Optimal Transfers with Conditional and Unconditional Focused Quantile Regressions

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Abstract

Social programs for poverty alleviation involve eligibility rules and transfer rules. Both kinds of rules depend on the characteristics of applicants. Often, statistical scores, such as for proxy-means tests, are used that summarize the information about these characteristics. However,these methods are often attacked for their mediocre targeting performances. In this paper, we explore the estimation of conditional and unconditional focused quantile regressions to generate fitted-values of living standards that are plugged into the poverty minimization program to obtain optimal transfer amounts. Incidentally, we provide a precise mathematical translation of the intuition of Bourguignon and Fields (1997) to define these optimal amounts, in terms of the calculus of variation. The use of these regression methods are suggested by a theoretical analysis of the poverty minimization problem. We illustrate these methods with simulations based on data from Egypt in 2013. In these simulation results, the Recentered Influence Function (RIF) regressions focusing on the poor correspond to the most efficient transfer scheme. However, most of the gain in poverty reduction is obtained by making transfer amounts varying across beneficiaries rather than by varying fitted-value estimation methods. In particular, using focussed RIF regressions instead of focussed quantile regressions delivers only marginal additional poverty alleviation. Nonetheless, using focussed RIF regressions centered on the proportion of poor households generates substantial reduction of the exclusion of the poor from the program, as compared to using other regression methods.

1. Introduction

Social assistance programs had for long broad and more complex objectives that place them at the core of social policies. However, one major aim of these programs in developing countries is poverty alleviation. More specifically, we study cash transfer programs directed against poverty. Indeed, most social assistance programs in the developing world have adopted a poverty focus and often resorted to categorical approaches and means-tests, or proxy means tests, for the identification and selection of beneficiaries. With severe public budget constraints, this makes a lot of sense, although it requires careful attention to find an optimal transfer formula.

In order to deal with these concerns, we explain a new econometric approach to this question, inspired by the theoretical analysis of the poverty minimization problem. Since fitted-values of living standard variables are a central ingredient of the approach, we estimate these fitted-values by using conditional and unconditional focused quantile regressions. We show how this may improve the targeting of the program. This paper is therefore mostly a methodological investigation, while we shall still provide a simple illustration of how these methods can work by running simulations based on data from Egypt. However, we do not intend to carry out a full application to Egypt social programs, which would be altogether another paper. The first subsection of the introduction discusses procedures for social programs and their inefficiencies. The second subsection review recent empirical progress. The third subsection describes the strategy used in this paper.

1.1. Social programs, proxy means tests and inefficiencies

Social programs involve, on the one hand, eligibility rules (i.e., the conditions for an individual to be accepted by the program), and, on the other hand, service delivery or transfer rules (i.e., the amount of cash or the kind of services that is delivered to an individual of given characteristics). Both of these rules generally depend on the characteristics of individual applicants. The design of these rules is critical for targeting efficiency and poverty reduction as they determine which kind of person will be assisted and whether positive discrimination, for example between extremely poor people and moderately por individuals can be performed. Typically, some thresholds of some variables, such as income or age, are used to identify the potential beneficiaries. Often, statistical scores, such as for Proxy-Means Tests (PMT), can assist the program manager in summarizing some relevant information about applicant characteristics. For example, transfer schemes aimed at poverty alleviation often used fitted-values of living standards that are based on OLS regressions estimated with household survey data. They are other methods to perform transfers than PMTs, while they are often found as yielding less efficient targeting, at least in terms of traditional poverty measures (as for Indonesia in Atalas, Banerjee, Hana and Tobias, 2012).

However, in seminal papers by Muller (2005) and Muller and Bibi (2010), PMTs have been found inefficient when typically based on ordinary least-squares (OLS) regressions. The authors have already shown that substantial progress could be achieved by, first, using quantile regressions of living standards that help *focusing* on the poor instead of OLS, that is: centered on the mean living standard; and second, associating this with optimal transfer formulae based on fitted values of living standards. Nonetheless, it is fair to say that the coverage of the poor by these improved transfer schemes is still limited, to say nothing about the huge monetary leakage of program benefits to non-targeted groups[1], which has been found in many contexts by various authors[2].

Availing of more statistically and theoretically efficient tools of policy design is likely to advance the way policies can enhance social protections. Optimal anti-poverty PMT may be well suited to this objective. Since weak targeting efficiency to the poor, substantial monetary leakages and exclusion of poor households are major concerns for the administrators of these transfer schemes, we hope that better focussed methods will attenuate these defects. This implies paying serious attention to the statistical methods that may improve the optimal selection of program beneficiaries, and the optimal transfer rules.

There is a small while relevant literature on designing efficient transfer schemes for poverty alleviation, which examines simplified problems. In this respect, the nineties were a time of fertile investigations. First, Besley and Kanbur (1988) characterize the theoretical first-order conditions for optimal food subsidies in order to minimize poverty. Then, Kanbur, Keen and Tuomala (1994a) and Immonen, Kanbur, Keen and Tuomala (1998) perform numerical simulations for nonlinear income taxation and poverty alleviation problems and elicit some theoretical stylized facts. Chakraborty and Mukherjee (1998) study the theoretical program for optimal subsidies to the poor in terms of the density function of incomes, under a priori normative restrictions on the subsidy function. More specifically, for FGT poverty indicators and poverty indicators that are 'discontinuous at the poverty line', Bourguignon and Fields (1990, 1997) suggest an intuitive solution for the

[1] The 'leakage'is the share of the transfer budget that ends up being allocated to non-targeted populations.

[2] Weiss (2005), Muller and Bibi (2010), AusAid (2011), Atalas et al. (2014), Kidd et al. (2017).

optimal allocation of transfers under perfect information. The Bourguignon and Fields's intuition is also well grasped in Skoufias (2001, p. 1778). We shall provide a mathematical translation of this intuition in terms of the calculus of variations. Besley (1990) studies how the first-order conditions are modified when the transfer scheme involve private and social costs. In all these studies, the emphasis is on trying to grasp the general theoretical properties of an efficient transfer system. We shall follow this approach although with the aim of guiding practical estimation and implementation of these schemes.

However, in this early literature the crucial empirical issue of how to deal with individual observed and unobserved heterogeneity, including with observable socio-demographic characteristics, is generally overlooked. This is important because the way to deal with observed and unobserved differences between people is what can make a transfer scheme efficient in terms of targeting. Moreover, the incomes and the living standards of the individuals in the general population are generally not observed, which implies that the findings in the purely theoretical literature are not readily usable for empirical work. In particular, the transfers to carry out in practice must be defined in terms of observable household characteristics. This leads to discuss the most recent empirical progress in the literature.

