total consumption and monthly food consumption using retrospective questions with varying recall periods depending on the item considered (from 7 days to 1 year). The consumption aggregate is compiled by aggregating the different food and non-food items including expenditure on education, health, durable assets and rent. In the framework of this study, we consider two welfare indicators from the PDM dataset. The first is the household total consumption expenditure per capita per month and the second is the household food consumption per capita per month.

For poverty imputation purposes, three datasets are constructed from the above datasets (*ProGres*, *Targeting*, *PDM*). The first, which we shall refer to as "*ProGres 2*", is obtained by appending the *ProGres* data to the end of the *PDM* data. As the *ProGres* and *PDM* data share only demographic variables, *ProGres 2* contains demographic variables for all observations, although only the observations from the *PDM* data have consumption expenditure. The second set of data constructed, "*Targeting 2"*, comes as a result of appending the *Targeting* data to the end of the *PDM* data. Therefore, "*Targeting 2"* contains demographic variables, asset and animal ownership, and coping strategies variables as well as consumption data. The last set of data, "*ProGres Targeting*", is obtained by first merging the *ProGres* and the *Targeting* data (matching 72% of observations), and then appending this data to the end of *PDM* data. This set of data is the more complete dataset in terms of variables. The motivation of the construction of these three sets of data is to check whether these different sources of data as well as different sets of variables generate different poverty figure, consequently determining the set that best predict poverty. To ensure comparability across the three datasets, we restrict the analysis to 16 of the 19 refugee sites. That is because the PDM data cover only 16 sites. Consequently, this study covers only refugees from the Central African Republic and Sudan, and not the Nigerian refugees and all estimates provided in the paper are not representative of all refugees living in the country.

IV. Estimation Results

As a first step, we check whether our data sets are representative of the same underlying population (Assumption 1) by performing means difference tests across key predictors. Given that the *PDM* is a subsample of the *Targeting* or *ProGres* data sets we need a test suitable for partially overlapping samples. Here we use the same test proposed by Verme at al. (2016, p. 58) applied to refugee ProGres data in Jordan. Table 1 provides the results. It shows that all variables are not significantly different in terms of means indicating that the two samples are representative of the same population.

To evaluate the performance of the welfare estimation model, we consider three models (Model 1, Model 2, Model 3). Model 1 includes demographic variables and geographic variables (region of residence, country of origin). This is the most parsimonious model and uses the variables that are most readily available in the *ProGres* dataset. Model 2 adds to Model 1 variables related to animal and asset ownership. Model 2 is richer than Model 1 but is more demanding in terms of the control variables, which may also be less reliable or more likely to be missing in census data. Model 3 adds to Model 2 variables measuring coping strategies. To test for multicollinearity, Table 2 reports the Variance Inflation Factor (VIF) for different models. It shows that no variable has a VIF that is over 5 and the mean VIF is smaller than this threshold. We shall conclude that multicollinearity is not an issue for any of the models considered.

Next, we test the out-of-sample performance of the three models using PDM data and the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as performance functions. To do so, the data set is split into 5 equal folds. In the first iteration, the first fold is used to test the model and the rest are used to train the model. In the second iteration, second fold is used as the testing set while the rest serve as the training set. This process is repeated until each fold of the 5 folds have been used as the testing set. Performance function is obtained as the mean across the five iterations. For the food consumption aggregate, the three models have similar measure of goodness-of-fit for both indicators. Model 1's RMSE is 0.55 while Model 2 and Model 3's RMSE is 0.54. For the MAE, Model 1 and 3 have a value of 0.42 whereas model 2 has a RMSE of 0.41. When we turn to the overall consumption aggregate, we note a small difference between the three models. RMSE values range from 0.53 to 0.58, with Model 3 and Model 1 having the smallest and highest RMSE respectively. MAE is quite similar across the three models, within a range from 0.39 with Model 3 to 0.41 with Model 2. These results suggest that no model consistently outperforms other models.

Table 4 and Table 5 applies the model to the three data sets described in the data section (ProGres 2, Targeting 2 and ProGres Targeting data) using the normal linear regression model and the empirical error model and three poverty lines: (i) a poverty line of US$1.9 a day (PPP) which represents the international poverty line for extreme poverty (Panel A), (ii) the national poverty line that corresponds to around US$2.6 (World Bank, 2013) represented in Panel A, (iii) the national food poverty line of US$1.8 (PPP) shown in Table 4. These three poverty lines are among the set of the arbitrary poverty lines considered in the general simulation above to evaluate the quality of the prediction.[6] With one exception, the predicted poverty rates are not statistically different from the true poverty rates. For the case of the food and international poverty lines, this is partly due to the large standard errors of the prediction estimates but these findings hold for the national poverty line where standard errors of the predicted values are much smaller.

