Focused Targeting against Poverty
Evidence from Tunisia

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Abstract

This paper introduces a new methodology to target direct transfers against poverty. Our method is based on observable correlates and on estimation methods that *focus on the poor*. Using data from Tunisia, we estimate 'focused' transfer schemes that improve anti-poverty targeting performances. Post-transfer poverty can be substantially reduced with the new estimation method. The impact of these schemes on the welfare of the poor is also much stronger than the current food subsidies system in Tunisia. Finally, the obtained levels of under-coverage of the poor is so low that 'proxy-means' focused transfer schemes becomes a realistic alternative to price subsidies, likely to avoid social unrest.

Résumé

Ce travail introduit une nouvelle méthode de ciblage des transferts directs contre la pauvreté. Cette méthode est basée sur des corrélats observables et sur des méthodes d'estimation qui se concentrent sur les pauvres. A partir de données Tunisiennes, nous estimons des programmes de transferts 'concentrés' qui améliorent beaucoup la précision du ciblage anti-pauvreté. Le nombre de pauvres post-transferts est divisé par deux avec la nouvelle méthode d'estimation. L'impact de ces programmes sur le bien-être des pauvres est également beaucoup plus efficace que le système de subventions alimentaires actuellement en place en Tunisie. Enfin, le degré obtenu de non-couverture est si faible que les transferts directs deviennent une alternative réaliste aux subventions des prix, susceptible d'éviter les troubles sociaux.

Key Words: Poverty; Targeting; Transfers.

JEL classification: D12; D63; H53; I32; I38.

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1. Introduction

Transfer schemes are one of the main policy tools to alleviate poverty. Cash transfers are the proviso of assistance in cash to the poor or to those who face a risk of falling into poverty. The schemes are generally based on predictions of household living standards used to calculate the transfers. Such predictions are obtained by regressing the living standard variable on household characteristics easy to observe. However, estimated transfer schemes are often little accurate and their impact on poverty is often disappointing. In this paper, we propose an estimation method of anti-poverty transfer schemes that focus on the poor and the near poor, thereby dramatically improving the scheme performance. We apply our new method to Tunisia.

In Tunisia, targeting transfers to poor people has become increasingly important because structural adjustment programs have imposed cuts in food subsidies, traditionally the main way to fight poverty. This is all the more so that the leakage from food subsidies to non-poor people is considerable, while failure to substantially serve all in the target group is common. The Tunisian Universal Food Subsidies Programme (TUFSP) is the main policy instrument for alleviating poverty in Tunisia. Since 1970, basic foodstuffs have been under subsidy to protect the purchasing power and the nutritional status of the poor. Even if the poor benefited from it, this program was inefficient and costly. Indeed, about 4 percent of the GDP was spend in subsidies by 1990 (10 percent of total government expenditure) and the richer households received much more from the program than the poor in absolute terms. In such situation, transfer schemes might alleviate poverty at a lower budgetary cost, provided that the method used to design the scheme performs well. This is consistent with one of the three key challenges identified by the World Bank to meet the goals of the 10th Economic Development Plan: to strengthen the performance of social programs while maintaining budget balances (The World Bank, 2004).

Several authors have studied assistance to poor people based on targeting when some characteristics of individuals can be observed, but not income.[3] Although incomes and living standards are measured with household surveys, they are generally badly known for the households that are not surveyed. Ravallion and Chao (1989) model the targeting problem as one of minimizing some specific poverty measures subject to a given anti-poverty budget by using groups defined by the location of individuals. A similar targeting approach, which we follow in this paper, is based on additional correlates of household living standards (Glewwe, 1992). We estimate the optimal solution of a poverty minimization program subject to an anti-poverty budget by allowing transfers to poor persons as a function of their observable characteristics.

In practice, anti-poverty targeting can be based on predictions of household living standards, obtained from regressions on observed characteristics, generally based on ordinary least squares estimates (OLS). However, the OLS method is anchored on the mean of the dependent variable (e.g., household income) and should provide accurate predictions around this mean only, which is often much higher than the poverty line. Then, accuracy loss in predicting the living standards of the poor and near poor may occur. This is the case when the mechanisms explaining the living standards of the non-poor differ from those of the poor. The latter is expected because poor households differ from other households not only by their capital and skills, but also by their access to social networks and credit possibilities, and by their economic activities.

In this situation, using OLS predictions may be sub-optimal. In this paper, we use estimation methods that 'focus' on the poor, so as to improve the predictions of the living

[3] For instance, see Besley and Coate (1992), Glewwe (1992), Besley and Kanbur (1993), Datt and Ravallion (1994), Chakravarty and Mukherjee (1998), Ahmed and Bouis (2002) and Schady (2002).

standards for the poor households and the households that are located just above the poverty line.

Various estimation methods are possible for this purpose. For example, a semi-non-parametric estimation of the income distribution could be implemented by using kernel estimation methods in which correlates are parametrically incorporated (e.g., in Pudney, 1999). However, analysts operating in statistical institutes in LDCs and in international organisations generally favor more straightforward estimation methods. Accordingly, Deaton (1997) insists on methods that can be actually implemented in the relevant institutions. For this reason we concentrate on two simple methods for estimating the predictive regressions: (i) censoring the dependent variable to eliminate the influence of observations located far from the poverty line; (ii) using quantile regressions. Then, *focusing on the poor* means that the predictions are calculated by defining the quantile regression or the censorship in terms of living standard levels judged representative of the poor or the near poor.

Another important issue is that OLS estimates for anti-poverty schemes are sensitive to the presence of outliers, to the non-normality of error terms when the sample size is not large, to heteroscedasticity and other misspecifications. Using quantile regression deals with these concerns for robustness (Koenker and Bassett, 1978) that are crucial in poverty analysis because of measurement errors in consumption surveys and the non-robustness of many poverty measures (Cowell and Victoria-Feser, 1996).

In that case, what is modeled is a chosen quantile of the distribution of the living standard variable conditionally on the correlates. This method has two shortcomings. Firstly, if the error terms are approximately normal, some efficiency may be lost as compared with OLS. Secondly, the focus property is only conditional on the set of correlates. That is, the chosen quantile is not that of the dependent variable, but the quantile of the error term in the estimated equation. However, that is the quantile of the error that may matter most if one is interested in the prediction error that affects the transfer scheme performance.

As mentioned above, a better focus of the scheme can also be obtained by eliminating part of the income distribution (the richest households for example) from the prediction. This suggests using Tobit regressions and censored quantile regressions instead of respectively OLS and quantile regressions.

Another interest of focused targeting is that it is logically related to the theoretically optimal transfer schemes with the transfers concentrated towards the poorest of the poor, the richest of the poor, or both (Bourguignon and Field, 1997). Indeed, from this theoretical perspective what need to be accurately determined are the transfers to these sub-populations. Then, focused predictions of the living standards of the poor and near poor may generate more efficient transfer schemes. However, focused estimation methods may be associated with efficiency losses in the predicting equations, because they may not take advantage as much as OLS of the information about households whose living standards are much higher than the poverty line.

Is it possible to improve anti-poverty transfers with living standard predictors that focus on the poor or near poor? The aim of the paper is to explore this question. Section 2 presents the anti-poverty transfer schemes. In Section 3, we apply our new method to the 1990 Tunisian household survey. We find that targeting by indicators is more effective than in force food subsidies. Moreover, focused targeting would reduce poverty much more than targeting based on OLS predictions of living standards. Finally, Section 4 concludes this paper.

2. Anti-Poverty Transfer Schemes

This paper is based on the following popular poverty measures of the FGT class (Foster et al., 1984) because of their attractive axiomatic properties: $P_\alpha(z,Y)=\int_0^z \left(\frac{z-y}{z}\right)^\alpha f(y)\,dy$, where z is a pre-specified poverty line, $f(.)$ is the c.d.f. of household income y (or household living standards) and α is a poverty aversion parameter.[4] Naturally, our approach could be extended to other poverty measures. Once an anti-poverty budget has been decided, it remains to design transfers that optimally allocate this budget across households. This can be represented by a program minimizing poverty under a budget constraint.

Let us first consider the situation when Y (the vector of incomes in a population before applying the vector of transfers $T=\{t^i,\ i = 1,\ldots,N\}$ is perfectly observed. In that case, the optimal allocation of benefits is the solution to:

$$\underset{\{t^i\}}{\mathrm{Min}}\ P_\alpha(z,Y+T)\equiv\frac{1}{N}\sum_{i=1}^{N}\left(\frac{z-(y^i+t^i)}{z}\right)^\alpha I_{[y^i+t^i<z]}$$

subject to

$$\sum_{i=1}^{N} t^i = B, \qquad \text{with } t^i \geq 0, \forall i,$$

where N is the population size, B is the budget to allocate, t^i is the income transfer to household i and y^i is pre-transfer income. It is also possible to weigh the objective function by the number of persons (or number of equivalent-scales) in each household to deal with poverty at the individual level rather than the household level. However, for expositional simplicity, we forget for the moment that households may include several members. The income transfers are required to be non-negative. How the fixed budget B is funded is not

[4] The $P_\alpha(.)$ is the head-count ratio if $\alpha = 0$, the poverty gap index if $\alpha = 1$, and the poverty severity index if $\alpha = 2$. The FGT poverty measures satisfy the transfer axiom if and only if $\alpha > 1$, and the transfer sensitivity axiom if and only if $\alpha > 2$. All these measures satisfy the focus axiom and are decomposable.

considered in this paper. When Y is perfectly observable by the policy-maker, the transfer solution to this problem is referred to as 'perfect targeting' and denoted t^i for household i.

