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“Targeting mechanisms for cash transfers using regional aggregates”

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# Targeting mechanisms for cash transfers using regional aggregates

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## Abstract

We propose an empirical method for improving food assistance scoring and targeting, which minimizes under-coverage and leakage of food and cash assistance programs. The empirical strategy relies on a joint econometric estimation of food insecurity and economic vulnerability indicators at the household level, using data-driven instead of predetermined quantiles. We apply the method to recent micro data on Syrian refugees in Lebanon, to explore how regional and community-based aggregates can improve the targeting effectiveness of aid programs, notably food aid by the World Food Program in Lebanon. Our results confirm that using regional aggregates are useful for augmenting the Balanced Poverty Accuracy Criterion, and our method performs much better than the current policy in terms of targeting effectiveness and accuracy for economically vulnerable households.

**Keywords** Targeting · Food security · Economic vulnerability · Food aid · Refugees

## 1 Introduction

A major challenge of food policy consists of targeting, in a cost-effective way, poor households that may be both food insecure and economically vulnerable. An efficient targeting would, in particular, succeed in limiting under-coverage and leakage of food cash assistance programs. When dealing with households' status of food security and economic welfare as the target of aid policies, it is important to distinguish between the concept of vulnerability and the one of insecurity. In general, (economic) vulnerability is a measure of the risk a household may drop below some welfare measure (usually, the

poverty line), while (food) insecurity indicates a current status of the household, regarding food access and consumption (see Dercon 2006).

The main objective of this paper is to derive an empirical method for improving food assistance scoring and targeting systems in situations of budget limitations, which can be used by decision makers and analysts. More precisely, we suggest a data-driven method for targeting food insecure households, using both household and community-level indicators of food security and welfare. Our empirical strategy explores how different levels of information on households and administrative (district) average characteristics can be used to reduce under-coverage and leakage of food cash assistance programs, in order to increase the performance of the food aid system in targeting poor households. Such empirical strategy relies on a robust, joint estimation of food insecurity and economic vulnerability indicators at the household level, using data-driven instead of predetermined quantiles.

We consider the World Food Programme's (WFP) food assistance system in Lebanon and analyze its scoring and targeting system for Syrian refugees in that country. Six years into the Syrian crisis, Lebanon hosts just over 1 million Syrian refugees, who are registered with the office of the United Nations High Commissioner for Refugees (UNHCR), about 50% of whom are under 15 years of age (WFP, 2016). Sequential surveys conducted by United Nations agencies have consistently found a large share of Syrian refugees in

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59 Lebanon to be living below the poverty line (71% in 2016), to  
60 experience some level of food insecurity and to be adopting  
61 coping strategies that involve the depletion of assets and in-  
62 curring of debt to cover food, health and rental expenses  
63 (WFP, 2016). In response, various humanitarian agencies have  
64 established multi-purpose cash assistance programs, in addi-  
65 tion to cash-based food assistance and in-kind food assistance  
Q3 66 targeting vulnerable households.

67 We use original and unique data for our statistical and  
68 econometric analysis on micro data collected from refugee  
69 households, to evaluate the determinants of food insecur-  
70 ity and economic vulnerability. We investigate the empir-  
71 ical relationship between food insecurity and economic  
72 vulnerability at the household level, by estimating a struc-  
73 tural system of simultaneous ordered Probit equations for  
74 both indicators.

75 The empirical methodology is based on a multi indi-  
76 cator system (proxy means, a point or a scoring system),  
77 which contains observable (and easy to verify) household  
78 characteristics. This system, devised through statistical  
79 analysis, allows prediction of food insecurity scores for  
80 the already sampled and remaining refugee population  
81 within a well-defined margin of error that reduces  
82 targeting inclusion and exclusion errors. This would  
83 prove useful in first analyzing the current food security  
84 status and the targeting mechanism of refugees using all  
85 available data. Second, introducing a model to identify  
86 refugee households' food security status allowing better  
87 targeting of the most vulnerable households, with observ-  
88 able exogenous indicators most closely correlated with  
89 food insecurity. Last, identifying key observable indica-  
90 tors, which could help in-depth monitoring through  
91 follow-up visits.

92 As described in a survey of food security by Barrett  
93 (2002), "effective targeting is fundamental to food aid  
94 policy (FAP) design and evaluation, particularly in to-  
95 day's era of shrinking FAP budgets as a proportion of  
96 government spending or gross domestic product (p. 58)".  
97 The purpose of cost-effective targeting is to reduce leak-  
98 age to unintended beneficiaries and to maximize the pro-  
99 portion of poor households effectively participating in the  
100 program (Borjas 2004). The literature on targeting cate-  
101 gories of populations is mostly dedicated to poverty allevi-  
102 ation policies and access to natural resources and energy  
103 (water utilities, etc.). Many papers have examined the  
104 performance of food stamp programs (in developing  
105 countries and mostly in the United States) when the pov-  
106 erty status of households is costly to verify and adminis-  
107 trative costs may reduce the amount of resources allocated  
108 to the poverty intervention (Wilde and Nord 2005; Barrett  
109 2002; Besley and Kanbur 1993). When reliable data on  
110 household income are difficult to obtain, proxy means test  
111 can be considered from a variety of instruments observed

with low cost, assumed correlated with household welfare  
and difficult to modify by households (Sen 1995; Glewwe  
1992). Moreover, even though poor household registra-  
tion and regular re-certification procedures may increase  
administrative costs dramatically in the short run, their  
impact on improving targeting is likely to be visible in  
the longer run.

Benfield (2007) considered indicators that may improve  
the performance of a food-stamp policy in Jamaica through  
better targeting by minimizing Type-I and Type-II errors.  
The paper confirms that a policy based on additional indi-  
cators, e.g., on housing conditions and durable goods, may  
perform better in targeting the poor. Another stream in the  
literature concerns spatial patterns of poverty and implica-  
tions for food policies of the spatial distribution of poor  
households in poor/non-poor geographical areas (Minot  
and Baulch 2005; Kam et al. 2005; Amarasinghe et al.  
2005; Elbers et al. 2007; Jaynes et al. 2001; Agostini and  
Brown 2011). Indeed, among the many factors that explain  
that targeting may not be cost-effective, there is the possi-  
bility that the target group is a spatially dispersed proportion  
of the general population (Barrett 2002). Barrett (2002) dis-  
tinguishes between ICAT (Indicator-Contingent  
Administrative Targeting) and self-targeting programs, the  
former relying on screening based on various food security  
indicators (including income and nutritional status) to deter-  
mine program eligibility of households. By contrast, self-  
targeting is designed so that only intended beneficiaries par-  
ticipate on a voluntary basis, with asymmetric information  
issues partly solved through some cost component or a re-  
duction in quality of the good or service. Some empirical  
research suggests that easy-to-collect indicators such as de-  
pendency ratio, rooms per capita, etc. can be fairly effective  
in identifying food-insecure households with some degree of  
cost savings (Haddad et al. 1997; Chung et al. 1997; Lipton  
and Ravallion 1995). See, e.g., Jaynes et al. (2001) for short-  
comings and caveats of such indicator-based targeting  
strategies.

The rest of the paper is organized as follows: Section 2  
details the materials and methods (theoretical and empirical  
methodologies) we employed throughout the analysis. This  
includes the description of the datasets and variables used in  
our empirical application, and the empirical strategy. In par-  
ticular, the specification of the simultaneous ordered Probit  
system of equations for food insecurity and economic vulner-  
ability is presented in detail. Section 3 presents the estimation  
results from the structural system of equations, and the perfor-  
mance of our empirical method in terms of targeting accuracy  
and effectiveness. Such performance analysis entails a com-  
parison of coverage and under-coverage of poor households,  
leakage and targeting differential associated with various  
specifications, including community-level and regional aggre-  
gates. Finally, concluding remarks are in Section 4.

**2 Materials and methods**

**2.1 Theoretical model**

As discussed above, better targeting of poor households may help to attain the objective of poverty alleviation at lower costs, but policy makers are faced with the prohibitive costs associated with the identification of households below the poverty line. The trade-off therefore involves monitoring costs on the one hand, and policy leakage (to non-poor households) on the other, with the general objective of increasing welfare of food insecure and/or economically vulnerable households. To formalize the terms of the trade-off, we introduce a simple model that represents the targeting issue in a stylized food policy.

