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Abstract: Social programmes for poverty alleviation involve eligibility rules and transfer rules that often proxy-means tests. We propose to specify the estimator in connection with the poverty alleviation problem. Three distinct stages emerge from the optimization analysis: the identification of the poor, the ranking of their priorities and the calculus of the optimal transfer amount. These stages are implemented simultaneous by using diverse distribution regression methods to generate fitted-values of living standards plugged into the poverty minimization programme to obtain the transfer amounts. We apply these methods to Egypt in 2013. Recentered Influence Function (RIF) regressions focusing on the poor correspond to the most efficient transfer scheme. Most of the efficiency gain is obtained by making transfer amounts varying across beneficiaries rather than by varying estimation methods. Using RIF regressions instead of quantile regressions delivers only marginal poverty alleviation, although it allows for substantial reduction of the exclusion of the poor.

Keywords: targeting, poverty, optimizing estimator
JEL classification: I32, C21, C54

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1. Introduction

As a consequence of the financial crisis and the global slowdown in economic activity, the living standards of the poor, and of other vulnerable households, have much deteriorated in many countries. As a response to these shocks, governments have often undertaken reforms, sometimes involving stabilization plans, which had severe poverty and social consequences. A natural response to this predicament is to develop more efficient, less costly and better targeted social programmes and safety nets.

More generally, the study is relevant to the context of cash transfer programmes, since most social assistance programmes 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. With severe public budget constraints, this makes a lot of sense, although it requires careful attention to find an optimal transfer, in a Rawlsian prioritarian perspective.

In order to deal with these concerns, we provide a new solution to this question by using a specification method of social transfer schemes that is connected to the analysis of the theoretical poverty minimization problem. Fitted-values of living standard variables appear as a central ingredient of the approach. We propose to estimate these fitted-values by using distribution regressions (Recentered Influence Regressions and quantile regressions).

1.1. Social programs, PMTs and inefficiencies

Social programs involve, on the one hand, eligibility rules, and, on the other hand, service delivery or transfer rules. Both of these rules generally depend on the characteristics of individual applicants. 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 are often based on fitted-values of living standards that are based on OLS regressions conducted 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, typical PMTs have been found inefficient when based on OLS estimation. It has already been shown that substantial progress can be achieved by, first, using quantile regressions of living standards that help focusing on the poor instead of OLS, and second, associating this with optimal transfer formulae based on fitted values of living standards (Muller, 2005; Muller and Bibi, 2010). 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 leakage of program benefits to non-targeted groups.

In this article, we study a potentially more efficient approach that consists of specifying the estimator of the eligibility rule and the delivery/transfer rule in connection with the optimization problem that defines the social objective. In that sense, we consider 'optimal targeting' rules for social programs. Then, we summarize the optimality by a one-dimensional statistical score. In these conditions, three distinct stages emerge from the optimization program: (1) the identification of the poor, (2) the ranking of transfer priorities, and, (3) the estimation of efficient transfer amounts. Finally, we implement statistically these tasks by using diverse estimation methods, including RIF (Recentered Influence Function) regressions and quantile regressions, all focusing on the poverty line location.

Availing of more efficient tools of policy design is likely to advance the way policies can enhance social protections. Optimal PMT approaches may be well suited to this objective. Weak targeting efficiency to the poor, substantial monetary leakages and exclusion of poor households are major concerns for all these academic authors as well as for all administrators of these transfer schemes. This is where we want to make some progress. Moreover, the incentives of governments to finance social programs may be affected by using optimal targeting. For example, the costs of social programs may be reduced by using optimally the available information about the targeted population. This suggests paying serious attention to statistical methods that favor the optimal selection of program beneficiaries, and optimal transfer/delivery rules.

There is a huge literature on nonlinear taxation[1]. However, we do not deal in this paper with the welfarist and continuous social objectives of this literature, and we do not allow for taxing the poor. In contrast, there is only a small, while relevant literature, on designing efficient transfer schemes for poverty alleviation[2].

The nineties were a time of emerging reflections in this area. Besley and Kanbur (1988) characterize the theoretical first-order conditions for optimal food subsidies

[1] For example: Auerbach and Hines (2002), Saez (2002), Chone and Laroque (2005), Lew and Pistaferi (2015), Ravallion and Chen (2015).

[2] Atkinson (1995), Muller (2005), Muller and Bibi (2011).

in order to minimize poverty. Kanbur, Keen and Tuomala (1994a) and Immonen, Kanbur, Keen and Tuomala (1998) perform numerical simulations for nonlinear income taxation and poverty alleviation problems. Chakraborty and Mukherjee (1998) study the optimal subsidies to the poor in terms of the density function of incomes, under a priori normative restrictions on the subsidy function. For FGT poverty indicators and poverty indicators that are 'discontinuous at the poverty line', Bourguignon and Fields (1990, 1997) provide an intuitive solution for the optimal allocation of transfers under perfect information. Besley (1990) studies how the first-order conditions are modified when there are private and social costs of the scheme. In all these studies, the emphasis is on trying to grasp the theoretical proportion of an efficient transfer system. We now discuss the more recent literature in two parts: statistical methods and new empirical progress.