Bourguignon and Fields (1990, 1997) show that perfect targeting minimizing the headcount ratio would start awarding transfers so as to lift the richest of the poor out of poverty: $t^i = z - y^i$ if $y^i < z$, $t^i = 0$ otherwise (in a decreasing order of income until all the budget is exhausted, 'r-type transfer'). In contrast, if the aim is to minimize a FGT poverty measure satisfying the transfer axiom ($\alpha > 1$), it is optimal to start allocating the anti-poverty budget to the poorest of the poor ('p-type transfer'). In that case, the transfer scheme would be: $t^i = y_{max} - y^i$ if $y^i < y_{\max}$; $t^i = 0$ otherwise, where $y_{\max}$ is the highest cut-off income allowed by the budget. As the anti-poverty budget rises, $y_{\max}$ increases up to the poverty line, z, and perfect targeting would permit to lift all the poor out of poverty if enough funding is available.

Unfortunately, perfect targeting is not feasible because incomes cannot be perfectly observed. Nevertheless, since the household living standards are correlated with some observable characteristics, it is possible, as in Glewwe (1992), to minimize an expected poverty measure subject to the available budget for transfers and conditioning on these characteristics. In practice, the approach followed in the literature or by practitioners for designing the transfer scheme is to replace unobserved living standards by predictions based on observed variables.

Let us first recall the standard procedure used in the literature for such predictions. Several empirical articles on anti-poverty targeting have appeared in the literature[5]. They generally follow a two-step procedure. First, the expectation of y^i conditional on x^i (the vector of living standard correlates for household i) is parametrically estimated by *OLS*. Then, if the

[5] Glewwe and Kanaan (1989), Glewwe (1992), Grosh and Baker (1995), Ravallion and Datt (1995), Bigman and Srinivasan (2002), Park et al. (2002), Schady (2002), Tabor (2002).

budget allows it, each predicted poor household receives the difference between its predicted income and the poverty line.

Some authors have assumed that there is no question with this model to assume that x^i causes y^i, but only that x^i can be used to predict y^i. However, endogenous variables would lead to inconsistent parameter estimates and therefore inconsistent predictions of y^i. Moreover, some variables could be easily modified by the households, raising moral hazard problems. We deal with this issue by avoiding as much as possible endogenous regressors, and by considering alternative sets of correlates, defined by their increasing presumed endogeneity.

What matters for anti-poverty targeting is the ability to identify the poor and predict their living standards. Our strategy is to focus on the poor and the near poor when predicting living standards. The concern for predictions adapted to the poor is present in Grosh and Baker (1995) in which targeting accuracy is improved when using only the poorest 50 percent of the population. However, censorship close to the poverty line is likely to provide better results than truncation since it does not throw away valuable information about the identification of the poor and of the non-poor. Then, we investigate if such censorship of living standards can improve the performance of the transfer scheme.

In this situation, if the error term in the latent equation of this model is normal, living standard predictions can be obtained by using a Tobit model, conditional upon some household characteristics. However, several issues may cause Tobit estimates to be inconsistent. First, the normality assumption on which the Tobit model is based is often rejected even for logarithm of living standards. Second, heteroscedasticity is likely to arise from household heterogeneity. Finally, the threshold y_{max} may be unknown. We deal with these difficulties by also using censored quantile regressions that are little sensitive to them[6].

[6] Other attempts to improve the focus on the poor could be based on combining census data and household survey data, although Bigman and Srinivasan (2002) and Schady (2002) found that the improvement in targeting in India and Peru are small. More recently, Elbers, Lanjouw and Lanjouw (2003) provide encouraging results for poverty estimation. We do not deal with this approach in this paper, which may not be well adapted to targeting

We now turn to the estimation results. We start by presenting the data used for the estimations.

3. Estimation Results

3.1. The data

We use data from the 1990 Tunisian consumption survey conducted by the INS (National Statistical Institute of Tunisia). This household survey provides information on expenditures and quantities for food and non-food items for 7734 households. Usual other information from household surveys is available such as the consumption of own production, education, housing, region of residence, demographic information, and economic activities.

Because the estimation of equivalence scales based on cross-section data has often been criticized,[7] and in order to concentrate on the issue of imperfect targeting, we assume that total consumption expenditure per capita is an adequate indicator of each household member's welfare.

We define in Table 1 the correlates of living standards used for the predictions, along with their expected link with living standards. The correlates are grouped to facilitate the discussion of their characteristics. The groups are ranked according to increasing difficulties of observation by the administration and increasing ease of modification or hiding by households. Set I contains the regional characteristics of the households[8]. Set II contains regional and demographic information on households, and characteristics of the household's dwelling. Set III adds information on the occupation of the household's head to that in Set II, and the education level of the household's head. The variables in Set II are unlikely to be

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schemes since census are conducted in special years, while transfer schemes may necessitate fresh information on household characteristics each year.

[7] Pollak and Wales (1979), Blundell and Lewbel (1991).

[8] For more information about regional targeting, see Kanbur (1987), Ravallion (1992), Datt and Ravallion (1993), Baker and Grosh (1994), Besley and Kanbur (1988), and Bigman and Fofack (2000).

manipulated by households and could be cheaply observed, yet those added in Set III are easier to conceal.

It has been found that price differences across households may affect poverty measurement, notably in situations of price discrimination correlated with living standards (Muller, 2002). In order to correct for this, account for substitution effects caused by price subsidies and control for spatial price dispersion, we introduce the equivalent-gain from food subsidies, Γ. The calculus of Γ is explained in Appendix 2 and is derived from the estimation of a QAIDS demand system, described in Muller and Bibi (2005). Both income and poverty line are converted into equivalent income. As Deaton (1981) signals, nothing can be learned about commodity taxes from consumer studies in which commodity demands are explaining conditionally on total expenditure and prices and which assume linear Engel curves. This, and the obtained gain in accuracy in describing substitution effects justifies our choice of basing the true price indices on the estimation of a quadratic almost ideal demand system. Our reference price system is the one without subsidies, which has the advantage of simplicity and puts all the considered policies on the same stand.

Then, they are three stages of estimation: (1) the estimation of a demand system used to infer equivalent-incomes that enter the definition of living standard variable; (2) the prediction of living standards from observed household characteristics; (3) the simulation of the effects of the transfer scheme. Let us turn to the living standard predictions.

3.2. Results for living standard predictions

Table 2 shows the descriptive statistics of the main variables used in the estimation. Mean total expenditure per capita is 804 TD (Tunisian Dinars). Tables 3 presents the results of OLS regressions, Tobit regressions (censored at 10%), quantile regressions (anchored on the first decile) and censored quantile regressions (censored at 50% and based on the first decile) of the logarithm of the household consumption per capita, on Sets I, II and III of explanatory variables. Other conventions, for censorships and quantiles lead to results in agreement[9]. We use for the dependent variable the logarithm of the equivalent income (i.e. with living standards corrected with true price indices inferred from the estimated demand system)[10]. Alternative results of this paper without adjustment or corrected by Laspeyres price indices are in agreement.

The censored quantile regression estimator for dependent variable y_i and quantile θ is obtained as the solution to the minimisation of $1/N \sum_i \rho_\theta[y_i - \max(0, X_i'\gamma)]$, where $\rho_\theta[u] = \{\theta - I_{[u < 0]}\} |u|$, X_i is a matrix of regressors, γ is a vector of parameters, N is the sample size. Quantile regressions correspond to replacing $\max(0, X_i'\gamma)$ with $X_i'\gamma$. Powell (1986) and Buchinsky and Hahn (1998) analyse these estimators. The estimation is obtained by a combination of a linear programming algorithm and sub-sample selection at each iteration of the optimisation. We estimate the confidence intervals of the censored quantile regression estimates by using the bootstrap method proposed by Hahn (1995) with 1000 bootstrap iterations.

It has been argued that quantile regressions could help the analysts to focus on the population of interest by choosing quantiles corresponding to the poor (Buchinsky, 1994). This argument is overstated since the quantile is that of the conditional distribution, i.e. of the error term, and not directly of the poverty index. However, if the concern is the prediction of the living standards of the poor or near poor, and if most of the prediction difficulties reside in the unobserved error terms in the living standard equations, quantile regressions anchored on small quantiles may help improving the prediction of living standards for these sub-

[9] The censorship at quantile 50 percent of the censored quantile regression is chosen because of two requirements. First, censored quantile regression estimates are inconsistent if too few observations are present in the uncensored subsample (a condition needs be satisfied which is unlikely with a too small sample). Second, excessive censoring leads to disastrous loss of accuracy in the estimation.

