Refining Targeting against Poverty Evidence from Tunisia*

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Abstract

We introduce a new methodology to target direct transfers against poverty. Our method is based on estimation methods that *focus on the poor*. Using data from Tunisia, we estimate 'focused' transfer schemes that highly improve anti-poverty targeting performances. Post-transfer poverty can be substantially reduced with the new estimation method. For example, a one-third reduction in poverty severity from proxy-means test transfer schemes based on OLS method to focused transfer schemes requires only a few hours of computer work based on methods available on popular statistical packages. Finally, the obtained levels of undercoverage of the poor are particularly low.

I. Introduction

The issue

Transfer schemes are among the main policy tools against poverty. Cash transfers are the provision of assistance in cash to the poor or to those who face a risk of falling

into poverty. Many of these schemes, called 'proxy-means tests' (PMT), are based on predictions of household living standards used to calculate the transfers. Such predictions are obtained by using household survey data for regressing the living standard variable on household characteristics that are easy to observe. However, the errors in using OLS for PMT against poverty are large, a key shortcoming of PMT. In this study, we show how these errors can be substantially reduced by using other statistical approaches.

Many countries have been using PMT to target transfers, particularly in (i) Latin America and the Caribbean, such as Chile for many years under the *Ficha CAS* system, Columbia under *SISBEN*, Mexico under the *Oportunidades* Program, Nicaragua, Jamaica, etc.; and (ii) Asia, such as India, Indonesia, China, Thailand and Philippines. In these countries, many theoretical and practical issues related to PMT have been studied. The performance of the estimated transfer schemes is quite variable (Coady, Grosh and Hoddinot, 2004). Raising their impact on poverty is of paramount importance as stressed in De Janvry and Sadoulet (2006b). However, the statistical foundations of these programmes have not received the attention that it deserves. We fill this gap in this study.

Concerned with improving anti-poverty transfer schemes, we propose an estimation method of anti-poverty PMT that focus on the poor and the near-poor, thereby dramatically enhancing the scheme performance. We evaluate different approaches to determine scores for PMT schemes. We apply our new method to Tunisia and find significant improvement when compared with traditional methods.

What is targeting?

Although living standards are measured with household surveys, they are generally badly known for the households that are not surveyed. Many authors have studied assistance to poor people based on targeting when some characteristics of individuals can be observed, but not income.[1] Recently, Coady, Grosh and Hoddinott (2004) reviewed 122 targeted anti-poverty programmes in 48 countries. Cash transfers based on PMT are generally found to provide the best results, although there is an enormous variation in targeting performances. They also find that targeting performance is better in rich countries and where governments are accountable. Lindert *et al.* (2005) measure the redistributive power of 56 transfer programmes in eight countries. They find that public transfers can be an efficient way of redistributing income, but often fail to do so. Moreover, the coverage of the poor is found far from 100% for the studied programmes. Some transfer programmes are conditional on prespecified behaviour by beneficiaries (e.g. child school attendance or child vaccination). We do not deal

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[1]For instance, see Ravallion (1991), Besley and Coate (1992), Glewwe (1992), Besley and Kanbur (1993), Datt and Ravallion (1994), Slesnick (1996), Chakravarty and Mukherjee (1998), Ahmed and Bouis (2002), Coady, Grosh and Hoddinott (2002), Schady (2002), Tabor (2002), Coady *et al.* (2004), Coady and Skoufias (2004), Skoufias and Coady (2007), Datt and Joliffe (2005), Lindert, Skoufias and Shapiro (2005), Africa Focus Bulletin (2006), DFID (2006) and Weiss (2005).

with these programmes in this study.[2] Behavioural consequences of conditions are also omitted as the work focus on unconditional transfers.

Ravallion and Chao (1989) model the targeting problem as one of minimizing some specific poverty measure subject to a given anti-poverty budget by using geographical groups of individuals. Additional correlates of household living standards can also be used (Glewwe, 1992). Note that PMT can only be sensibly used to target programmes to the chronic poor and not to transitory poverty, given the constancy of the score 'weights' over time.

The implementation and administration of cash transfer programmes, which is separate from the targeting difficulties we study, can be complex, as for any social programmes. This is discussed in Muller (2009). In particular, costs should include not only the total amount of monetary transfers to implement, but also administrative costs that may be non-negligible. In the literature, most measured administrative costs of transfer schemes range from < 5% to about 15% of the targeting budget (Grosh and Baker, 1995; Alderman and Lindert, 1998; Coady *et al.*, 2002). Therefore, the conclusions of our study are unlikely to be offset by administrative costs exclusively.[3] The presence of small systems of direct transfers and the large universal subsidies programme in Tunisia suggest that administrative implementation on a larger scale is doable. However, quantitative analysis would be needed to clarify how balancing the pros and cons.

Some households may change or hide their true characteristics by which they are targeted in an attempt to secure a larger transfer. Yet, it is unlikely that the net benefit of such strategies will be non-negative for many characteristics, such as location and dwelling types. In our results, the characteristics that can reasonably be modified or hidden by households (education and occupation variables) do not add much to the performance of the scheme.

Targeting performance

Returning to design issues, two indicators, Leakage and Undercoverage, are popular for measuring targeting performance. With imperfect targeting, only people among the poor who are predicted as poor can benefit from poverty alleviation. On the other hand, non-poor people predicted as poor receive transfers. Thus, two types of errors characterize imperfect targeting. The *Type I error* (*Undercoverage*), central in Ravallion (1991), 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. It is estimated by the probability of not receiving any

[2]The interested reader can consult De Janvry *et al.* (2006) and De Janvry and Sadoulet (2006a,b) for comparisons of conditional and unconditional cash transfers.
[3]Besley (1990) discusses the theoretical consequences of such costs and other costs of means testing. Some costs would come from the demeaning nature of transfers, as had been observed in the United States 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 United States, and thus may not afford to be excessively proud.

transfer, while poor. The *Type II error* arises where benefits are awarded to ineligible people under perfect targeting. The *Leakage* of programme benefits is a monetary assessment of this error, obtained by adding (i) the transfers given to those whose pretransfer living standard is above the poverty line, and (ii) the transfers received by pretransfer poor who are unnecessary because the post-transfer living standards exceeds the poverty line.[4] Unnecessary transfers are those in excess for all households lifted up above the poverty line, as from this level of living standards they are no longer poor. If the aim is minimizing poverty, there is no justification to transfer cash to households once they have been lifted up to the poverty line as this would not change the final poverty level. The *Leakage ratio* is obtained by dividing the Leakage indicator by the available budget. A last measure of the programme efficiency is the reduction in a poverty measure due to transfers.[5]

Living standard predictions
In practice, anti-poverty targeting can be based on predictions of household living standards, generally obtained from ordinary least squares (OLS) regressions on observed characteristics (e.g. Datt and Joliffe, 2005, using data from 1997 Egypt). However, the OLS method is centred on the mean of the dependent variable (e.g. household living standard) and should provide accurate predictions around this mean only, which is often located far from the poverty line. Then, the predicted living standards of the poor and near-poor may be inaccurate. This explains why significant Undercoverage of the poor is common (as in Grosh and Baker, 1995).

   Alternative estimation methods are possible for our purpose of improving the schemes. For example, a semi-parametric estimation of the income distribution could be implemented by using kernel estimation methods in which correlates are parametrically incorporated (e.g. Pudney, 1999). Even full nonparametric estimation of conditional distributions of living standards could be adapted to the problem at hand. However, nonparametric methods suffer from slow consistency, inaccurate estimation of the distribution tail and are subject to the 'multidimensional curse' requiring unavailable large information. These are serious issues because of the numerous correlates included in proxy-means tests. Moreover, analysts in national statistical institutes favor simpler estimation methods. Accordingly, Deaton (1997) emphasizes methods that can be actually implemented in the relevant institutions.

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   [4]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.
   [5]Other measures of transfer efficiency have been proposed, while we concentrate on the main indicators related to our concerns, to avoid drowning the reader under figures for a paper that already contains a lot of them. Bibi and Duclos (2007) propose indicators of horizontal inequity, and Coady *et al.* (2004) and Lindert *et al.* (2005) propose to use the Distribution Characteristic Indicator, which shows the change in social welfare marginal benefit achieved by transferring a standardized budget to the programme, and the Coady–Grosh–Hoddinott index, which allows the comparison of the actual performance to the outcome that would result from neutral targeting. Many inequality, concentration and progressivity indices could also be used.