1.2. Statistical literature

Some relevant research took place in the statistical literature that relate optimization objectives with econometric estimators, somehow like our approach in this paper. For example, as early as Hansen (1982), one can avail of asymptotic characterization of estimators based on moment equations. Other researchers, as Shapiro (1989), have investigated estimators defined from a stochastic optimization program. Then, it is well known how estimation methods, and their asymptotic properties, can be derived from smooth unconstrained optimization criteria. One could then think that it would be easy to avail of this literature to obtain optimal policy functions minimizing our poverty objective. However, two difficulties arise. First, our social objective of interest includes non-differentiabilities, and sometimes non-continuities, which make it impossible to use straightforwardly these theoretical statistical results. Second, some implementation constraints and design constraints may perturb the analysis of the statistical behavior of such estimators. This is all the more so when there is a large number of such constraints, such as systematically imposing the non-negativity of transfers for all individuals. This problem is akin to the issue of incident parameter in panel data econometrics.

Several methods can be found in the econometric literature for analyzing living standard distributions, and we call them ‘distribution regressions’. 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 applications and 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 have already been used for investigating poverty issues (e.g., in Essama-Nssah and Lambert, 2013, for studying pro-poorness of growth in Bangla Desh).

One obstacle in designing optimal social programs is the problem of unobserved heterogeneity of individuals. Indeed, individual heterogeneity matters for policy, as has been noticed by researchers for some time. Manski (2004) analyses policy treatment rules of a utilitarian social planner for heterogenous populations, with a focus on endogeneity issues, even though he does not deal with optimal targeting. As a matter of fact, there is a huge literature on treatment effects that tries to account for heterogeneity in program impacts.[3]

Using quantile regressions can be seen as a way of dealing with heterogeneity by making observations. Gutenbrunner and Jureckova (1992) found that using quan-

[3] Heckman et al. (1997) or Blundel and Costa-Dias (2009).

tile regression is a computationally convenient approach to rank the location of the linear model across observations. Quantile regressions is indeed a practical tool to investigate distributional effects, and individual heterogeneity, including under endogeneity (Chernozhukov and Hansen, 2003, Kim and Muller, 2005, Muller, 2017). However, quantile regressions describe conditional distributions and one may be more interested by unconditional distributions of living standards for targeting purposes. For this, we can avail of Firpo, Fortin and Lemieux (2009)'s RIF regressions.

1.3. Empirical progress

Little by little, some progress has also been done on the empirical side from the 1980s. For a sample of surveyed households Ravallion and Chao (1989) minimize numerically a poverty measure, 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 funding spent than planned. Other authors investigated regional poverty targeting.[4] Ravallion and Chao's approach can also be used with additional correlates of household living standards, as in Glewwe (1992), and still yield substantial results.

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 analyzed for improving screening applicants. We do not examine these issues in this paper. As pointed out by Ravallion (2009), improved

[4] Park, Wang and Wu (2002, Bigman and Srinivasan (2002, Bigman and Fofack (2002, Schady (2002).

targeting does not necessary translate into improved impact on poverty and more cost-effective intervention. We examine simultaneously several poverty measures and several targeting indicators to assess the performance of our new method in all these dimensions. In order to report a fair comparison, the transfer budget is fixed by hypothesis, which implies that the comparisons can also be interpreted in terms of cost-effectiveness.

Muller (2005) and Muller and Bibi (2011) have pursued these research lines by showing how to adjust the Bourguignon and Fields' method to practical statistical estimation that avoids the numerical difficulties in the applied literature. Namely, they estimate fitted values of a living standard variable, obtained by using quantile regression 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 implemented in Mauritius and Seychelles (Muller, 2010), notably for the project Social Register of Mauritius, which performs transfers thus targeted to the poor[5].

However, it seems fair to say that not all difficulties have been solved for transfers against poverty, far from it, both theoretically and empirically. Targeting performance, even for focused transfer schemes is still quite limited, and there may be scope for further methodological improvement.

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

Let us consider a few theoretical issues. The non-negativity of transfers is a fundamental but inevitable snag in designing poverty alleviation policies. Indeed, it makes little normative and operational sense to ask poor persons to contribute financially to transfer schemes. The same kind of issue with a large number of constraints in the optimization is likely to arise from many other individual constraints, such as incentive constraints or imperfect/incomplete markets. In that sense, dealing with non-negative constraints in a prototype problem is a first analytical stage to be able to deal with general complex optimization under individual constraints. The consequence of this situation is that the way the non-negativity constraints for transfers are dealt with should be theoretically and statistically justified.