[10] To remain close to common practices we did not weigh the estimation by the sampling scheme. However, we checked that using sampling weights in this case yields similar results, in part because the sampling probability at each sampling stage of this survey are almost proportional to population sizes.

populations. Then, our choice of the quantile in the quantile regressions is motivated by the focus on the population of the poor or near poor, so that the data about rich households plays only a minor role in the estimation. This approach corresponds to specifying quantiles close to the poverty line in the living standard regressions.

Let us take a look in Table 4 at the ratios of the variance of the prediction errors over the variance of the logarithm of the living standards. These ratios are measures of the prediction performance of the estimation methods for the mean of the logarithms of living standards. They are provided for three subpopulations: the whole population of households, the households in the first quintile of the living standards, the households in the first and second quintiles. For the OLS, the considered ratio is equal to $1-R^2$.

The results show that quantiles regressions (anchored at quantile 0.1) generally perform much better than the other methods for predicting the logarithms of living standards *of the poor* (here defined as belonging to the first or second decile of the living standard distribution), to the exception of censored quantile regressions that are better for the poor under the first quintile. In contrast, the best method for predicting the mean of the logarithms of living standards in the whole population is the OLS method. Predicting the logarithms of living standards by using Tobit regressions (with censorship at 10 or 30 percent) does not improve on OLS predictions for the whole population in this data set. Moreover, Tobit predictions for the poor remain much inferior to the predictions obtained with quantile regressions, and censored quantile regressions, for the poor. Finally, the predicting performance of the censored quantile regressions is disappointing for the whole population, and dominated by that of the quantile regressions for the poor in the second quintile, which is worrying since the realistic poverty lines in Tunisia lie between the first and second quintile. An additional difficulty with censored quantile regressions is that they rely on estimation algorithm difficult to readily implement in most national statistical institutes of less developed countries.

Then, if our business is predicting the logarithms of living standards of the poor or near poor, the quantile regressions look like the most promising method. In contrast, censoring living standards with Tobit models does not seem to provide improved predictions of the logarithms of living standards of the poor.

Our approach consists in exploiting the better predictive performance of quantile regressions for the living standards of the poor to improve the performance of anti-poverty transfer programs. Appropriate assessment will be obtained by estimating the scheme with different methods and examining the results. We now turn to the results of the prediction equations in Table 3. The signs of most coefficient estimates (significant at 5 percent level) correspond to the expected effects of variables and are consistent across all estimation methods.

The dummy variable for Tunis is the reference. The dummy variable for the eastern regions (Northeast, Sfax, Southeast) have generally less negative coefficients. Residents in the East are richer than most other households, while poorer than households living in Tunis. This corresponds to well-known features of the geographical dispersion of the poor in Tunisia (The World Bank, 2000).

The two estimated coefficients associated with the age of the head imply an inverse-U shape effect consistent with life cycle theories. The other variables describing household composition have almost always negative effects. Indeed, numerous members in young age classes generate high economic burden. In contrast, the variables describing the activities of members, the numbers of active members by gender and the number of adult members over 19 years old, have positive effects associated with members' contributions to household income. As expected, the male contribution is larger than the female one. The coefficients of the housing characteristics have signs consistent with durable consumption and investment decisions that are correlated with household income. Living in a flat and the number of rooms per capita are positively associated with living standards. Hovel dwellers and dwellers in Arab house are relatively poorer. Households who rent or acquired their lodgings on lease are generally better off. This is consistent with the higher cost of these accommodation options.

The estimated negative coefficients describing the school participation of children reflect corresponding expenditure. In contrast, the estimated positive coefficients of the education level of the household head are related to the returns to past human capital investment. Then, households with more children at school are on average poorer, while households with better educated heads are richer.

The omitted occupation categories are ‘managers, executives and other qualified white collar or self-employed workers’. The household heads in these categories are generally not poor, which explains the negative coefficients of the included occupations. Households whose head are unemployed or are agricultural labourers are often less well off. However, agricultural labourers in the Southwest (respectively the Southeast), where rain is scarcer and aridity is fiercer (respectively less scarce, respectively less fierce), are more (respectively less) handicapped by their occupation than agricultural labourers in other regions. Households whose head is an industry worker have intermediate living standards between those of agricultural labourers and farmers.

In a second step in the analysis, the predicted household living standards are used to simulate poverty levels resulting from the targeting scheme. We now examine the results of these simulations, first by using poverty curves.

3.3. Simulated poverty curves

The calculation of the transfer $T_{\alpha}(.)$ in the simulations, according to the Bourguignon and Fields' rule, requires the determination of the cut-off income, y_{max}, beyond which no transfer takes place. Under perfect targeting, the y_{max} permitted by the budget currently devoted to food subsidies is TD 358 (Tunisian Dinars), greater than poverty lines estimated for Tunisia.[11] Even if the budget is sufficient to eliminate poverty under perfect targeting, under imperfect targeting additional resources are necessary, and the budget is exhausted. We present our simulation results in the form of poverty curves describing stochastic dominance situations.

In Sub-Section 3.4., we shall use a poverty line equal to TD 250 to estimate targeting efficiency measures, consistently with the most credible poverty line in The World Bank (1995), corresponding to a head-count index of 14.1 percent. This poverty line corresponds to an *equivalent poverty line of TD 280* without subsidies. However, the qualitative results of this paper go through with poverty lines at reasonable levels, as is illustrated in the poverty curves.

The top of Figure 1 shows the upper ('max') and lower ('min') curves corresponding to the 5 percent bootstrap confidence bounds of ΔP_0 (difference in the head-count indices) obtained with (1) the transfer scheme based on one of the estimation methods and (2) the food subsidies. These curves exhibit the significance of the differences in the proportion of the poor obtained after the implementation of the two considered policies under fixed budget and for a range of poverty thresholds. That is, a transfer method significantly first-order dominates price subsidies if the lower bound curve of the interval is over zero. The results show that all the considered transfer methods (except Tobit for a short interval of poverty lines)

[11] The poverty line estimated by the National Statistic Institute and the World Bank (1995) – see also Ravallion and van der Walle (1993) - on the basis of needs in food energy corresponds to TD 196, the poverty lines by Ayadi and Matoussi (1999) vary between TD 213 and 262, and the poverty lines by Bibi (2003) vary between TD 227 and 295. Poverty lines calculated by the World Bank for 1995 (The World Bank, 2000) are between TD 252 to TD 344.

significantly first-order dominate price subsidies for reasonable levels of the poverty line. This is confirmed by the bottom of Figure 1 that shows the same type of curves but this time for the second order stochastic dominance (differences in Poverty Gaps, ΔP_1). Clearly, all the considered situations correspond to lower poverty levels reached by the transfer schemes as compared to the case of subsidies. Aggregate poverty would be unambiguously diminished by implementing these transfer schemes in place of price subsidies.

Figure 2 shows the 5 percent bootstrap confidence intervals of the poverty curves obtained with two transfer schemes based on two prediction methods among: OLS, Tobit, quantile regressions and censored quantile regressions anchored on the first decile and censored at 50 percent. Here, the first-order dominance (poverty measured by the head-count index) is insufficient to produce an unambiguous ordering of these methods. In contrast, for realistic poverty lines, with the second-order dominance (poverty measured by the poverty gap), the estimates of poverty after the transfers based on quantile regressions are significantly second-order dominated by poverty after Tobit-based transfers, which is itself second-order dominated by poverty after OLS-based transfers. These results are valid for any poverty line below a threshold well above TD 280, the poverty line we use in the next section to assess the targeting efficiency. In contrast, for unrealistically high poverty lines, the performance of quantile-regression-based transfers is clearly dominated by the performance of OLS- and Tobit-based transfers. This exhibits the specificity of the 'focus' on low-incomes for quantile-regression-based transfers.

Thus, the resulting ranking of the curves in terms of poverty reduction across the considered estimation methods is akin to the ranking that has been found for the goodness-of-fit of the logarithm of living standard regressions for the poor. We simulated the poverty curves by using the alternative price indices to correct the household living standard indicators. The ordinal comparison results across curves corresponding to different anti-poverty schemes do not change.

Moreover, the curves of stochastic dominance show that the bulk of the gain obtained with our new method corresponds to a population of the poor whose living standards are much below the half-mean of the living standard distribution.

The better performance of quantile regressions may be attributed to the focus properties of this method. However, an alternative interpretation could be that the robustness of the quantile regressions is what matters in practice. To control for this alternative interpretation of our results we run Huber robust regression estimations. It happens that Huber regressions yield almost the same results than OLS estimates whether for the estimated coefficients or for the poverty curves. The better performance of the quantile regressions for anti-poverty targeting scheme is therefore not due to robustness. However, poverty curves provide only qualitative insights. We now turn to quantitative measures of targeting efficiency and their estimators.