1.2. Recent empirical progress

Some progress has also been done on the empirical side since the 1980s by introducing information on individual characteristics in the population. At first, Ravallion and Chao (1989) minimize numerically a poverty measure for a sample of surveyed households, under a given transfer budget by using exclusively information on the individual regional location. They deal with negative transfers by dropping them when they occur, and end up with less budget spent than planned. Other authors investigated regional poverty targeting.[3] This geographical approach based on empirical simulations can be extended to additional correlates of household living standards, as in Glewwe (1992), which can yield substantial targeting improvement. Besides, the choice of the covariates may be a substantial driver of the efficiency of transfer schemes, as investigated in many papers (e.g., in Aguila, Kapteyn and Tassot, 2012, for Mexico, and Bah et al., 2014, for Indonesia). Kleven and Kopczuk (2011) show how the practical complexity of the selection rules of actual social programs can be scrutinized for improving screening applicants. However, we do not examine these issues in this paper that concentrates on the role of estimation methods.

What we brought to this literature, and pursue in this paper, is the following. Given the available information on the correlates, how can the choice of estimation methods improve the targeting efficiency of the scheme. Skoufias, Davis and de la Vega (2001) use a LAD estimator (based on the median) insteade of OLS for a PMT formula. However, in this case this choice is guided by the need of a robust estimator, not at all the focus on the poverty line. As a matter of fact, since in their application the threshold target corresponds to the 75^{th} quantile, using LAD instead of OLS acutally degrades the focus of the estimation, in the sense of the focus notion that we introduced. On top of that, as pointed out by Ravallion (2009), improved targeting does not necessary translate into improved impact on poverty or into more cost-effective intervention. This justifies examining together the consequences of the scheme not only on poverty reduction, but also on targeting and on misspent budget.

[3] Skoufias, Davis and de la Vega (2001), Park, Wang and Wu (2002), Bigman and Srinivasan (2002), Bigman and Fofack (2002), Schady (2002).

Muller (2005) and Muller and Bibi (2011) have pursued these research lines by showing how Bourguignon and Fields' intuition can be used to practical statistical estimation that avoids some numerical difficulties of the applied literature. Namely, they estimate fitted values of a living standard variable, obtained by using quantile regressions that 'focuses on the poor'. That is: a censored quantile regression for a quantile index corresponding to the poverty rate is employed to generate the living standard fitted values. Then, these fitted values are substituted for the observed living standards into the analog poverty minimization program for a survey sample. Using data from Tunisia, Muller and Bibi (2010) show that such estimated transfer schemes can highly improve poverty alleviation performances. In particular, the post-transfer poverty and the under-coverage of the poor can be substantially reduced with this approach. This method was also implemented in Mauritius and Seychelles (Muller, 2010), notably for the project Social Register of Mauritius, which performs transfers thus targeted to the poor[4]. Recently, using data from African countries, Brown, Ravallion and van de Walle (2018) confirm that focussed estimation methods based on quantile regression for PMTs do better than OLS, while their assessed poverty reduction result is still relatively modest, when uniform transfers are used for all beneficiaries. What we investigate in this paper is whether using RIF regressions instead of quantile regressions can generate further improvement in th scheme performance, notably because it may handle better the censorship at the poverty line which is part of the definition of any poverty measure.

[4]We designed the methodology of this project, which was awarded the 2014 Award of the International Social Security Association.

1.3. Our strategy

The goal of this paper is to investigate whether anti-poverty transfer schemes can be improved by using conditional and unconditional quantile regressions to generate fitted values. We specify the estimator of the eligibility rule and the delivery/transfer rule in connection with the analysis of the poverty minimization problem. Then, we express the optimal solution by using a one-dimensional linear statistical score. In these conditions, three distinct stages emerge from the optimization program that can be monitored by using the statistical score: identifying the poor, ranking transfer priorities, and, estimating efficient transfer amounts. We implement statistically these tasks by using conditional and unconditional quantile regressions, all focusing on the poverty line location. In our simulations, the transfer budget is fixed by hypothesis, which implies that the results can also be interpreted in terms of cost-effectiveness.

Since the core of our contribution will be on using unconditional and conditional quantile regressions in the estimation of transfer schemes, it seems worthwhile to dwell on them briefly. Several methods can be found in the econometric literature for analyzing living standard distributions. Among them, quantile regressions have been made popular in the 1980s by the availability of new algorithms, as pointed out in the seminal article of Koenker and Basset (1982). Many developments are now available for quantile regressions (Koenker, 2005). Recently, unconditional quantile regressions have been proposed by Firpo, Fortin and Lemieux (2009), in the form of Recentered Influence Function (RIF) regressions. RIF regressios have been used for investigating poverty issues (e.g., in Essama-Nssah and Lambert, 2013, for studying pro-poorness of growth in BanglaDesh). We follow this line, and investigate the use of conditional and unconditional focused quantile regressions for targeting.

Using quantile regressions can be seen as a way of dealing with heterogeneity by ranking observations. Gutenbrunner and Jureckova (1992) found that using quantile regression is a computationally convenient approach to rank the location of the linear model across observations. Quantile regressions is a practical tool to investigate distributional effects, and individual heterogeneity, including under endogeneity (Chernozhukov and Hansen, 2003, Muller, 2017, Kim and Muller, 2018).

There are a few related topics that are not dealt with in this paper. For example, conditional cash transfers have be investigated in the literature, with an emphasis on encouraging good behavior by beneficiaries, such as in Galiani and McEwans (2013). Aside from this incentives issues are a hot topic of for studies of social programs (e.g., Saez, 2002, Low and Pistaferri, 2015 and Ravallion and Chen, 2015). In this respect, in the context of cash transfers, using numerical simulations, Kanbur, Keen and Tuomala (1994b) examine jointly labor supply and targeting of poverty alleviation programs in LDCs. More recently, Lorenz and Sachs (2012) extend the analysis to labor participation taxes in Germany. However, in this paper we only focus on the technical difficulty of targeting against poverty, not on incentives issues.

Finally, although there is an empirical illustration included, we reiterate that this is a methodological paper with methodological goals. There is no intention of running a fully fledged application to the Egyptian social system. The choice of Egypt for the illustration is just for convenience because of data availability in a country in which social transfers based on PMTs are important.