For these reasons, we investigate two simple restrictions of the predictive regressions: (i) censoring the dependent variable to eliminate observations located far from the poverty line; and (ii) using quantile regressions. The knowledge of the quantile regressions centred on all observed quantiles is equivalent to the knowledge of the empirical conditional distribution. This distribution is the main information missing to make imperfect targeting optimization identical to perfect targeting optimization, of which solution will be presented in section II. It is therefore what is needed to solve optimally the targeting problem. However, there are too many quantiles to consider for a practical procedure, although good results may be obtained by just trying one quantile around the poverty line. Then, *focusing on the poor* means that the predictions are calculated by defining the quantile regression or the censorship threshold in terms of living standard levels representative of the poor.

Assume that the equation used to predict living standards has the form $y_i = X_i'b + u_i$, where y_i is the living standard of household i, $\mathbf{X}_i$ is a vector of exogenous correlates of living standard for household i, u_i is an error term and $\mathbf{b}$ is a vector of parameter to estimate. OLS estimates correspond to imposing the restriction $E(y_i|\mathbf{X}) = \mathbf{X}'\mathbf{b}$, which implies $E(u_i|\mathbf{X}) = 0$. Quantile regression estimates centred in quantile θ correspond instead to the restriction $q_\theta(y_i|\mathbf{X}) = \mathbf{X}'b$, where function q_θ denotes the conditional quantile function of order θ, conditional on the values of the variables $\mathbf{X}$. This restriction implies $q_\theta(u_i|\mathbf{X}) = 0$. That is, the quantile on which a quantile regression is centred relates to error quantiles. Thus, the vectors $\mathbf{b}$ differ when different quantiles are specified.

In that case, what is predicted is a chosen quantile of the distribution of the living standards *conditionally on the correlates*. This method has two shortcomings. First, if the error terms are approximately normal, some efficiency may be lost when compared with OLS (the MLE under normality). This matters for targeting purposes as large variance of predictions may yield poor predictive performance for any social indicator. Secondly, the focus is conditional on the set of correlates. That is, the chosen quantile is not that of the dependent variable, but the quantile of the error in the estimated equation. However, that is precisely the quantile of the error that may matter most if one is interested in the prediction error that affects the transfer scheme's performance.

Quantile regressions, centred on the poverty line, should improve targeting, when compared with OLS, precisely because they are centred on the distribution location that identifies the poor, i.e. the poverty line threshold. Indeed, typically in regression methods, the prediction error is minimal at the central tendency used to define the regression method (mean for OLS regression, median for least-absolute deviation regression, a given quantile for quantile regression), whereas it increases quadratically with the distance of the data from the chosen central tendency. As the living standards of the poor are usually quite different from the mean living standard in a population, OLS predictions are mediocre for the poor. In contrast, if the centreing quantile is chosen close to the poverty line, the prediction errors for the poor should be moderate with quantile regressions. Even if absolute prediction differences among

methods may be reduced when running regressions of log-living standards, they become inflated again when using the exponential function to recover predicted living standards.

Another important issue is that OLS predictions for anti-poverty schemes are degraded by: presence of outliers, non-normality of error terms with finite sample size, heteroscedasticity and other misspecifications. These issues matter for targeting purposes as they are likely to occur with typical household survey data. Quantile regressions deal with these concerns for robustness (Koenker and Bassett, 1978), which are crucial in poverty analysis because of: (i) outliers generated by transaction omissions in consumption surveys; and (ii) the non-robustness of many poverty measures (Cowell and Victoria-Feser, 1996). Censored quantile regressions have been found useful to obtain robust explanations of chronic and seasonal–transient poverty (Muller, 2002b).

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

Another interest of focused targeting is that it is directly related to the theoretically optimal transfer schemes, in which the transfers are concentrated towards the poorest of the poor, the richest of the poor or both (Bourguignon and Fields, 1997). From this theoretical perspective what needs to be well determined are the transfers to these subpopulations. Then, focused predictions of the living standards of the poor and near-poor may generate more efficient transfers.

Comparison with Elbers, Lanjouw and Lanjouw
Another field where living standard predictions obtained in a first regression stage using household survey data are subsequently used in a second stage for poverty simulation is the small area literature. For example, Elbers, Lanjouw and Lanjouw (2003), ELL from now, combine census data and household survey data. We do not deal in detail with this approach as it raises additional and specific difficulties.

Although transfer programmes based on PMT rely on observable household characteristics, in contrast with ELL they use neither census data nor the locality-specific variables (local census enumeration area). Should they use such information? Perhaps, but there are reasons to doubt it. First, information on many household characteristics from census data is infamously known as being of mediocre quality. Second, using accurate location for designing transfer schemes may lead to migrations from households attempting to capture the transfers. Third, in the household living standard survey used to estimate the predicted incomes, only few local areas are observed. The non-use of census data and location-specific variables constitutes a major difference of our approach with that of ELL.

Furthermore, we deal with model error and sampling error in different ways than ELL. We are interested in model error in that it determines transfers, but not for estimating the accuracy of poverty estimators or transfer performance estimators.

For the latter stage, we examine only the sampling standard error of these estimators as the transfer schemes to compare are considered as given.

In footnote 5 of ELL, the authors claim that using quantile regressions give results non-significantly different from using OLS. As quantile regressions of living standard dependent variables have routinely been found to significantly vary across the centreing quantiles, we presume that they found this result using least-absolute deviation (i.e. median quantile) estimators or another arbitrary quantile. There is no mention of selecting a given quantile to *focus* the regression in their study.

Is it possible to improve anti-poverty targeting by using living standard predictors that focus on the poor? The aim of this study is to explore this question. However, our intention is not to propose a detailed reform of the anti-poverty policy in Tunisia nor to deal with all the practical implementation difficulties of such policy. Section II presents the anti-poverty transfer schemes. In section III, we apply our new method to the 1990 Tunisian household survey. In section IV, we discuss programme efficiency results. We find that: (i) focused targeting would reduce poverty much more than targeting based on OLS; and (ii) Undercoverage of the poor can be massively reduced. Finally, section V concludes.

II. Anti-poverty cash transfers

This study is based on the following popular poverty measures of the FGT class (Foster, Greer and Thorbecke 1984) because of their attractive axiomatic properties: $P_\alpha = \int_0^z ((z-y)/z)^\alpha f(y) \mathrm{d}y$, where z is a pre-specified poverty line, $f(.)$ is the density function of household income y (or household living standard) and α is a poverty aversion parameter.[6] Naturally, our approach could be extended to other poverty measures. Given an anti-poverty budget, one must design transfers that optimally allocate this budget across households.

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

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

subject to (1)

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

where N is the population size, B is the budget to allocate, t^i is the non-negative cash transfer to household i and y^i is its pretransfer income. The objective function can

[6]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. We call poverty measures satisfying all these axioms: 'axiomatically appealing'.

be weighed by the household size (or some equivalent scale) in each household to deal with poverty at the individual level rather than the household level. However, for expositional simplicity, we neglect for the moment the possibility that households may include several members. We do not consider how the budget B is funded. When $\mathbf{Y}$ is perfectly observable, the 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 head-count ratio would start awarding transfers so as to lift the richest of the poor out of poverty (in a decreasing order of income until all the budget is exhausted, 'r-type transfer'):

$$
\begin{aligned}
t^i &= z - y^i, && \text{if } y^i < z; \\
t^i &= 0, && \text{otherwise.}
\end{aligned}
\tag{2}
$$

In contrast, if the aim is to minimize an 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:

$$
\begin{aligned}
t^i &= y_{\max} - y^i, && \text{if } y^i < y_{\max}; \\
t^i &= 0, && \text{otherwise,}
\end{aligned}
\tag{3}
$$

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. For the poverty gap ($\alpha = 1$), both rules of transfer allocation are equivalent provided the poor incomes are never lifted strictly above the poverty line.

Unfortunately, perfect targeting is not feasible because incomes cannot be perfectly observed. Nevertheless, as 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.[7] They generally follow a two-step procedure. First, the expectation of y^i conditional on $\mathbf{X}_i$ (the vector of living standard correlates for household i) is parametrically estimated by OLS. Then, if the budget allows it, each predicted poor household receives the difference between its predicted income and the poverty line. Other dependent variables could be used in such regressions, sometimes with different meaning of the objective function. Our method can be easily adapted to these cases.