3.4. Measures of targeting efficiency

Let us first devote a few words to the measures of targeting efficiency of the transfer scheme. With imperfect targeting, only poor people who are predicted as poor can benefit from poverty alleviation as long as their predicted living standard is below the threshold y_{max} for a 'p-type' transfer, or between y_{max} and z for a 'r-type' transfer. On the other hand, non-poor people predicted as non-poor or with their predicted living standard in the above intervals bounded by y_{max}, are excluded from the transfers of this program. Thus, two types of errors characterize imperfect targeting, and depend on the prediction method, the type of transfer chosen and the available budget. The *Type I error* (*undercoverage*) is that of failing to reach some members of the targeted group. As Atkinson (1995) noted, this failure generates horizontal inefficiency when compared with perfect targeting. The *Type II error* arises where benefits are awarded to some people who would be ineligible under perfect targeting. The *leakage* of program benefits is obtained by adding the transfers given to those whose pre-transfer income is above the poverty line and the transfers which, although received by pre-transfer poor, are unnecessary because the post-transfer living standards are raised above the poverty line.[12] The *leakage ratio* is obtained by dividing the leakage with the available budget. A final measure of the program efficiency is the reduction in poverty measures due to the transfer scheme: $\Delta \mathrm{P}_{\alpha} = \mathrm{P}_{\alpha}(z, Y) - \mathrm{P}_{\alpha}(z, Y + \hat{T})$, where $\hat{T}$ is the vector of the estimated transfer for each household *h*.

To assess the performance of anti-poverty transfers, we compare the outcomes of the transfer scheme with those of the Tunisian food subsidy scheme, the main Tunisian poverty alleviation program. To achieve this aim, we compute the equivalent gain of the food subsidies scheme: $Y_e(p^r, p^s, Y) = Y + \Gamma$, where $Y_e(.)$ is the equivalent-income function vector for observed households, p^r is the benchmark price vector ('reference prices') composed of the prices obtained without food subsidies, p^s is the price vector under food subsidies, and Γ is the vector of the equivalent-gains under food subsidies. The estimation of the equivalent-income is described in Appendix 2.

The poverty measure under price subsidies is calculated as follows, transforming the incomes into their equivalent values when prices are the observed p^s instead of the reference p^r. Since the poverty line z = *TD 280* has been defined for prices without subsidies p^r, we have $Y_e(p^r, p^r, z) = z$. Then, $\mathrm{P}_\alpha[Y_e(p^r, p^r, z), Y_e(p^r, p^s, Y)] = \mathrm{P}_\alpha(z, Y + \Gamma)$. The net effect on

[12] Grosh and Baker (1995) and Cornia and Stewart (1995) do not consider the second component of the leakage cost. Creedy (1996) distinguishes between vertical expenditure inefficiency, equal to the leakage ratio as estimated by Grosh and Baker (1995) and by Cornia and Stewart (1995), and poverty reduction efficiency equal to our leakage ratio.

poverty of implementing a transfer scheme instead of price subsidies is therefore $\mathrm{P}_\alpha(z, Y+\hat{T}) - \mathrm{P}_\alpha(z, Y+\Gamma)$.

Table 5 presents simulation results for (1) two measures of targeting accuracy (leakage and undercoverage), and (2) the levels of poverty reached with the transfer schemes and with price subsidies. As mentioned above, a poverty line of TD 280 per capita per year without subsidies is used, consistently with The World Bank (1995). An individual having an income of TD 280 without subsidies has the same welfare level with TD 250 and subsided prices: $Y_e(p^r, p^s, 250) = Y_e(p^r, p^r, 280)$. Since OLS predictions based on geographical dummies is the usual approach for transfer scheme, we use the corresponding results as a benchmark in our comparisons.

In all simulations and all the targeting criteria the performance of the subsidies is much worse than that of any transfer scheme, except when undercoverage is considered since with subsidies it is zero because all households consume at least one subsidized good. Then, in our comments we emphasize only the comparison amongst transfer methods. The standard errors suggest that targeting indicators results for different estimation methods are generally significantly different. This is indeed generally the case when explicit tests of differences are implemented, as illustrated with the bootstrap intervals of Figures 1 and 2. The results based on regressor Set I, corresponding to regional targeting, show that this typical targeting scheme, based on OLS, improves on food subsidies in terms of the number of the poor remaining after the policy. However, if the aim is to reduce the number of the poor, the transfers based on quantile regressions anchored on the third decile are the best scheme among the considered options. Meanwhile, if the aim is to reduce poverty measured by the poverty gap P_1 or the poverty severity measure P_2, the preferred scheme is that based on quantile regressions anchored on the first decile. Moreover, leakage and undercoverage are also lower with this method.

However, the picture slightly changes when we extend the set of regressors. With regressor Set II, which adds information on dwelling and demographic characteristics to the information on regional dummies, substantial improvements, as compared to results with set I, can be reached whether in terms of poverty statistics, leakage or undercoverage. With Set II, the quantile regression based on the first quantile remains the best approach for reducing P_2 and undercoverage. As it happens, these two criteria may often be considered decisive. Indeed, P_2 gives a stronger weight to the poorest of the poor, which confers it better axiomative properties than P_0 and P_1. On the other hand, undercoverage is related to probably indispensable political conditions since policies leaving aside a large proportion of the poor are unlikely to be implementable in Tunisia. Censored quantile regressions allow us even larger reduction of undercoverage, although they are less straightforward to implement. However, with Set II if the aim is merely to diminish the number of the poor, OLS based transfers would provide better results, while if the aim is to reduce P_1 or leakage, the quantile regressions based on the third decile would be preferable.

Finally, the additional benefits coming from introducing information from Set III on educational level or occupation of households' head are relatively small. The quantile regression based on the first decile (and sometimes the censored quantile regressions) remain preferable if the aim is to alleviate P_1, P_2 and leakage, while OLS are better if the aim is to cut the number of the poor. Using censored quantile regressions anchored on the first decile would lead to lower undercoverage, although quantile regressions based on the first decile, which are simpler to implement, provide good results with undercoverage of about 8 percent. The other methods generally yield disastrous outcomes for undercoverage.

Omitting correction or correcting with household price indices gives similar results. On the whole, the quantile regressions based on the third decile most often appears as the best method for reducing P_0, while the quantile regressions based on the first decile are best for diminishing P_1, P_2, leakage and perhaps undercoverage. Often, the censored quantile regressions anchored on quantile 0.1 with a 50 percent censorship dominate the quantile regressions based on the first decile for reducing undercoverage, but they seem unlikely to be used in most applied contexts since this method is not available in standard statistical packages[13].

Three important points may be noted at this stage. First, the gaps between the estimated reductions in P_2 with different prediction methods are considerable. The statistical method used to design the transfer scheme is a crucial ingredient of the performance of the scheme. If we consider the results obtained with our best estimates (based on quantile regressions anchored on the first decile, especially for reducing P_2, the progress is spectacular as compared to the results obtained with the subsidy scheme. An additional 6.97 percent of the population potentially disappear from the poor with the new transfer method. Even when compared with other estimation methods (e.g. OLS), substantial improvement of the poverty situation measured by P_2 can be obtained. The percentage of excluded poor households from the scheme dramatically falls (to 8.1 percent) as compared with what is obtained with OLS predictions based on geographical dummies (for which it is 24.7 percent). Second, the usually employed method, based on OLS estimates, appears as the less performing approach compared to other ways of focusing the prediction of living standards on the poor. However, when considering only the number of the poor, the OLS provide acceptable predictions for the richest of the poor that are not discounted when compared with the poorest.

Although it looked like a good idea, the censorship of the richer half of the sample is statistically too crude to make much impact on the performance of anti-poverty schemes through Tobit predictions even if they may slightly improve on OLS. Besides, Tobit

[13] Note that a characteristic of the censored regression method is that it may coincide with quantile regression estimates for low quantile. This comes from the fact that both estimators are derived from solving linear programming problems that may yield the same optimal kink. Such situation occurred several times in our results.

regressions may yield inconsistent estimates if the error terms in predicting equations are not strictly normal. Getting rid of the normality assumption by using censored quantile regressions generally yields worse results than what can be obtained with quantile regressions, except for undercoverage.

3.5. Policy consequences

What are the policy consequences of our new method of focused transfer schemes? Clearly, massively improved performances can be attained for transfer schemes by adapting the statistical method used for the prediction of living standards. Lower poverty levels, smaller leakage and undercoverage statistics can be obtained by focusing the estimation of transfer schemes. In Tunisia, the gain of efficiency of such scheme, as compared to the usual OLS-based geographical targeting scheme, is so great that it should deserve serious policy consideration.

The econometric results have shown that decisive progress can be reached in the design of the scheme. First, the regressors used for predicting living standards should be extended beyond geographical characteristics, and this already can yield substantial improvement of the anti-poverty targeting. Other useful regressors easy to observe (not available in our data) are the characteristics of health equipment, the type of access to water and other characteristics of the environment. Collecting information about such regressors would assist the implementation of anti-poverty transfers. Second, the choice of the econometric method for predicting living standards is crucial for the performance of the transfer scheme. Adopting an econometric method that focus on the poor in various senses improves the efficiency of the transfer scheme. In our data, the method of quantile regression based on a quantile close to the expected poverty line provides the best results.

There is already a small transfer scheme in operations in Tunisia: the ‘Programme des Familles Nécessiteuses’ (République Tunisienne, 1991). However, to implement a large transfer program would necessitate raising large funds. A logical consequence of our analysis is to make possible the transfer of some of the public funds allocated to price subsidies towards a national focused transfer scheme. Our results show that in Tunisia an opportunity exists to reach much better objectives of poverty alleviation by substituting the in force price subsidies with direct transfers based on observable characteristics of households, and at a lower public cost.

