View metadata, citation and similar papers at core.ac.uk

brought to you by CORE

provided by Institutional Knowledge at Singapore Management University

Singapore Management University
Institutional Knowledge at Singapore Management University

Research Collection School Of Economics

School of Economics

5-2007

Poverty Alleviation through Geographic Targeting

Chris ELBERS
Free University Amsterdam

Tomoki FUJII
Singapore Management University, tfujii@smu.edu.sg

Peter LANJOUW
World Bank

Berk OZLER
World Bank

Wesley YIN
University of Chicago

DOI: https://doi.org/10.1016/j.jdeveco.2006.02.001

Follow this and additional works at: https://ink.library.smu.edu.sg/soe_research

Part of the Economic Policy Commons, and the Income Distribution Commons

Citation

ELBERS, Chris; FUJII, Tomoki; LANJOUW, Peter; OZLER, Berk; and YIN, Wesley. Poverty Alleviation through Geographic Targeting. (2007). *Journal of Development Economics*. 83, (1), 198-213. Research Collection School Of Economics.
Available at: https://ink.library.smu.edu.sg/soe_research/269

This Journal Article is brought to you for free and open access by the School of Economics at Institutional Knowledge at Singapore Management University. It has been accepted for inclusion in Research Collection School Of Economics by an authorized administrator of Institutional Knowledge at Singapore Management University. For more information, please email libIR@smu.edu.sg.

Published in Journal of Development Economics
Volume 83, Issue 1, May 2007, Pages 198-213
https://doi.org/10.1016/j.jdeveco.2006.02.001

Poverty alleviation through geographic targeting: How much does disaggregation help?☆

Chris Elbers[a,b], Tomoki Fujii[c], Peter Lanjouw[d,*], Berk Özler[d,*], Wesley Yin[e]

[a] *Free University, Amsterdam, The Netherlands*
[b] *Tinbergen Institute Amsterdam, The Netherlands*
[c] *Singapore Management University, Singapore*
[d] *World Bank, USA*
[e] *Harris School of Public Policy at the University of Chicago, USA*

Abstract

In this paper, we employ recently completed "poverty maps" for three countries as tools for an ex ante evaluation of the distributional incidence of geographic targeting of public resources. We simulate the impact on poverty of transferring an exogenously given budget to geographically defined sub-groups of the population according to their relative poverty status. We find large gains from targeting smaller administrative units, such as districts or villages. However, these gains are still far from the poverty reduction that would be possible had the planners had access to information on household level income or consumption. Our results indicate that a useful way forward might be to combine fine geographic targeting using a poverty map with within-community targeting mechanisms.

JEL classification: C15; I32; H53
Keywords: Targeting; Poverty; Poverty maps

☆ We thank the editor and two anonymous referees for their helpful advice and suggestions for improvement. We are also grateful to Jenny Lanjouw, Martin Ravallion, Norbert Schady, and participants in the "Poverty and Applied Microeconomics" seminar series at the World Bank for useful discussions and comments. We thank the government of Japan, via its Millenium PHRD Grant, for financial support. These are the views of the authors and should not be attributed to the World Bank or any affiliated organization.

* Corresponding authors.
E-mail addresses: planjouw@worldbank.org (P. Lanjouw), bozler@worldbank.org (B. Özler).

1. Introduction

Public policies in developing countries are often articulated in terms of poverty reduction objectives. Resources for such purposes are invariably scarce relative to the number and magnitude of competing claims, and it is often desirable to target social transfers to those beneficiaries whose needs are most urgent. Coady and Morley (2003) survey experience with such targeted transfer programs and show that it is difficult to avoid errors of inclusion and exclusion. Improved targeting of public spending generally involves reducing either one, or sometimes both, of these types of errors.

Governments often exploit geographic variability in the design of targeting schemes: poverty may be more concentrated in some areas of a country than others and most countries have an administrative structure that operates at the sub-national level. Resources aimed at poverty reduction can thus be directed to those localities where poverty is concentrated and administration of these transfer schemes can be carried out at the relevant local level. Despite their intuitive appeal, however, transfer schemes targeting poor communities remain difficult to design. Data on incomes or consumption expenditures tend to derive from sample surveys that are not large enough in size to permit estimates of poverty at a highly disaggregated level. Absent detailed information on local-level poverty, policymakers have often sought to use proxies. When such indicators are used for targeting rather than direct estimates of poverty, there is mis-targeting both due to the targeting errors noted above and due to problems with the proxy welfare index at the community level.[1] Partly as a response to such mis-targeting of resources, recent years have seen growing experience with the development of “poverty maps” that combine household survey with population census data to impute income or consumption to each household in the census.[2] The resulting household-level estimates can then be aggregated into welfare indices at different levels of geographic aggregation, and have been found to yield fairly precise estimates of welfare at the local level.