Figure 1 repeats the exercise of Table 3 for the *ProGres Targeting* data and all poverty lines between the 66th and 99th quantile of consumption. Panel A and Panel B are respectively the Normal Linear Model and the Empirical Errors Model. The results suggest that Model 1 and Model 2 predict the "true welfare" rates for different poverty lines well. The predicted poverty rates are within the 95% confidence interval for all arbitrary poverty lines considered. The predictions are also very similar across the normal and empirical error models. However, Model 3 overestimates the "true welfare" rates and the predicted poverty rates provided are outside the 95% confidence interval of the "true welfare" rates for the set of different poverty lines considered. As model 3 adds variables related to coping strategies, it might be that households are not accurate in reporting these strategies, for example by overestimating the frequency of using these strategies in order to receive more assistance from humanitarian organizations.

Figure 2 shows the predicted welfare rates for the set of different poverty lines for all three models, but this time with a focus on food security. Welfare based on food security is defined in humanitarian settings as the inability to afford the minimum expenditure basket required to purchase a food basket based on basic-needs. The Minimum Expenditure Basket is defined by the World Food Programme "as what a household requires in order to meet their essential needs, on a regular or seasonal basis, and its average cost" (WFP, 2018). The results are very similar to the overall welfare results displayed in Figure 1. Results indicate that Model 1 and Model 2 predict the actual welfare rates well based on food security for different poverty lines and are within the 95% confidence interval for all arbitrary poverty lines considered. The predictions are also very similar for the two different estimation models of error terms that are the Normal Linear Model

[6] See also Table A3 in annex for the full base model.

and Empirical Errors Model. Again, model 3 overestimates the “true welfare” rates and the predicted welfare rates are outside the confidence interval of the “true welfare” rates.[7]

In summary, Figures 1 and 2 suggest Models 1 and 2 to underestimate welfare for low poverty lines and overestimate for high poverty lines but are within the confidence intervals. Model 3 always overestimates “true welfare” for smaller poverty lines and its predictions are outside the confidence interval. In general, Model 1 and 2 predict the “true welfare” rates and the “true welfare based on food security” well for different arbitrary poverty lines. Based on these results, we conclude that these two models provide fairly accurate aggregate welfare estimations of refugees living in Chad and that the variables currently available in the *ProGres* UNHCR registration system can be combined with other survey data to efficiently predict aggregate welfare of refugees.

The cross-survey imputation literature[8] stresses the importance of selecting a few key predictors and our results from Model 1 that contain only demographic variables are in line with this empirical evidence. Previous empirical studies also highlight that adding household assets help to improve on poverty estimates and Model 2, which adds asset and animal ownership to Model 1, is consistent with this evidence. However, adding more variables may lead to overfitting, resulting in less accurate welfare estimates. The results of Model 3 could be placed in this context.

V. Targeting performance

The imputed welfare estimates can be useful in evaluating ex-post the inclusion/exclusion errors of the food assistance programs administered by the government and humanitarian organizations during the 2016/17 period. The targeting strategy for food assistance was agreed to and implemented by the UNHCR, WFP, and the Government agency in Chad responsible for refugees, the CNARR. We perform an analysis to show how accurately the current targeting strategy identifies poor households in terms of inclusion (leakage) and exclusion (undercoverage) errors.

[7] To check possible heterogeneity, we split the sample with respect to country of origin. The results were similar except larger estimate variances (less precision) that might be due to sample size for refugee from Central African Republic.

[8] Dang at al., 2017a; Dang and Lanjouw, 2018; Dang and Verme, 2019; Luca et al., 2018.

Both error types are important but from different perspectives. The inclusion error matters primarily from a budget perspective as it represents a waste of resources. The exclusion error summarizes the program's failure to cover households in need.

The current UNHCR/WFP/CNARR targeting approach relies on the Food Consumption Score (FCS) generated by WFP's PDM surveys, which is a composite score based on dietary diversity, food consumption frequency, and relative nutritional importance of different food items. As any index, the FCS is contingent on the selection of the food group weights as well as the food items thresholds that are based on inherently subjective choices. Survey-to-survey methods have been shown to outperform these types of index approaches whereas the Dang et al. (2017) cross-imputation method has been shown to perform better than Proxy Means Testing also in refugee contexts (Dang and Verme, 2019).[9]

In light of these previous findings, we empirically evaluate how the UNHCR/WFP/CNARR targeting strategy performs relatively to the targeting method based on predicted consumption and also relatively to the available international evidence. Table 6 shows the undercoverage and leakage rates for the different approaches. The method we propose (Panel B) outperforms the targeting method currently used in Chad (Panel A) for all poverty line except the 25th percentile poverty line. These errors are not low overall with the UNHCR/WFP/CNARR undercoverage rates ranging from 9 to 32% and the leakage rates from 12 to 36% and our model based undercoverage rates ranging from 6 to 40% and the leakage rates from 9 to 41%. However, they perform relatively well when compared to international evidence. For example, Skoufias et al. (2001) find that the undercoverage and leakage rates for the POGRESA program in Mexico were 7% and 70% respectively for a poverty rate of 25%, a better performance on the undercoverage rate but a much worse performance on the leakage rate as compared to the other two programs.