This is all the more fortunate that price subsidies that distort prices are a source of inefficiency for the functioning of the whole economy. Thus, replacing these subsidies with cash transfers would not only alleviate poverty, but may also improve market efficiency and thereby contribute to a greater economic growth.

But growth is not everything. Previous attempts at eliminating subsidies in Tunisia ended in riots. Indeed, since all the poor, and other population categories, benefit from price subsidies, a statistically better aid system to the poor based on direct transfers may alleviate poverty, but may also leave aside a large proportion of the poor. If this risk is perceived as high by the population, social unrest may follow, especially because the Tunisian society is very aware of social policies. In this country, advanced social policies have been implemented from the independence, and are almost considered as a right by many. Therefore, replacing subsidies by OLS-based geographical transfers is likely to be impossible. Indeed, our results show that about one quarter of the poor would be excluded from the benefits of such transfers and would simultaneously lose the benefits they extract from subsidies.

However, using instead focused transfers, would allow the government to reduce the undercoverage of the scheme to such a level, at most 8 percent of the poor, that: (1) the reform should be politically viable, and (2) the reform would not generate severe risks for a large proportion of the poor. As a matter of fact, it is exceptional that such a limited proportion of the population would suffer from a large social reform. Moreover, considering the gain in efficiency caused by the elimination of price distortions, and the saving of public funds, the actual percentage of the poor suffering from the reform may even turn out to be negligible.

4. Conclusion

Leakage to the non-poor is often substantial from universal food subsidy programs directed to the poor. Because of their large budgetary cost, many governments have moved away from them towards better targeted programs, such as self-targeting (workfare), and regional targeting. It has been noted that benefits can also be awarded to the poor on the basis of household characteristics and making transfers contingent on such characteristics. However, transfer schemes may be inaccurate because the statistical predictions involved in their design are too much oriented towards the mean of the living standard distribution and not enough towards the potentially poor.

This paper improves on past methods by deliberately focusing on the poor and near poor for the design of transfer schemes based on estimated living standard equations. This is achieved by using quantile regressions and censorship for the prediction of living standards.

Our estimation results based on data from Tunisia reveal considerable potentialities for poverty alleviation with our new approach, notably as compared to in force price subsidies. The improvement is also substantial as compared with usual targeting schemes based on OLS predictions: with our method based on quantile regressions the population of the poor may potentially be divided by two in Tunisia. In contrast, censoring the living standard distribution does not improve the performance of transfer schemes, except for reducing undercoverage.

One shortcoming of transfer schemes is that some households may be able to change some of their characteristics by which they are targeted or to hide their true characteristics in an attempt to receive a larger transfer. While the marginal benefit of altering some characteristics may outweigh the marginal effort required from the household, it is unlikely that the net benefit of such behavior will be non-negative for many characteristics, like location and dwelling types. In our results, the characteristics that can easily be modified or hidden by households are precisely the ones that do not add much to the performance of the scheme.

Targeting by indicators may be relatively cheap to implement, as opposed to the huge financial burden of price subsidies. This is notably the case if it can be carried out just after a national census since the variables contributing to the efficacy of the transfer scheme are easy to observe from a census. Moreover, in such situation the scheme can be improved by using the methods in Elbers, Lanjouw and Lanjouw (2003), taking full advantage of the census information[14]. In contrast, education and occupation variables, which are more difficult to observe accurately in a census, do not contribute much to the performance of the investigated transfer schemes in Tunisia.

In the literature, most measured administrative costs of transfer schemes range from 5 percent to about 15 percent of the targeting budget (e.g., in Grosh and Baker, 1995). Therefore, the conclusions of our study are unlikely to be offset by administrative costs only[15]. The fact that there already exists in Tunisia a small system of direct transfers to the poor (the 'programme des familles nécessiteuses'), more precisely to the elderly, the

[14] It is likely that poverty mapping can be improved by estimating methods focusing on the poor. We leave this question for future work. Finally, the assessment of the welfare impact of public spending (van de Walle, 1998) could be based on focusing statistical approaches.

[15] Besley (1990) discusses the theoretical consequences of such costs and other costs of means testing. Other types of costs would come from the demeaning nature of transfers, as had been observed in the US with food stamps. However, monetary transfers, such as pensions are generally not considered demeaning, and the poor in Tunisia are generally needier than most of the poor in the US, and thus may not afford to be excessively proud.

handicapped, schoolchildren, and needy families, suggest that administrative implementation on a larger scale is doable.

However, the implementation of direct cash transfer programs is likely to meet two difficulties. First, the program administration may be complex. In particular, updating the eligibility lists is costly and subject to political and social bias (as in Park et al., 2002). Moreover, overlap between different assistance programs may make their management delicate. All this could be dealt with by studies of the administrative implementation of these programs. Notably, relying on decentralized administrations may be more efficient, as was found in Bangla-Desh (Galasso and Ravallion, 2005). Another difficulty is the political context. Indeed, changing the assistance system in Tunisia implies that some households will lose from such change, even if it benefits to the majority of the poor. In such situation, the considerable leakage of the usual assistance systems would be associated with negative political incentives since the potential losers in the change would be likely to oppose it. The social troubles in 1984, after the first attempt to eliminate food price subsidies, have encouraged caution in political circles against replacing these subsidies by direct transfers. Our new focused approach provides an opportunity to change the political balance of anti-poverty policies in Tunisia (and in other countries such as Egypt where a similar situation exists, see Ahmed and Bouis, 2002, and Gutner, 2002) in that focused transfers only leave aside a very minor proportion of the poor, and are likely to increase market efficiency, thus contributing to stimulate growth. What seems needed in this context is first a special effort of public explanation of the benefits of focused direct transfers against price subsidies, and second a system of compensation, e.g. by creating new jobs from the saved funds, aimed at the few households the most likely to suffer from the suppression of price subsidies.

Other econometric ways of focusing on the poor are possible, for example by using non-parametric regressions, shadowing the shape of the living standard distribution. It is unclear what the optimal econometric techniques to use to implement this focus concern are and we conjecture that they may depend on the data at hand. On the whole, the important point in our approach is the adaptation of the estimation method for household living standard predictions in order to improve the performance of the anti-poverty targeting scheme. Using quantile regression improves this performance dramatically in the case of Tunisia. However, other variants and improvement are probably possible and left for future work.

Appendix 1: Tables

Table 1: Definition of the variables

Set I: Area	
Great Tunis	1 if household lives in Great Tunis, 0 otherwise.
Northeast	1 if household lives in Region Northeast, 0 otherwise.
Northwest	1 if household lives in Region Northwest, 0 otherwise.
Middle East	1 if household lives in Region Middle east, 0 otherwise.
Middle west	1 if household lives in Region Middle west, 0 otherwise.
Sfax	1 if household lives in Sfax, 0 otherwise.
Southeast	1 if household lives in Region Southeast, 0 otherwise.
Southwest	1 if household lives in Region Southwest, 0 otherwise.
Complement for Set II:	
Demographic information	
Nc2	Number of children in household old less than 2 years old.
Nc3-6	Number of children aged between 3 and 6 years.
Nc7-11	Number of children aged between 7 and 11 years.
Na12-18	Number of adults aged between 12 and 18 years.
Na19p	Number of adults old more than 19 years.
Age	Age of the household head (HH).
Age2	Squared age of the HH.
Type of house	
Nbroompc	Number of rooms per capita
Detached House	1 if household lives in a detached house, 0 otherwise.
Flat	1 if household lives in a flat, 0 otherwise.
Arab house	1 if household lives in an Arab house, 0 otherwise.
Hovel	1 if household lives in a hovel, 0 otherwise.
Tenure Mode	
Owner	1 if household is owner of the house.
Rent	1 if household is renting a house.
Locvte	1 if household has a hire-purchase or leasing for his house
Free	1 if household lives in a free of charge house.

Complement for Set III:	
<u>Occupation of HH</u>	
Unemp	Dummy variable for HH is unemployed.
Agrilab-se	Dummy variable for HH living in the Southeast and agricultural labourer.
Agrilab-sw	Dummy variable for if HH living in the Southwest and agricultural labourer.
Agrilab-an	Dummy variable for if HH living in another region and agricultural labourer.
Nonagrilab	Dummy variable for if HH is an industry worker.
Agrifar	Dummy variable for if HH is a farmer.
Agrifar-nw	Dummy variable for if HH living in the Northwest and agricultural farmer.
Sms	Dummy variable for if HH is self-employed or manager.
Another	Dummy variable for if HH has another type of job.
Nbbud	Number of participants in the household's budget.
Nactiff	Number of female workers.
Nactifm	Number of male workers.
<u>Schooling level of HH</u>	
Illiterate	Dummy variable for HH is illiterate.
Prim	Dummy variable for HH has a primary schooling level.
Sec-J	Dummy variable for HH has a junior secondary schooling level.
Sec-S	Dummy variable for HH has a senior secondary schooling level.
Higher	Dummy variable for HH has a higher educational level.
Nbetud	Number of students.
Nbelspv	Number of children in private secondary school.
Nbelspu	Number of children in public secondary school.
Nbelppv	Number of children in private primary school.
Nbelppu	Number of children in public primary school.