Consider a food-aid planner whose objective is to target poor households with a given cash transfer denoted  $A$  (per HH), from a total population of size  $(N, \text{known})$ . The unit administrative cost of transferring  $A$  to a household is denoted  $\tau$ , the proportion of poor (non-poor) households in the total population is  $\beta_P$  (respectively,  $\beta_{NP}$ ). Let  $p_1(\alpha)$  and  $p_2(\alpha)$  respectively denote the probability of under-coverage (not targeting a poor household) and leakage (targeting a non-poor household), which depend on the effort of collecting and treating information on households, denoted  $\alpha$ . The cost of effort is  $F(\alpha)$  and we assume

$$\frac{dp_1(\alpha)}{d\alpha} \leq 0, \frac{dp_2(\alpha)}{d\alpha} \leq 0, \frac{dF(\alpha)}{d\alpha} > 0. \tag{1}$$

For a given level of effort  $\alpha$ , the social planner wishes to obtain a particular level of targeting and, therefore, a given level of social welfare as an outcome. We assume the social planner solves this problem by determining both the optimal for effort ( $\alpha$ ) and the level of cash transfer ( $A$ ).

There are several options the social planner can, in theory, choose from to determine the optimal food policy. A first option for the social planner is to define a proportion of population to be assisted, say,  $\beta_P$ , and then solves for the optimal level of targeting effort jointly with the unit level of cash transfer. Note that in such a case, targeting is meaningful, at least in the sense defined above, that is, identifying poor households to receive aid. When such an option is selected, households are simply ranked by increasing order of income or wealth and the first  $N\beta_P$  receive assistance.

A second possibility is that the social planner determines the optimum level of aid per household (i.e., the monetary level of cash transfer) by dividing total budget by the number of poor households,

$$A^* = \frac{(B-F(\alpha))}{N\tau\beta_P}, \tag{2}$$

i.e., accounting for administrative costs. In this case, the minimization problem becomes, after substituting for  $A^*$  and using  $\beta_{NP} = 1 - \beta_P$

$$\max_{\alpha} C = [B-F(\alpha)] \times \left\{ [1-p_1(\alpha)] - \frac{1-\beta_P}{\beta_P} p_2(\alpha) \right\}, \tag{3}$$

which gives

$$\begin{aligned} \frac{\partial F(\alpha)}{\partial \alpha} \times \left\{ [1-p_1(\alpha)] - \frac{1-\beta_P}{\beta_P} p_2(\alpha) \right\} \\ = -[B-F(\alpha)] \times \left\{ \frac{dp_1(\alpha)}{d\alpha} + \frac{1-\beta_P}{\beta_P} \times \frac{dp_2(\alpha)}{d\alpha} \right\} \geq 0, \end{aligned} \tag{4}$$

which implies that  $\{ [1-p_1(\alpha)] - \frac{1-\beta_P}{\beta_P} p_2(\alpha) \} \geq 0$ , provided the cost of effort does not exceed the initial budget, i.e.,  $[B-F(\alpha)] \geq 0$ . This second option is obviously not relevant when the objective is to help poor households reach some poverty line level. With such a policy, some assisted households could become better off than non-assisted ones, which would introduce distortions in the distribution of households.

A third possibility is that the social planner first determines exogenously the cash transfer that corresponds to a minimum level of food expenditure to ensure food security. For example, some minimum expenditure level can be computed given local prices, based on requirements for food and nutrient intake provided by international standards. More precisely, the social planner would equate direct and indirect utility levels

$$V(p, \underline{y} + A) = U(FS), \tag{5}$$

where  $V(\cdot)$  and  $U(\cdot)$  are indirect (Hicksian) and direct (Marshallian) utility functions respectively,  $p$  is the vector of market prices faced by households,  $\underline{y}$  is exogenous income (not depending on cash transfers) and  $FS$  is the level of food expenditure to guarantee food security. Solving for cash transfer in the equation above allows the social planner to determine the optimal level of transfer to reach food security, denoted  $A^*$ , given available income and price levels. Then, in a second stage, the social planner solves the following program:

$$\begin{aligned} \max_{\alpha} C = A^* \times \tau \times N \\ \times \{ \beta_P [1-p_1(\alpha)] - \beta_{NP} p_2(\alpha) \} - F(\alpha), \end{aligned} \tag{6}$$



246 such that  $C \leq B$  (total budget available). We have

$$\frac{\partial F(\alpha)}{\partial \alpha} = -(A^* \tau N \beta_p) \times \left\{ \frac{dp_1(\alpha)}{d\alpha} + \frac{1-\beta_p}{\beta_p} \times \frac{dp_2(\alpha)}{d\alpha} \right\}. \quad (7)$$

249 In other words, the optimal level of effort to obtain infor- 298  
 250 mation about food insecurity through, e.g., additional surveys, 299  
 251 is determined when the marginal cost of such effort (on the 300  
 252 LHS) equals the marginal benefits of effort in terms of better 301  
 253 targeting (on the RHS). Such benefits are a weighted sum of 302  
 254 marginal effects (with respect to targeting effort) in under- 303  
 255 coverage and leakage probabilities, where the weight is the 304  
 256 ratio of the non-poor over the poor proportion of households 305  
 257 in the total population. Under such constraint, given a 306  
 258 predetermined level of cash transfer per household, the policy 307  
 259 maker determines the optimal level of targeting that ultimately 308  
 260 determines the proportion of poor households to be provided 309  
 261 with assistance. 310

262 This last policy corresponds to the one employed in prac- 311  
 263 tice in our application, and we will consider it in the rest of the 312  
 264 paper. 313

265 When the level of effort tends to infinity, we expect both 314  
 266 policy under-coverage and leakage to tend to zero, so that the 315  
 267 total cost of the targeting policy would converge to 316  
 268 317

$$C = (A^* \tau N \beta_p) \times \left\{ 1 + \frac{1-\beta_p}{\beta_p} \times 0 \right\} - F(\alpha) \quad (8)$$

$$= (A^* \tau N \beta_p) - F(\alpha).$$

272 This would violate the condition that  $C \leq B$  if  $F(\alpha)$  is large 323  
 273 enough. However, a trade-off can be determined by solving 324  
 274 the above problem, for a limited budget and expected gains 325  
 275 from targeting. In practice, it is essential to be able to identify 326  
 276 effective gains from targeting poor households, and compare 327  
 277 them with the cost of effort associated with data collection on 328  
 278 households. This is achieved by sampling over the target pop- 329  
 279 ulation to estimate the proportion of poor households therein, 330  
 280 providing an estimate for  $\beta_p$ . When the sample includes 331  
 281 households benefiting from cash transfers as well, then the 332  
 282 probabilities of under-coverage and leakage can also be esti- 333  
 283 mated. The empirical analysis of the present paper proposes a 334  
 284 system of targeting equations that serve such a purpose by 335  
 285 illustrating the way increasing information on households 336  
 286 can increase the performance of targeting policies, by reduc- 337  
 287 ing probabilities  $p_1(\alpha)$  and  $p_2(\alpha)$ . To make the connection 338  
 288 between the above model and our application, we assume a 339  
 289 direct relationship between targeting effort and information 340  
 290 collected on the population of households. As information 341  
 291 increases through (costly) repeated surveys, the precision on 342  
 292 coverage and leakage probabilities also increase in a way 343

limited by the trade-off discussed, until the marginal benefit 294  
 of targeting effort equals its marginal cost. 295

## 2.2 Empirical methodology 296

In this paper we are interested in analyzing the targeting ef- 297  
 fectiveness of cash transfers with respect to two variables: 298  
 food insecurity and economic vulnerability. As will be shown 299  
 below, both dependent variables are discrete ordered, and they 300  
 are interlinked. This requires a specific empirical estimation 301  
 strategy, which is detailed here. 302

303 Instead of specifying a reduced-form system of equations 304  
 in which both indicators would appear dependent upon the 305  
 same set of socio-economic explanatory variables, we consid- 306  
 er instead a structural specification where food insecurity de- 307  
 pends on economic vulnerability as well. The argument be- 308  
 hind such specification is that it provides a simple way to 309  
 disentangle the effect of socio-economic drivers of food inse- 310  
 curity from the ones (possible in common) that condition wel- 311  
 fare and economic vulnerability. Moreover, with such repre- 312  
 sentation, it is straightforward to simulate the impact of a 313  
 change in income following, e.g., a decrease in the cash trans- 314  
 fer, and its impact on the food insecurity indicator. In any case, 315  
 the recursive representation at the household level is consis- 316  
 tent with the evidence that, even though identical socio- 317  
 economic determinants may jointly explain food insecurity 318  
 and economic vulnerability, the former is also determined by 319  
 the level of economic welfare. 320