We present the theoretical model in Section 2. In Section 3, we analyse the theoretical poverty minimization problem. In Section 4, we discuss the estimation method. Empirical simulation results based on data from Egypt in 2013 are reported in Section 5. Finally, Section 6 concludes.

2. The Model

2.1. The poverty alleviation problem

Let $P(F_{y,X}; z)$ be the poverty measure, which is defined in terms of the joint distribution $F_{y,X}$ of the individual incomes y and of the observed individual characteristics X, and of a given poverty line z. For each individual i of characteristics X_i, we consider the transfer function $t(X_i)$ that defines the value of her received monetary transfer. The transfer function embodies the transfer rules that describe the monetary amount given to an individual i of characteristics X_i. It also incorporates the eligibility rules in terms of this characteristics since eligibility is equivalent to $t(X_i) > 0$. Thus, $y + t(X)$ is the variable of post-transfer incomes whose cdf, $F_{y+t(X)}$, can be calculated from $F_{y,X}$.

In these conditions, it makes sense to assume that the poverty measure depends only on the poverty line and on the cdf of $y + t(X)$, $F_{y+t(X)}$. To simplify the exposition, we now assume that the considered living standard distributions are continuous with a well-defined density function f. In that case, Riemann integrals can be employed. We adopt a notation with a marginal cdf F_X for characteristics in X, and a marginal cdf F_y for income y. Let B be the total budget available for transfers.

The corresponding poverty alleviation problem is the following.

$$\min_{t(.)} P(F_{y,X}; z)$$

$$\begin{aligned} \text{subject to} \ : \quad & \int t(X) dF_X(X) \leq B \\ \text{and } t(X) \quad & \geq \quad 0. \end{aligned}$$

In practice, transfers are often made to households rather than to individuals. Moreover, household living standard variables are generally used instead of individual incomes so as to account somewhat for the heterogeneity in individual and environment characteristics, and for household compositions. As a consequence, the results of this paper can easily be adapted to the case of households and living standards, notably for our empirical illustration. However, in order to simplify the discussion, we only discuss individuals and incomes in the theoretical analysis.

Almost all poverty measures used in applied work can be written as

$$P(y; z) \equiv \int_0^\infty k(y/z) I_{[y<z]} dF_y(y) = E\left\{k(y/z) I\left[y < z\right]\right\}, \tag{1}$$

where $k(.)$ is a kernel function that is non-increasing in its argument and I is the indicator function that is equal to 1 when the condition in brackets is satisfied, and zero otherwise. We focus on this case. Then, when distributions are continuous, and when conditional and marginal densities $f(y|X)$ and $f_X(X)$ can be defined, the ex-post policy objective to minimize in $t(.)$ can be written as: $E\left\{k((y + t(X))/z) I\left[y + t(X) < z\right]\right\}$, and is

subject to $\int ... \int \int t(X) f(y|X) I_{[y+t(X)<z]} dy f_X(X) dX = B$

and $t(X) \geq 0$ for all X.

From these formulae, two remarks are the basis of our estimation strategy. First, as noticed in Muller and Bibi (2011), since $f(y|X)$ is the only distributional element that is not fully observed, it must be estimated. Second, the dummy identifying the post-transfer poor, $I_{[y+t(X)\ <\ z]}$, introduces a censorship that should be taken into account in designing appropriate estimation methods.

2.2. The empirical analog

However, only a sample of individuals with information on y and X can be observed instead of the whole population. An analog estimator of $t(.)$ could therefore be based on the following problem.

$$\begin{aligned} &\min_{t(.)} \sum_{i=1}^{n} k\left(\left[y_i + t(X_i)\right]/z\right) I_{[y_i+t(X_i)<z]} \\ \text{subject to:} \quad &\sum_{i=1}^{n} t(X_i) \leq T \text{ and } t(X_i) \geq 0 \text{ for all } i, \end{aligned} \tag{2}$$

where n is the sample size, i is the individual index.

In this setting, there are two fundamental issues for the estimation of $t(.)$. First, the y_i are unobserved for out-of-sample individuals, and only some $X_i's$ can be observed for most individuals. Second, the number of positivity constraints is increasing as fast as the sample size. The following theoretical analysis is the next section will provide guidance about how to select estimation methods to deal with their unobservability and positivity constraint issues.

3. Theoretical Analysis

3.1. Solving by ranking Euler equation gradients

Differentiating the Euler equations of the optimization problem is the key to dealing with the positivity constraints. Indeed, looking at the gradient of the kernel function of the objective will first inform us about what the individual to serve first is, when one additional transfer unit becomes available marginally. Then, we shall see that because of the specific shape of the Euler equations in that case, this individual is also the individual that will receive the most. This is this property that will allow us to avoid the issue of the non-negativity constraints for transfers, since individual can be ranked accordingly to the transfer size down to zero.

However, it will also be necessary to assess, during the transfer process, when the sequentially calculated sum of transfers hits the budget constraint, and to stop the transfer process at this stage.

Let be a poverty measure under the integral form, $\int_0^z k(y)f(y)dy$. We leave aside poverty function with non-differentiable kernels $k(.)$.

We now change into notations familiar to readers of the calculus of variation literature. Here, the 'time variable' t will stand for the income y, and we consider a 'state' variable $x(t)$, consistently with usual calculus notations. We assume that the 'time derivative' of the state variable, denoted $\dot{x}(t)$ as usual with these notations, is the product of the transfer function by the density function, that is: $\dot{x}(t)$ in the new notations stands for $t(y)f(y)$ in the initial notations. As a result, we have by integration between the time bounds t_0 and t_1: $x(t_0) = 0$ and $x(t_1) = B$, with $t_0 = 0$ and $t_1 = z$. Then, the poverty minimization problem, omitting the non-negativity constraints, can be translated in the new notations as follows, with $f^0(x(t), \dot{x}(t), t) = f^0(t + \frac{\dot{x}(t)}{f(t)}, t) \equiv k(t + \frac{\dot{x}(t)}{f(t)})f(t)$, which stands for $k(y + t(y))f(y)$ in the initial notations. Therefore, the problem of calculus of variations to solve becomes:

$$\max_{\mathbf{x}(.)} \int_{t_0}^{t_1} f^0(x(t), \dot{x}(t), t)dt$$

subject to $x(t_0) = 0$ and $x(t_1) = B$.