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[7]Glewwe and Kanan (1989), Glewwe (1992), Grosh and Baker (1995), Ravallion and Datt (1995), Bigman and Srinivasan (2002), Park, Wang and Wu (2002), Schady (2002) and Tabor (2002).

Some correlates might be modified by 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 sensitivity to moral hazard. What matters for anti-poverty targeting is the ability to predict the living standards of the poor. Our strategy is to focus on the poor when predicting living standards. We now turn to the estimation results, first by presenting the data used for the estimations.

III.   Data and methodology

The data

In Tunisia, targeting transfers to poor people has become increasingly urgent because structural adjustment programmes have imposed cuts in food subsidies (Tunisian Universal Food Subsidies Program), traditionally the main way to fight poverty. Since 1970, basic foodstuffs have been under subsidy to protect the purchasing power and the nutritional status of the poor. This programme was inefficient and expensive. Indeed, about 2.9% of GDP was spent in subsidies by 1990 (still slightly $< 2\%$ nowadays). Furthermore, non-poor households received much more from the programme than the poor. Improvement on subsidies has been limited by preference patterns, income inequality and the size of individual subsidies (Alderman and Lindert, 1998). In such situation, transfer schemes may 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 key challenges to meet the goals of the 10th Tunisian Economic Development Plan: to strengthen the performance of social programmes while maintaining budget balances (The World Bank, 2004). Meanwhile, maintaining social stability through a better safety net is still a major challenge in Tunisia (Hassan, 2006). A former government attempt at substituting food subsidies with direct cash transfers to the poor ended in riots in the 1980s because the proposed transfer system was perceived as leaving aside a large proportion of the poor. Other issues about social welfare, inequality and horizontal inequity could be raised about such policies in Tunisia (as in Bibi and Duclos, 2007). In this study we focus on poverty.

We use data from the 1990 Tunisian consumption survey conducted by the INS (National Statistical Institute of Tunisia). This is the most recent national consumption survey data available in Tunisia, where official data dissemination rules are stringent. The survey provides information on expenditures and quantities for food and non-food items for 7,734 households. Usual additional information from household surveys is available, such as the consumption of own production, education, housing, region of residence, demographic information and economic activities.

Because estimated equivalence scales based on cross-section data has often been criticized,[8] and in order to concentrate on the issue of imperfect targeting, we assume that living standard based on per capita consumption expenditure is an adequate

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

indicator of each household member's welfare. Other equivalence scales have been tried and provide qualitatively similar results.

In Table 1, we define the correlates of living standards used for the predictions. The correlates are grouped according to increasing difficulties of administrative recording and increasing ease of modification or hiding by households. Set I contains regional dummies. Using it along with OLS corresponds to 'regional targeting' and the regional poverty profile estimated in Muller (2007).[9] Set II includes regional and demographic information on households and characteristics of the household's dwelling. Set III adds information on occupation and education of the household's head to that in Set II. The correlates in Set II are unlikely to be manipulated by households and could be cheaply recorded, yet those added in Set III are easier to conceal. So, Set II would be the set to include in the regression analyses based on the need for these to be verifiable by programme offices and not easily manipulated by households.

It has been found that price differences across households may affect poverty measurement (Muller, 2002a). In order to correct for this, account for substitution effects caused by the elimination of price subsidies (which is the origin of the budget for cash transfers) and control for spatial price dispersion, we estimate the equivalent-gain from food subsidies. The calculus of the equivalent-gain is explained in the working paper by Muller and Bibi (2006). It is derived from our estimation of a quadratic almost ideal demand system. Both income and poverty line are converted into equivalent-incomes. Our reference price system is the one without subsidies as the subsidies' budget is assumed to be reallocated to cash transfers.

On the whole, there are four stages of estimation: (i) the estimation of a demand system to infer equivalent-incomes that enter the definition of living standard variable; (ii) the predictions of living standards from observed characteristics; (iii) the calculus of the optimal transfers corresponding to the predicted living standards, using perfect targeting optimization; and (iv) the simulation of the welfare effects of the transfer scheme. Let us turn to the living standard predictions, which is the stage where we introduce our focused estimation.

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 TD 804 (Tunisian Dinars), while mean equivalent-income (i.e. correcting for subsidies and spatial price variations) is TD 746. The first decile values for the equivalent-income variable are shown together with the mean equivalent-income and the mean log equivalent-income globally and for the first five decile groups, and finally with the poverty lines and logarithms of the poverty lines. Tables 3 presents the results of OLS regressions, quantile regressions (anchored on the first decile) and censored quantile regressions (censored at 50% and based on the

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[9]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).

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
Accommodation Mode	
Owner	1 if household is owner of the house
Rent	1 if household is renting a house
Locvte	1 if household has a leasing agreement for his house
Free	1 if household lives in a free of charge house
Complement for Set III	
Occupation of HH	
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
Schooling level of HH	
Illiterate	Dummy variable for HH is illiterate
Prim	Dummy variable for HH has a primary schooling level

TABLE 1

(*continued*)

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 Greater Tunis, the most prosperous region and largest industrial centre. Zone 5 corresponds to the Middle East (Sousse, Monastir, Mahdia), which is the second economic region of Tunisia. It is reputed for its thriving tourist industry. As 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 Northeast (Nabeul, Bizerte, Zaghouen), which is the third-most important economic region of Tunisia. We expect the coefficient of this variable to have the smallest magnitude among the zone coefficients in the prediction equation. Zone 3 corresponds to the Northwest where the highest poverty incidence is. Its coefficient should have the largest magnitude among the zone coefficients. Zone 4 is the Middle West, which is also very poor. Zone 6 is the Sfax area, which is economically prosperous as one the main industrial centre after Tunis and the Middle East. Zone 7 is the Southwest where Tozeur oasis stands as an important producing area of dates. It is also an increasingly prosperous tourism centre. Other important towns in this area are Gafsa (with a declining production of phosphates) and Kbelli. Zone 8 is the Southeast, 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 'hovel'. Arab's houses are traditional houses that do not satisfy standard requirements of modern houses. Walls may not be straight. Construction materials used for roof, walls and floor are often of poor quality.

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, no information on the cultivated areas or 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 HH. The remaining categories are denoted: Illiterate (no education), Prim (6 years of primary education or less) and 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. As 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 (7,734 observations)

Variables	Mean	Standard deviation	Minimum	Maximum
Yearly total expenditure	4066	3456	99	54,234
Yearly total expend. p.c.	804	809	47	20,531
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

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TABLE 2

(continued)

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Variables	Mean	Standard Deviation		Minimum	Maximum
Nbelspu	0.403	0.789		0	5
Nbelppv	0.006	0.093		0	3
Nbelppu	1.007	1.198		0	7

Decile		Upper threshold	Mean	Mean of logarithms	Lower poverty line	Medium poverty line	Upper poverty line
Equivalent-incomes in Tunisian Dinars, per year and per capita							
1		231	173	5.11			
2		311	271	5.60			
3		384	347	5.84			
4		465	424	6.04			
5		555	510	6.23			
All sample	Mean		746	6.33	225	280	360
	In logarithm				5.46	5.64	5.88

first decile) of the logarithm of the household consumption per capita respectively, on Sets I, II and III of explanatory variables.[10] The regression predictions are applied to the whole sample, here and throughout the study. The dependent variable is the logarithm of the equivalent income (i.e. with living standards corrected with the true price indices inferred from the estimated demand system).[11] Other conventions, for censorships and quantiles, lead to results in agreement,[12] as well as not adjusting for prices or correcting by Laspeyres price indices.

The censored quantile regression estimator for dependent variable y_i and quantile θ is obtained as the solution to the minimization of

$$\sum_i \rho_\theta[y_i - \max(0, \mathbf{X}_i'\gamma)], \tag{4}$$

where $\rho_\theta[u] = \{\theta - I_{[u<0]}\}|u|$, $\mathbf{X}_i$ is a matrix of regressors and γ is a vector of parameters. Quantile regressions correspond to replacing $\max(0, \mathbf{X}_i'\gamma)$ with $\mathbf{X}_i'\gamma$. Powell (1986) and Buchinsky and Hahn (1998) analyse these estimators. The estimation is obtained by using a linear-programming algorithm and subsample selection at each iteration of the optimization. We estimate the confidence intervals of the censored

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[10]Other estimation methods could be used such as Probit models of the probability of being poor, or non-linear specifications for the right-hand-side variables. We tried a variety of such methods. However, to limit the length of the article, we only show some of the better performing and more relevant estimates.