This paper asks how much the higher degree of spatial disaggregation offered by poverty maps can help to improve targeting schemes aimed at reducing poverty. The paper builds on the earlier analysis in Ravallion (1993) who finds that geographic targeting at the broad regional level in Indonesia – the lowest level at which household survey data provide reliable estimates of poverty – improves targeting, but only to a modest extent. As in Ravallion (1993), we consider the distribution of a hypothetical budget to a country’s population. We assume that we have no information about the poverty status of this population other than the geographic location of residence and the level of poverty in each location.[3] As a benchmark case, we make the extreme assumption of no knowledge whatsoever about the spatial distribution of poverty – in which case our given budget is distributed uniformly to the entire population. We set up a series of comparisons to this benchmark, where we assume knowledge about poverty levels in progressively smaller sub-populations. For a given level of disaggregation, we ask how knowledge of poverty levels

[1] For further discussion of the latter problem, see Hentschel et al. (2000).

[2] See Elbers et al. (2002, 2003) and Demombynes et al. (2002).

[3] In this paper, as in preceding papers by Kanbur (1987) and Ravallion (1993), geographic targeting means cash transfers to every individual must be equal within the targeted area, but can differ across such localities.

across localities can help design transfer schemes to improve the overall targeting performance relative to the benchmark case.

We consider two transfer schemes that make use of this knowledge in different ways: a very simple and intuitive transfer scheme and an optimal scheme, where expected poverty at the national level is minimized subject to the available information and budget constraint. We compare performance across these schemes and consider their relative performance at alternative levels of disaggregation. Finally, we ask how close "optimal geographic targeting" comes to the hypothetical scenario of "perfect targeting" to get a sense of the potential benefits from combining detailed geographic targeting with additional targeting mechanisms such as means-testing or self-selection within communities.

Our simulations use poverty maps for three countries: Ecuador, Madagascar and Cambodia. These countries are highly heterogeneous in terms of their geographic location, social and political structures, and stages of overall development. A key objective of the paper is to ascertain to what extent availability of local-level poverty data is beneficial in these very different settings.

We find that there are potentially large gains in targeting performance from disaggregating to the local level. In all three countries examined, significant benefits from geographic targeting become increasingly evident as one makes use of more and more disaggregated data on poverty. For example, in Cambodia, the poverty reduction that can be achieved with a uniform transfer to everyone can be achieved with 55% of the total budget if the six provinces of Cambodia are targeted, but with only 31% of those same funds if the targeting is at the level of the country's 1594 communes. When the targeting scheme makes only crude use of local level poverty estimates, we find that the gains are generally more muted, but even then, they can be significant. However, in all countries, we find that overall targeting performance remains far from perfect. This implies that there may be scope for combining geographic targeting with other targeting methods in order to reduce errors of inclusion and exclusion even further.

In the next section, we briefly summarize the methodology and data underpinning the poverty map estimates in Ecuador, Madagascar and Cambodia. We emphasize that these spatially disaggregated data are estimates, with confidence bounds, rather than actual measures of poverty. Section 3 describes the different targeting schemes that are assessed in the simulation stage, and characterizes how one such scheme can be designated as optimal in the sense of ensuring the maximum possible gains from geographic targeting subject to a budget constraint. Section 4 describes the simulation procedures and presents results. Section 5 provides a concluding discussion.

2. Producing local estimates of poverty

We employ a methodology for producing local-level estimates of poverty that has been described in detail in Elbers et al. (2002, 2003). Let W be a welfare indicator based on the distribution of a household level variable of interest, y_h. Using a detailed household survey sample, we estimate the joint distribution of y_h and observed correlates x_h. By restricting the explanatory variables to those that are also observed at the household level in the population census, parameter estimates from this "first stage" model can be used to generate the distribution of y_h for any target population in the census conditional on its observed characteristics and, in turn, the conditional distribution of W. Elbers et al. (2002, 2003) study the precision of the resulting estimates of W and demonstrate that prediction errors will fall (or at least not rise) with the number of households in the target population, and will also be affected by the properties of the first stage models, in particular the precision of parameter estimates.[4]

The first-stage estimation is carried out using household survey data.[5] The empirical models of household consumption allow for an intra-cluster correlation in the disturbances (see Elbers et al., 2002, 2003 for more details). Failing to take account of spatial correlation in the disturbances would result in underestimated standard errors in the final poverty estimates. Different models are estimated for each region and the specifications include census mean variables and other aggregate level variables in order to capture latent cluster-level effects. All regressions are estimated with weights and with parsimonious specifications to be cautious about overfitting. Heteroskedasticity is also modeled in the household-specific part of the residual.