In that case, since function f^0 does not depend directly on $x(t)$, the necessary Euler conditions of this calculus boil down in that case to $\frac{d}{dt}\frac{\partial f^0}{\partial \dot{x}} = 0$, that is: $\frac{d}{dt}k'(t + \frac{\dot{x}(t)}{f(t)}) = 0$, which is equivalent to imposing that $k'(t + \frac{\dot{x}(t)}{f(t)})$ is constant over t. Returning to our initial notations in a discrete distribution setting, and considering two distinct income observations y_1 and y_2, this corresponds to the equality:

$$k'(y_1 + t(y_1)) = k'(y_2 + t(y_2)).$$

In our approach, both requirements of identifying the poor and ranking them by transfer priority will be solved with the same estimation method since the last possibly served poor is the last ranked. In that sense, the method to escape the predicaments of both the non-negativity constraints and the non-differentiability of the objective kernel at the poverty line is to rank the estimated $\hat{k}'(y)$. Moreover, in that case, an estimator of the transfer *amount* can also be defined sequentially.

The sequential rule is as follows, consistently with the intuitive approach of Bourguignon and Fields (1990). Even though these authors did not derive the optimality conditons in an explicit mathematical way, their intuitions brought them essentially to the same result for perfect targeting, in the case of the poverty severity index for example. Namely, an optimal budget allocation, in that case, amounts to start giving to the poorest of the poor, and sweeping through the income distribution upward while bringing all encountered individuals at the same income level, until all budget is spent. What we do here is to provide a full mathematical translation of Bourguignon and Fields. Beyond this, a substantial difference here is that the income levels considered are fitted values, instead of perfectly observed incomes.

The Rule: (1) One ranks the $k'(y_i)$, for the observed $y_i, i = 1, \ldots, N$, by using a consistent estimator $\hat{k}'(y_i)$ of $k'(y_i)$.

The gradient of k informs us on who the individual to serve first is. This is because a numerical method of Newton based on this gradient, from the initially observed situation, could be used to obtain convergence towards the post-transfer theoretical equilibrium. Because of the shape of the Euler conditions, with this algorithm the individual to serve first is also the individual that will receive the most. Although this algorithmic property may sound like a shortcoming, this is in fact not the case because, for axiomatically correct poverty measures, it corresponds to giving the most to the poorest. In these conditions, the fact that the poorest is served first is just a consequence of the sequentiality of the algorithm. Besides, once the specific transfer amounts to give to each household are calculated, the actual timing of the serving order can be fully changed if wished.

(2) One identifies the individual i, with income y_i corresponding to the highest $\hat{k}'(y_i)$, and the following ranked individual j corresponding to the next highest $\hat{k}'(y_j)$.

(3) One implements non-negative transfers $\hat{t}(y^i)$ and $\hat{t}(y^j)$, respectively to individual i and j, and defined so that $y^i + \hat{t}(y^i) = y^j + \hat{t}(y^j)$, in order to bring them at the same living standard levels, and, as a consequence, at the same transfer priority level. The transfer rule begins with an amount $y_j - y_i$, given the individual i (the first to be served). Then, one continues to raise the monetary transfers up, while still keeping $y^i + t(y^i) = y^j + t(y^j)$, so as to maintain equal levels of $\hat{k}'(y_i + t(y^i)) = \hat{k}'(y_j + t(y^j))$, until one reaches the next ranked individual, say individual k with $\hat{k}'(y_k)$.

(4) The procedure proceeds this way, by sweeping cumulatively all the individuals until reaching the individuals of income level equal to the poverty line, or until the transfer budget is spent.

Note that the budget may be spent while there is an important share of individuals who falls under the poverty line and still do not benefit from any transfer. However, this corresponds to the optimal strategy when it occurs. For example, for the poverty severity index, what really matters is to serve the extremely poor, whether some moderately poor are not served may be in fact optimal.

3.2. Conditioning on an income score based on covariates

According to the remarks in subsection 2.1, about the importance of $f(y \mid x)$ in the formulae of the poverty alleviation problem, we now introduce the observed income correlates, X, through conditioning on a linear income score $y(X)$ based on X. This index has to be estimated, as $\hat{y}(X)$, and can then be used to replace variable y in the above reflexions, including for the discussion of the Euler equations, and the ranking of individuals to serve. These variables correspond to the information on which the transfer scheme can be based.

Practically, similarly to Muller and Bibi (2005), we want to substitute a fitted-value $\hat{y}(X)$ for y, and make transfers so that $k'(z, \hat{y}(X) + t(X))$ is constant for all the ex ante poor identified by $\hat{y}(X)$, up to a certain income level determined by the available budget. As a consequence, we search for the most accurate estimators of $\hat{y}(X)$ for the poor. In practice, it may be enough to generate fitted-values that are accurate only around the poverty line. It seems natural to use conditional and unconditional quantile regressions for estimating the fitted-values, not only because the problem is about income distribution but also because they can be used to better focus on the poverty line.

If we now assume that the identification of the poor has been perfectly solved (in fact the identification of the individual to be served with the available budget), the computation of the transfer amount is based on the condition:

$$k'(z, \hat{y}(X) + t(X)) = c, \text{ with } c \text{ a constant} \tag{3}$$

The non-negativity constraints can be discarded, thanks to the ranking of households according to their needs, because only non-negative transfers will have to be performed, in a decreasing order in terms of transfer size. In the next section, we discuss the estimation methods, partly in relation with the theoretical analysis that we just discussed.

4. Estimation Methods

4.1. Focussed fitted values of living standards and quantile regressions

The quantile regressions of y on X can be used to describe the conditional cdf $F_{y|X}$. As mentioned before, it may therefore be seen as a natural tool to deal with poverty minimization program that can be written in terms of this distribution. We have shown in Muller (2005) that focusing on quantiles closer to the population social objective should provide better targeting than using OLS because the OLS estimates characterize living standard levels from those of the poor.

Focusing the targeting around the poverty line suggests to consider two quantile estimation methods, respectively conditionnally and unconditionnally on the covariates. This is in contrast with the situation when centering the targeting in the mean of the distribution with OLS. Indeed, in the standard OLS linear regression model based on $E(y|\ X) = X\beta$, we have an equivalent interpretation of the coefficient vector β, when conditioning or not. On the one hand, $\beta = \frac{\partial E(y|\ X)}{\partial \mu_X}$, where μ_X is the mean vector of the independent variables. On the other hand, we also have $\beta = \frac{\partial E(y)}{\partial \mu_X}$. Thus, here the vector of coefficients informs on the effects of the mean of X on both the expectation and the conditional expectation of the living standard variable.