The estimated targeting rates for Chad are also better than the median performance of similar scores of programs across the world (see Table 7). Coady et al. (2004) report an index of targeting performance obtained by dividing the proportion of beneficiaries falling within the target population by the proportion of beneficiaries that would result from a random allocation. For

[9] On optimal targeting in humanitarian contexts see also Verme and Gigliarano (2019).

example, if the bottom 40 percent of the income distribution receives 60 percent of the funding, the performance indicator is 1.5 (60/40). The higher the indicator, the greater is the performance of the targeting strategy. Table 6 reports this indicator for the 85 programs considered by Coady et al. (2004) (A), for the UNHCR/WFP/CNARR targeting program (B) and for our proposed methodology (C). Our methodology outperforms the UNHCR/WFP/CNARR targeting program and the median value of the programs covered by Coady et al. (2004) while the UNHCR/WFP/CNARR does not perform poorly when compared with the international evidence.

VI. Limitations

The objective of this work was to test how cross-survey imputation methods perform in estimating poverty for refugee populations using Chad as a cease-study. While the results of our cross-survey imputation exercise show that key demographic variables from *ProGres* predict well the welfare measure captured in the *PDM* at the aggregate level, additional work is needed to assess how well this methodology performs in refugee contexts, particularly in poor countries and data scarce environments. To do this, datasets should ideally contain more detailed information on consumption and should be matched by individual household using IDs available in the *ProGres* registration data.

Further, the *PDM* data measures consumption using relatively fewer variables than the round 4 of the Chadian Household Consumption and Informal Sector Surveys (ECOSIT4). As such, the “true” measure from the PDM could be improved. The UNHCR and the World Bank are working closely to improve and increase comparable refugee data to nationals. Thanks to recent efforts on the part of the World Bank and the UNHCR, in 2018/19 refugees have been included for the first time in the Chadian Household Consumption and Informal Sector Survey, round 4 (ECOSIT4). When these data will be made available, it will be possible to run a similar analysis to assess how cross survey imputation fares using nationally representative consumption measures for poverty and to understand how cross survey imputation can predict household poverty outcomes for refugees and host populations alike with comparable data.

While the work presented in this paper remains a valid experiment for cross-survey imputations, data did not cover the entirety of refugees in Chad including some refugees who live outside camps. As the latter live in different environments, predicting their welfare may require different sets of variables. Also, measuring consumption among refugees who rely on a combination of hand outs and informal incomes is also a relatively new science. Existing survey instruments may need to be adapted and the meaning of concepts such as utility and capabilities among refugees needs to be reconsidered.

VII. Conclusion

The UN General Assembly Sustainable Development Goal 1 – *End poverty in all its forms* –by 2030 explicitly pledges that 'no one will be left behind'. Tracking progress made with respect to this objective requires the availability of high-quality household consumption surveys. However, the majority of countries across the world, especially developing countries, face challenges in collecting poverty data. High quality consumption surveys comparable for forcibly displaced and their hosts are and will remain in limited supply given the cost and challenges associated with these types of surveys. In the meantime, cross survey imputation methods can provide a second-best alternative that can potentially save time and money.

This study combined survey and census-type data of refugees to estimate welfare for refugees in Chad. We showed how different sets of variables as well as different sources of data fare in the identification of poor households, in particular how well the set of variables available in the *ProGres* database can predict poverty. In a second step, this paper estimated the accuracy of the current UNHCR/WFP/CNARR's targeting strategy and compared it to the targeting strategy based on imputed consumption in the light of the international evidence.

The results suggest that the set of variables available in ProGres accurately predicts the welfare rates for different poverty lines. Adding variables related to asset and animal ownership provide predictions very close to the ones with only variables available in the ProGres dataset. These results are especially promising as UNHCR *ProGres* data is available in most refugee locations where the UNHCR runs the registration system, and thus these methods are replicable in many forcibly displaced settings.

The current targeting strategy used for food, livelihoods and cash-based assistance, despite its simplicity, is rather accurate when compared to the existing international evidence. The targeting errors resulting from the current UNHCR/WFP/CNARR targeting strategy for a poverty rate of 25% are in the same error range of other existing targeting methods around the world as reported in Coady et al. (2004). We also showed that the existing targeting method can be improved by imputing consumption using the methodology proposed in this paper.