Let us finally mention two last issues that have theoretical, statistical and practical consequences. First, the incomes and the living standards of the individuals of general population are generally not observed, which implies that the findings in the theoretical literature are not readily usable. As a consequence, the transfers and the delivery services must be defined in terms of observable household characteristics only. Second, individual incentives must be controlled, particularly regarding the statement by individual themselves of their characteristics. For example, characteristics easy to hide or manipulate by individuals should not be used as covariates in the design of a transfer scheme, since applicants would be incentivized to change or hide them in order to access the program benefits.

1.4. Our strategy

In this paper, we propose an optimal approach to transfers against poverty, which consists of connecting the estimator from the policy targeting problem through focused fitted-valued of living standards. The study of the associated Euler equations shows that it is possible to conveniently approximate these equations by estimating a one-dimensional statistical score for the fitted-values of individual living standards. We optimally implement this statistical score, by using diverse distribution regression methods for: (1) the identification of the poor, (2) the ranking of their priorities, and (3) the estimation of optimal transfers.

There are a few related topics we do not deal with. 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). Incentives are a booming topic of studies for social programs (e.g., Saez, 2002, Chone and Laroque, 2005, Low and Pistaferri, 2015 and Ravallion and Chen, 2015). 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 difficulty of targeting against poverty, not on incentive processes.

We present the model in Section 2. In Section 3, we analyse the theoretical poverty minimization problem. In Section 4, we discuss the estimation method. An empirical application to Egypt in 2013 is 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. 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 adopt a Lebesgue 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.

$$\begin{aligned} & \min_{\beta} \; P(F_{y,X}; z) \\ \text{subject to} \;\; : \quad & \int t(X) dF_X(X) \leq B \\ \text{and } t(X) \quad \geq \quad & 0. \end{aligned}$$

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 and will easily be adapted to the case of households and living standards, notably for our empirical application. However, in order to simplify the discussion, we first and only mention 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. We focus on this case. Then, when distributions are continuous, and densities $f(y|X)$ and $f_X(X)$ can be defined, the ex-post policy objective to minimize in $t(.)$ can be written as: $E\left\{k\left(\left(y+t(X)\right)/z\right) I\left[y+t(X)<z\right]\right\}$

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, 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 can also be exploited 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. The analog criterion to minimize under this imperfect information is therefore a poverty *estimator*. Because the cdf $F_{y,X}$ is unknown, the formula of the transfer function $t(.)$ can only be approximately obtained for a sample of n observations of X and y, taken from a household survey. 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 and I is the indicator function that is equal to 1 when the condition in brackets is satisfied, and zero otherwise. Note that the sum sign in Problem (2) plays two roles. It replaces the expectation operators both over $F_{y,X}$ and over F_y in the poverty measure and in the budget constraint.

This program corresponds to a simple random sampling scheme. In the case of complex sampling schemes, the estimator can be modified to account for stages of sampling, clustering and stratification. To simplify the exposition, we focus on the case of simple random sampling schemes.

In this setting, there are two fundamental issues for the estimation of $t(.)$. First, the y_i are unobserved for most out-of-sample individual, and only some $X_i's$ can be observed for most individuals. Second, the number of constraints is increasing as fast as the sample size.

3. Theoretical Analysis

3.1. The issue of non-negative transfers

Directly introducing n non-negativity constraints in a optimization program, such as (2), that is: as many constraints as observations, makes it impossible to identify statistically its optimal solution, without appealing to some special structure of the problem. It is indeed the special formula of the poverty index that allows us to derive a tractable solution method.

As a matter of fact, direct estimation of $t(.)$ from the analog poverty minimization problem is infeasible when performed only with the resources of brute computation force[6]. In such situation, to make progress, we need to use some structural information about the poverty problem. Moreover, even without non-negativity constraints, the function in the integral of the objective is discontinuous at z, which constitutes an additional numerical challenge.

In the next subsection, we show how to generate simple optimization procedures by analyzing a first-order Taylor expansion of the Euler equations of the problem.

3.2. Solving by ranking Euler equation gradients

Differentiating the Euler equations of the optimization problem is the key to the solution. Indeed, looking at the gradient of the kernel function of the objective will inform us about what the individual to serve first is, when one additional transfer unit becomes available. 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 the property that will allow us to avoid the issue of the

[6] As we checked numerically, by using constrained GMM estimation.

non-negativity constraints for transfers.