However, given a linear conditional quantile regression model $Q_\theta(y|\ X) = X\beta$, for a quantile index $0 < \theta < 1$, we have $\beta = \frac{\partial Q_\theta(y|\ X)}{\partial \mu_X}$, which does NOT implies $\beta = \frac{\partial Q_\theta(y)}{\partial \mu_X}$. Then, one could wonder whether focusing on unconditional quantiles would not generate still better targeting results than focusing conditional quantiles. In Muller and Bibi (2010), we applied censored quantile regressions focussing on the poverty line to raise the targeting performance of PMTs in Tunisia. Let us now turn to the RIF regressions that will allow the focus to be made instead in terms of the unconditional marginal distribution of the living standards.

4.2. RIF regressions

The unconditional quantile (RIF) regressions were developed by Firpo, Fortin and Lemieux (2009). In the case of the unconditional θ^{th}-quantile of y, with marginal cdf F, denoted q_θ, the influence function is $IF(y,F) = \frac{\theta - I_{[y_t<0]}}{f_\theta(y_t)}$, where f is the marginal pdf de y, and $f(q_\theta) = f_\theta(y)$. The corresponding recentered influence function is $RIF(y,F) = q_\theta + \frac{\theta - I_{[y_t<0]}}{f_\theta(y_t)}$.

By conditioning on X, one can be rewritte the conditional quantile y, which is $E\left(RIF(y;F)\right)$ since $E\left(IF(y;F)\right) = 0$ by construction as $\int E\left(RIF(y;F) \mid X = x\right)\, dF_X(x)$. In that way, the natural population counterpart, $E\left(RIF(y;F) \mid X = x\right)$, of the OLS regression of the $RIF(y;F)$ on X is exhibited. It is interesting for targeting because this make it possible to run this regression using income and correlates information using some household survey data.

Let us examine how the RIF regressions are linked to the conditional density function, $f(y|x)$. If $y_t = x_t\beta + u_t$, then $f(y|x)$ is the conditional and unconditional distribution of u_t if x_t and u_t are independent. This is what the quantile regressions estimate, when considering all quantiles. Instead, the RIF regressions are the OLS regressions of the recentered influence function of the quantile, which is $q_\theta + \frac{\theta - I_{[y<0]}}{f_\theta(y)}$, where $f_\theta(y)$ is the marginal density of y at its θ^{th} quantile, which is q_θ.

We therefore model, through this OLS regression, the conditional expectation of $q_\theta + \frac{\theta - I_{[y<0]}}{f_\theta(y)}$, which is the recentered influence function of the quantile and can be seen as a first-order approximation of y. However, using the RIF regressions may look less relevant theoretically than the quantile regressions that directly describe the $f(y|x)$. Still, the focus on z may be improved in part if the condition $I_{[y_t<z]}$ is better captured that way. Moreover, if there is some misspecification of the list of covariates (e.g., with large outliers in X), there may be some uncontrolled biases with quantile regressions, and these biases may be larger than the ones occuring with RIF regressions. Indeed, the quantile regressions are robust against outliers in the error terms, but not against outliers in the covariates.

The estimation procedure of a model of unconditional quantiles is as follows. First, a quantile regression model is estimated to produce a fitted-value $\hat{q}_\theta$ for the θ^{th} unconditional quantile of y, q_θ, for example without including regressors.

Second, the marginal density of y at the quantile q_θ is estimated nonparametrically, using a kernel density estimate denoted $\hat{f}(q_\theta)$.

Third, for each equation, the dependent variable $RI\hat{F}(y;F) \equiv \hat{q}_\theta + \frac{\theta - I_{[y \leq q_\theta]}}{\hat{f}(q_\theta)}$ is constructed, where $\hat{q}_\theta$ is the estimated θ^{th} empirical quantile in the observed household sample.

Fourth, an OLS regression of $RI\hat{F}(y_i;F)$ on X_i, $i = 1, ..., N$, is run.

Finally, the estimated regression results are integrated with respect to the marginal distribution of the covariates to obtain the predictions of interest**lesquelles?**. In the next section, we examine the performance of using this method for improving targeting through exploratory simulations based on Egyptian data.

5. Empirical Illustration

5.1. The context

The choice of Egypt as an empirical case is justified by several considerations. First, this is a country that has a long tradition of pro-poor cash transfers.[5] Second, convenient survey data is available and relatively standard as they correspond to the HIECS surveys that have been implemented in many MENA countries with little methodological variation. Third, in the current situation of social unrest, as before, the government is anxious to limit the exclusion of the poor from social programs (Gutner, 2002). Therefore, understanding how to estimate better cash transfer formulae may contribute to answer these concerns.

However, we emphasize again that the simulation results in this paper pertain to an investigation of the statistical properties of different methods. There is no ambition of developing a full-fledged analysis of social transfers and of the existing social assistance programs in Egypt. For this, a thought analysis of the policy context would be necessary, while this is not the objective of this paper. Therefore, the results should not be viewed as statements about how feasible or how improved the actual system would be by moving straightforwardly to these new estimation methods; but rather as bringing additional worthwhile elements of reflexions to complex policy design. This notably justifies that we are relatively brief in the description of the existent social assistance programs in Egypt.

It may also be that the results would differ in different countries, or with using different data, or different poverty line definitions[6], or different covariates for

[5] Aassal and Rauchky (1999), Ahn and Bouis (2002), Galal (2003), Sieverding and Selwan (2012).

[6] Other poverty lines, for example for 2013, are available on the internet site of the Central Agency for Public Mobilization and Statistics (www.CABMAS.org).

Egypt. For example, a more extended set of poverty correlates could be used, or the ELMPS survey, instead of HIECS, could provide a larger sample is wished. Again, the aim of the paper is not to provide definitive answers about the complete design of cash transfer programs, but only to show the feasibility of the new estimation methods and to exhibit a few lessons from a specific practical case.

Egypt is a dynamic emerging economy with severe social problems. After a period of nationalization, socialist economic policies and redistribution early under President Nasser, the economy returned to opening, reprivatization and liberal policies after the 1967 war with Israel. Adams (2002) find that non-farm income was the most important inequality-decreasing source of income, while agricultural income was the best inequality increasing source. The massive liberalization reforms from 2006 to 2008 spurred high levels of growth (about 7 per cent yearly). Since then, Abid, O'Donoghue and Sologon (2016) find that changes in the expenditure structure and demographics were inequality-decreasing in Egypt.

However, poverty is still pervasive and the political situation, in the aftermath of the 2011 revolution, remains unstable. These circumstances hurt social outcomes in general, which are damaged by much lower growth than before, around two per cent in the last three years. We now turn to the data.