HH = 'household head'. Zone 1 corresponds to the Grand Tunis, the most prosperous region and largest industrial center. Zone 5 corresponds to the Centre-East (Sousse, Monastir, Mahdia), which is the second economic region of Tunisia. It is reputed for its thriving tourist industry. Since Zones 1 and 5 are omitted, the sign of the coefficients of the other zones should be negative in the prediction equation of living standards. Zone 2 is the Nord-Est (Nabeul, Bizerte, Zaghouen), which is the third most important economic region of Tunisia. We expect that the coefficient of this variable would have the smallest magnitude among the zone coefficients in the prediction equation. Zone 3 corresponds to the North-West where the highest poverty incidence is. Its coefficient should have the largest magnitude among the zone coefficients. Zone 4 is the Centre-West, which is also very poor. Zone 6 is the Sfax area, which is economically prosperous as one the main industrial center after Tunis and the Centre-East. Zone7 is the South-West where Tozeur oasis stands as an important producing area of dates. It is also an increasingly prosperous tourism center. Other important towns in this area are Gafsa (with a declining production of phosphates) and Kbelli. Zone 8 is the South-East, which includes Gabes (relatively wealthy although less than Sfax), Mednine and Tataouine. Its coefficient in the prediction equation should be negative.

As for the housing characteristics, the number of rooms per capita should be correlated with living standards. The omitted category for the housing type is 'villa'. Therefore, the coefficients of the remaining categories should have negative signs, especially for 'arab house' and 'gourbi'.

The activities of members are likely to matter for living standards. The number of participants in the household budget (nbbud) and the number of male and female active members (respectively actifm, actiff) should be positively correlated with the living standard. The categories for professionals, managers, industrials and traders are omited in the prediction equations. Then, except for the category Agrifar (farmer), the included professional categories should have negative coefficients. The sign of the coefficient for farmer may be ambiguous because the questionnaire does not distinguish small and large producers. Moreover, neither the information on cultivated areas, nor on the agricultural activity is available.

Education variables are often correlated with living standards. We omit the categories corresponding to university or the second cycle of the secondary level (at least 4 years of secondary education beyond the 6 years of primary education) for the education of the household head. The remaining categories are denoted: Illiterate (no education); Prim (6 years of primary education or less); Sec1 (3 years of secondary education or less). The coefficients of these dummy variables should be negative. Nbetud denotes the variable indicating the number of students in the household. Since education is likely to be a normal good, we expect its coefficient to be positively correlated with the household living standard.

Table 2: Descriptive Statistics

Variables	Mean	Std. Deviation	Minimum	Maximum
Yearly total expenditure	4066	3456	99	54234
Yearly total expend. p.c.	804	809	47	20531
Great Tunis	0.216	0.412	0	1
Northeast	0.138	0.345	0	1
Northwest	0.152	0.359	0	1
Middle East	0.127	0.333	0	1
Middle west	0.134	0.341	0	1
Sfax	0.088	0.283	0	1
Southeast	0.089	0.284	0	1
Southwest	0.055	0.228	0	1
Nc2	0.322	0.565	0	4
Nc3-6	0.612	0.824	0	5
Nc7-11	0.748	0.933	0	5
Na12-18	0.995	1.167	0	7
Na19p	3.001	1.433	0	11
Age	48.27	13.79	16	99
Nbroompc	0.544	0.366	0.05	4.5
Detached House	0.185	0.388	0	1
Flat	0.048	0.214	0	1
Arab house	0.733	0.442	0	1
Hovel	0.033	0.179	0	1
Owner	0.801	0.399	0	1
Rent	0.079	0.269	0	1
Locvte	0.061	0.239	0	1
Free	0.059	0.235	0	1
Unemp	0.014	0.117	0	1
Agrilab-se	0.009	0.096	0	1
Agrilab-sw	0.006	0.077	0	1
Agrilab-an	0.076	0.265	0	1
Nonagrilab	0.309	0.462	0	1
Agrifar	0.137	0.344	0	1
Agrifar-nw	0.031	0.173	0	1
Sms	0.132	0.339	0	1
Another				
Nbbud	0.518	1.116	0	8
Nactiff	0.303	0.621	0	5
Nactim	1.209	0.866	0	7
Illiterate	0.476	0.499	0	1
Prim	0.289	0.453	0	1
Sec-J	0.072	0.258	0	1
Sec-S	0.091	0.287	0	1
Higher	0.041	0.197	0	1
Nbetud	0.045	0.243	0	4
Nbelspv	0.052	0.245	0	3
Nbelspu	0.403	0.789	0	5
Nbelppv	0.006	0.093	0	3
Nbelppu	1.007	1.198	0	7

7734 observations

Table 3: Prediction Equations

The living standard variable is the equivalent income.

Variables	OLS V1	OLS V2	OLS V3	Tobit V1	Tobit V2	Tobit V3	UQ01 V1	UQ01 V2	UQ01 V3	CQ01 V1	CQ01 V2	CQ01 V3
Constant	6.631	6.38	6.567	6.574	6.135	6.363	5.779	5.832	6.000	5.779	5.992	6.04
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Northeast	-0. 197	-0.061	-0.054	-0.245	-0.116	-0.102	-0.243	-0.069	-0.048	-0.243	-0.063	-0.037
	(0.000)	(0.004)	(0.006)	(0.000)	(0.012)	(0.025)	(0.000)	(0.040)	(0.133)	(0.000)	(0.014)	(0.149)
Northwest	-0. 557	-0. 364	-0.314	-0.545	-0.398	-0.340	-0.574	-0.398	-0.333	-0.574	-0.344	-0.288
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mid. west	-0. 496	-0. 223	-0.19	-0.472	-0.272	-0.241	-0.534	-0.287	-0.261	-0.534	-0.294	-0.236
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sfax	-0. 336	-0. 306	-0.274	-0.337	-0.356	-0.329	-0.390	-0.320	-0.288	-0.390	-0.240	-0.158
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Southeast	-0. 350	-0. 194	-0.151	-0.098	-0.003	0.048	-0.223	-0.041	-0.042	-0.223	0.005	0.041
	(0.000)	(0.000)	(0.000)	(0.077)	(0.957)	(0.411)	(0.000)	(0.256)	(0.254)	(0.000)	(0.851)	(0.159)
Southwest	-0. 47	-0. 273	-0.208	-0.381	-0.263	-0.176	-0.420	-0.239	-0.169	-0.420	-0.151	-0.088
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Age		0.009	0.009		0.007	0.009		0.011	0.008		0.006	0.003
		(0.002)	(0.003)		(0.259)	(0.116)		(0.027)	(0.143)		(0.099)	(0.479)
Age2		-0.0001	-0.0001		-0.0001	-0.0001		-0.0001	-0.0001		-0.0001	-0.0000
		(0.000)	(0.003)		(0.079)	(0.084)		(0.003)	(0.190)		(0.024)	(0.573)
Nc2		-0.082	-0.084		-0.068	-0.074		-0.101	-0.077		-0.113	-0.075
		(0.000)	(0.000)		(0.001)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Nc3-6		-0.115	-0.122		-0.083	-0.098		-0.104	-0.116		-0.110	-0.120
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Nc7-11		-0.087	-0.122		-0.062	-0.087		-0.092	-0.108		-0.100	-0.118
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Na12-18		-0.055	-0.116		-0.033	-0.093		-0.056	-0.114		-0.052	-0.114
		(0.000)	(0.000)		(0.003)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Na19p		0.04	-0.050		0.063	-0.024		0.036	-0.05		0.022	-0.057
		(0.000)	(0.000)		(0.000)	(0.039)		(0.000)	(0.000)		(0.000)	(0.000)

Nbroompc	0.653	0.542	1.118	0.856	0.526	0.453	0.129	0.133
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Flat	0.103	0.072			0.055^{-}	0.107	-0.017^{-}	-0.013
	(0.008)	(0.050)			(0.374)	(0.067)	(0.720)	(0.785)
Arab house	-0.341	-0.175	-0.339	-0.219	-0.43	-0.243	-0.322	-0.127
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Hovel	-0.68	-0.448	-0.665	-0.488	-0.871	-0.581	-0.792	-0.496
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Free	0.021	-0.003	0.036	0.003	-0.027	-0.013	0.015	0.015
	(0.426)	(0.903)	(0.453)	(0.955)	(0.544)	(0.754)	(0.659)	(0.661)
Rent	0.154	0.080	0.231	0.130	0.160	0.057	0.086	0.056
	(0.000)	(0.001)	(0.003)	(0.084)	(0.000)	(0.162)	(0.005)	(0.079)
Locvte	0.213	0.151	0.247	0.178	0.244	0.189	0.137	0.086
	(0.000)	(0.000)	(0.003)	(0.028)	(0.000)	(0.000)	(0.000)	(0.009)
Nbbud		0.027		0.049		0.022		0.015
		(0.000)		(0.001)		(0.039)		(0.071)
Nactiff		0.125		0.049		0.121		0.066
		(0.000)		(0.032)		(0.000)		(0.000)
Nactim		0.168		0.185		0.176		0.143
		(0.000)		(0.000)		(0.000)		(0.000)
Unemp		-0.342		-0.312		-0.443		-0.433
		(0.000)		(0.000)		(0.000)		(0.000)
Agrilab-an		-0.226		-0.182		-0.209		-0.208
		(0.000)		(0.000)		(0.000)		(0.000)
Agrilab-sw		-0.331		-0.321		-0.223		-0.34
		(0.000)		(0.000)		(0.027)		(0.000)
Agrilab-se		-0.197		-0.197		-0.074		-0.119
		(0.000)		(0.061)		(0.414)		(0.102)
Notagrilab		-0.121		-0.066		-0.102		-0.051
		(0.000)		(0.045)		(0.000)		(0.011)
Agrifar		-0.037		0.019		0.016		0.043
		(0.093)		(0.681)		(0.656)		(0.138)