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

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

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 is the product of the transfer function by the density function, that is: $\dot{x}(t)$ stands for $t(y)f(y)$. As a result, we have by integration: $x(t_0) = 0$ 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 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 $k(y + t(y))f(y)$. Therefore, the problem of calculus of variations to solve becomes:

$$
\begin{aligned}
& \max_{\mathbf{x}(.)} \int_{t_0}^{t_1} f^0(x(t), \dot{x}(t), t)dt \\
\text{subject to } x(t_0) &= 0 \text{ and } x(t_1) = B.
\end{aligned}
$$

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:

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

All the logic of our solution method is concentrated in this simple equation. As noticed in Bourguignon and Fields (1990), this is the knowledge of the shape of function k that allows us to deduce the sequential ranking for serving individuals according to their priorities. This ranking is the inverse of that of the $k'(y_i)$, as $k'(y_i)$ is also the gradient of the kernel function of the poverty objective. That is: transferring a marginal transfer to the individual with the highest gradient will increase more the objective than any other transfer. Invoking such marginal transfer also requires considering a marginal change in the total budget, that is: to perform a comparative statics operation. In its turn, the marginal shift in the total budget constraint implies a marginal change in the Lagrange function of the optimization problem. Finally, this generates a marginal change in the FOCs, which is described by this gradient.

All this implies that what should be needed for ranking individuals are estimators $\hat{k}'(y_i)$ of $k'(y_i)$ for all individuals. Recall however that our reasoning so far is valid only provided we have already solved the problem of identifying the poor. In that sense, the identification of the poor is a preliminary requirement in order to avail of an efficient estimation method for the transfers.

In our approach, both requirements of identifying the poor and ranking them will be solved with the same estimation method since the last possibly served poor is the last ranked. In that sense, our 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. Therefore, there is a certain unity of action in solving our three fundamental questions: identification, ranking and calculus of the transfer amounts.

The sequential rule is as follows:

(1) One ranks the $k'(y_i)$, for 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 what 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 converge towards the post-transfer theoretical equilibrium. Because of the shape of the Euler conditions, the individual to serve first is also the individual that will receive the most.

(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 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 than the poverty line, or until the whole transfer budget is spent.

An analog continuous case could also be discussed similarly. This procedure, which is similar to the one in Bourguignon and Fields (1990) and Muller and Bibi (2010), only depends on the Euler conditions, which include the budget constraint condition. All the completed transfers are non-negative by construction. As mentioned before, using the ranking of the $\hat{k}'(y_i)$ also solves all the other numerical problems in the optimization procedure. This is related to the fact that the optimization program including non-negativity constraints must be seen as if it was a global problem since it is not a convex problem for which the local FOCs would be sufficient information.

Making the formal connection with the optimization problem clarifies its intuitive justification, and where the fitted values intervene: i.e., in the assessment of $\hat{k}'(y_i)$. In particular, we can see that using the fitted-values $\hat{y}_i$ to rank the $k'(\hat{y}_i)$, instead of an estimator $\hat{k}'(y_i)$, may not be a statistically optimal method, since different accuracies may be obtained, for $\hat{y}_i$, $k'(\hat{y}_i)$ or $\hat{k}'(y_i)$, even though theoretically ranking the y_i and ranking the $k'(y_i)$ is equivalent. Though, we shall show that there are examples where these approaches exactly coincide.

Let us return to our Lebesgue, or continuous, initial notations. Given fitted values of incomes, $\hat{y}_i$, the equation defining the last served living standard, y^*, i.e. the 'stopping rule', is:

$$\int_0^{y^*} t(\hat{y}) dF_{\hat{y}}(\hat{y}) = B,$$

where $t(\hat{y})$ is constructed sequentially as already discussed and $F_{\hat{y}}$ is the cdf of income fitted values. Differentiating the Euler equations as an examination of the comparative statics when the budget changes marginally yields: $k''(y+t(y)).(dy+dt)=0$. This implies $dt=-dy$, i.e., $t'(y)=-1$, for all poverty indices such as the kernel function k is differentiable and not linear affine. That is: transfer differences perfectly compensate for differences in incomes, for the poor.

We can now rewrite the above expression of the budget constraint using integration by parts. This yields, using $t'(y)=-1$:

$B=\int_0^{y^*} t(\hat{y})f_{\hat{y}}(\hat{y})d\hat{y}$

$=[t(\hat{y})F_{\hat{y}}(\hat{y})]_0^{y^*}-\int_0^{y^*} t'(\hat{y})F_{\hat{y}}(\hat{y})d\hat{y}=t(y^*)F_{\hat{y}}(y^*)+\int_0^{y^*} F_{\hat{y}}(\hat{y})d\hat{y},$

where $\int_0^{y^*} F_{\hat{y}}(\hat{y})d\hat{y}\equiv F_{\hat{y}}^{[2]}(y^*)$ is the usual second-degree stochastic dominance statistics, commonly used in inequality or risk analyses.