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Table 1 : Means Difference Tests

	PDM			ProGres Targeting			Two-sided p-value
	Mean	Std. Dev.	N Obs.	Mean	Std. Dev.	N Obs.	t-test for overlapping groups
Demographics and geographical variable							
HH size	4.76	2.96	1440	4.11	2.53	65943	0.83
Gender	0.65	0.48	1440	0.69	0.46	65943	0.96
Age of HH head	42.34	14.01	1441	42.19	14.70	65943	0.97
Education							
No Education	0.63	0.48	1440	0.55	0.50	56838	0.81
Koranic School	0.15	0.36	1440	0.19	0.39	56838	0.99
Primary	0.12	0.33	1440	0.15	0.36	56838	0.90
Secondary	0.09	0.28	1440	0.10	0.30	56838	0.92
Higher	0.01	0.07	1440	0.01	0.08	56838	0.99
Marital status							
Married	0.08	0.28	1440	0.10	0.30	65934	0.91
Divorced	0.08	0.28	1440	0.10	0.30	65934	0.90
Widowed	0.18	0.38	1440	0.11	0.31	65934	0.96
Single	0.05	0.22	1440	0.08	0.27	65934	0.90
Occupation is agriculture	0.49	0.50	1439	0.789	0.408	65943	0.99
Origin	0.467	0.499	1441	2.79	0.41	65943	0.61
Asset and animal ownership							
HH has phone	0.15	0.36	1440	0.17	0.38	65943	0.99
HH has carts	0.02	0.14	1440	0.03	0.18	65943	0.92
HH has bike	0.05	0.23	1440	0.02	0.15	65943	0.98
HH has moto	0.02	0.12	1440	0.02	0.13	65943	0.98
HH has radio	0.06	0.23	1440	0.08	0.27	65943	0.91
HH has cattle	0.02	0.15	1441	0.02	0.13	65943	0.98
HH has donkeys	0.07	0.25	1441	0.44	0.50	65942	0.87
HH has sheep	0.04	0.19	1441	0.09	0.29	65943	0.16
HH Has goats	0.06	0.24	1441	0.14	0.35	65943	0.18
HH Has horses	0.06	0.23	1441	0.04	0.19	65942	0.87
HH Has poultry	0.09	0.28	1441	0.17	0.38	65943	0.19
Coping strategies							
Consume seeds	0.17	0.38	1104	0.17	0.38	65943	0.92
Sell assets	0.01	0.07	1104	0.06	0.24	65943	0.80
Send children for Begging	0.03	0.16	1104	0.05	0.21	65943	0.99
Sell last breeding Female	0.01	0.10	1104	0.05	0.22	65943	0.87
Region of residence	4.74	2.19	1441	5.08	2.02	65943	0.97
Region 1	0.13	0.32	1441	0.101	0.30	65943	0.95
Region 2	0.19	0.39	1441	0.12	0.32		0.88
Region 3	0.18	0.38	1441	0.07	0.25	65943	0.80
Region 4	0.09	0.30	1441	0.18	0.48	65993	0.61
Region 5	0.16	0.37	1441	0.03	0.17	65943	0.74
Region 6	0.09	0.29	1441	0.18	0.38	65943	0.86
Region 7	0.15	0.36	1441	0.13	0.338	65943	0.96

Source: Authors' calculations.

Table 2: Collinearity Tests

	Model 1		Model 2		Model 3	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
HH size	1.15	0.87				
Age of head of HH	1.29	0.77	1.33	0.75	1.29	0.77
HH is Farming	1.37	0.73	1.4	0.71	1.34	0.75
Head of HH has primary education	1.25	0.80	1.27	0.79	1.27	0.78
Head of HH attended Islamic School	1.14	0.87	1.2	0.83	1.23	0.81
Head of HH has Secondary education	1.16	0.86	1.19	0.84	1.36	0.74
Head of HH has Higher education	1.02	0.98	1.03	0.97	1.06	0.95
HH is Female	1.41	0.71	1.5	0.66	1.42	0.70
Head of HH is divorced	1.16	0.86	1.19	0.84	1.14	0.88
Head of HH is widowed	1.35	0.74	1.4	0.71	1.49	0.67
Head of HH is single	1.14	0.87	1.19	0.84	1.14	0.88
Country origin is Soudan	3.71	0.27	4.94	0.20	3.46	0.29
Region 2	2.12	0.47	2.69	0.37	1.91	0.52
Region 3	2.3	0.43	3.01	0.33	2.3	0.43
Region 4	1.9	0.53	1.96	0.51	1.5	0.66
Region 5	2.08	0.48				
Region 6	2.07	0.48	2.21	0.45	1.71	0.59
Region 7	1.79	0.56	1.81	0.55	1.66	0.60
HH has Phone			1.21	0.83	1.23	0.81
HH has Carts			1.15	0.87	1.14	0.87
HH has Bikes			1.21	0.83	1.4	0.71
HH has Moto			1.05	0.95	1.08	0.93
HH has Radio			1.17	0.85	1.22	0.82
HH has Cattle			1.06	0.94	1.07	0.94
HH has Horses			1.30	0.77	1.31	0.76
HH consumes seeds as coping strategies					1.15	0.87