Let  $i, i = 1, 2, \dots, N$ , denote the household index and consid- 321  
 er the general simultaneous-equation model: 322

$$\begin{cases} y_{1i}^* = \delta_1 + x_{1i}\beta_1 + u_{1i}, y_{2i}^* = \delta_2 + \gamma y_{1i}^* + x_{2i}\beta_2 + u_{2i}, \end{cases} \quad (9)$$

where  $y_{1i}^*$  and  $y_{2i}^*$  are two (continuous) latent variables that can 323  
 be defined as measures of welfare related to income and food 324  
 respectively. They are associated with two observed simulta- 325  
 neous welfare levels (respectively, food insecurity and eco- 326  
 nomic vulnerability) and are assumed to be positive when 327  
 corresponding levels are observed. Vectors of explanatory var- 328  
 iables  $x_{1i}$  and  $x_{2i}$  may have some common components,  $u_{1i}$  329  
 and  $u_{2i}$  are random variables with a correlation coefficient 330  
 between denoted  $\rho$  (assumed constant). We assume the fol- 331  
 lowing exogeneity restrictions apply:  $E(x_{1i}u_{1i}) = E(x_{2i}u_{2i}) =$  332  
 $0, \forall i.$  333

Both latent variables typically lie in the real line, as 334  
 both food insecurity and economic vulnerability levels 335  
 may be normalized to correspond to a set of non- 336  
 overlapping intervals with negative and positive values. Let 337  
 $\{S_j^k = [c_{j-1}^k, c_j^k], j = 1, 2, \dots, J_k; k = 1, 2\}$  denote such 338  
 non-overlapping sets, with  $\cup_j S_j^k = R, \forall k = 1, 2, c_0^k = -\infty,$  339  
 $c_{J_k}^k = \infty, \forall k,$  and  $c_{j-1}^k \leq c_j^k, \forall k, \forall j.$  340

341 In the dataset we observe ordered dependent variables:  
 342  $y_{1i} = 1$  if  $y_{1i}^* \in S_j^1$  and  $y_{2i} = 1$  if  $y_{2i}^* \in S_j^2$ ,  $j = 1, 2, \dots$ ,  
 343  $J_1, k = 1, 2, \dots, J_2$ .

344 From the structural system of Eq. (1), we have:

$$\begin{aligned}
 & Prob(y_{1i}^* \in S_j^1, y_{2i}^* \in S_k^1) = Prob(y_{1i} = j, y_{2i} = k) \\
 & = Prob(c_{j-1}^1 \leq y_{1i}^* < c_j^1, c_{k-1}^2 \leq y_{2i}^* < c_k^2) \\
 & = \Phi_2 \left[ c_j^1 - \delta_1 - x_{1i} \beta_1, \theta (c_k^2 - \gamma \delta_1 - \gamma x_{1i} \beta_1 - \delta_2 - x_{2i} \beta_2), \underline{\rho} \right] \\
 & - \Phi_2 \left[ c_{j-1}^1 - \delta_1 - x_{1i} \beta_1, \theta (c_k^2 - \gamma \delta_1 - \gamma x_{1i} \beta_1 - \delta_2 - x_{2i} \beta_2), \underline{\rho} \right] \\
 & - \Phi_2 \left[ c_j^1 - \delta_1 - x_{1i} \beta_1, \theta (c_{k-1}^2 - \gamma \delta_1 - \gamma x_{1i} \beta_1 - \delta_2 - x_{2i} \beta_2), \underline{\rho} \right] \\
 & + \Phi_2 \left[ c_{j-1}^1 - \delta_1 - x_{1i} \beta_1, \theta (c_{k-1}^2 - \gamma \delta_1 - \gamma x_{1i} \beta_1 - \delta_2 - x_{2i} \beta_2), \underline{\rho} \right],
 \end{aligned} \tag{10}$$

345 where  $\Phi_2(\cdot, \cdot, \cdot)$  is the bivariate standard normal cumulative  
 346 distribution function, and  $\theta = (1 + 2\gamma\rho + \gamma^2)^{-1/2}$ ,  $\underline{\rho} = \theta$   
 347  $(\gamma + \rho)$  ..

348 The expression (2) can be evaluated for any pair of out-  
 349 comes  $(j, k)$  and all contributions of the sort are used to con-  
 350 struct the log-likelihood of the sample, to obtain consistent  
 351 Maximum Likelihood estimates of the bivariate ordered  
 352 Probit (see Sajaia 2007).  $J_1 + J_2 - 1$  cut off values  $(c_j^k)$  are  
 353 estimated together with parameters  $(\beta_1, \beta_2, \gamma, \rho)$ , but intercept  
 354 terms  $\delta_1$  and  $\delta_2$  are not identified (in fact, cut offs are identified  
 355 up to a constant term). Parameters in (1) are only identified if  
 356 we impose exclusion restrictions, that is, at least one variable  
 357 in  $x_{1i}$  should be excluded from  $x_{2i}$ . An interesting candidate for  
 358 such exclusion is an exogenous variable that determines eco-  
 359 nomic vulnerability but not food insecurity (such as the par-  
 360 ticular assets possessed by the household, as in the  
 361 application).

362 Our model specification has economic vulnerability  $y_1^*$  as  
 363 an explanatory variable in the equation for food insecurity and  
 364 this variable is endogenous by construction. If error terms  $u_1$   
 365 and  $u_2$  are correlated ( $\rho \neq 0$ ), it implies that  $y_{1i}^*$  is correlated  
 366 with  $u_{2i}$ , and the second equation in the system (1) cannot be  
 367 estimated independently. In our empirical analysis of joint  
 368 estimation of food insecurity and economic vulnerability, this  
 369 endogeneity issue is essential to avoid simultaneity bias in  
 370 parameter estimates.

371 To test for the endogeneity of  $y_{1i}^*$  in the equation for  $y_{2i}^*$ , we  
 372 estimate the structural system of equations by bivariate  
 373 (ordered) Probit and the Full Information Maximum  
 374 Likelihood (FIML) method. We then use a Wald Test of  $\gamma =$   
 375  $0$  in the second one, see Sajaia (2007). Note that we do not  
 376 consider, for the sake of space limitation, an alternative esti-  
 377 mation method that would consider a bivariate ordered Probit

applied to the reduced form of the system of equations. Even  
 though such specification could be considered to provide us  
 with consistent parameter estimates (as long as exogeneity of  
 $y_2^*$  in the sense defined above is rejected), we are able to obtain  
 structural parameter estimates directly by FIML with the bi-  
 variate ordered Probit procedure.

The log-likelihood function over  $N$  observations is

$$\log L = \sum_{i=1}^N \sum_{j=1}^J \sum_{k=1}^K I(y_{1i} = j, y_{2i} = k) \log Prob(y_{1i} = j, y_{2i} = k) \tag{11}$$

if observations are identically and independently distributed.  
 This may not be the case, in particular when unobserved ran-  
 dom effects come in addition to random errors  $u_1$  and  $u_2$ . A  
 possibility in this case is to specify the joint distribution of  
 such effects and to integrate them out from the following log-  
 likelihood:

$$\log L(\pi) = \int f(y|x, u, \pi) \phi(u|\mu_u, \Sigma_u) du, \tag{12}$$

where  $\pi$  is the vector of structural parameters,  $u$  is the vector of  
 random effects with joint distribution defined by the density  
 function  $\phi(u|\mu_u, \Sigma_u)$ . Such integral can be approximated by  
 Gauss-Hermite quadrature, see, e.g., Rabe-Hesketh et al.  
 (2005) and Skrondal and Rabe-Hesketh (2004). We now de-  
 scribe the main data sets used by WFP for targeting, as well as  
 the ones we use in the paper to construct our food security and  
 welfare indicators.

### 2.3 Main datasets used

To deal with an ever-increasing number of refugees reaching  
 Lebanon from the Syrian border, international organization  
 such as the WFP, the United Nations Children’s Fund  
 (UNICEF), and the UNHCR in Lebanon initiated the yearly  
 Vulnerability Assessment on Syrian Refugees (VASyR), for  
 programmatic purposes (UNHCR, UNICEF and WFP 2015).  
 It aims to construct eligibility criteria for targeting beneficia-  
 ries using individual data from refugee surveys containing  
 both observed and self-reported variables. Based on VASyR,  
 WFP in Lebanon developed a vulnerability scoring system  
 dedicated to household targeting (see Drummond et al. 2015).