Moreover, since for the marginal income y^* the residual transfer is zero ($t(y^*)=0$), then we have $B=F_{\hat{y}}^{[2]}(y^*)$, which implies $y^*=\left(F_{\hat{y}}^{[2]}\right)^{-1}(B)$.

This equation can for example be solved graphically using second-degree stochastic dominance curves. Numerical solutions are also easy in that case since $F_{\hat{y}}^{[2]}$ is a continuous invertible function.

Explicit solutions can be obtained for some special parametric distributions. For example, with the logistic law: $F_Y^{[2]}(y)=\int_0^y \frac{1}{1+e^{-x}}dx=\int_0^y \frac{e^x}{1+e^x}dx$. Then, the change in variable $u=e^x$ yields $F_Y(y)=\int_1^{e^y} \frac{u}{1+u}\frac{du}{u}=\int_1^{e^y} \frac{1}{1+u}du=\ln(1+e^y)-\ln(2)$. In this case, it would be easy to solve, $1+e^{y^*}=2e^B$, which yields $y^*=\ln\left(2e^B-1\right)$. Of course, one should rather use estimated affine transformations of standard logit distributions for more realistic cases. Pareto distributions also yield explicit formulae for y^*.

Note that the intuitive reasoning by Bourguignon and Fields can be slightly generalized here since they did not discuss the possibility of individuals escaping poverty in groups after transfers, or the use of mixed discrete-continuous distributions. This is because they examine only finite populations under perfect information. More substantial differences with these authors will occur though when we introduce an index based on covariates in the next subsection. Indeed, we now need to recall that the incomes y_i are in fact unobserved for most of the population, for which only the covariate vector X_i is assumed observable.

3.3. Conditioning on an income index based on covariates

We now introduce the observed income correlates, X, through conditioning on a linear income index $y(X)$ 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 reflections, 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, we substitute a fitted-value $\hat{y}(X)$ for y, and consider the rule: $k'(z, \hat{y}(X) + t(X)$ as constant for all the ex ante poor identified by $\hat{y}(X)$. Then, we search for the most accurate or relevant estimators of $\hat{y}(X)$ for the poor. In practice, it may be enough to generate fitted-values accurate only around the poverty line. It seems natural to use distribution regressions for quantifying 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, this boils down to the condition:

$$k'(z, \hat{y}(X) + t(X)) = c. \tag{3}$$

We now discuss the issue of non-negativity constraints.

3.4. Non-negativity constraints

Were it there not for the non-negativity of transfers, eq. (3) suggests that the problem could be tractable. However, these constraints exist, and they are so numerous that they cannot be directly incorporated in the solution to the optimization problem.

To understand how to deal with non-negativity constraints, a first-order expansion of the Euler equations will be useful. This will allow us to show that the non-negativity constraints can be discarded because only non-negative transfers will have to be performed, albeit in a decreasing order in terms of transfer size. As before, this is the consideration of the first-order Taylor expansion of the Euler equations that allows the ordering of transfers down to zero.

As an exercise of comparative statics with the total budget changing marginally, the Euler equation (3), $k'(y+t) = c$, can be expanded, approximately, as $k''_{y^2}dy + k''_{y^2}dt = 0$.

As a consequence, we can see that the dy and the dt entirely offset each other (when the objective is convex): they are infinitely substitutable, which can be clearly seen in the expansion. In that case, $dt = -dy$, and the ranking of the transfers is the opposite of the ranking of the incomes. In the next section, we discuss our estimation method.

4. The Estimation Method

4.1. Fitted values of living standards

Conditioning on a 'synthetic' living standard covariate X in the theoretical formula of Subsection 3.3. naturally introduces the regression of y on X, embodied in the conditional cdf $F_{y|X}$.

Our statistical estimators are defined in connection to the optimal solution of the theoretical program, provided one accepts to use linear scores based on observable information for defining the transfer rules. These estimators must be expressed in terms of the empirical distributions of the observed variables in a sample of surveyed households.

Let us consider the standard OLS linear regression model $E(y|\ X) = X\beta$. In that case, we have a dual interpretation of the coefficient vector β: 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, we have shown in Muller (2005) that focusing on quantiles closer to the population social objective should provide better targeting than using OLS because these concerns are likely to be far apart of relevant living standard levels for the poor.

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 regression estimators to raise the targeting performance of PMTs in Tunisia.

In this paper we use unconditional quantile regressions developed by Firpo, Fortin and Lemieux (2009). In that way, we shall be able to focus on the location of the unconditional distribution of the living standards that corresponds to the poverty line. This may improve the performance of the transfer scheme in terms of poverty alleviation.