Table 3: Models Out of Sample Performance, Individual Level

	Food Consumption aggregate			Overall Consumption aggregate		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
RMSE	0.5	0.5	0.5	0.6	0.5	0.5
MAE	0.4	0.4	0.4	0.4	0.4	0.4

Note:* The sample size of PDM dataset that 1441 is divided into five parts. Performances functions (RMSE and MAE) are obtained as the mean across the five iterations.

Source: Authors' calculations.

Table 4: Predicted Total and Food Poverty Rates Compared to the International and National Poverty Lines*

	ProGres 2	*Targeting 2*			*ProGres Targeting*		
	Model 1 (1)	Model 1 (2)	Model 2 (3)	Model 3 (4)	Model 1 (5)	Model 2 (6)	Model 3 (7)
Panel A: Poverty rates at international standard							
Normal Linear regression model	80.9	76.4	76.0	75.4	78.1	79.7	79.8
	(4.2)	(3.42	(3.4)	(4.2)	(3.5)	(3.6)	(4.2)
Empirical Error Model	81.5	77.0	76.55	75.5	79.0	80.5	80.4
	(4.2)	(3.6)	(3.6)	(4.4)	(3.5)	(3.6)	(4.3)
True Poverty Rate							
	78.8						
	(1.9)						
Panel B: Poverty rates at national standard							
Normal Linear regression model	90.9	88.0	87.5	87.0	88.6	90.0	90.0
	(2.4)	(2.1)	(2.7)	(2.7)	(2.2)	(2.1)	(2.6)
Empirical Error Model	91.6	89.0	88.4	87.4	89.7	90.9	90.1
	(2.1)	(21)	(21)	(2.7)	(2.1)	(2.0)	(2.5)
True Poverty Rate							
	89.7						
	(1.5)						
Control Variables							
Demographics & Employment	Y	Y	Y	Y	Y	Y	Y
Asset and animal ownership	N	N	Y	Y	N	Y	Y
Coping Strategies	N	N	N	Y	N	N	Y
R^2 adjusted	0.57	0.55	0.57	0.66	0.52	0.55	0.62
Observations (N)	65242	82468	82467	82467	56830	56829	56829

Note:*The international total poverty line is $1.88 PPP per person per day while the most recent national total (Food) poverty line in Chad is $2.60 ($1.88) per person per day. Robust standard errors in parentheses are clustered at the camp level. We use 1,000 simulations for each model run.

Source: Authors' calculations.

Table 5: Food Poverty

	ProGres Targeting		
	Model 1	Model 2	Model 3
	(1)	(3)	(3)
Food Poverty rates			
Normal Linear regression model	82.1	83.4	81.6
	(3.5)	(3.2)	(4.0)
Empirical Error Model	82.8	83.2	82.0
	(3.3)	(3.3)	(4.2)
True poverty		80.1	
		(1.9)	

Table 6: Comparison of Coverage and Leakage Rates (%)

	Poverty lines			
	25th Percentile	50th Percentile	80th Percentile	90th Percentile
A. Current UNHCR/WFP/CNARR targeting strategy approach				
Undercoverage Rate	32	32	19	9
Leakage Rate	36	36	22	12
B. Our predicted consumption-based targeting				
Undercoverage Rate	40	26	12	6
Leakage Rate	41	28	14	9
C. PROGRESA's method targeting				
Undercoverage Rate	7	10	16	
Leakage Rate	70	43	16	

Source: Authors' calculations for UNHCR/WFP/CNARR Targeting Strategy and *Skoufias et al. (2001).*

Table 7: Targeting Performance of sample of programs, current UNHCR/WFP/CNARR, and our imputed consumption-based Targeting

	Poverty lines								
	10th Percentile			20th Percentile			40th Percentile		
	Median	Min	Max	Median	Min	Max	Median	Min	Max
A. All 85 programs in Coady et al. (2004).	2.8	0.8	7.5	2.2	0.7	4.3	1.5	1.0	2.1
B. UHNCR Targeting	4			3.1			1.6		
C. Imputed Consumption based Targeting	5.5			3.3			1.9		