[11]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 is almost proportional to population sizes.

[12]The censorship at quantile 50% 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 is needed, which is unlikely with a too small sample). Second, excessive censoring leads to disastrous loss of accuracy in the estimation.

TABLE 3

Prediction Equations

Variables	OLS V1	OLS V2	OLS V3	UQ01 V1	UQ01 V2	UQ01 V3	CQ01 V1	CQ01 V2	CQ01 V3
Constant	6.631	6.38	6.567	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)
Northeast	−0.197	−0.061	−0.054	−0.243	−0.069	−0.048	−0.243	−0.063	−0.037
	(0.000)	(0.004)	(0.006)	(0.000)	(0.040)	(0.133)	(0.000)	(0.014)	(0.149)
Northwest	−0.557	−0.364	−0.314	−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)
Mid. west	−0.496	−0.223	−0.19	−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)
Sfax	−0.336	−0.306	−0.274	−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)
Southeast	−0.350	−0.194	−0.151	−0.223	−0.041	−0.042	−0.223	0.005	0.041
	(0.000)	(0.000)	(0.000)	(0.000)	(0.256)	(0.254)	(0.000)	(0.851)	(0.159)
Southwest	−0.47	−0.273	−0.208	−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)	(0.005)
Age		0.009	0.009		0.011	0.008		0.006	0.003
		(0.002)	(0.003)		(0.027)	(0.143)		(0.099)	(0.479)
Age2		−0.0001	−0.0001		−0.0001	−0.0001		−0.0001	−0.0000
		(0.000)	(0.003)		(0.003)	(0.190)		(0.024)	(0.573)
Nc2		−0.082	−0.084		−0.101	−0.077		−0.113	−0.075
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Nc3-6		−0.115	−0.122		−0.104	−0.116		−0.110	−0.120
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Nc7-11		−0.087	−0.122		−0.092	−0.108		−0.100	−0.118
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Na12-18		−0.055	−0.116		−0.056	−0.114		−0.052	−0.114
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Na19p		0.04	−0.050		0.036	−0.05		0.022	−0.057
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Nbroompc		0.653	0.542		0.526	0.453		0.129	0.133
		(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		−0.43	−0.243		−0.322	−0.127
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Hovel		−0.68	−0.448		−0.871	−0.581		−0.792	−0.496
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Free		0.021	−0.003		−0.027	−0.013		0.015	0.015
		(0.426)	(0.903)		(0.544)	(0.754)		(0.659)	(0.661)
Rent		0.154	0.080		0.160	0.057		0.086	0.056
		(0.000)	(0.001)		(0.000)	(0.162)		(0.005)	(0.079)
Locvte		0.213	0.151		0.244	0.189		0.137	0.086
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.009)
Nbbud			0.027			0.022			0.015
			(0.000)			(0.039)			(0.071)

continued overleaf

TABLE 3

(*continued*)

Variables	OLS V1	OLS V2	OLS V3	UQ01 V1	UQ01 V2	UQ01 V3	CQ01 V1	CQ01 V2	CQ01 V3
Nactiff			0.125			0.121			0.066
			(0.000)			(0.000)			(0.000)
Nactim			0.168			0.176			0.143
			(0.000)			(0.000)			(0.000)
Unemp			−0.342			−0.443			−0.433
			(0.000)			(0.000)			(0.000)
Agrilab-an			−0.226			−0.209			−0.208
			(0.000)			(0.000)			(0.000)
Agrilab-sw			−0.331			−0.223			−0.34
			(0.000)			(0.027)			(0.000)
Agrilab-se			−0.197			−0.074			−0.119
			(0.000)			(0.414)			(0.102)
Notagrilab			−0.121			−0.102			−0.051
			(0.000)			(0.000)			(0.011)
Agrifar			−0.037			0.016			0.043
			(0.093)			(0.656)			(0.138)
Agrifar-nw			−0.032			−0.098			−0.152
			(0.426)			(0.141)			(0.004)
Illiterate			−0.374			−0.381			−0.245
			(0.000)			(0.000)			(0.000)
Prim			−0.224			−0.203			−0.099
			(0.000)			(0.000)			(0.000)
Sec-J			−0.055			−0.049			0.021
			(0.042)			(0.276)			(0.543)
Nbetud			0.111			0.013			0.032
			(0.000)			(0.782)			(0.391)
Nbelspv			0.158			0.182			0.157
			(0.000)			(0.000)			(0.000)
Nbelspu			0.074			0.105			0.106
			(0.000)			(0.000)			(0.000)
Nbelppv			0.213			0.249			0.084
			(0.002)			(0.006)			(0.239)
Nbelppu			0.04			0.038			0.049
			(0.000)			(0.025)			(0.000)
Nb. Obs.	7734	7734	7734	7734	7734	7734	7734	7734	7734

The living standard variable is the equivalent income.
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).
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

	OLS	Quantile regressions (quantile 10%)	Quantile regressions (quantile 30%)	Censored quantile regressions threshold 50% (quantile 10%)
Whole population				
Set I	0.897	2.291	1.146	3.251
Set II	0.551	1.413	0.693	2.259
Set III	0.473	1.223	0.589	1.991
The poor under the first quintile				
Set I	0.832	0.105	0.410	0.059
Set II	0.420	0.080	0.210	0.062
Set III	0.338	0.080	0.177	0.066
The poor under the second quintile				
Set I	0.845	0.120	0.370	0.134
Set II	0.428	0.147	0.211	0.158
Set III	0.350	0.152	0.185	0.155

quantile regression estimates with the bootstrap method proposed by Hahn (1995) and 1,000 bootstrap iterations.[13]

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.[14] These ratios measure 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 and the households in the first and second quintiles.

The results show that quantiles regressions (centred at the first decile) perform much better than the other methods for predicting the logarithms of living standards *of the poorest households* (here defined as belonging to the first or second decile of the living standard distribution), to the exception of censored quantile regressions that perform better for the households with living standards below 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. Finally, the predicting performance of the censored quantile regressions is disappointing for the whole population, and

[13] We also tried with a Tobit model. However, this yielded mediocre prediction performance as Tobit estimates are generally inconsistent. Indeed, first the normality assumption on which the Tobit model is based is often rejected. Second, heteroscedasticity is likely to arise from household heterogeneity. Finally, the threshold y_{max} may be unknown. All the results associated with the Tobit estimates are provided in the study of Muller and Bibi (2006).

[14] The interpretation of the R^2 as a percentage of variation explained is dependent on the use of OLS to compute the fitted values. This is why we use instead the ratio of variances as our prediction performance indicator. For the OLS only, the considered ratio is equal to $1 - R^2$.

dominated for the households with living standards below the second quintile by that of the quantile regressions. This is worrying as realistic poverty lines in Tunisia lie between the first and second quintiles. Moreover, censored quantile regressions rely on algorithms difficult to implement in most national statistical offices. Then, if our business is predicting the logarithms of living standards of the poor, the quantile regressions look like the most promising method.

Beyond general prediction performance, we shall show that using quantile regression predictions is useful if the aim is to improve transfer schemes. Appropriate assessment will come from estimating the schemes with different methods and examining the results. Let us first briefly turn to the results of the prediction equations in Table 3, which are related to typical living standard explanations in Tunisia. The signs of most coefficient estimates (significant at 5% level) correspond to the expected effects of variables and are consistent across all estimation methods. In the next section, the predicted household living standards are used to simulate targeting efficiency measures resulting from the considered schemes.

IV.   Programme efficiency results

The calculation of the transfers in the simulations requires the determination of the cut-off income, y_{max}. The p-type transfer is: y_{max} minus the predicted income, for each household predicted poor, and zero for households predicted non-poor. Under perfect targeting, the y_{max} permitted by the budget currently devoted to food subsidies is TD 358, greater than the poverty lines typically estimated for Tunisia.[15] However, even if the budget is sufficient to eliminate poverty under perfect targeting, under imperfect targeting additional resources are needed and the budget is exhausted.