4.2. Recentered influence function regressions

Let us consider a score statistics that is a linear functional of the cdf F of y: $T(F) = \int \psi(y)dF(y)$, for a kernel function ψ. For example, in the case of the mean, $\psi(y) = y$. The influence function $IF(y;F)$ of the functional T at F is defined as

$\lim\limits_{\varepsilon\to 0} \frac{T(F\varepsilon,y_0)-T(F)}{\varepsilon}$, where $F\varepsilon, g = (1-\varepsilon)F + \varepsilon 1_g$ and 1_g is a Dirac cdf at g. It measures the impact of observation y_0 on the functional T. One can calculate $IF(y;F) = \psi(y) - \int \psi(y)dF(y)$.

We have by construction $E\left(IF(y;F)\right) = 0$. This suggests that this term would not disturb the specification of the dependent variable in a least-square regression model.

Accordingly, the Recentered Influence Functions (RIF) is defined as:

$RIF(y;F) = T(F) + IF(y,F)$. For a linear functional as above, we have $RIF(y;F) = \psi(y)$, which allows us to isolate the kernel function of the functional. By construction, we have: $E(RIF) = T(F)$. By conditioning on X, we can rewrite the initial functional as $T(F) = \int E\left(RIF(y;F) \mid X = x\right)\ dF_X(x)$. In that way, we have elicited the natural population counterpart, $E\left(RIF(y;F) \mid X = x\right)$, of the regression of the $RIF(y;F)$ on X. It is possible to run this regression using income and correlates information from some survey data.

In the case of the functional equation equal to the unconditional θ^{th}-quantile of Y, denoted q_θ, the influence function is $IF(y;F) = \frac{\theta - 1[y \leq q_\theta]}{f(q_\theta)}$. The corresponding recentered influence function is $RIF(y;F) = q_\theta + \frac{\theta - 1[y \leq q_\theta]}{f(q_\theta)}$.

4.3. Estimation procedure

The estimation procedure of a model for 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 regressors.

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

Third, for each equation, we construct the dependent variable $RI\hat{F}(y;F) \equiv \hat{q}_\theta + \frac{\theta - 1[y \leq q_\theta]}{\hat{f}(q_\theta)}$, where $\hat{q}_\theta$ is the empirical quantile of order θ in the observed household sample.

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

Finally, we integrate the estimated regression with respect to the marginal distribution of the X_i to obtain the predictions of interest. In the next section, we apply this method to Egyptian data.

5. Empirical Application

5.1. The context

Egypt is a dynamic emerging economy with severe social problems. After a period of nationalization, socialist economic principles and redistribution early under President Nasser, the economy returned to opening, reprivatization and liberal policies after the 1967 defeat in the war with Israel. The massive liberalization reforms from 2006 to 2008 spurred high levels of growth (about 7 per cent yearly). Since then, Egypt has developed intensive economic and trade relationships with the European Union, the United States, and Middle East countries, but also with farther markets. 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. This conjuncture damages social outcomes, which are handicapped by much lower growth than before, around 2 per cent in the last three years.

The Egyptian socio-economic setting is complex, and rooted in history, as pointed out by Farsoum (1988) in the past, and Rougier and Lacroix (2015) more recently. However, it is still useful to try to understand it when approximating living standards with some observable survey correlates.

In the nineteenth century, the royal family, absentee landlords, professionals, and businessmen, as well as foreigners in Cairo and Alexandria, made up the top social classes. However, starting from this historical basis, some degrees of social mobility emerged, pushed by development of the economy and general progress in education. The sons of higher and middle classes, of wealthy farmers and civil servants were able to find government jobs as professionals, which in turn stimulated formal education. Unfortunately, this educational dynamics has now led to an excess supply of high school and college graduates who can no longer find employment corresponding to their skill levels. However, education level should still be seen as a major determinant of incomes, even though the return for higher education may be lower than in other countries.

Dwelling characteristics are often used as proxies of household wealth in the development literature. However, in the Egyptian context, house information may not be as useful as elsewhere as an instrument to distinguish the poor from the non-poor. Indeed, returning labor migrants are also known to carry out substantial housing investment, despite their low observed incomes.

In contrast, socio-demographic family variables are probably essential for predicting living standards, for usual reasons pertaining to their correlations with needs and earnings capacities, but also for more special ones. In Egypt, social positions are defined as much by family background than by wealth. In particular, kinship much determines access to economic positions. For example, business activities generally require personal and kinship relationships, for access to economic networks. Indeed, small producers, small service providers and small traders often reproduce themselves socially along kinship lines.

The Egyptian case is also special in that small economic agents, including small family businesses, often invest in stock markets, land or housing. This diversification of investment by relatively poor households and the corresponding multiplicity of their incomes may blur any attempt of assessing living standards by using correlates that describe their earnings opportunities. In that sense, we are compelled to accept the presence of considerable unobserved individual heterogeneity in the equations from which living standard fitted-values will be built. Another factor contributing to the unobserved heterogeneity of earnings processes is the fact that civil servants often have a second job after-hours, or an additional business, or gain revenues from real estate investment. In this context, the prediction of living standards from observed covariates may be inaccurate.