Source: Authors' calculations for UNHCR/WFP/CNARR Targeting Strategy and compilations based on data *in Coady et al. (2004).*

Figure 1: Predicted welfare and True welfare for different poverty lines, *ProGres Targeting*

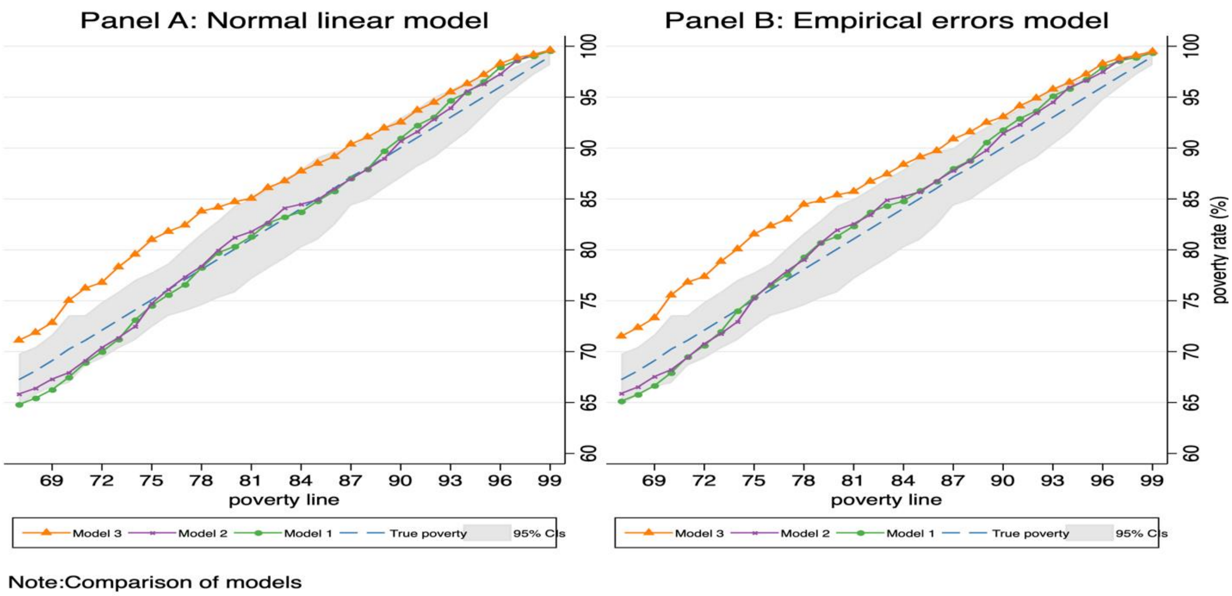


Figure 2 : Predicted welfare based on food security and true welfare based on food security for different poverty lines, ProGres Targeting