We 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%. This poverty line corresponds to an *equivalent poverty line of TD 280* without subsidies. However, the qualitative results of this study go through with poverty lines at reasonable levels, as it is illustrated in the poverty curves corresponding to the stochastic dominance analyses shown in Muller and Bibi (2006).

The best 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, we ran Huber robust regressions, which yielded almost the same results than OLS whether for the estimated coefficients or the poverty curves. So, using Huber regressions does not modify the coefficients obtained with OLS-based predictions,

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[15]The poverty line estimated by the National Statistic Institute and The World Bank (1995) – see also Ravallion and Van de 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 344.

and therefore does not improve the quality of predictions. The best performance of the quantile regressions is therefore not due to robustness. However, poverty curves provide only qualitative insights. We now turn to quantitative estimates of targeting efficiency.

Estimates of targeting performance

Table 5 presents simulation results for: (i) two measures of targeting accuracy (Leakage and Undercoverage, as defined in Section 1.4); (ii) the levels of poverty severity (P_2) reached with the transfer schemes; and (iii) the share of transfers to the targeted population. As mentioned above, a poverty line of TD 280 per capita per year without subsidies is used, corresponding to TD 250 with subsidized prices. We also show qualitatively similar conclusions for two other poverty lines in the Appendix. To concentrate the discussion on targeting performance, we discuss the poverty results for P_2 only. Results for other poverty indices and results under price subsidies are in provided in the study of Muller and Bibi (2006).

In our comments, we emphasize the comparison among transfer methods. The sampling standard errors of poverty and targeting indicators were obtained by bootstrapping, taking as given the demand estimation and prediction procedures. That is, we compare given PMT schemes, without incorporating the uncertainty involved in all the stages necessary to develop the PMT formulae. The standard errors suggest that the estimated targeting indicators significantly vary with the prediction methods. This is indeed generally what we found when we implemented tests of null differences, as obvious with bootstrap confidence intervals. If the aim is to reduce poverty measured by the axiomatically appealing poverty severity measure P_2, quantile regressions anchored on the first decile are best. 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 of Set I, substantial improvements can be reached whether in terms of poverty statistics, Leakage or Undercoverage. Remember also that Set II is our chosen set of correlates for actual programme offices. With Set II, the quantile regression based on the first quantile remains the best approach for reducing P_2 and Undercoverage. Low Undercoverage indicators may be related to desirable political conditions as policies leaving aside a large proportion of the poor are unlikely to be implementable in Tunisia. Censored quantile regressions would allow even larger reduction of Undercoverage.

Using information on education or occupation of household head gains little ground. The quantile regressions based on the first decile (and sometimes the censored quantile regressions) remain preferable if the aim is to alleviate P_2, whereas OLS are better if the aim is just to cut the number of the poor down (see results with the head-count index in the study of Muller and Bibi, 2006). Using censored quantile regressions anchored on the first decile would lead to the lowest Under-

TABLE 5

Measures of targeting efficiency for z = TD 280

	P_2(in %)	Leakage	Undercoverage	Share of transfers to the targeted population
OLS 1	0.758	84.5	41.6	30.30
	(0.10)	(4.34)	(2.88)	
OLS 2	0.439	72.4	21.6	47.10
	(0.05)	(3.67)	(1.58)	
OLS 3	0.385	72.5	18.5	51.67
	(0.04)	(3.60)	(1.37)	
QR10 1	0.739	75.6	13.2	26.07
	(0.08)	(3.41)	(1.97)	
QR10 2	0.344	70.0	10.2	40.35
	(0.04)	(3.11)	(1.00)	
QR10 3	0.272	69.5	8.67	44.80
	(0.03)	(3.07)	(0.91)	
QR30 1	0.776	78.3	33.2	27.94
	(0.09)	(3.88)	(2.88)	
QR30 2	0.376	70.5	15.4	44.64
	(0.04)	(3.31)	(1.32)	
QR30 3	0.312	73.0	13.1	50.18
	(0.03)	(3.35)	(1.16)	
QRC01 1	0.739	75.6	13.2	26.07
	(0.08)	(3.42)	(1.97)	
QRC01 2	0.404	68.9	9.92	37.42
	(0.04)	(3.02)	(0.95)	
QRC01 3	0.298	70.9	6.92	43.11
	(0.03)	(3.09)	(0.76)	
Pro-poor Uniform OLS3	0.977	69.5	64.4	54.55
Pro-poor Uniform QR10 3	0.444	75.4	6.72	33.78

The living standard variable is the equivalent income.
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.
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.
QR10 1: Transfers based on quantile regressions centred on quantile 0.1 with Set I variables.
QR10 2: Transfers based on quantile regressions centred on quantile 0.1 with Set II variables.
QR10 3: Transfers based on quantile regressions centred on quantile 0.1 with Set III variables.
QR30 1: Transfers based on quantile regressions centred on quantile 0.3 with Set 1 variables.
QR30 2: Transfers based on quantile regressions centred on quantile 0.3 with Set II variables.
QR30 3: Transfers based on quantile regressions centred on quantile 0.3 with Set I variables.
QRC01 1: Transfers based on censored quantile regressions centred on quantile 0.3, censored at quantile 0.5, with Set I variables.
QRC01 2: Transfers based on censored quantile regressions centred on quantile 0.3, censored at quantile 0.5, with Set II variables.
QRC01 3: Transfers based on censored quantile regressions centred on quantile 0.3, censored at quantile 0.5, with Set III variables.
Pro-poor Uniform OLS3: Uniform transfers based on OLS 3: Set III variables.
Pro-poor Uniform QR10 3: Uniform transfers based on quantile regressions centred on quantile 0.1 with Set III variables.
Each of measures presented in this table has been multiplied by 100 for easy interpretation.
7734 observations. Sampling errors in parentheses.

coverage. Meanwhile, quantile regressions based on the first decile, which are simpler to implement, still yield low Undercoverage of 8.7%, a remarkably low result. The other methods may produce disastrous Undercoverage outcomes.

However, if the aim is to reduce Leakage, although quantile regressions based on the first decile perform better than OLS, using censored quantile regressions may be very slightly preferable. As a matter of fact, no prediction method generates substantial fund savings through Leakage reduction. Leakage always remains high (above 68%) whatever may be the used method.

Omitting price correction or deflating with household Laspeyre price indices gives similar results. On the whole, the quantile regression based on the first decile is best for diminishing P_2 and perhaps Undercoverage. Sometimes, the censored quantile regressions anchored on the first decile with a 50% censorship dominate the quantile regressions based on the first decile for reducing Undercoverage, but they seem unlikely to be used in most applied contexts as this method is not available in standard statistical packages.[16]

Three important points may be noted. 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. When compared with other cash transfer methods, substantial improvement of the poverty situation measured by P_2 can be obtained (with our preferred estimation based on Set II: from 0.385% with the best OLS method to 0.272% with the best quantile regression method – centred in the first decile). Moreover, the percentage of excluded poor households from the scheme dramatically falls (to 8.6%) when compared with what is obtained with OLS predictions based on geographical dummies (for which it is 41.6%). Second, the usually employed method, based on OLS estimates, appears as the worst performing approach in contrast with methods focusing the predictions on the poor. However, when considering only the number of the poor, the OLS may provide acceptable predictions for the richest of the poor that are not in that case discounted when compared with the poorest. With limited budget, one could push still further the transfer performance by using quantile regressions centred about the poverty line for r-type transfers and centred on small quantiles for p-type transfers, consistently with the theoretical definitions of these transfer types.

The censorship of the wealthier half of the sample is statistically too crude to make much impact on the performance of anti-poverty schemes through censored quantile regressions. They generally yield worse results than what can be obtained with quantile regressions, except for Undercoverage.

On the whole, using prediction methods focusing on the relevant part of the living standard distribution substantially raises transfer efficiency. Even better results

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[16]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.

could be reached by trying a large set of quantiles instead of using arbitrarily the first and third deciles to centre the regressions. Systematic search of the centreing quantile, although time-consuming, could be implemented in any context where a household living standard survey is available in order to optimize the transfer performance.