5.2. The data

The data are taken from the 2013 Egypt Household Income, Expenditure and Consumption Survey (HIECS). They provide us with information on household living standards, which are measured here as household per capita expenditure. It is important to use recent data, as it has been found that the 2011 Egyptian uprising has had substantial impact on the population spending behaviour, notably for education. It is likely that some households surveyed in the HIECS receive social assistance. However, this kind of information is badly recorded in this survey and we neglect it in these simple methodological simulations.

There are many published statistics about poverty in Egypt that all concur to a general picture of relatively high unemployment and poverty.[7] As a matter of fact, most of the young are unemployed, destitute and they face high food prices in Cairo.

The poverty lines used for the simulations roughly corresponds to most international poverty estimates for Egypt, at about the *first quartile of per capita consumption expenditure among households, and second at about the 32nd quantile*. This particular choice allows us to run plausible simulations of the studied methods. Nonetheless, there is a large variety of poverty lines that have been used in Egypt, which we now discuss.

Accordingly, the estimates of the poverty rate in Egypt vary with the information source, while they remain reasonably close. They are of 22 percent in 2008, from the CIA fact yearbook 2015; of 26,3 percent from the French Central Bank in 2010; of 25.2 percent in 2010 from the World Bank in 2016. Furthermore, other official poverty lines sometimes yield figures of poverty rates as high as 40 percent.[8] Finally, using a rough definition of poverty, more than 15 million Egyptians have been said to live on less than US $ 1 a day (Henry, 2012). The Minister

[7] This was also the case before the revolution as can be seen in El-Laithy, Lokshin and Banerjee (2009).

[8] The government official poverty lines for expenditure per capita also vary across regions. These latter lines, which are estimated from the 2005 HIECS, reflect a severe nutritional benchmark of 2470 calories per day per person. The Ministry of Economic Development and the World Bank agreed on a typology of the poor according to which those who spent less than EGP 1423 per year are considered poor. Among them, individuals with a per capita expenditure of EGP 995 per year in 2005 should be considered extreme poor. Finally, those who spent less than EGP 1853 per year are merely seen as near poor. With these definitions, 44.4 percent of the Egyptians are in some kind of (from extreme to near) poverty (Nawar, 2007).

of Economic Development also claimed that the poverty rate had risen from 19 percent in 2005 to 21 percent in 2009 (Saleh, 2009), while Farid (2013) discusses government figures stating that the 2010/2011 poverty rate reached 25 percent of the population.

Given this variety of estimates, the poverty lines that are used in this paper are a reasonable compromise. Namely, the chosen poverty line for this methodological investigation are the *first quartile of the household living standards*, which corresponds to a poverty rate of 31.8 percent; and another poverty line that corresponds to the first quartile of individual income per capita. Other tried reasonable poverty lines yielded qualitatively similar methodological conclusions. The budget to spend is arbitrarily defined as the quarter of the first decile of the per capital consumption from the survey data.

The list of covariates, although somewhat arbitrary as usual, reflect, on the one hand the kind of household characteristics typically used in PMTs, and, on the other hand, the variables easily obtainable from the HIECS data. Of course, other lists of covariates could be tried, while this is not our focus in this paper.

Table 1 reports a few descriptive statistics for 7528 households and the main variables used in our simulations. Half of all households live in urban areas. The household size is slightly over four persons on average, while it varies from one to twenty-eight persons in this sample. Some households have many children, while the presence of elderly members is not very frequent. In most cases, only one or two members bring most earnings home. No couple lives in one fifth of the surveyed households. Less than one fifth (18 percent) of households are led by women, who are mostly widows.

Three quarters of households state to be living in an 'apartment', and only very few in a 'hovel'. However, the housing size, measured by the number of rooms, is small on average, next to three rooms, and often smaller. Almost all dwellings have access to pipe water (89 percent), while only slightly more than half of the dwellings have a modern toilet.

Household heads are often little educated. A large proportion of households (45 percent) have a head with no education, while 12 percent of the heads have reached primary education only, and 26 percent secondary education. Even though, two-third of the heads can read and write. Finally, almost all households own a television set (95 percent), a fridge (93 percent), a washing machine (94 percent), or even a satellite dish (88 percent). Fewer are the households who can avail of a vehicle (6 percent a car and 14 percent some bicycle).

5.3. The results

Table 2 shows the estimation results for the predictive living standard equation, for OLS estimation, quantile regressions and RIF regressions, respectively for two different focus: the 25^{th} and 32^{nd} quantiles. Qualitatively, i.e. in terms of significant signs of the estimated coefficients, the different estimation methods all deliver the same kind of effects of the covariates of living standards. First, urban residence is associated with higher living standards. Second, household composition is strongly correlated with living standards: negatively for household size and the number of children under 14 years old, albeit sometimes positively for the number of elderly in the cases of OLS and quantile regression at the 32^{nd} quantile. Obviously, a higher number of income earners in the household clearly implies a higher living standard. Whether there is no couple in the household, which may be signalling a young and active single person before her or his marriage, with no family burden, is also associated with higher living standards. This is not to be confused with the case of widows (widowers being rare), which can generally be proxied by the dummy variable for female household heads. These households have in general lower standards of living. This feature is a well-known characteristic associated with poverty in most countries.

Dwelling characteristics also appear as significant correlates of living standards when trying to identify and measure poverty. Living in an apartment is clearly related to much higher living standards than on average. Surprisingly, living in a hovel is not significantly correlated with the living standard variable, as opposed to the strong positive relationship of the number of rooms with living standards. It may be that this specific house characteristics has been badly collected with respondents being reluctant to call their home in this way. Moreover, living in a place with no access to pipe water is not significantly linked to living standard levels.

As expected, education is another efficient marker of living standards. There is a systematically positive correlation of education level of the head with household living standards, as obvious from the reported coefficients, with higher education as the excluded benchmark category. Finally, households in which the head can read have generally higher living standards than those with illiterate heads.

Some information on household equipment may be used to target the poor better. Having a modern toilet inside the house is a definite sign of higher living standards, as well as ownership of some durables is (cars and other motor vehicles, cycles and motorcycles, satellite dishes and refrigerators). Interestingly, owning a television set or a washing machine is not connected to the level of living standard. This may be because these pieces of equipment are spread in the whole population in Egypt, including for the poorer classes.