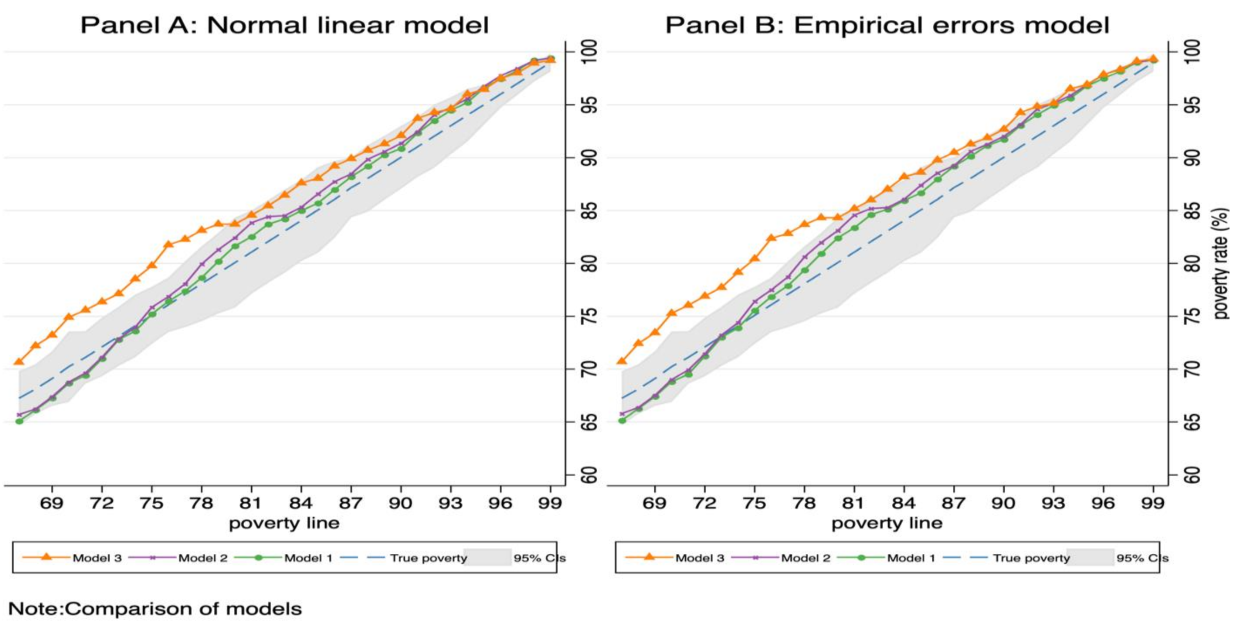
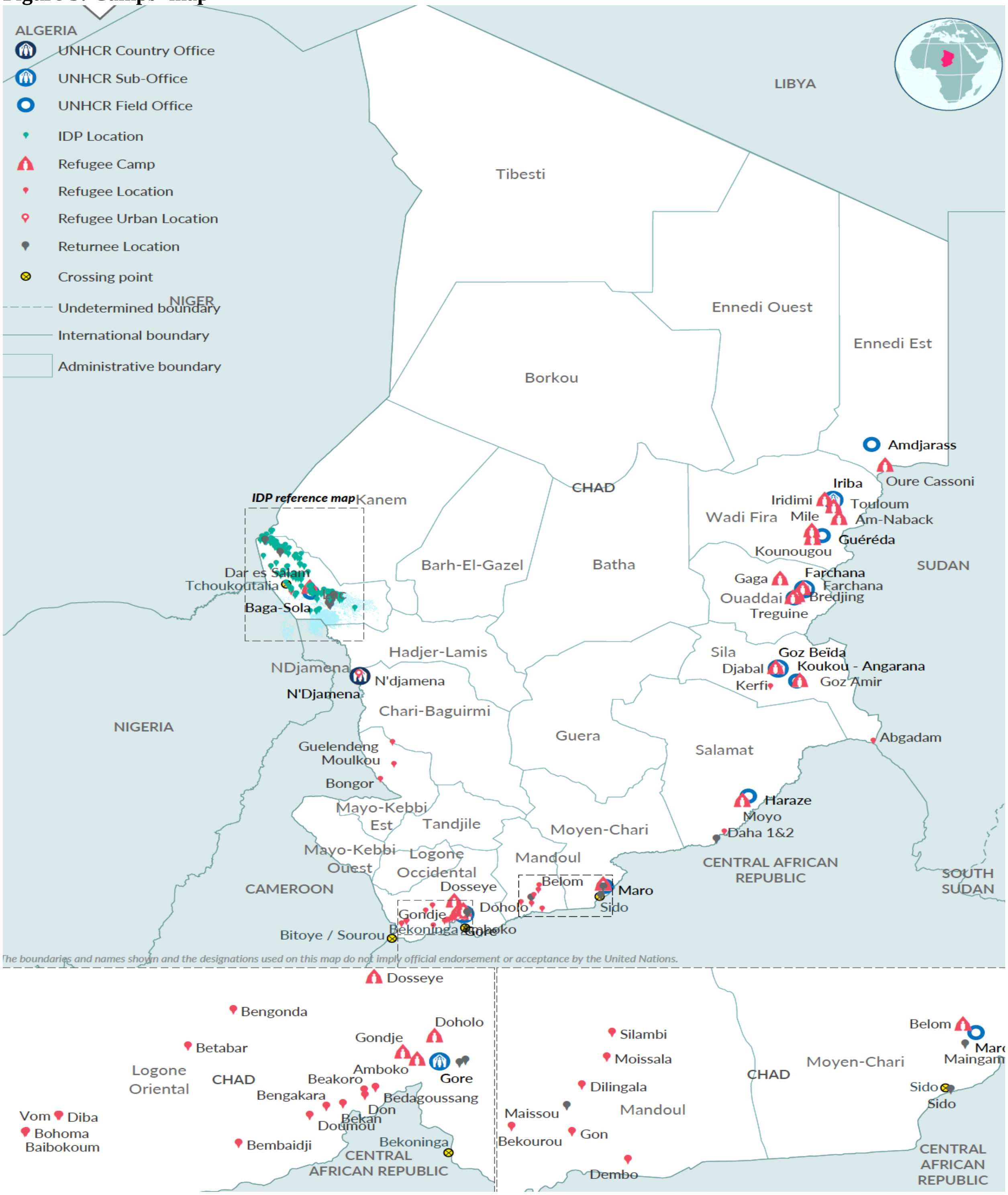


Figure 3: Camps' map



Source: UNHCR, 2018

Annex:

Table A1: Distribution of persons of concern by Group in Chad

Type	Number	Proportion
Refugee and Asylum seeker	459809	68.9
Returnees	5746	0.9
IDPs	165313	24.8
Chadian Returnees from CAR	16718	2.5
Others	20000	3.0
Total	667586	100.0

Source: Authors' calculations, ProGres.