Household vulnerability is generally defined as the likeli-  
 hood of a household to not cover basic needs of all members  
 without engaging in irreversible coping strategies due to a lack  
 of financial resources (World Food Program 2016). In this  
 regard, it is a measure of the risk of moving to a less favorable  
 status, and it needs to be distinguished from the food security  
 status of the household (a current state that may be affected  
 by factors external or internal to the household). This

423 distinction is important to recall here, because the  
 424 “vulnerability” assessment of VASyR includes both economic  
 425 vulnerability and food security dimensions, as discussed be-  
 426 low, whereas our empirical analysis is directed towards two  
 427 indicators only: food insecurity and economic vulnerability.  
 428 Eligibility criteria in the formula used by the WFP include  
 429 indicators of food security and economic vulnerability, as well  
 430 as self-reported coverage of household basic needs. Eight  
 431 sector-specific vulnerabilities are included in the WFP vulner-  
 432 ability scoring system, including food security, economic vul-  
 433 nerability, education, health, non-food items, protection, shel-  
 434 ter, etc. A household is classified into one of four vulnerability  
 435 categories according to each of these eight sectors, and the  
 436 sector scores are then summed to produce a global vulnerabil-  
 437 ity score comprised of five vulnerability categories: low, mild,  
 438 moderate, high and severe.

439 The main datasets used in our paper are detailed below:

### 440 2.3.1 VASyR 2015

441 The VASyR 2015 (Vulnerability Assessment on Syrian  
 442 Refugees) is a nationally representative two-stage cluster sur-  
 443 vey of Syrian refugees living in Lebanon (see World Food  
 444 Program 2016), conducted in May–June 2015 and includes  
 445 around 4100 households for an estimated 21,300 individuals.  
 446 VASyR 2015 was used as the main data set to estimate and test  
 447 improved food security and economic vulnerability indices.  
 448 The data set was subject to data cleaning (duplicate observa-  
 449 tions, multiple heads of households, etc.) for a final sample  
 450 size of 3850 households.

### 451 2.3.2 ProGres

452 The Profile Global Registration System (ProGres) is the main  
 453 global database used by the UNHCR and the data provided  
 454 include all registered refugees in Lebanon (about 1.05 million  
 455 individuals in October 2015). Although valuable because of  
 456 its size and the inclusion of key socioeconomic characteristics  
 457 on refugees, the database does not contain variables measur-  
 458 ing welfare. Although registration is only voluntary, due to  
 459 immigration rules in hosting countries and UNHCR proced-  
 460 ures and incentives to register, most refugees would register  
 461 at some point in time.

462 The household is considered the main unit of measurement  
 463 for the VASyR survey. It is defined by WFP as a group of  
 464 people, who routinely eat out of the same pot, live in the same  
 465 compound (or physical location), and share the same budget,  
 466 managed by the head of household. In contrast, the “case” is  
 467 used by UNHCR to register refugees in the ProGres data base  
 468 and is defined as: “A processing unit similar to a family head-  
 469 ed by a Principal Applicant. It comprises (biological and non-  
 470 biological) sons and daughters up to the age 18 (or 21) years,  
 471 but also includes first degree family members emotionally

472 and/or economically dependent and for whom a living on their  
 473 own and whose ability to function independently in society/in  
 474 the community and/or to pursue an occupation is not granted,  
 475 and/or who require assistance from a caregiver.”<sup>1</sup>

476 WFP’s targeting process starts from blanket coverage and  
 477 then focuses on identifying and removing households and  
 478 individuals who do not need food assistance according to a  
 479 certain vulnerability threshold. UNHCR’s targeting of its un-  
 480 conditional cash transfers moves in the opposite direction by  
 481 focusing on identifying the refugees who are most in need of  
 482 economic assistance, and then expanding coverage as re-  
 483 sources allow and as needy cases are identified.

484 The WFP vulnerability scoring system is then applied on  
 485 the households visited using the common multi-agency ques-  
 486 tionnaire (over 90,000 households) and used for targeting pur-  
 487 poses: households are excluded from assistance if they fall  
 488 within the better off vulnerability categories (low, mild, mod-  
 489 erate), and according to a combination of economic consider-  
 490 ations and Multi-functional Team (MFT) revisions.

491 There are obvious limitations of the WFP vulnerability  
 492 scoring system, including lengthy and expensive household  
 493 visits and the fact that it includes over 50 variables, some of  
 494 which are duplicated within the score, rendering it difficult to  
 495 use as a desk formula. Finally, the formula includes both input  
 496 and output variables, which would lead to endogeneity prob-  
 497 lems in a desk formula. For example, some of the variables  
 498 used to calculate the WFP vulnerability score include the food  
 499 consumption score and a coping strategies index both of  
 500 which can be considered outcome variables for food security.  
 501 The score also includes input variables such as dependency  
 502 ratio, education, gender of the head of household, members  
 503 with a disability amongst other input variables.

504 Appendix 1 details the derivation of the food security indi-  
 505 cator, obtained through a fully data-driven procedure directly  
 506 from individual surveys. The major advantage of our proced-  
 507 ure is that empirical quantiles allow determining empirical  
 508 values that do not depend on external standards that may be  
 509 inconsistent with local conditions. Moreover, in designing our  
 510 indicators, we carefully exclude variables likely to reflect de-  
 511 cisions from households that may depend on other explanato-  
 512 ry variables (the endogeneity problem, see below).

513 Table 1 displays the proportion of households classified  
 514 into five groups of vulnerability (regarding food insecurity),  
 515 according to the index derived in Appendix 1.

516 Defining food insecurity by a gradient above 4, the propor-  
 517 tion of food insecure households in the VASyR2015 sample is  
 518 around 61%.

519 As for economic vulnerability, we consider a welfare-  
 520 dependent variable that proxies economic vulnerability, on a  
 521 set of independent variables that are thought to determine the

<sup>1</sup> [http://cega.berkeley.edu/assets/miscellaneous\\_files/35-ABCA\\_-Targeting\\_and\\_Welfare.pdf](http://cega.berkeley.edu/assets/miscellaneous_files/35-ABCA_-Targeting_and_Welfare.pdf)



t1.1 **Table 1** Proportion of households in VASyR 2015 classified into categories of vulnerability to food insecurity

t1.2	Lowest to highest vulnerability to food insecurity	Proportion of households to food insecurity
t1.3	1 – lowest	13.3%
t1.4	2	10.6%
t1.5	3	14.7%
t1.6	4	33.2%
t1.7	5 – highest	28.2%

**Table 2** Economic vulnerability quantiles

Economic vulnerability quantile	Value (USD/month/head)	Observation s in sample	t2.1	t2.2
10%	41.66	269	t2.3	t2.4
20%	55.33	328	t2.5	t2.6
30%	67.50	458	t2.7	t2.8
40%	78.33	500	t2.9	t2.10
50%	90.46	633	t2.11	t2.12
60%	104.62	552		
70%	121.68	511		
80%	146.80	337		
90%	195.38	183		
Average	112.47	3771		

522 variation in the welfare aggregate. We adopt per capita expendi-  
 523 ture as our welfare aggregate. Economic vulnerability is  
 524 therefore measured through monthly expenditure per capita  
 525 in USD. The expenditure aggregate is constructed by sum-  
 526 ming up 18 self-reported expenditure items from the VASyR  
 527 questionnaire with a recall period of 30 days. The household  
 528 aggregate is then divided over the number of household mem-  
 529 bers. Following the approach used by UNHCR, the upper  
 530 limit of the per capita expenditure aggregate was restricted  
 531 to 250 USD to exclude most outliers. As for the food insecuri-  
 532 ty indicator, we construct an ordinal variable based on  
 533 bootstrapped quantiles of the monthly expenditure per capita,  
 534 with values from 1 to 9. Quantiles of economic vulnerability  
 535 are reported in Table 2, as monthly values in USD per capita,  
 536 together with the corresponding number of households in the  
 537 sample.

538 **2.4 Model specification**

539 Two targeting models are detailed below, ranging from the  
 540 inclusion of ProGres only variables to appending community  
 541 level indicators. Recall that in all model specifications, the  
 542 equation for food insecurity contains the endogenous variable  
 543  $y_1$  (economic vulnerability) as an explanatory variable.