Let us mention a few exceptions to this general picture that is mostly valid over all estimation methods. These exceptions correspond to coefficients that are insignificant at the 5 percent level with some estimation methods. They particularly interest us because they often concern the RIF regression focusing on the poor, which we want to assess them as a potential way to improve the transfer scheme. First, for the two focus levels, which corresponds to the 25^{th} or 32^{nd} quantiles of living standards, the urban residence is no longer significantly associated with higher living standards in the RIF regressions (though, it is weakly so at the 10 percent level in the second case). Then, it seems that something qualitatively distinct about urban areas may occur for the poor in these data. Insignificant coefficients in the RIF regression results also occur for: the number of elderly members (also for quantile regressions at the 25^{th} quantile at the 5 percent level, while not at the 10 percent level); absence of a couple; ownership of refrigerators (for RIF regression at the 32^{nd} quantile, and quantile regression at the 25^{th} quantile); and finally the dummy for the female heads. The insignificance of the coefficients of the urban residence dummy and the female head dummy is particularly notable if one recalls that these variables are often used as clear correlates of poverty and living standard levels, in Egypt as in most developing countries. This result is not necessarily counter-intuitive because what is measured here is the correlation of these variables with living standards at a certain quantile of living standards, and not over the whole distribution or for the mean living standard. However, it is worrying if the aim of the estimation is to provide accurate fitted values of the living standards. It suggests than RIF regressions may be approriate in terms of focus, while perhaps not in terms of prediction precision.

Beyond the results about significance, the magnitude of the estimated coefficients vary substantially across the estimation methods. Assessing the performances of the estimation methods in terms of poverty reduction and targeting for the diverse associated transfer schemes will tell us more about the consequence of these numerical differences in their estimates. We now turn to the analyses of these performances, using simulations based on the same sample of observations.

Table 3 reports our simulation results for poverty and targeting indicators: head-count index, poverty gap, poverty severity index, exclusion rate for the poor (the proportion of the poor that are not included in the program), and finally monetary leakage indicator of program benefits (that is: the proportion of the transfer budget that does not reach its target). Note that the leakage indicator is *not* the inclusion rate. The estimates of these social indicators are based on equations of the selected estimation methods and on the elicited formula of the theoretically optimal transfers.

Before to comment these results, let us discuss a few simple points of methodology. First, we found that availing of a sufficient transfer budget to spend is necessary to be able to generate some performance gaps between estimation methods. Otherwise, the transfers are almost all equal to zero and little differential impacts can be seen, notwithstanding the perturbations coming from small numbers. Second, it is also necessary to incorporate enough covariates in the predictive equations to be able to obtain useful conclusions. With too few regressors, all the methods just generate some estimates of their respective central tendencies, albeit with little heterogeneity in the fitted-values. In that case, it would make little sense to compare estimation methods.

The estimation results show that what is minimized matters. In Section 3, we have theoretically analyzed transfer schemes that aim at reducing inequality-sensitive poverty, such as for example measured by the poverty severity index P_2. As a consequence, in theory the calculated 'optimal transfers' do not necessarily imply an excellent performance in terms of other social indicators such as: poverty rate, exclusion or leakage of the benefits. This is something that we examine through these simulations.

The RIF regressions centered on the quantile corresponding to the proportion of poor households (instead of the poverty rate based on individuals), that is: the first quartile, is the method that delivers the highest poverty severity reduction, down to 0.01046 from 0.0235. This may be because the prediction equations are based on household samples and not on individual samples, and they may therefore better fit poverty thresholds defined at household level. They may also better fit the way some social programs operate: at the household level rather than at the individual level.

However, the performance of the RIF regressions centered on the (individual) poverty rate is very close (at 0.01052 for the 32^{nd} quantile), as is the performance of the quantile regression centered on the proportion of poor households (at 0.010516). The other methods yield less good performance, although they are still close, with the worst result obtained with the transfer scheme based on uniform transfers derived from OLS regressions (0.0116). In that case, the use of the optimal transfer formulae that vary with individuals seems to matter more than the estimation method used. This may be because the poverty line is actually not that far for the mean living standard in this sample.

The results for the poverty gap P_1 have a similar flavour, although this time the RIF regression centered on the poverty rate yields the slightly best result. In the case of the poverty rate, the uniform transfers based on OLS are the ones with the higher reduction in the head-count index P_0. The next best method for P_0 are the optimal OLS, then the two quantile regressions, with the RIF regressions performing less well. However, again the estimates are quite close.

In contrast, looking at other targeting indicators reveal where the actual gap in performance of the examined estimation methods are. Regarding the exclusion rate indicator, the RIF regressions is the best method again, with a lowest level of exclusion at 38.95 percent when they are centered on the proportion of poor households (first quartile). Here, the differences in exclusion rate estimates across estimation methods are substantial, for example with optimal OLS excluding 49.43 percent of the poor instead and yield the worst results among the examined method. the latter shows that the optimal heterogeneity of transfers amount that suffice to solve the exclusion here, and perhaps does not help much for this. Indeed, uniform OLS-based transfers lead to a lower exclusion rate (43.45 percent) that optimal OLS-based transfers. The other examined estimation method do not distinguish themselves as much of optimal OLS-based method, in terms of post-transfer exclusion (41.8 percent, with RIF regression based on the 32^{rd} quantile; 42.9 percent for quantile regression based on the 25^{th} quantile, 44.7 percent for quantile regression based on teh 32^{nd} quantile); in any case clearly inferior to the performance of the best estimation method. This suggests that the monetary leakage of the program benefits is always high for all estimation methods based on theoretically optimal transfers that vary with individuals. More than one third of the budget is wasted in that case. The best performance in this respect (34.99 percent), among the tried optimal transfer methods, is reached again by the RIF regressions centered on the proportion of poor households. On the contrary, the leakage rate is much worse for uniform transfers, at least when they are estimated with OLS (41.26 percent).

6. Conclusion

Most social assistance programs in the developing world have adopted a poverty focus and therefore often resorted to selectivity criteria that include categorical approaches and means-tests or proxy means tests for the identification and selection of beneficiaries. However, with severe public budget constraints this requires careful attention to find an optimal transfer, in a Rawlsian prioritarian perspective.

A natural response to the mediocre targeting performances of the current cash transfer programs in the developing world is to develop more efficient, less costly and better targeted social programs and safety nets (AusAid, 2011, Del Ninno and Mills, 2015, Brown et al., 2018). On these lines, following our seminal papers on focussed targeting (Muller, 2005, Muller and Bibi, 2010), we propose a specification method of social transfer schemes that is connected to the theoretical poverty minimization problems. We first provide a precise mathematical translation of the correct intuition in Bourguignon and Fields (1997) characterizing the solution to the problem under perfect information. Then, a bridge between theory and practice is made by using fitted-values of living standard variables that can be obtained by regressing living standard variables on a few household characteristics, as is typical of the proxy-means test method. The focus on the poor in these methods is obtained by estimating these fitted-values by using Recentered-Influence-Function (RIF) regressions and quantile regressions that are centered on assumed poverty line locations.