Furthermore, in modern Egypt, consumerism and status consumption are everywhere, somewhat mixed with indigenous traditional cultural traits. This implies that 'status goods', such as visible household equipment, may not assist the analyst in identifying the levels of household living standards as well as in other countries.

All these reflections have implications for choosing the covariates included in our living standard equation for Egypt, and we tried to account for them. However, it seems fair to say that the main limits to the specification of this equation are not necessarily only such sociological and economic stylized facts, but the mere availability of covariates in the data. We now turn to these data.

5.2. The data

The data are taken from the 2013 Egypt Household Income, Expenditure and Consumption Survey (HIECS). This data source provides us with household living standard measures, which are defined as the household per capita expenditure variables.

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

Our chosen poverty line for the simulations is the first quartile of per capita consumption expenditure at household level, which corresponds roughly to most international poverty estimates. International estimates of the poverty rate are of 22 % in 2008, from the CIA fact yearbook 2015; of 26,3% from the French Central Bank in 2010; of 25.2% in 2010 from the World Bank in 2016.

However, other official poverty lines, depending on their definition, may also sometimes yield figures of poverty rates as high as 40 percent. The government official poverty lines for expenditure per capita also vary across the regions. They are estimated from the 2005 Household Income, Expenditure and Consumption Survey (HIECS). Namely, they are calculated as corresponding to the cost of a consumption basket securing 2470 calories per day per person. By comparing with the expenditure data, the Ministry of Economic Development and the World Bank stated that individuals with a per capita expenditure of EGP 995 per year in 2005 should be considered extreme poor. Those who spent less than EGP 1423 per year are considered poor. Finally, those who spent less than EGP 1853 per year are seen as near poor. With these definitions, 44.4% of the Egyptians are in some kind of (from extreme to near) poverty (Nawar, 2007). Respectively, 21% of the Egyptians are near poor, 19.6% are (moderately) poor, and 3.8% are extremely poor.

Finally, using a rougher definition of poverty, more than 15 million Egyptians have been said to live on less than US$ 1 a day (Henry, 2012). The Minister of Economic Development also mentioned 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% of the population. In front of this variety of point of views and estimates, the poverty lines that are used amount to a reasonable compromise. Namely, the chosen poverty line for these experiments is the first quartile of the household living standard, which corresponds to a poverty rate of 31.8 percent. Other tried reasonable poverty lines yielded qualitatively similar conclusions in the estimations.

Table 1 shows some descriptive statistics for the main variables used in our simulations for 7528 households. Half of all households live in urban areas. The mean household size is slightly over 4 persons, while it varies from one to twentyeight persons in this sample. Some households have many children, while it is not very frequent that there is an elderly member. In most cases, only one or two members bring earnings. In one fifth of the surveyed households, there is no couple living there. Less than one fifth (18%) of household 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'. The housing size, measured by the number of rooms, is small on average with about three rooms, and sometimes even smaller. Almost all dwellings have access to pipe water (89%), while only slightly more than half of the dwellings have a modern toilet.

The education level of household heads is often low. A large proportion of households (45 %) have a head with no education, while 12% of the heads have reached primary education only, and 26% secondary education. Even though, two-third of the heads can read and write. Finally, almost all households own a tv (95%), a fridge (93%), a washing machine (94%), or even a satellite dish (88%). Fewer are the households who can avail of a vehicle (6% a car and 14% some cycle).

5.3. The results

Table 2 shows the estimation results for the predictive living standard equation, for the tried estimation method, including quantile regressions and RIF regressions. 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 in the living standard regressions. 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 quantile 0.32. 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 is perhaps often a sign of young active bachelor household before 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 described 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 useful 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. Moreover, living in a place with no access to pipe water is not significantly linked to living standard levels in Egypt.

As expected, education is another efficient marker of living standards. There is a systematic 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 in the table. Finally, households in which the head can read have generally higher living standards that those with illiterate heads.

Information on the household equipment is valuable to better target the poor. Having a modern toilet inside the house is a definite sign of higher living standards, as well as is ownership of some equipment: 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 suggests that these pieces of equipment may have generally spread in the whole population in Egypt, including the poorer categories.