As shown in the Appendix, robustness checks based on two other poverty lines yield similar qualitative results. In Muller and Bibi (2006), stochastic dominance tests show that the qualitative results for poverty measures can be extended to a broad range of poverty lines.

Uniform transfers and graphs of targeting errors

Results shown in Table 5 also indicate the performances of uniform transfers to the poor respectively based on OLS predictions and (first decile) quantile regression predictions, in both cases using the largest set of regressors. The performances are disastrous with OLS-based uniform transfers yielding the worst reached levels of P_2 and Undercoverage. They are better for quantile regression-based uniform transfers, while with mediocre level for P_2 (although only slightly less good than with optimal transfer based on OLS). The lowest Undercoverage can be obtained with uniform transfers based on quantile regressions. This is because all the identified poor receive transfers, whereas with optimal transfers some well-identified poor are not covered for the lack of sufficient funds.

As mentioned before, we prefer to estimate Leakage statistics that do not include 'unnecessary' transfers in the sense that they would raise households above the poverty line. Indeed, such transfers would not diminish any usual poverty index (satisfying the focus axiom). If this point is taken into account in the Leakage statistics, then even under uniform transfers, Leakage and Undercoverage are not mirror images. As expected, estimated Leakage statistics under uniform transfers remain high.

Another possible indicator of target efficiency is the share of transfers going to the targeted population, shown in the last column of Table 5. For all estimation methods, this share rises with the size of the set of used correlates in the living standard prediction equation. The more information used, the greater the share of transfers going to the initially poor. However, this indicator is a mediocre measure of anti-poverty targeting as can be seen by further examining the estimates. Indeed, the estimated share with OLS appear to be systematically greater than the estimated shares for the tried (censored or not) quantile regressions. This is unexpected as the latter methods have been found more efficient for anti-poverty targeting than OLS, for all other efficiency criteria. This surprising result is due to several features. First, the transfers sent to pretransfer poor households are not relevant when they lift the households' living standards above the poverty line. Then, high shares of transfers to the poor may characterize an inefficient outcome if some poor receive excessive amounts, whereas other destitute households are left below the poverty line. Second, we have

shown the importance of accounting for the heterogeneity of living standards among the poor. Identifying who is poor is far from being enough for anti-poverty transfers. What really make the policy efficient are accurate estimates of the living standards of the poor. For the latter task, OLS perform badly, while they may be enough to just identify the poor, as illustrated by their corresponding high shares of transfers to the poor for uniform transfers. What happens is that using OLS leads to giving too much to many poor or non-poor, whether because the transfer lifts them above the poverty line, or because still poorer households receive less and therefore the budget is not employed optimally. All these yield high estimated shares of transfers going to the poor, an indicator hiding the actual misallocation of funds.

Finally, we show graphs of targeting errors against initial living standard levels for $z = $ TD 280, following Coady and Skoufias (2004) (see Figure 1). On the left of the poverty line, the curve shows the percentage of the pretransfer poor not reached by transfers. On the right of the poverty line, it shows the percentage of the pretransfer non-poor unduly receiving transfers.

One can see that OLS and quantile regressions essentially differ by their capacity to calculate accurately transfers for the extremely poor households, whereas their performances are closer for households around the poverty lines. On the other hand, the OLS would better target non-poor households if it were useful. These features are apparent if optimal transfers are calculated (in Graphs 1 and 2) or if pro-poor uniform transfers are used (in Graphs 3 and 4). Graphs 3 and 4 also indicate, on the left of
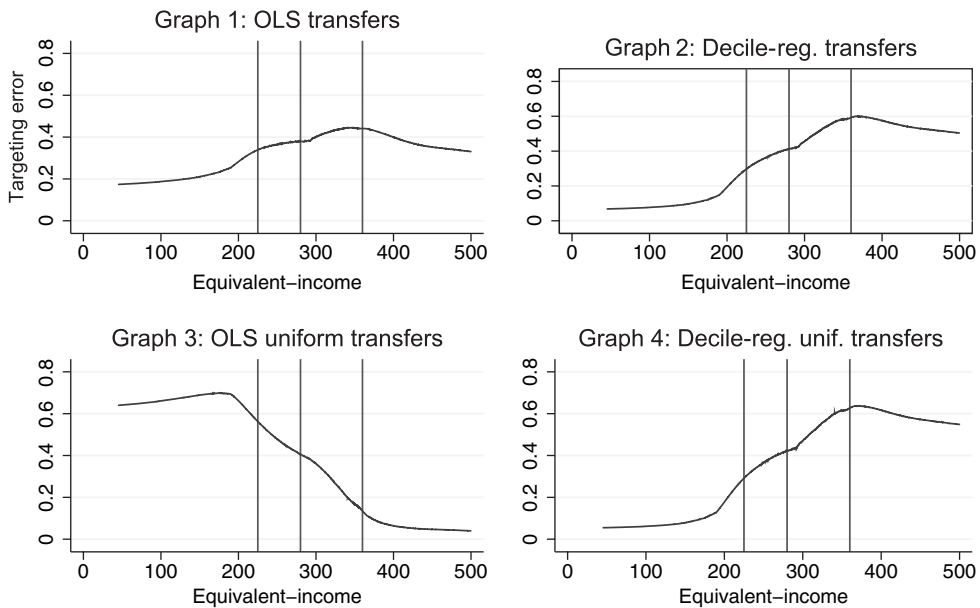
The vertical are poverty lines at 225, 280 and 360 TD

Figure 1. Ex post and ex ante targeting errors

the poverty line, the percentage of post-transfer poor for each level of pretransfer living standard. This representation is possible with uniform transfers and the chosen poverty line because there are enough funds to lift all the poor who can be identified above the poverty line.

These graphs allow the visual separation of the performances of the pure uniform targeting transfer schemes (Graphs 3 and 4) from optimized transfer schemes (Graphs 1 and 2). Additional post-transfer targeting errors may occur during the adjustment of the transfer levels to the predicted living standards. Indeed, with optimized transfers and a given available budget, not all households can generally be served by the transfer scheme. In contrast, with uniform transfers all households identified as poor are served, but they receive amounts that are not related to their living standard.

For uniform transfers, the bulk of targeting errors from OLS are below the poverty line and large. They are much less substantial for optimized OLS transfers, for which the errors elicit a smooth peak at the centre of the graph. In contrast, decile-regression targeting errors are much smaller at the left of the poverty line, whether for optimized or uniform transfers. Meanwhile, on the right-hand side of the poverty line, these errors are larger than from OLS. However, decile-regression targeting errors do not differ very much when considering optimized and uniform transfers. This is because with the considered transfer budget and poverty line, only about 3.5% of households are simultaneously identified as poor (using quantile regressions based on Set III) and cannot be served because of budget exhaustion. It appears that the main gain obtained from moving from uniform to optimized transfers, as far as targeting based on decile regressions is concerned, occurs around the used poverty line. The graphs make clear that the use of quantile regressions is important for better targeting of the poor, whether for uniform or optimized transfers.

Policy consequences

What are the policy consequences of the new focused transfer schemes? The first one is that improving existing schemes is concretely and easily possible. Lower poverty levels, smaller Leakage and Undercoverage statistics can be attained by focusing the estimation of transfer schemes. In Tunisia of 1990, the gain of efficiency, notably in terms of Undercoverage, is so large that it should deserve serious practical consideration. In terms of poverty severity, 3.9% is already the level reached with the best OLS method. Another half reduction in poverty requires only a few hours of simple statistical work easy to do with common package (e.g. Eviews: Quantitative Micro Software, LLC, 4521 Campus Drive, #331, Irvine, CA, 926122621, USA; Stata Corp LP, 4905 Lakeway Drive, College Station, Texas 77845, USA). Moreover, this reduction is much larger than that obtained by adding education and occupation variables to the list of regressors in OLS regressions.

There is already a small transfer scheme in operations in Tunisia: the 'Programme des Familles Nécessiteuses' (République Tunisienne, 1991). However, a large trans-

fer programme would necessitate raising large funds. A possible consequence of our results is that the transfer of some public funds allocated to price subsidies towards a national focused transfer scheme may be easier with our new technique.