Agrifar-nw			-0.032			-0.128			-0.098			-0.152
			(0.426)			(0.052)			(0.141)			(0.004)
Illiterate			-0.374			-0.413			-0.381			-0.245
			(0.000)			(0.000)			(0.000)			(0.000)
Prim			-0.224			-0.243			-0.203			-0.099
			(0.000)			(0.001)			(0.000)			(0.000)
Sec-J			-0.055			-0.207			-0.049			0.021
			(0.042)			(0.025)			(0.276)			(0.543)
Nbetud			0.111			0.022			0.013			0.032
			(0.000)			(0.783)			(0.782)			(0.391)
Nbelspv			0.158			0.303			0.182			0.157
			(0.000)			(0.000)			(0.000)			(0.000)
Nbelspu			0.074			0.113			0.105			0.106
			(0.000)			(0.000)			(0.000)			(0.000)
Nbelppv			0.213			0.051			0.249			0.084
			(0.002)			(0.756)			(0.006)			(0.239)
Nbelppu			0.04			0.023			0.038			0.049
			(0.000)			(0.135)			(0.025)			(0.000)
Nb. Obs.	7734	7734	7734	7734	7734	7734	7734	7734	7734	7734	7734	7734

V1 : Version 1 estimation using Set I variables (regional variables).
V2 : Version 2 estimation using Set II variables (Set I + demographic and dwelling variables).
V3 : Version 3 estimation using Set III variables (Set II + occupation and schooling level of household head).
Tobit : Censored (10)
UQ01 : Uncensored quantile (0.1) regression.
CQ01 : Censored (50) quantile (0.1) regression.
P-value in parentheses. 7734 observations

Table 4: Variance of the Prediction Errors over the Variance of the Logarithms of Living Standards

Whole population

R^2	OLS	Tobit Threshold 10%	Tobit Threshold 30%	Quantile Regressions (Quantile 10%)	Quantile Regressions (Quantile 30%)	Censored Quantile Regressions Threshold 50% (Quantile 10%)
Set I	0.897	0.908	0.900	2.291	1.146	3.251
Set II	0.551	0.635	0.568	1.413	0.693	2.259
Set III	0.473	0.546	0.490	1.223	0.589	1.991

The poor under the first quintile

R^2	OLS	Tobit Threshold 10%	Tobit Threshold 30%	Quantile Regressions (Quantile 10%)	Quantile Regressions (Quantile 30%)	Censored Quantile Regressions Threshold 50% (Quantile 10%)
Set I	0.832	0.806	0.814	0.105	0.410	0.059
Set II	0.420	0.408	0.406	0.080	0.210	0.062
Set III	0.338	0.333	0.326	0.080	0.177	0.066

The poor under the second quintile

R^2	OLS	Tobit Threshold 10%	Tobit Threshold 30%	Quantile Regressions (Quantile 10%)	Quantile Regressions (Quantile 30%)	Censored Quantile Regressions Threshold 50% (Quantile 10%)
Set I	0.845	0.826	0.825	0.120	0.370	0.134
Set II	0.428	0.448	0.423	0.147	0.211	0.158
Set III	0.350	0.373	0.344	0.152	0.185	0.155

7734 observations.

Table 5: Measures of Targeting Efficiency for z = TD 280

The living standard variable is the equivalent income.

	P0	P1	P2	Leakage	Under-coverage
SUBV	13.86	3.44	1.30	90.05	**0.00**
	(0.75)	(0.24)	(0.11)	(1.24)	(0)
OLS 1	10.50	2.24	0.74	80.74	24.73
	(0.67)	(0.21)	(0.10)	(4.34)	(2.88)
OLS 2	7.52	1.37	0.40	73.57	19.54
	(0.47)	(0.12)	(0.05)	(3.67)	(1.58)
OLS 3	6.79	1.22	0.36	72.39	17.50
	(0.40)	(0.10)	(0.04)	(3.60)	(1.37)
TB10 1	10.90	2.26	0.74	80.88	33.26
	(0.68)	(0.21)	(0.09)	(4.43)	(3.24)
TB10 2	7.58	1.34	0.38	73.26	20.89
	(0.47)	(0.11)	(0.04)	(3.98)	(1.67)
TB10 3	6.76	1.15	0.32	71.82	19.50
	(0.42)	(0.09)	(0.03)	(3.88)	(1.51)
TB30 1	10.71	2.25	0.74	80.84	33.26
	(0.67)	(0.21)	(0.10)	(4.51)	(3.24)
TB30 2	**7.29**	1.32	0.38	73.17	19.40
	(0.46)	(0.11)	(0.04)	(3.69)	(1.55)
TB30 3	6.63	1.16	0.33	71.86	16.50
	(0.40)	(0.09)	(0.03)	(3.63)	(1.34)
QR10 1	10.91	**2.19**	**0.68**	**80.37**	**13.15**
	(0.66)	(0.19)	(0.08)	(3.41)	(1.97)
QR10 2	8.16	**1.24**	**0.31**	72.75	9.04
	(0.53)	(0.11)	(0.04)	(3.11)	(1.00)
QR10 3	6.89	**1.01**	**0.25**	**70.85**	8.09
	(0.45)	(0.09)	(0.03)	(3.07)	(0.91)
QR30 1	10.58	2.21	0.72	80.52	24.73
	(0.66)	(0.20)	(0.09)	(3.88)	(2.88)
QR30 2	7.51	**1.24**	0.33	**72.61**	13.71
	(0.49)	(0.11)	(0.04)	(3.31)	(1.32)
QR30 3	**6.52**	1.07	0.30	71.27	12.93
	(0.40)	(0.09)	(0.03)	(3.35)	(1.16)
QRC01 1	10.91	2.19	**0.68**	**80.37**	**13.15**
	(0.66)	(0.19)	(0.08)	(3.42)	(1.97)
QRC01 2	8.45	1.36	0.35	73.77	**8.19**
	(0.55)	(0.11)	(0.04)	(3.02)	(0.95)
QRC01 3	7.37	1.09	0.27	71.54	**6.01**
	(0.48)	(0.09)	(0.03)	(3.09)	(0.76)

Set I of independent variables includes only regional variables. Set II includes in addition to Set I, demographic and dwelling variables. Set III includes in addition to Set II, occupation and schooling level of household head.
SUBV: Current subsidies scheme.
OLS 1: Transfers based on OLS 1 : Set I variables.
OLS 2: Transfers based on OLS 2 : Set II variables.
OLS 3: Transfers based on OLS 3 : Set III variables.
TB10 1: Transfers based on Tobit censured at 10 percent with Set I variables.
TB10 2: Transfers based on Tobit censured at 10 percent with Set II variables.
TB10 3: Transfers based on Tobit censured at 10 percent with Set III variables.
TB30 1: Transfers based on Tobit censured at 30 percent with Set I variables.

TB30 2: Transfers based on Tobit censured at 30 percent with Set II variables.
TB30 3: Transfers based on Tobit censured at 30 percent with Set 3 variables.
QR10 1: Transfers based on quantile regressions anchored on quantile 0.1 with Set I variables.
QR10 2: Transfers based on quantile regressions anchored on quantile 0.1 with Set II variables.
QR10 3: Transfers based on quantile regressions anchored on quantile 0.1 with Set III variables.
QR30 1: Transfers based on quantile regressions anchored on quantile 0.3 with Set 1 variables.
QR30 2: Transfers based on quantile regressions anchored on quantile 0.3with Set II variables.
QR30 3: Transfers based on quantile regressions anchored on quantile 0.3with Set I variables.
QRC01 1: Transfers based on censored quantile regressions anchored on quantile 0.3, censored at quantile 0.5, with Set I variables.
QRC01 2: Transfers based on censored quantile regressions anchored on quantile 0.3, censored at quantile 0.5, with Set II variables.
QRC01 3: Transfers based on censored quantile regressions anchored on quantile 0.3, censored at quantile 0.5, with Set III variables.

Each of measures presented in this table has been multiplied by 100 for easy interpretation.
7734 observations.