Let us nonetheless mention a few exceptions to this general picture roughly valid over all estimation methods. These exceptions correspond to coefficients that are insignificant at the 5% level with some estimation methods. They interest us because they often concern the RIF regression focusing on the poor, which we suspect to be our best estimation approach to improve the transfer scheme. First, for the two levels of focus, which corresponds to the quantiles 0.25 or 0.32 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% level in the second case). Then, it seems that something qualitatively distinct may take place for the poor, as far as significant covariates of living standards are concerned. Insignificant coefficients of RIF regressions also occur for: the number of elderly members (also for quantile regressions at the quantile 0.25 at the 5% level, while not at the 10% level); the dummy that signals the absence of a couple in the household; ownership of refrigerators (for RIF regression at the quantile 0.32, and quantile regression at the quantile 0.25); and finally the dummy for the female heads. The insignificance of the coefficients of the rural residence dummy and of 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.

Beyond the results about significance, the estimated coefficients vary substantially across the estimation methods. Assessing the performances 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 the estimations. 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 ex post poverty and ex post targeting indicators. They are based on the chosen estimation methods, on the formula of the optimal transfers, and on several social indicators: the head-count index, the poverty gap, the poverty severity index, the program exclusion rate (for the poor), and finally the leakage indicator of program benefits (i.e., the proportion of the transfer budget that does not reach its target).

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 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.

Our estimation results show that what is minimized matters. We have analyzed transfer schemes that aim at reducing inequality-sensitive poverty, such as measured by the poverty severity index P_2. However, in theory this method does not necessarily imply an excellent performance in terms of poverty rates, exclusion or leakage of the scheme benefits. These dimensions must be investigated empirically as complements to our main objective, and this is what we do through these simulations.

Our estimation results show that the RIF regressions centered on the quantile corresponding to the proportion of poor households (instead of the poverty rate based on individuals) is the method that delivers the highest poverty severity reduction, down to 0.0105 from 0.0235. This may be because the prediction equations are based on household samples and not individual samples. This is also how some social programs function: at the household level rather than at the individual level.

However, the performance of the RIF regressions centered on the poverty rate is very close (at 0.010520), 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 optimal transfers varying with individuals seems to matter more than the estimation method used. This may be because the poverty line is actually not 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 ex post 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.

For the exclusion indicator, the RIF regressions become the best method again, with a lowest level of exclusion at 38.95% when they are centered on the proportion of poor households. Here, the differences in estimates across methods are substantial, for example with optimal OLS excluding 49.43 % of the poor instead. The leakage of the program benefits is always high for methods based on theoretically optimal transfers varying with the individuals. More than one third of the budget is wasted in that case. The best performance in this respect (34.99%), among optimal transfers, is reached again by the RIF regressions centered on the proportion of poor households, while it is much worse for uniform transfers, at least when estimated with OLS (41.26%).

6. Conclusion

Most social assistance programmes 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 often disastrous social performances of the current cash transfer programmes in the developing world is to develop more efficient, less costly and better targeted social programs and safety nets. In order to deal with these concerns, we provide a new solution to this question with a specification method of social transfer schemes that is connected to the analysis of the theoretical poverty minimization problems. Fitted-values of living standard variables appear as a central ingredient of the approach. We propose to estimate these fitted-values by using distribution regressions (Recentered Influence Function Regressions and quantile regressions).

Finally, we report an empirical application to the case of 2013 Egypt. In Egypt, social issues have led to the unrest of the 2011 revolution. A likely cause of this political instability is the arrival of numerous young and educated age classes on the labor market who cannot find jobs fitting their acquired skills. Added to a growing sensitivity in Egypt to corruption issues, this situation generate political demands by the populations for fairer and more efficient social protection programs.

Our empirical application to Egyptian data shows that our new method can improve the targeting performances and diminish poverty, as compared to the current situation. However, the difference between the performance of different estimation methods remains small in that case. Interestingly, this is for avoiding the exclusion of the poor that a choice of the estimation method preferring RIF regressions makes the most impact - which is substantial in that case.

These 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) seem promising. Second, more analytical progress could be achieved by tackling the inclusion of multidimensional covariates without the intermediary device of fitted-values, and by using nonparametric econometric estimators. Finally, further constraints should be introduced in the poverty alleviation problem, such as: incentives, waiting time, travel costs, administrative costs, delivery of social services, etc.

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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 0.25	(3) RIF 0.32	(4) QR 0.25	(5) QR 0.32
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		

pval in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Simulations of performances of transfer schemes

	P0	P1	P2	Exclusion	Leakage
Reference	.3177344	.0704923	.0235137	-	-
OLS uniform	.2556068	.0438787	.0116324	.4345234	.41258
OLS optimal	.2563285	.0419584	.0108588	.4943606	.362233
RIF 0.25	.2609147	.0415027	.0104603	.3895343	.349952
RIF 0.32	.2590609	.0415016	.0105208	.4179949	.350672
QR 0.25	.2571256	.0415401	.0105163	.429417	.351866
QR 0.32	.2588524	.041618	.010604	.4474443	.353747

7528 observations.