Previous attempts at eliminating subsidies in Tunisia ended in riots. Indeed, as all the poor benefit from price subsidies, an alternative system of cash transfers may not only further alleviate aggregate poverty, but also leave aside a large proportion of the poor. If this risk is perceived as high by the population, social unrest may follow. Therefore, replacing subsidies by OLS-based PMT transfers is likely to meet political obstacles as about between one-quarter and one-fifth of the poor would be excluded from the benefits. Another possibility would be to replace food subsidies with targeted food subsidies based on PMT programmes. However, this seems difficult as it would imply to administer expenditure transactions by targeted households.

However, using focused cash transfers would allow the government to reduce Undercoverage to such a low level that: (i) the reform may be politically viable; and (ii) the reform would not generate severe risk for a large proportion of the poor. As a matter of fact, it seems exceptional that such a small proportion of the population would suffer from a large social reform. Moreover, considering the gain in efficiency caused by eliminating 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 in the end.

V. Conclusion

Leakage to the non-poor is often substantial from universal food price subsidy programmes directed to the poor. Because of their large budgetary cost, many governments have moved away from them towards better targeted methods, such as PMT cash transfers. Indeed, benefits can be awarded to the poor contingently on their characteristics. However, transfer schemes may be inaccurate because the statistical predictions involved in their design are centred on the mean of the living standard distribution and not enough oriented towards the potentially poor.

This study improves on past methods by focusing on the poor and near-poor for the design of transfer schemes based on estimated living standard equations.[17] This is achieved by using quantile regressions. Moreover, the method can be adapted to any social programme based on 'household assessment', that is, predictions of household characteristics (as in Case and Deaton, 1998, or Hanmer *et al.*, 1998).

Our estimation results based on data from Tunisia reveal potential for poverty alleviation with our new approach. The improvement is also substantial when compared with usual targeting schemes based on OLS predictions: with our method based on quantile regressions, poverty could be massively reduced in Tunisia. Moreover, large reduction in Undercoverage is possible, even when compared with the best

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[17]Therefore, not for food subsidies for which distinguishing among households for eligibility of benefits is not feasible.

OLS-based transfers. In contrast, censoring the living standard distribution does not improve the performance of transfer schemes, except sometimes for reducing Under-coverage. On the whole, with the new techniques, targeting by indicators may be relatively cheap to implement, when compared with the huge financial burden of price subsidies.[18]

Other ways of focusing on the poor are possible, for example by using nonpara-metric regressions, shading 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 impor-tant 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.

Finally, future research should be applied to repeated cross-sections from house-hold budget surveys separated by a few years. It would tell us how badly targeting efficiency degrades when targeting rules derived from a survey in year T are applied to data in year $T + s$.

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Appendix: Robustness checks with two other poverty lines

Table for z = TD 360

	P_2 (in %)	Leakage	Undercoverage
OLS 1	1.93	69.0	47.3
OLS 2	1.31	50.4	29.9
OLS 3	1.17	48.1	27.3
QR10 1	1.98	61.9	16.9
QR10 2	1.26	50.1	16.6
QR10 3	1.07	47.3	15.3
QR30 1	1.98	63.7	37.6
QR30 2	1.24	49.0	23.1
QR30 3	1.05	48.3	20.7
QRC01 1	1.98	61.9	16.9
QRC01 2	1.39	50.5	15.9
QRC01 3	1.13	49.6	14.0
Pro-poor uniform OLS3	1.29	50.8	45.0
Pro-poor uniform QR10 3	1.82	63.7	38.4

[18]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.

Table for z = TD 225

	P_2(in %)	Leakage	Undercoverage
OLS 1	0.311	93.8	38.2
OLS 2	0.154	85.4	17.5
OLS 3	0.134	86.5	16.0
QR10 1	0.272	84.3	12.6
QR10 2	0.092	83.0	6.76
QR10 3	0.071	84.0	7.05
QR30 1	0.312	87.3	32.9
QR30 2	0.118	83.9	11.2
QR30 3	0.098	87.8	10.1
QRC01 1	0.272	84.3	12.6
QRC01 2	0.112	81.0	7.14
QRC01 3	0.080	85.0	5.47
Pro-poor uniform OLS3	0.688	24.4	82.5
Pro-poor uniform QR10 3	0.098	86.4	16.1

References

Africa Focus Bulletin (2006). *Africa: Social Transfers*, Dfid, February, posted on Web, no page number (http://www.africafocus.org/docs06/soc0604.php–accessed January 20, 2010).

Ahmed, A. U. and Bouis, H. E. (2002). 'Weighing what's practical: proxy means tests for targeting food subsidies in Egypt', *Food Policy*, Vol. 27, pp. 519–540.

Alderman, H. and Lindert, K. (1998). 'The potential and limitations of self-targeting food subsidies', *The World Bank Research Observer*, Vol. 13, pp. 213–230.

Atkinson, A. B. (1995). 'On targeting social security: theory and western experience with family benefits', in van de Walle D. and Nead K. (eds), *Public Spending and the Poor, Theory and Evidence*, The Johns Hopkins University Press for the World Bank, Washington, D.C., pp. 25–68.

Ayadi, M. and Matoussi, M. S. (1999). *Analyse de la Pauvreté en Tunisie: Comparaison Spatiale et Temporelle en Utilisant des Enquêtes Ménages*, Paper presented in the ERF Sixth Annual Conference, Cairo, pp. 28–31, October.

Baker, J. and Grosh, M. E. (1994). 'Poverty reduction through geographic targeting: how well does it work', *World Development*, Vol. 22, pp. 983–995.

Besley, T. (1990). 'Means testing versus universal provision in poverty alleviation', *Economica*, Vol. 57, pp. 119–129.

Besley, T. and Coate, S. (1992). 'Workfare vs. welfare: incentive arguments for work requirements in poverty alleviation programs', *American Economic Review*, Vol. 82, pp. 249–261.

Besley, T. and Kanbur, R. (1988). 'Food subsidies and poverty alleviation', *The Economic Journal*, Vol. 98, pp. 701–719.

Besley, T. and Kanbur, R. (1993). 'Principles of targeting', in Lipton M. and van der Gaag J. (eds), *Including the Poor*. Washington, DC: The World Bank, pp. 67–90.

Bibi, S. (2003). 'Comparing the impact of food subsidies and regional targeting on poverty: evidence from Tunisia', *Journal of Development and Economic Policies*, Vol. 6, pp. 5–37.

Bibi, S. and Duclos, J.-Y. (2007). 'Equity and policy effectiveness with imperfect targeting', *Journal of Development Economics*, Vol. 83, pp. 109–140.

Bigman, D. and Fofack, H. (2000). 'Geographical targeting for poverty alleviation: an introduction to the special issue', *The World Bank Economic Review*, Vol. 14, pp. 129–145.

Bigman, D. and Srinivasan, P. V. (2002). 'Geographical targeting of poverty alleviation programs: methodology and application in rural India', *Journal of Policy Modelling*, Vol. 24, pp. 237–255.

Blundell, R. and Lewbel, A. (1991). 'The information content of equivalence scales', *Journal of Econometrics*, Vol. 50, pp. 49–68.

Bourguignon, F. and Fields, G. (1990). 'Poverty measures and anti-poverty policy', *Recherches Economiques de Louvain*, Vol. 56, pp. 409–428.

Bourguignon, F. and Fields, G. (1997). 'Discontinuous losses from poverty, general P_α measures, and optimal transfers to the poor', *Journal of Public Economic*, Vol. 63, pp. 155–175.

Buchinsky, M. (1994). 'Changes in the U.S. wage structure 1963–1987: application of quantile regression', *Econometrica*, Vol. 62, pp. 405–458, March.

Buchinsky, M. and Hahn, J. (1998). 'An alternative estimator for the censored quantile regression model', *Econometrica*, Vol. 66, pp. 653–671, May.

Case, A. and Deaton, A. (1998). 'Large cash transfers to the elderly in South Africa', *The Economic Journal*, Vol. 108, pp. 1330–1361.

Chakravaty, S. R. and Mukherjee, D. (1998). 'Optimal subsidy for the poor', *Economics Letters*, Vol. 61, pp. 313–319, North-Holland.

Coady, D. P., Grosh, M. and Hoddinott, J. (2002). *Targeting Anti-Poverty Interventions: A Selected Annotated Bibliography*, mimeo The World Bank.

Coady, D. P., Grosh, M. and Hoddinott, J. (2004). 'Targeting outcomes redux', *World Bank Research Observer*, Vol. 19, pp. 61–85, Spring.

