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“Targeting mechanisms for cash transfers using regional aggregates”

Jad Chaaban, Hala Ghattas, Alexandra Irani and Alban Thomas

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.

165 **2 Materials and methods**

166 **2.1 Theoretical model**

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

178 Consider a food-aid planner whose objective is to target
 179 poor households with a given cash transfer denoted A (per
 180 HH), from a total population of size (N, known) . The unit
 181 administrative cost of transferring A to a household is denoted
 182 τ , the proportion of poor (non-poor) households in the total
 183 population is β_P (respectively, β_{NP}). Let $p_1(\alpha)$ and $p_2(\alpha)$ re-
 184 spectively denote the probability of under-coverage (not
 185 targeting a poor household) and leakage (targeting a non-
 186 poor household), which depend on the effort of collecting
 187 and treating information on households, denoted α . The cost
 188 of effort is $F(\alpha)$ and we assume

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

191
 192 For a given level of effort α , the social planner wishes to
 193 obtain a particular level of targeting and, therefore, a given
 194 level of social welfare as an outcome. We assume the social
 195 planner solves this problem by determining both the optimal
 196 for effort (α) and the level of cash transfer (A).

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

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

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

i.e., accounting for administrative costs. In this case, the min- 212
 imization problem becomes, after substituting for A^* and 213
 using $\beta_{NP} = 1 - \beta_P$ 214

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

which gives 216

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

which implies that $\{ [1-p_1(\alpha)] - \frac{1-\beta_P}{\beta_P} p_2(\alpha) \} \geq 0$, provided the 218
 cost of effort does not exceed the initial budget, i.e., $[B - 219$
 $F(\alpha)] \geq 0$. This second option is obviously not relevant when 220
 the objective is to help poor households reach some poverty 221
 line level. With such a policy, some assisted households could 222
 become better off than non-assisted ones, which would intro- 223
 duce distortions in the distribution of households. 224

225 A third possibility is that the social planner first deter- 226
 mines exogenously the cash transfer that corresponds to a 227
 minimum level of food expenditure to ensure food secu- 228
 rity. For example, some minimum expenditure level can 229
 be computed given local prices, based on requirements for 230
 food and nutrient intake provided by international stan- 231
 dards. More precisely, the social planner would equate 232
 direct and indirect utility levels 233

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

234 where $V(\cdot)$ and $U(\cdot)$ are indirect (Hicksian) and direct 235
 (Marshallian) utility functions respectively, p is the vector 236
 of market prices faced by households, \underline{y} is exogenous 237
 income (not depending on cash transfers) and FS is the 238
 level of food expenditure to guarantee food security. 239
 Solving for cash transfer in the equation above allows 240
 the social planner to determine the optimal level of trans- 241
 fer to reach food security, denoted A^* , given available 242
 income and price levels. Then, in a second stage, the 243
 social planner solves the following program: 244

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

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

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

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

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

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

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

2.2 Empirical methodology

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

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

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

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

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

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

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:

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

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 δ_1 and δ_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 π 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.”¹

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

¹ 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 expen-
 523 diture 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 insecur-
 532 ity 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

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

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

3 Results

3.1 Estimation results

We now present estimation results for our model specifications with increasing information used to represent simultaneously food insecurity and economic vulnerability: model (I) with ProGres variables only, and model (II) adding district-level indicators. For each model considered, random effects at

district level are accounted for, as described above, to evaluate the log-likelihood function of the bivariate ordered Probit. Parameter estimates are presented in Table 4. To interpret correctly the sign of the effect of a given explanatory variable, It has to be remembered that a higher value of the dependent variable *percap_exp_quant* corresponds to a lower economic vulnerability, while a higher value of the variable *fsgradient* is associated with a higher degree of food insecurity.