544 The first specification with ProGres variables only does not  
 545 require new data collection and uses variables already collect-  
 546 ed from refugees upon registration. The data are also updated  
 547 on a regular basis by UNHCR. For this first model specifica-  
 548 tion, the sets of explanatory variables are

549 
$$x_1 = (HH\ size, homogeneous, Access\_Phone, HOH\ education, valuable\ assets, HHshares),$$

$$x_2 = (HH\ size, homogeneous, HOH\ education, HHshares),$$

553 where HHshares contains empirical proportions of household  
 554 members related to age, gender, employment and disability  
 555 status, and education level of the head of household (HOH).  
 556 Variable *homogeneous* is introduced to capture the influence  
 557 of the density of refugees from the same district of origin (in  
 558 Syria) and living now in the same district (in Lebanon) as the  
 559 considered household. It is computed as a proportion as well,  
 560 using the information from ProGres on places of origin and  
 561 current residence. To capture the role of having a means of  
 562 communication, we include a dummy variable *Access\_Phone*,  
 563 equal to 1 if the household has positive expenditures on cell  
 564 (GSM) or land-line phone(s). The possession by the house-  
 565 hold of appliances (or other household durable goods) with a  
 566 significant market value (in case of sale on a local market) is  
 567 captured by the variable *valuable assets*. As it is assumed to  
 568 influence only economic vulnerability and not food insecurity,  
 569 it does not include appliances that can be used for home  
 570 cooking, and is not included in the list of variables  $x_2$ .

571 The second specification includes community-specific av-  
 572 erages at the district level, including access to drinking water,  
 573 sanitation status, crowdedness index, share of (as well as of  
 574 heads of) households with chronic disease, share of house-  
 575 holds receiving medical care.

576 The list of variables and indicators included in the targeting  
 577 models is included in the tables below. They include house-  
 578 hold (HH) characteristics, shares of members with certain  
 579 characteristics, housing conditions, location characteristics  
 580 and other socio-demographic indicators. Variables are either  
 581 available in VASyR 2015 only or in both VASyR 2015 and  
 582 ProGres. Community level indicators have also been calculat-  
 583 ed based on VASyR 2015 variables and are appended to the  
 584 corresponding cases in ProGres. For example, the share of HH  
 585 living in crowded conditions was calculated for each of the 26  
 586 districts using the VASyR 2015 data set. The calculated share  
 587 was then appended to each case in ProGres by corresponding  
 588 district. Even though the variables needed to calculate

591 community level indicators are not available in ProGres, they  
592 can be calculated based on the VASyR 2015 data set or any  
593 newer nationally representative sample and appended to cases  
594 in ProGres.

595 Table 3 reports descriptive statistics for variables used in  
596 the various model specifications.

## 597 3 Results

### 598 3.1 Estimation results

599 We now present estimation results for our model specifica-  
600 tions with increasing information used to represent simulta-  
601 neously food insecurity and economic vulnerability: model (I)  
602 with ProGres variables only, and model (II) adding district-  
603 level indicators. For each model considered, random effects at

604 district level are accounted for, as described above, to evaluate  
605 the log-likelihood function of the bivariate ordered Probit.  
606 Parameter estimates are presented in Table 4. To interpret cor-  
607 rectly the sign of the effect of a given explanatory variable, It  
608 has to be remembered that a higher value of the dependent  
609 variable *percap\_exp\_quant* corresponds to a lower economic  
610 vulnerability, while a higher value of the variable *fsgradient* is  
611 associated with a higher degree of food insecurity.

612 In both model specifications, the exogeneity assumption  
613 for economic vulnerability in the equation of food insecurity  
614 is strongly rejected, with a *p*-value of the Wald test less than  
615 0.001 in all cases. The level of economic welfare (as measured  
616 by the empirical quantile of household expenditures per head)  
617 is negative and significant in all specifications for food inse-  
618 curity, which was expected. The null hypothesis of no-  
619 correlation between random terms in the system of equations  
620 (food insecurity and economic vulnerability), given covariates

t3.1 **Table 3** Descriptive statistics of  
t3.2 the sample

	Variable	Specification(s)	Mean	Standard Deviation
t3.3	<i>fsgradient</i>	(I), (II), HH	4.9506	2.198
t3.4	<i>percap_exp_quant</i>	(I), (II), HH	5.5049	2.8737
t3.5	<i>HHsize</i>	(I), (II), HH	5.2099	2.3289
t3.6	<i>HHsize2</i>	(I), (II), HH	32.7195	31.8355
t3.7	<i>homogeneous</i>	(I), (II), HH	0.1026	0.0954
t3.8	<i>hoh_education_level = intermediate</i>	(I), (II), HH	0.187	0.39
t3.9	<i>hoh_education_level = none</i>	(I), (II), HH	0.1577	0.3645
t3.10	<i>hoh_education_level = primary_school</i>	(I), (II), HH	0.4379	0.4962
t3.11	<i>hoh_education_level = read_write</i>	(I), (II), HH	0.0927	0.2901
t3.12	<i>hoh_education_level = secondary_school</i>	(I), (II), HH	0.0732	0.2606
t3.13	<i>hoh_education_level = technical</i>	(I), (II), HH	0.0156	0.1239
t3.14	<i>hoh_education_level = university</i>	(I), (II), HH	0.0358	0.1859
t3.15	<i>Access_Phone</i>	(I), (II), HH	0.8963	0.3048
t3.16	<i>valuable_assets<sup>(*)</sup></i>	(I), (II), HH	0.9203	0.2709
t3.17	<i>less_than_5_share</i>	(I), (II), HH	0.1973	0.1891
t3.18	<i>btw_5_and_17_share</i>	(I), (II), HH	0.2904	0.2374
t3.19	<i>btw_51_and_70_share</i>	(I), (II), HH	0.0568	0.1521
t3.20	<i>aged_more_than_71_share</i>	(I), (II), HH	0.0111	0.0701
t3.21	<i>btw_18_and_50_male_share</i>	(I), (II), HH	0.2131	0.183
t3.22	<i>btw_18_and_51_female_share</i>	(I), (II), HH	0.2311	0.1477
t3.23	<i>disabled_share</i>	(I), (II), HH	0.0277	0.0908
t3.24	<i>water_access_hh_share</i>	(II), Dist	0.8422	0.2226
t3.25	<i>drinkingwater_access_hh_share</i>	(II), Dist	0.4659	0.2196
t3.26	<i>sanitation_access_hh_share</i>	(II), Dist	0.4106	0.2226
t3.27	<i>crowded_hh_share</i>	(II), Dist	0.5483	0.0927
t3.28	<i>chronichoh_hh_share</i>	(II), Dist	0.2103	0.0672
t3.29	<i>chronic_hh_share</i>	(II), Dist	0.4007	0.1003
t3.30	<i>receivehealth_hh_share</i>	(II), Dist	0.1049	0.0562

3850 observations. <sup>(\*)</sup>: equation for economic vulnerability only. Specifications are as follows. (I): ProGres variables only; (II): (I) + district variables. HH and Dist: evaluated at household and district level respectively

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t4.1 **Table 4** Estimation results. Simultaneous structural equations, ordered Probit