Coady, D. P. and Skoufias, E. (2004). 'On the targeting and redistributive efficiency of alternative transfer instruments', *Review of Income and Wealth, Ser*. Vol. 50, pp. 11–27, March.

Cornia, G. A. and Stewart, F. (1995). 'Two errors of targeting', in van de Walle D. and Nead K. (eds), *Public Spending and the Poor, Theory and Evidence*, The Johns Hopkins University Press for the World Bank, Baltimore, pp. 350–386.

Cowell, F. A. and Victoria-Feser, M.-P. (1996). 'Poverty measurement with contaminated data: a robust approach', *European Economic Review*, Vol. 40, pp. 1761–1771.

Creedy, J. (1996). 'Comparing tax and transfer system: poverty, inequality and target efficiency', *Economica*, Vol. 63, pp. S163–S174 (Supplement: Economic policy and income distribution).

Datt, G. and Joliffe, D. (2005). 'Poverty in Egypt: modeling and policy simulations', *Economic Development and Cultural Change*, Vol. 53, pp. 327–346, January.

Datt, G. and Ravallion, M. (1993). 'Regional disparities, targeting and poverty in India', in Lipton M. and van der Gaag J. (eds), *Including the Poor*, Washington, DC: The World Bank, pp. 91–114.

Datt, G. and Ravallion, M. (1994). 'Transfer benefits from public works employment: evidence for rural India', *Economic Journal*, Vol. 104, pp. 1346–1369.

Deaton, A. (1997). *The Analysis of Household Survey: A Microeconomic Approach to Development Policy*, Baltimore: Johns Hopkins University Press.

De Janvry, A., Finan, F., Sadoulet, E. and Vakis, R. (2006). 'Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks?' *Journal of Development Economics*, Vol. 79, pp. 349–373.

De Janvry, A. and Sadoulet, E. (2006a). *When to Use a CCT Versus a CT Approach*, mimeo University of California at Berkeley, July.

De Janvry, A. and Sadoulet, E. (2006b). 'Making conditional cash transfer programs more efficient: designing for maximum effect of the conditionality', *The World Bank Economic Review*, Vol. 20, pp. 1–29.

DFID (2006). 'Using social transfers to improve human development', *Social Protection Briefing Note Series*, No. 3, February.

Elbers, C., Lanjouw, J. O. and Lanjouw, P. (2003). 'Micro-level estimation of poverty and inequality', *Econometrica*, Vol. 71, pp. 355–364, January.

Foster, J., Greer, J. and Thorbecke, E. (1984). 'A class of decomposable poverty measures', *Econometrica*, Vol. 52, pp. 761–765.

Glewwe, P. (1992). 'Targeting assistance to the poor, efficient allocation of transfers when household income is not observed', *Journal of Development Economics*, Vol. 38, pp. 297–321.

Glewwe, P. and Kanan, O. (1989). *Targeting Assistance to the Poor: A Multivariate Approach Using Household Survey Data*, Policy Planning and Research Working Paper, No. 86, Washington, DC.

Grosh, M. and Baker, J. L. (1995). *Proxy Means Tests for Targeting Social Programs*, LSMS Working Paper, No. 118, Washington, DC: The World Bank.

Hahn, J. (1995). 'Bootstrapping quantile regression estimators', *Econometric Theory*, Vol. 11, pp. 105–121.

Hanmer, L. C., Bijlmakers, L., Basset, M. T., Sanders, D. and Chapman, G. (1998). 'Human capital, targeting and social safety nets: an analysis of household data from Zimbabwe', *Oxford Development Studies*, Vol. 26, pp. 245–265, June.

Hassan, F. M. A. (2006). *Tunisia: Understanding Successful Socioeconomic Development*, Washington: The World Bank.

Kanbur, R. (1987). 'Measurement and alleviation of poverty, with an application to the effects of macroeconomic adjustment', *IMF Staff Papers*, Vol. 34, pp. 60–85.

Koenker, R. and Bassett, G. (1978). 'Regression quantiles', *Econometrica*, Vol. 46, pp. 33–50.

Lindert, K., Skoufias, E. and Shapiro, J. (2005). *Redistributing Income to the Poor and the Rich: Public Transfers in Latin America and the Caribbean*, Discussion Draft, LACEA, Washington, D.C., October.

Muller, C. (2002a). 'Prices and living standards. Evidence for Rwanda', *Journal of Development Economics*, Vol. 68, pp. 187–203.

Muller, C. (2002b). 'Censored quantile regressions of chronic and transient poverty in Rwanda', *Journal of African Economies*, Vol. 1, pp. 503–541.

Muller, C. (2007). 'Poverty change in Tunisia', *Korean Journal of Economics*, Vol. 14, pp. 295–333, Autumn.

Muller, C. (2009). *Implementation Issues in Social Targeting*, mimeo University of Cergy-Pontoise.

Muller, C. and Bibi, S. (2006). *Focused Targeting against Poverty: Evidence from Tunisia*, Discussion Paper, University of Alicante IVIE.

Park, A., Wang, S. and Wu, G. (2002). 'Regional poverty targeting in China', *Journal of Public Economics*, Vol. 86, pp. 123–153.

Pollak, R. A. and Wales, T. J. (1979). 'Welfare comparison and equivalence scales', *The American Economic Review*, Vol. 69, pp. 216–221.

Powell, J. L. (1986). 'Censored regression quantiles', *Journal of Econometrics*, Vol. 32, pp. 143–155.

Pudney, S. (1999). 'On some statistical methods for modelling the incidence of poverty', *Oxford Bulletin of Economics and Statistics*, Vol. 61, pp. 385–408.

Ravallion, M. (1991). 'On coverage of public employment schemes for poverty alleviation', *Journal of Development Economics*, Vol. 34, pp. 57–79.

Ravallion, M. (1992). 'Poverty alleviation through regional targeting: a case study for Indonesia', in Braverman A., Hoff K. and Stiglitz J. (eds), *The Economics of Rural Organization*, Oxford University Press for the World Bank, New York.

Ravallion, M. and Chao, K. (1989). 'Targeted policies for poverty alleviation under imperfect information: algorithms and applications', *Journal of Policy Modeling*, Vol. 11, pp. 213–224.

Ravallion, M. and Datt, G. (1995). 'Is targeting through a work requirement efficient? some evidence for rural India', in van de Walle D. and Nead K. (eds), *Public Spending and the Poor, Theory and Evidence*, Johns Hopkins University Press, Baltimore, pp. 413–444.

Ravallion, M. and Van de Walle, D. (1993). *A Profile of Poverty in Tunisia 1990*, Document Policy Research Department, The World Bank, Washington, D.C.

République Tunisienne (1991). *Seminaire National sur les Politiques de Promotion Sociale des Categories de Population les plus Defavorises*, Juin: Ministère des Affaires Sociales.

Schady, N. R. (2002). 'Picking the poor: indicators for geographic targeting in Peru', *Review of Income and Wealth, Serie* Vol. 48, pp. 413–433, September.

Skoufias, R. and Coady, D. P. (2007). 'Are the welfare losses from imperfect targeting important?' *Economica*, Vol. 74, pp. 656–776.

Slesnick, D. T. (1996). 'Consumption and poverty: how effective are in-kind transfers', *The Economic Journal*, Vol. 106, pp. 1527–1545, November.

Tabor, S. R. (2002). *Assisting the Poor with Cash: Design and Implementation of Social Transfer Programs*, Social Protection Discussion Paper Series No. 0223, The World Bank, Washington, DC.

The World Bank (1995). *Republic of Tunisia, Poverty Alleviation: Preserving Progress While Preparing for the Future*, Middle East and North Africa Region, Report No. 13993-TUN, Washington, DC.

The World Bank (2000). *A Profile of Poverty in Tunisia 1995*, Washington, DC: The World Bank.

The World Bank (2004). *Republic of Tunisia. Country Assistance Strategy for the Period of July 2004 to July 2008*, Public Information Notice 105, Washington DC: The World Bank.

Van de Walle, D. (1998). 'Assessing the welfare impacts of public spending', *World Development*, Vol. 26, pp. 365–379.

Weiss, J. (2005). *Poverty Targeting in Asia*, Cheltenham, UK: Edward Elgar.