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

Table 3 Descriptive statistics of the sample

Variable	Specification(s)	Mean	Standard Deviation
<i>fsgradient</i>	(I), (II), HH	4.9506	2.198
<i>percap_exp_quant</i>	(I), (II), HH	5.5049	2.8737
<i>HHsize</i>	(I), (II), HH	5.2099	2.3289
<i>HHsize2</i>	(I), (II), HH	32.7195	31.8355
<i>homogeneous</i>	(I), (II), HH	0.1026	0.0954
<i>hoh_education_level = intermediate</i>	(I), (II), HH	0.187	0.39
<i>hoh_education_level = none</i>	(I), (II), HH	0.1577	0.3645
<i>hoh_education_level = primary_school</i>	(I), (II), HH	0.4379	0.4962
<i>hoh_education_level = read_write</i>	(I), (II), HH	0.0927	0.2901
<i>hoh_education_level = secondary_school</i>	(I), (II), HH	0.0732	0.2606
<i>hoh_education_level = technical</i>	(I), (II), HH	0.0156	0.1239
<i>hoh_education_level = university</i>	(I), (II), HH	0.0358	0.1859
<i>Access_Phone</i>	(I), (II), HH	0.8963	0.3048
<i>valuable_assets^(*)</i>	(I), (II), HH	0.9203	0.2709
<i>less_than_5_share</i>	(I), (II), HH	0.1973	0.1891
<i>btw_5_and_17_share</i>	(I), (II), HH	0.2904	0.2374
<i>btw_51_and_70_share</i>	(I), (II), HH	0.0568	0.1521
<i>aged_more_than_71_share</i>	(I), (II), HH	0.0111	0.0701
<i>btw_18_and_50_male_share</i>	(I), (II), HH	0.2131	0.183
<i>btw_18_and_51_female_share</i>	(I), (II), HH	0.2311	0.1477
<i>disabled_share</i>	(I), (II), HH	0.0277	0.0908
<i>water_access_hh_share</i>	(II), Dist	0.8422	0.2226
<i>drinkingwater_access_hh_share</i>	(II), Dist	0.4659	0.2196
<i>sanitation_access_hh_share</i>	(II), Dist	0.4106	0.2226
<i>crowded_hh_share</i>	(II), Dist	0.5483	0.0927
<i>chronichoh_hh_share</i>	(II), Dist	0.2103	0.0672
<i>chronic_hh_share</i>	(II), Dist	0.4007	0.1003
<i>receivehealth_hh_share</i>	(II), Dist	0.1049	0.0562

3850 observations. (*): 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	btw_5_and_17_share	(0.39)	(0.05)	(0.14)	(0.01)
t4.31	btw_51_and_70_share	0.6455	0.3642	0.5532	0.4298
t4.32	aged_more_than_71_share	(0.64)	(0.36)	(0.54)	(0.42)
t4.33	btw_18_and_50_male_share	1.4382	1.0899	0.3310	0.1903
t4.34	btw_18_and_51_female_share	(1.42)	(1.08)	(0.33)	(0.19)
t4.35	less_than_5_share	1.6759	1.3100	0.6336	0.4870
t4.36	btw_5_and_17_share	(1.62)	(1.26)	(0.61)	(0.47)
t4.37	btw_51_and_70_share	2.0983**	1.7359*	0.3456	0.1807
t4.38	aged_more_than_71_share	(2.08)	(1.72)	(0.34)	(0.18)
t4.39	btw_18_and_50_male_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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. ρ is the correlation coefficient between both equations; LR is the Likelihood Ratio test (distributed as a χ^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
678 of 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)² 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

² 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 807 Insecurity Indicator 808

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.³ 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

³ 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	FCS Q1	5.51	2.82	2.58	1.74	2.52
t9.4	FCS Q2	4.98	2.80	3.24	2.53	3.44
t9.5	FCS Q3	5.33	4.08	4.95	4.02	3.62
t9.6	FCS Q4	5.59	3.40	4.28	5.46	3.90
t9.7	FCS Q5	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	FCS Q1	5.51	2.82	2.58	1.74	2.52
t11.4	FCS Q2	4.98	2.80	3.24	2.53	3.44
t11.5	FCS Q3	5.33	4.08	4.95	4.02	3.62
t11.6	FCS Q4	5.59	3.40	4.28	5.46	3.90
t11.7	FCS Q5	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-
907

908
909

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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