t4.2	Dep. variable	Percap_exp_quant		fsgradient	
t4.3		(I)	(II)	(I)	(II)
t4.4	Percap_exp_quant	–	–	–0.0773***	–0.0916***
t4.5		–	–	(10.92)	(12.94)
t4.6	HHsize	–0.3322***	–0.3566***	–0.1134***	–0.1334***
t4.7		(11.87)	(12.69)	(4.14)	(4.87)
t4.8	HHsize2	0.0158***	0.0168***	0.0028	0.0036*
t4.9		(8.28)	(8.76)	(1.46)	(1.90)
t4.10	homogeneous	–0.2190	–0.5330***	–0.0636	–0.2383
t4.11		(1.22)	(2.93)	(0.34)	(1.26)
t4.12	hoh_edu1	–0.2769***	–0.3098***	0.1186	0.0934
t4.13		(2.76)	(3.07)	(1.22)	(0.96)
t4.14	hoh_edu2	–0.5001***	–0.5193***	0.3182***	0.3021***
t4.15		(4.90)	(5.07)	(3.22)	(3.05)
t4.16	hoh_edu3	–0.3359***	–0.3841***	0.1589*	0.1300
t4.17		(3.50)	(3.99)	(1.72)	(1.41)
t4.18	hoh_edu4	–0.3885***	–0.3866***	0.3264***	0.3193***
t4.19		(3.61)	(3.57)	(3.11)	(3.04)
t4.20	hoh_edu5	–0.2840**	–0.3600***	0.1496	0.1034
t4.21		(2.56)	(3.23)	(1.39)	(0.96)
t4.22	hoh_edu6	0.0694	–0.0093	0.0959	0.0443
t4.23		(0.42)	(0.06)	(0.60)	(0.28)
t4.24	hoh_edu7	REF	REF	REF	REF
t4.25	Access_Phone	0.6275***	0.5617***	–	–
t4.26		(10.49)	(9.35)	–	–
t4.27	valuable_assets	0.2831***	0.2789***	–	–
t4.28		(4.38)	(4.31)	–	–
t4.29	less_than_5_share	0.3898	0.0540	0.1424	–0.0120
t4.30		(0.39)	(0.05)	(0.14)	(0.01)
t4.31	btw_5_and_17_share	0.6455	0.3642	0.5532	0.4298
t4.32		(0.64)	(0.36)	(0.54)	(0.42)
t4.33	aged_more_than_71_share	1.4382	1.0899	0.3310	0.1903
t4.34		(1.42)	(1.08)	(0.33)	(0.19)
t4.35	less_than_5_share	1.6759	1.3100	0.6336	0.4870
t4.36		(1.62)	(1.26)	(0.61)	(0.47)
t4.37	btw_5_and_17_share	2.0983**	1.7359*	0.3456	0.1807
t4.38		(2.08)	(1.72)	(0.34)	(0.18)
t4.39	aged_more_than_71_share	1.1717	0.8970	0.5462	0.4423
t4.40		(1.16)	(0.89)	(0.54)	(0.44)
t4.41	disabled_share	–0.3245*	–0.3471*	0.2731	0.2654
t4.42		(1.74)	(1.85)	(1.47)	(1.43)
t4.43	P	0.0664 (1.05)	0.2174*** (4.46)	LR = 1.07 (p-value = 0.31)	LR = 17.61 (p-value = 0.00)

3771 observations. Random effects for districts of origin and destination in all specifications. Specifications are as follows. (I): ProGres variables only; (II): (I) + district variables. See Appendix Table 12 for list of variables. *t*-statistics are in parentheses. \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .  $\rho$  is the correlation coefficient between both equations; LR is the Likelihood Ratio test (distributed as a  $\chi^2$  (1) under the null assumption of independence)

621 and under the random effect specification, is rejected at the 5%  
 622 level of confidence for model specification (II) (with district  
 623 variables) but is not rejected for model specification (I).

The household size is strongly significant and it has a neg- 624  
 ative effect in all model specifications for both equations, and 625  
 it is decreasing and convex in specifications (I) and (II) for 626

t5.1 **Table 5** Targeting effectiveness, food security

t5.2	Food Insecurity line = (fsgradient = 4)	Coverage of the food insecure (1)	Under-coverage (2)	Leakage (3)	Targeting differential = (1)–(3)
t5.3	Currently assisted	74.23	25.77	38.98	35.25
t5.4	ProGres variables	52.38	47.62	32.76	19.62
t5.5	ProGres + district variables	55.81	44.19	32.40	23.41

Undercoverage is percent of poor individuals that do not receive transfer

Leakage is percent of individuals that receive transfer and are not poor

The targeting differential is the difference between the coverage rate and the participation rate for non-poor

627 economic vulnerability, while *HHsize2* is significant only at  
628 the 10% level for food insecurity and specification (II). All  
629 else being equal, a larger size of household decreases per head  
630 expenditures and it also increases food security. A possible  
631 explanation for such finding is that there are economies of  
632 scale in food consumption within the household (less food  
633 per head for larger households, resulting in a lower food inse-  
634 curity index).

635 Let us now turn to the variable *homogeneous*, measur-  
636 ing the extent to which refugees of the same district of  
637 origin tend to regroup in the host country (Lebanon). This  
638 variable is significant only in the equation for economic  
639 vulnerability for the last specification (II) (with district  
640 variables), where it is negative, while it does not explain  
641 food insecurity. Such a finding indicates that a higher  
642 proportion of refugees from the same Syrian district and  
643 living now in the same Lebanese district has a negative  
644 effect on economic welfare. Hence, to cope with econom-  
645 ic vulnerability, the strategy of refugees consisting in liv-  
646 ing close to households of the same origin is not improv-  
647 ing their economic status (although it does not modify the  
648 food insecurity status). A possible interpretation of such  
649 result is a negative one: it may well be the heterogeneity  
650 of households in terms of origin (in Syria) that is profit-  
651 able to refugees, instead of a greater concentration of in-  
652 dividuals coming from the same geographical area.

653 Consider now education level as a determinant of food  
654 insecurity and economic vulnerability. The reference for  
655 education level is the higher category, i.e., university de-  
656 gree, and all other binary variables for education are to be  
657 interpreted with respect to this maximum education level.  
658 Estimation results show that a higher educational level  
659 (university level being used as reference in both equa-  
660 tions) tends to decrease economic vulnerability (equiva-  
661 lently, to increase economic welfare), and it also has a  
662 negative impact on food insecurity. This is expected, as  
663 a higher educational level may be associated with a great-  
664 er ability to cope with changing conditions of access to  
665 food as well as less economic vulnerability in general.  
666 The possession of at least one cell phone, captured by  
667 variable *Has\_Cell\_Phone*, has a positive and significant  
668 effect on economic welfare in both specifications. This  
669 can be interpreted by the fact that such portable commu-  
670 nication device is an essential means for accessing infor-  
671 mation on economic opportunities (e.g., informal work),  
672 leading to less economic vulnerability.

673 The possession of valuable assets in the equation for eco-  
674 nomic vulnerability is positive and significant (it was omitted  
675 from the food insecurity equation to achieve identification, as  
676 was variable *Access\_Phone*). This can illustrate the fact that  
677 households with valuable assets, that can be sold on formal of  
678 informal markets or between neighbours, are less vulnerable,

t6.1 **Table 6** Targeting effectiveness, economic vulnerability

t6.2	Poverty line = (60% percentile of HH expenditure, around 114 USD)	Coverage of the poor (1)	Under-coverage (2)	Leakage (3)	Targeting differential = (1)–(3)
t6.3	Currently assisted	81.20	18.80	25.21	55.99
t6.4	ProGres variables	84.60	15.40	19.38	65.32
t6.5	ProGres + district variables	85.66	14.34	18.75	66.91

Undercoverage is percent of poor individuals that do not receive transfer

Leakage is percent of individuals that receive transfer and are not poor

The targeting differential is the difference between the coverage rate and the participation rate for non-poor

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t7.1 **Table 7** Targeting Accuracy, food security

	Total	Food Insecurity Status		
		FI	FS	BPAC
t7.4 Currently assisted	100	59.02	40.98	45.81
t7.5 ProGres Variables	100	66.24	33.75	51.38
t7.6 ProGres + district variables	100	66.47	33.52	54.68

Benefits' incidence is: (Sum of all transfers received by all individuals in the group)/(Sum of all transfers received by all individuals in the population). Aggregated transfer amounts are estimated using household size-weighted expansion factors

679 such assets being used as more or less liquid savings. Consider  
 680 finally demographic characteristics of the household, represented  
 681 by proportions or shares of household members. The  
 682 only significant demographic variables (although at the 10 or  
 683 5% level only) in the equation of *percap\_exp\_quant* are the  
 684 proportion of household members between 51 and 70  
 685 (*btw\_51\_and\_70\_share* with a positive effect) and the proportion  
 686 of disabled household members (*disabled\_share*, with a  
 687 negative effect). Household shares are not significant in the  
 688 equation for food insecurity, indicating the recursive nature of  
 689 such demographic variables, which affect food insecurity only  
 690 through economic vulnerability.

691 **3.2 Targeting effectiveness and accuracy**

692 The purpose of this section is to examine the performance of  
 693 our procedure for improving the targeting of poor and food-  
 694 insecure households. To do this, we need to evaluate the effectiveness  
 695 and accuracy of policies using regional and district-level aggregates  
 696 for targeting, compared with the actual policy of the World Food Program  
 697 in Lebanon.