We gauge this methodological approach with simple empirical simulations for

2013 Egypt as a benchmark. Although one should be cautious not to draw conclusions on the actual social protection system in Egypt, and stick to methological conclusions at that exploratory stage, the results of the empirical simulations show that using RIF regressions to carry out optimal anti-poverty transfers may help to improve the targeting performances. However, the performance gap of different estimation methods remains small with these data. Interestingly, this is for avoiding the exclusion of the poor that using RIF regressions makes the most impact - which is substantial in that case.

These new methodological results call for further development. For example, applications to other questions, such as the estimation of poverty maps like in Elbers, Lanjouw and Lanjouw (2003) may be possible. Second, more analytical progress could be achieved by tackling the inclusion of multidimensional covariates directly without the intermediary device of fitted-values, and by using nonparametric estimators. However, the most interesting challenge seems to be able to understand why using RIF regressions for generating fitted-values in PMT allows us to diminish so much the exclusion rates with these data, typically a major concern in cash transfer schemes.

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Table 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Log living standard	7528	8.80	.562	7.01	11.7
Urban	7528	.443	.496	0	1
Household size	7528	4.34	1.93	1	28
Number of members under age 14	7528	1.34	1.35	0	12
Number of members aged 65 +	7528	.220	.490	0	3
Number of bread winners	7528	1.64	.868	0	10
Apartment	7528	.751	.432	0	1
Hovel	7528	.00464	.0680	0	1
Education head : none	7528	.453	.497	0	1
Education head : primary	7528	.122	.327	0	1
Education head : secondary	7528	.255	.436	0	1
Number of rooms	7528	3.62	1.20	1	20
No couple	7528	.218	.413	0	1
Pipe water	7528	.894	.307	0	1
Connected toilet	7528	.525	.499	0	1
Car, etc...	7528	.0571	.232	0	1
Cycles	7528	.142	.350	0	1
TV, etc	7528	.951	.214	0	1
Satellite dish, receiver, etc...	7528	.878	.327	0	1
Refrigerator, water cooler, etc...	7528	.933	.249	0	1
Washing machine	7528	.941	.234	0	1
Female head	7528	.178	.383	0	1
Head literacy	7528	.671	.469	0	1

Table 2: Estimates of Fitted-Value Equations

VARIABLES	(1) OLS	(2) RIF 25th quantile	(3) RIF 32nd quantile	(4) QR 25th quantile	(5) QR 32nd quantile
Urban	0.0817***	-0.0055	0.0244*	0.0550***	0.0632***
	(0.000)	(0.697)	(0.083)	(0.000)	(0.000)
Household size	-0.1210***	-0.0836***	-0.0889***	-0.1101***	-0.1107***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of members under age 14	-0.0837***	-0.1055***	-0.1052***	-0.0811***	-0.0861***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of members aged 65 +	0.0350***	-0.0090	-0.0065	0.0199*	0.0250**
	(0.000)	(0.433)	(0.575)	(0.065)	(0.015)
Number of bread winners	0.0716***	0.0702***	0.0709***	0.0764***	0.0750***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Apartment	0.0735***	0.1019***	0.0862***	0.0650***	0.0672***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hovel	0.1158*	0.1104	0.1357*	0.1096	0.0970
	(0.071)	(0.185)	(0.078)	(0.143)	(0.174)
Education head : none	-0.2242***	-0.1481***	-0.1399***	-0.2123***	-0.2025***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education head : primary	-0.2084***	-0.1229***	-0.1698***	-0.1873***	-0.1894***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education head : secondary	-0.1609***	-0.0876***	-0.0940***	-0.1409***	-0.1467***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of rooms	0.0884***	0.0545***	0.0624***	0.0713***	0.0734***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

No couple	0.2457***	-0.0246	0.0062	0.1347***	0.1537***
	(0.000)	(0.247)	(0.778)	(0.000)	(0.000)
Connected toilet	-0.0080	0.0011	-0.0018	0.0057	0.0010
	(0.603)	(0.959)	(0.933)	(0.752)	(0.952)
Car, etc...	0.5045***	0.0962***	0.1322***	0.4501***	0.4406***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cycles	0.0522***	0.0919***	0.0911***	0.0563***	0.0586***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TV, etc	0.0057	-0.0051	0.0280	0.0248	0.0100
	(0.826)	(0.888)	(0.427)	(0.414)	(0.729)
Satellite dish, receiver, etc...	0.0778***	0.0642***	0.0568**	0.0962***	0.0904***
	(0.000)	(0.006)	(0.013)	(0.000)	(0.000)
Refrigerator, water cooler, etc...	0.0730***	0.0714**	0.0422	0.0365	0.0494**
	(0.000)	(0.014)	(0.118)	(0.124)	(0.029)
Washing machine	0.0289	-0.0104	0.0188	0.0172	0.0240
	(0.166)	(0.709)	(0.492)	(0.481)	(0.302)
Female head	-0.1911***	-0.0028	-0.0145	-0.1309***	-0.1344***
	(0.000)	(0.900)	(0.527)	(0.000)	(0.000)
Head literacy	0.0736***	0.0542***	0.0805***	0.0594***	0.0819***
	(0.000)	(0.008)	(0.000)	(0.001)	(0.000)
Constant	8.7459***	8.4148***	8.4499***	8.5455***	8.5967***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	7,528	7,528	7,528	7,528	7,528
R-squared	0.565	0.299	0.329		

p-value in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Simulations of performances of transfer schemes

	Poverty Rate (P_0)	Poverty Gap (P_1)	Poverty Severity (P_2)	Exclusion rate	Monetary Leakage rate
Reference	.3177344	.0704923	.0235137	-	-
OLS uniform	.2556068	.0438787	.0116324	.4345234	.41258
OLS optimal	.2563285	.0419584	.0108588	.4943606	.362233
RIF 25th quantile	.2609147	.0415027	.0104603	.3895343	.349952
RIF 32nd quantile	.2590609	.0415016	.0105208	.4179949	.350672
QR 25th quantile	.2571256	.0415401	.0105163	.429417	.351866
QR 32nd quantile	.2588524	.041618	.010604	.4474443	.353747

7528 observations.