Appendix 2: The estimation of the equivalent-incomes

The calculus of the equivalent-incomes is based on the estimation of a food demand system. Non-food products have been excluded from the estimation because no price data are available for these products. We consider that the spatial variation of prices is such that households living within a cluster face the same price vector, a usual convention (Deaton, 1988). Further, we assume that before the implementation of the food subsidy scheme, household *h* living in cluster *c* has an exogenous income y_c^h and faces the price vector $\mathbf{p}_c^o$. After the food subsidies, household *h* faces a new price vector $\mathbf{p}_c^p$. To compare the living standards of households facing different prices, we choose a reference price vector, denoted by $\mathbf{p}^r$, and we define the equivalent-income as in King (1983). For a given budget constraint ($\mathbf{p}$, y), the household equivalent income is defined as the income level which allows the same utility level at the reference prices. Formally, we have $v(\mathbf{p}^r, y_e) = v(\mathbf{p}, y)$, where $v(.)$ is the indirect utility function, $\mathbf{p}$ is a price vector, and y is a vector of the household per capita living standards. We use income per capita for the living standard indicator to avoid complications in the definition of equivalent scales. Because $\mathbf{p}^r$ is fixed across all households, and y_e is an increasing monotonic transformation of $v(.)$, variable y_e is an exact monetary metric of the actual utility $v(\mathbf{p}, y)$. The equivalent-income function $y_e(.)$ can also be obtained in terms of the expenditure function $e(.)$: $y_e = e\big(\mathbf{p}^r; v(\mathbf{p}, y)\big) = y_e(\mathbf{p}^r, \mathbf{p}, y) = \Gamma$ as a short-script notation.

A measure of the households' valuation of the food subsidy programme is the change in their equivalent-income consecutive to the subsidies. This measure is denoted the equivalent-gain per capita of the subsidy programme for household *h*, E^h_{FS}, and it is given by $\mathrm{E}_{FS}^h = y_e(\mathbf{p}^r, \mathbf{p}_c^{FS}, y^h) - y_e(\mathbf{p}^r, \mathbf{p}_c^r, y^h)$, where 'FS' indicates that the considered programme is that of food subsidies.

Now, if direct transfers T_c^h are awarded to households predicted poor after removing food subsidy programme, the valuation of moving from the reference situation to the new situation for household *h* is $\mathrm{E}_c^h(\hat{T}) = y_e(\mathbf{p}^r, \mathbf{p}_c^r, y_c^h + \hat{T}_c^h) - y_e(\mathbf{p}^r, \mathbf{p}_c^r, y_c^h)$. Then, poverty measured by P_α will fall following targeting by indicators instead of subsidies if $\mathrm{P}_\alpha[z_e, y_e(\mathbf{p}^r, \mathbf{p}_c^r, y + \hat{T})] - \mathrm{P}_\alpha[z_e, y_e(\mathbf{p}^r, \mathbf{p}_c^{FS}, y)] < 0$, and z_e is the equivalent-income function applied to the poverty line.

The equivalent income y_e for each household is calculated from the estimates of the QAIDS demand system of Banks et al. (1993). The wage share of commodity j in this system is

$$w_j(\mathbf{p}, y) = \omega_j^* + \sum_k^K \theta_{jk} \ln(p_{ck}) + \gamma_j \ln\left(\frac{y}{z(\mathbf{p}_c)}\right) + \frac{\delta_j}{\delta(\mathbf{p}_c)}\left[\ln\left(\frac{y}{z(\mathbf{p}_c)}\right)\right]^2,$$

where

$$\ln z(\mathbf{p}_c) = \ln(\omega_0) + \sum_j \omega_j \ln(p_{cj}) + \frac{1}{2}\sum_j \sum_k \theta_{jk}^* \ln(p_{cj}) \ln(p_{ck}), \quad \delta(\mathbf{p}_c) = \prod_k p_{ck}^{\delta_k} \text{ with } \sum_k \delta_k = 0,$$

p_{cj} is the price of good *j* in cluster *c*, p_c is the price vector for cluster *j*, *y* is the income and where ω_0, ω_j, ω^*_j, θ_{jk}, θ^*_{jk}, δ_j and γ_j are parameters to estimate.

Once the parameters of the QAIDS model are estimated, it is possible to compute the equivalent-income of each household, for any price vector p^s_c and any transfer T^h. This yields

$$\ln y_e(\mathbf{p}^r, \mathbf{p}_c^s, y_c^h + T_c^h) = [b(\mathbf{p}^r) - \ln z(\mathbf{p}^r)]\left[\left(\frac{\ln(y_c^h + T_c^h) - \ln z(\mathbf{p}_c^s)}{b(\mathbf{p}_c^s) - \ln z(\mathbf{p}_c^s)}\right)^{-1} + \delta(\mathbf{p}^r) - \delta(\mathbf{p}_c^s)\right]^{-1} + \ln z(\mathbf{p}^r),$$

$\ln b(\mathbf{p}_c) = \ln z(\mathbf{p}_c) + \prod_j p_{cj}^{\gamma_j}$. The demand system estimates are presented in Muller and Bibi (2005).

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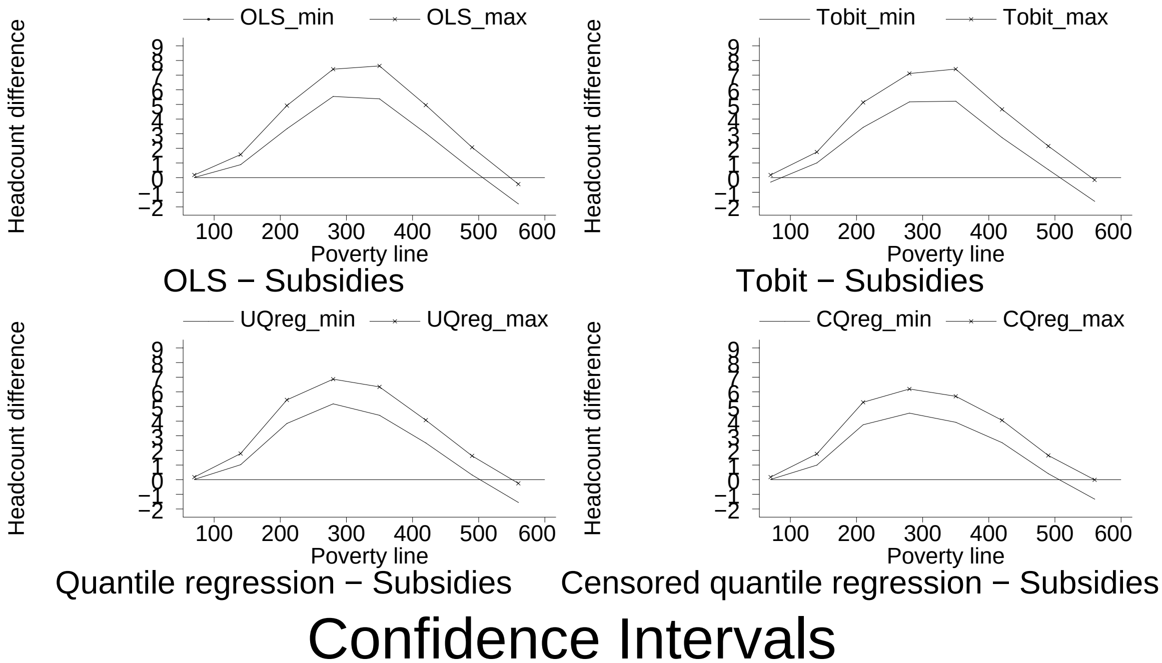
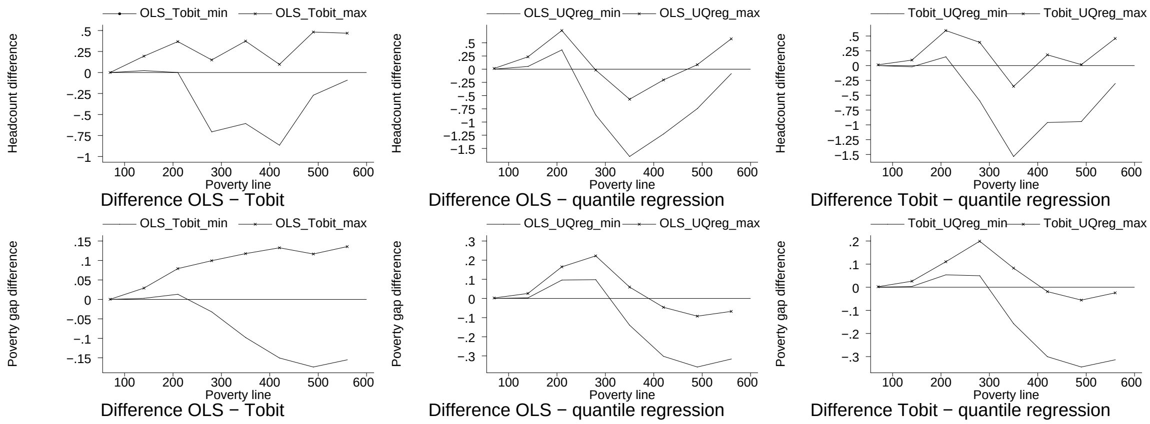


Figure 1: Differences of Poverty Curves



Confidence Intervals

Figure 2: Differences of Poverty Curves