698 Consider first the relationship between food insecurity and  
 699 poverty at the household level. This link is conceptually clear,  
 700 especially in an urban context where economic access to food  
 701 (purchasing power) is the dominant factor in food security.  
 702 Hence, a particular dimension of food insecurity (alongside

t8.1 **Table 8** Targeting Accuracy, economic vulnerability

	Total	Poverty Status		
		P	NP	BPAC
t8.2 Poverty line = (60% percentile of HH expenditure, around 114 USD)				
t8.4 Currently assisted	100	72.83	27.17	66.42
t8.5 ProGres Variables	100	79.01	20.98	75.03
t8.6 ProGres + district variables	100	80.16	19.83	75.75

In percent. P: poor; NP: non-poor; BPAC: Benefits' incidence is: (Sum of all transfers received by all individuals in the group)/(Sum of all transfers received by all individuals in the population). Aggregated transfer amounts are estimated using household size-weighted expansion factors

703 limited availability, low stability and insufficient utilization,  
 704 see Dilley and Boudreau 2001) can be defined as “food poverty”,  
 705 that is, the status of a household regarding its access to  
 706 food as a direct function of its purchasing power. Assuming a  
 707 relationship with available income for access to food when  
 708 defining food poverty, then it is expected that food poverty  
 709 and overall poverty can be identified as different points on the  
 710 same scale of income, and that people in need of food would  
 711 be a smaller subset of those in overall poverty.

712 Let us first distinguish between individuals living either  
 713 under or above some poverty line that identifies food poverty,  
 714 and which can be defined by the Minimum Expenditure  
 715 Basket (MEB)<sup>2</sup> set at 114\$ per person per month which includes  
 716 the cost of food plus other needs. However, since we are  
 717 measuring food security and not food poverty with our newly  
 718 developed index, we expect to find some discrepancy between  
 719 food insecure and poor households. And because we are using  
 720 ordered values for economic vulnerability to represent  
 721 quantiles of household expenditures, we can only approximate  
 722 such value. In fact, the poverty line discussed above  
 723 corresponds roughly to the 60% quantile of the dependent  
 724 variable, so that we consider all households below such  
 725 quantile in our sample as poor. Note that the 60% quantile in  
 726 consumption expenditure over the whole sample is different in  
 727 general from the value corresponding to 60% of a given  
 728 household's consumption expenditure.

729 As for food insecurity, we consider the fourth gradient value  
 730 of the variable *fsgradient* as the threshold delimiting food  
 731 insecurity. To explore the robustness of our method, we also tested  
 732 an alternative food insecurity threshold, by considering the  
 733 third value *fsgradient* =3 instead of 4. Results regarding food  
 734 insecurity were very similar in terms of targeting accuracy.

735 Tables 5, 6, 7 and 8 present the performance of the targeting  
 736 policy using only ProGres or using district-level aggregates as  
 737 well, regarding food insecurity and economic vulnerability.  
 738 Such performance is measured by the effectiveness and the  
 739 accuracy of the targeting policy in both cases, which account  
 740 for coverage, under-coverage and leakage rates of each policy  
 741 (actual, ProGres variables, ProGres and district-level variables).  
 742 A convenient indicator to measure accuracy of the targeting  
 743 policy is the benefits' incidence. It is the transfer amount received  
 744 by a group (in this case, poor or food insecure households) as  
 745 a proportion of total transfers received by the population.  
 746 Although the WFP Vulnerability Score leads to the highest  
 747 percentage of transfers going to poor versus non-poor  
 748 households, all two ProGres models have a higher Balanced  
 749 Poverty Accuracy Criterion (BPAC), defined as Poverty

<sup>2</sup> The Minimum Expenditure Basket (MEB) is an index that is used to construct poverty lines in various contexts, including for refugee populations. It is emerging as a primary index to develop a cost and market based expression of minimum needs of refugees in any given country. It broadly follows the notion of a “cost of basic needs approach” as outlined in the World Bank Poverty Manual from 2005.



750 Accuracy minus the absolute difference between under-  
 751 coverage and leakage. The model with ProGres and district-  
 752 level variables for economic vulnerability has the best perfor-  
 753 mance in terms of having the highest coverage, lowest leakage,  
 754 highest percentage of transfers to the poor and highest BPAC.

755 The targeting effectiveness of the economic vulnerability  
 756 models was much higher than for the food security models  
 757 (the first model specification only includes variables collected  
 758 during registration, while the second includes district level  
 759 variables (geographic aggregates). The coverage rate of poor  
 760 households reached 84.60% and 85.66% in the economic vul-  
 761 nerability model (see Table 6), compared with 52.38% and  
 762 55.81% in both model specifications of the food security mod-  
 763 el (see Table 5). Likewise, targeting accuracy was better in the  
 764 economic vulnerability models, where the BPAC reached  
 765 75.03 and 75.75 compared with 51.38 and 54.68 in the food  
 766 security model (see Tables 7 and 8).

767 **4 Discussion**

768 Using recent micro data from Syrian refugees in Lebanon, the  
 769 paper investigated the empirical relationship between food  
 770 insecurity and economic vulnerability at the household level.  
 771 By estimating a system of structural equations for food inse-  
 772 curity and economic vulnerability, we showed how  
 773 community-based variables such as population density and  
 774 homogeneity of refugee households with respect to districts  
 775 of origin and of arrival (residence) can improve the targeting  
 776 effectiveness of aid programs, notably food aid. This is partic-  
 777 ularly important for increasing the performance of food aid  
 778 policies when budgets are limited and/or decreasing.

779 A major result of interest to policy makers is that regional  
 780 and community-based aggregates can be used to improve the  
 781 targeting effectiveness of aid programs, e.g., food aid by the  
 782 World Food Program dedicated to refugee population. Our  
 783 results confirm that using such aggregates can augment the  
 784 Balanced Poverty Accuracy Criterion, specially in our case,  
 785 in terms of targeting effectiveness and accuracy for  
 786 economically-vulnerable households.

787 With the cost of construction of aggregate indicators being  
 788 in general less than individual-level data collection, a more  
 789 accurate targeting of poor households may help attaining pov-  
 790 erty alleviation objectives at a lower cost, when policy makers  
 791 are faced with significant costs of poor households identifica-  
 792 tion. As for poor and food-insecure households, being better  
 793 targeted from the start allows them to benefit from a more  
 794 efficient food aid system by, e.g., optimizing follow-up visits  
 795 for in-depth monitoring.

796 By helping to reduce under-coverage and leakage of food  
 797 and cash assistance programs., the empirical procedure con-  
 798 sidered in this paper can be used for policies based on in-kind  
 799 as well as on cash transfers, because its purpose is to help

identifying food-insecure and/or economically-vulnerable 800  
 households, independently from the vector of aid. 801

**Compliance with ethical standards** 802

**Conflict of interest** The authors declare that they have no conflict of 803  
 interest. 804

**Appendix 1: Computation of the Food Insecurity Indicator** 805  
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As part of the overall WFP vulnerability score, the food secu- 809  
 rity sector score is constructed from three variables: food con- 810  
 sumption score, food expenditure share and coping strategies 811  
 index. The resulting score is converted into ordinal classes 812  
 (categories) according to a formula developed by WFP 813  
 VAM.<sup>3</sup> This score has been derived through an iterative pro- 814  
 cess, and is based on several endogenous variables, which 815  
 would be problematic in predictive models of food insecurity. 816  
 We reviewed the VASyR dataset and considered all food secu- 817  
 rity related variables in the dataset, to be used as potential 818  
 food security outcomes ( $y$ ) in a targeting formula. 819

The following indicators were considered, and were con- 820  
 structed according to standard WFP methods (World Food 821  
 Program 2009): 822

- Food Consumption Score (FCS) – *a measure of quality of* 823  
*food utilization at household level; widely used to estab-* 824  
*lish prevalence of food insecurity* 825
- Child Diet Diversity Score – *access to food quality by the* 826  
*most vulnerable* 827
- Coping Strategies Index (CSI) – *a measure of household* 828  
*economic access to food, food quality and food quantity;* 829  
*used in targeting food assistance in various contexts* 830
- Reduced Coping Strategies Index (rCSI)- *cross culturally* 831  
*validated measure of access to food* 832
- Food Expenditure Share – *a measure of household eco-* 833  
*nomical access to food* 834

It has been highlighted that reliance on a single measure 835  
 which captures one dimension of food insecurity can misclas- 836  
 sify the food insecure, and that combining indicators can im- 837  
 prove the measurement of food insecurity (see Maxwell et al. 838  
 2013; Jones et al. 2013). 839