Table A2: Summary of data

Number	Dataset	Overview	Date	Implementing Agency	Existence of Consumption expenditure information	Relevant Variables to poverty imputation available
			Panel A: Data available			
1	UNHCR Registration Data (ProGres)-	Census for all refugee households	June 2017	UNHCR	No	1. Demographics
2	Targeting Database 2017- All Chad	Census for all refugee households	June-July 2017	UNHCR/WFP and CNARR	No	1. Demographics 2. Asset and animal ownership 3. Coping strategies
3	Post Distribution Monitoring 2017-	Sub-Sample of refugees	2017	WFP	Yes	1. Demographics 2. Asset and animal ownership 3. Coping strategies 4. Consumption expenditure
			Panel B: Data constructed for poverty imputation			
1	ProGres 2	CAR and Sudanese refugees living in regions covered by PDM	-	Constructed by authors	-	1. Demographics 2. Consumption expenditure for observations from PDM
2	Targeting 2	CAR and Sudanese refugees living in regions covered by PDM	-	Constructed by authors	-	1. Demographics 2. Asset and animal ownership 3. Coping strategies 4. Consumption for observations from PDM
3	ProGres Targeting	CAR and Sudanese refugees living in regions covered by PDM	-	Constructed by authors	-	1. Demographics 2. Asset and animal ownership 3. Coping strategies 4. Consumption for observations from PDM

Source: Authors calculations

Table A3: Estimation Model

	(1) Model 1	(2) Model 2	(3) Model 3
HH size	-0.16***	-0.15***	-0.14***
	(0.01)	(0.01)	(0.01)
Age of head of HH	-0.00	0.00	-0.00
	(0.00)	(0.00)	(0.00)
HH is Farming	0.08*	0.11**	0.18***
	(0.05)	(0.04)	(0.05)
Head of HH has primary education	-0.06	-0.01	-0.06
	(0.06)	(0.05)	(0.07)
Head of HH attended Islamic School	-0.00	-0.09	-0.18**
	(0.08)	(0.07)	(0.09)
Head of HH has Secondary education	0.07	-0.06	-0.11
	(0.09)	(0.09)	(0.10)
Head of HH has Higher education	-0.23	-0.25	-0.55*
	(0.33)	(0.31)	(0.30)
HH is Female	-0.18***	-0.12**	-0.21***
	(0.05)	(0.05)	(0.06)
Head of HH is divorced	0.00	0.01	0.11
	(0.09)	(0.08)	(0.13)
Head of HH is widowed	-0.19***	-0.13*	-0.25***
	(0.07)	(0.07)	(0.08)
Head of HH is single	0.04	0.05	0.11
	(0.12)	(0.10)	(0.16)
Country origin is Soudan	0.42***	0.59***	0.84***
	(0.10)	(0.11)	(0.11)
Region 2	-0.60***	-0.30**	-0.45***
	(0.11)	(0.12)	(0.14)
Region 3	-1.13***	-0.94***	-0.77***
	(0.12)	(0.12)	(0.14)
Region 4	-0.44***	-0.51***	-0.66***
	(0.07)	(0.07)	(0.09)
Region 5	0.00	0.00	0.00
	(.)	(.)	(.)
Region 6	-0.38***	-0.45***	-0.63***
	(0.08)	(0.07)	(0.10)
Region 7	0.03	0.01	-0.03
	(0.06)	(0.06)	(0.06)
HH has Phone		0.07	0.09
		(0.06)	(0.07)
HH has Carts		0.33**	0.39*
		(0.14)	(0.20)
HH has Bikes		0.11	0.15
		(0.13)	(0.16)
HH has Moto		0.35*	0.32
		(0.21)	(0.21)
HH has Radio		0.20**	0.15
		(0.09)	(0.11)
HH has Cattle		-0.05	-0.11
		(0.12)	(0.14)
HH has Horses		0.08	0.09
		(0.07)	(0.11)
HH consumes seeds as coping strategies			0.01
			(0.07)
_cons	6.43***	6.06***	5.99***
	(0.13)	(0.13)	(0.15)
N	803	803	503
R^2 adjusted	0.52	0.55	0.62

Source: Authors' calculations, PDM survey.

Note: Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the log of household expenditure per capita and results obtained from the PDM survey alone.