FCS and dietary diversity tend to capture elements of diet 840  
 quality and diversity, whereas CSI and rCSI reflect quantity or 841  
 sufficiency. Of these, child dietary diversity was not further 842  
 explored as this would have reduced the sample of the dataset 843  
 to households with children under the age of 2 years only. The 844  
 Coping Strategies Index (CSI) asks a series of questions about 845

<sup>3</sup> WFP VAM Targeting verification criteria document

Targeting mechanisms for cash transfers using regional aggregates

t9.1 **Table 9** Cross classification of bootstrapped quantiles of FCS and rCSI, % of households falling into each category

t9.2		rCSI Q1	rCSI Q2	rCSI Q3	rCSI Q4	rCSI Q5
t9.3	<b>FCS Q1</b>	5.51	2.82	2.58	1.74	2.52
t9.4	<b>FCS Q2</b>	4.98	2.80	3.24	2.53	3.44
t9.5	<b>FCS Q3</b>	5.33	4.08	4.95	4.02	3.62
t9.6	<b>FCS Q4</b>	5.59	3.40	4.28	5.46	3.90
t9.7	<b>FCS Q5</b>	4.76	3.39	4.71	5.22	5.13

846 how households manage to cope with a shortfall in food for  
 847 consumption and consists of a numerical score. It was not  
 848 possible to construct the CSI according to standard methods  
 849 as the VASyr 2015 posed the coping strategies questions in a  
 850 way that does not allow the computation of the full index. The  
 851 reduced Coping Strategies Index is a subset of the CSI that  
 852 focuses on five food-related coping strategies and results in a  
 853 cross-culturally validated tool to assess access to food. As the  
 854 rCSI has been shown to reflect food insecurity as well as the  
 855 full CSI, the rCSI was considered instead. Conceptually, we  
 856 considered food expenditure as an economic determinant of  
 857 food insecurity and therefore used it to validate the food secu-  
 858 rity measure rather than as a component of the measure itself.

859 We therefore used FCS and rCSI as proxies of food quality  
 860 and quantity, and used an empirical approach to derive cut-  
 861 offs for relative vulnerability to food insecurity within this  
 862 population, rather than international cut-offs developed for  
 863 use in acute emergency settings.

864 Using FCS and rCSI as continuous variables, we derived  
 865 both empirical and bootstrapped quantiles for each of the var-  
 866 iables. As both of these approaches yielded similar results, we  
 867 used the bootstrapped data in order not to impose restrictions  
 868 on quantiles.

869 The simplest approach to combine the two variables was to  
 870 cross classify these quantiles in the derivation of a food inse-

871 curity gradient, as has been done by others elsewhere  
 872 (Maxwell et al. 2013). This cross classification yields a gradi-  
 873 ent of vulnerability to food insecurity. Considering rCSI Q1 to  
 874 be the quantile with lowest coping, and FCS Q1 to be that with  
 875 highest food consumption score, cases falling in the top left  
 876 cell in Table 1 therefore have the lowest vulnerability to food  
 877 insecurity. Conversely, cases falling in the bottom right cell  
 878 (rCSI Q5 and FCS Q5) have the highest vulnerability to food  
 879 insecurity. **880**

881 In order not to impose arbitrary cut-off lines in classifying  
 882 vulnerability to food insecurity, we tested the food insecurity  
 883 gradient against economic variables conceptualized as deter-  
 884 minants of vulnerability to food insecurity; food expenditure,  
 885 total expenditure, extreme poverty (below SMEB) & overall  
 886 poverty (below MEB).

887 Assuming a food insecurity gradient across quantiles of  
 888 rCSI and FCS, leads to 9 levels of vulnerability to food inse-  
 889 curity (along diagonals of Table 1). Table 2 displays average  
 890 food and total monthly household expenditures (in USD),  
 891 proportion of households categorized as poor and extreme  
 892 poor by food insecurity gradient in the sample. Data show  
 893 that, as the food insecurity gradient increases, mean monthly  
 894 food expenditures and total expenditures decrease, while pov-  
 895 erty, extreme poverty and percentage share of food expendi-  
 896 ture increase.

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t10.1 **Table 10** Economic characteristics of households at different levels of the food insecurity gradient

t10.2	Food security gradient	Percent of population	Monthly food expenditures (mean, USD)	p-value*	Total monthly expenditures (mean, USD)	p-value*	Below poverty line (%)	Below extreme poverty (%)
t10.3	1	5.51	246.10		651.80		37.6	2.2
t10.4	2	7.8	236.65	0.55	574.80	0.06	51.3	2.9
t10.5	3	10.71	203.40	0.00	500.95	0.03	53.2	8.1
t10.6	4	14.65	177.15	0.01	423.69	0.00	66.5	8.0
t10.7	5	18.16	155.34	0.01	417.43	0.01	73.8	10.2
t10.8	6	15.13	147.92	0.34	347.54	0.12	78.3	16.3
t10.9	7	13.79	133.55	0.07	297.07	0.01	86.0	17.8
t10.10	8	9.12	128.60	0.54	295.18	0.92	87.2	19.5
t10.11	9	5.13	136.19	0.45	310.46	0.51	85.1	12.5

\*p-values for differences between means across gradients

t11.1 **Table 11** Cross classification of bootstrapped quantiles of FCS and rCSI, according to gradient thresholds

t11.2		rCSI Q1	rCSI Q2	rCSI Q3	rCSI Q4	rCSI Q5
t11.3	<b>FCS Q1</b>	5.51	2.82	2.58	1.74	2.52
t11.4	<b>FCS Q2</b>	4.98	2.80	3.24	2.53	3.44
t11.5	<b>FCS Q3</b>	5.33	4.08	4.95	4.02	3.62
t11.6	<b>FCS Q4</b>	5.59	3.40	4.28	5.46	3.90
t11.7	<b>FCS Q5</b>	4.76	3.39	4.71	5.22	5.13

ability to food insecurity were derived. In brief, where there were significant differences in expenditures across gradients, a threshold line was drawn, yielding five categories of vulnerability to food insecurity. Table 3 displays the cross classification of the bootstrapped quantiles, with thresholds drawn between gradients 2 and 3, 3 and 4, 4 and 5, and 6 and 7.

899 Based on an analysis of differences in mean monthly food  
900 and total expenditures across gradients, thresholds of vulner-  
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910 **Appendix 2**

t12.1 **Table 12** Description of variables

t12.2	Variable	Description
t12.3	fsgradient	Food Security gradient (ordered 1–9)
t12.4	Percap_exp_quant	Household expenditure quantile (1–10)
t12.5	HHsize	Number of household members
t12.6	HHsize2	HHsize squared
t12.7	Homogeneous	Proportion of sample HH in Lebanese district from same district of origin in Syria, see text
t12.8	hoh_education_level = intermediate	1 if head of HH education level: intermediate
t12.9	hoh_education_level = none	1 if head of HH education level: none
t12.10	hoh_education_level = primary_school	1 if head of HH education level: primary
t12.11	hoh_education_level = read_write	1 if head of HH education level: read and write
t12.12	hoh_education_level = secondary_school	1 if head of HH education level: secondary
t12.13	hoh_education_level = technical	1 if head of HH education level: technical
t12.14	hoh_education_level = university	1 if head of HH education level: higher
t12.15	Access_Phone	1 if HH expenditures on phone(s) are positive
t12.16	valuable_assets	1 if HH possesses valuable assets (durable goods)
t12.17	less_than_5_share	Proportion of HH members under 5 years of age
t12.18	btw_5_and_17_share	Proportion of HH members aged 5 to 17
t12.19	btw_51_and_70_share	Proportion of HH members aged 51 to 70
t12.20	aged_more_than_71_share	Proportion of HH members aged >70
t12.21	btw_18_and_50_male_share	Proportion of male HH members between 18 and 50
t12.22	btw_18_and_51_female_share	Proportion of female HH members between 18 and 50
t12.23	disabled_share	Proportion of disabled HH members
t12.24	water_access_hh_share	Share of HH with access to sufficient amount of water for drinking, cooking, washing and toilet purposes
t12.25	drinkingwater_access_hh_share	Share of HH with access to safe drinking water
t12.26	sanitation_access_hh_share	Share of HH with access to flush toilets
t12.27	crowded_hh_share	Share of HH living in crowded conditions
t12.28	chronichoh_hh_share	Share of HH where Head of HH is chronically ill
t12.29	chronic_hh_share	Share of HH who have one or more chronically ill members
t12.30	receivehealth_hh_share	Share of HH who receive health care/drugs regularly

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