Simulation methods are applied to predict per-capita expenditure at the level of each household in the population census. Predicted household-level per-capita consumption in the census takes into account not only the parameter estimates from the first stage consumption models estimated in the survey, but also of the precision of these estimates and of those parameters describing the disturbance terms in the consumption models. Thus, we do not produce just one predicted consumption level per household in the census, but rather, r predicted expenditures are simulated for each household (in our three countries, we carry out 100 replications). For each respective r, parameter estimates are drawn from a multivariate normal distribution that respects the variance–covariance matrices estimated in the survey-based consumption and heteroskedasticity regressions. In addition, disturbance terms at the cluster and household level are drawn from their respective (parametric or semi-parametric) distributions. These draws are then applied to the census-level regressors and per-capita consumption is predicted. For the next r, a new set of parameters and disturbances are drawn and a new per-capita consumption measure is predicted. The resulting database of r predicted expenditures for every single household in the population census is the key database underpinning "poverty maps" and the policy-simulation exercise explored here.[6]

The data used in this study consists of a household survey and a population census from each of Ecuador, Madagascar, and Cambodia. Table 1 presents the basics on each of the data sources, such as year, sample size, stratification, etc. More detail on each country's data sources, and on the specific procedures followed to produce their "poverty maps" can be found in the studies listed in Table 1.

[4] The relationship between precision of the poverty map estimates and the size of the community is influenced to a large extent by the explanatory power of the 'first stage' regression models that underpins the idiosyncratic error associated with the poverty estimates. Experience in a variety of countries has shown that when R^2 values are around 0.6 or higher, that component of the overall error that varies with size of target population is effectively negligible when dealing with communities of 1000 households or more. With lower explanatory power, the minimum size of the target population in the census needs to be larger (see Elbers et al., 2002, 2003).

[5] These surveys are stratified at the region or state level, as well as for rural and urban areas. Within each region, there are further levels of stratification, and also clustering. At the final level, a small number of households (a cluster) are randomly selected from a census enumeration area.

[6] The poverty map estimate of poverty in community, province or region c is produced from this database in the following manner: for every replication r, poverty is estimated over all households in c (after weighting by household size). The average of all poverty estimates, over the r replications, yields the estimated poverty rate in community c, and the standard deviation yields the associated estimated standard error.

3. Transfer schemes

As described in Section 1, our main objective in this paper is to see to what extent the availability of poverty estimates for different geographic locations can help to reduce poverty for a given, exogenous, budget. We postulate that the government has a budget, S, available for

Table 1
Data summary

	Ecuador	Madagascar	Cambodia
Household survey			
Year	1994	1993–1994	1997
Source	Encuesta de Condiciones de Vida (ECV)	Enquête Permanente Auprès des Ménages (EPM)	Cambodia Socio-Economic Survey (CSES)
Sample Size	4500 households	4508 households	6010
Population census			
Year	1990	1993	1998
Coverage	About 10 million individuals in 2 million households	About 11.9 million individuals in 2.4 million households	About 11.0 million individuals in 2.15 million households
Geographic units of Analysis			
1st administrative level			
Name	Provincia	Faritany	Province
Number of localities	21	6	24
Average number of households	45 783	405 072	88 773
Average number of persons	223 026	1 981 848	458 071
2nd administrative level			
Name	Canton	Fivandrona	District
Number of localities	195	111	180
Average number of households	4930	21 896	11 836
Average number of persons	24 018	107 127	61 076
3rd administrative level			
Name	Parroquia	Firaisana	Commune
Number of localities	915	1248	1594
Average number of households	1051	1933	1337
Average number of persons	5119	9404	6897
References	Hentschel and Lanjouw (1996); Hentschel et al. (2000), Elbers et al. (2002, 2003).	Mistiaen et al. (2002)	Fujii (2006)

distribution and wishes to transfer this budget in such a way as to reduce poverty. The government can vary the amounts transferred to localities around the country, but it cannot transfer different amounts to different individuals within a community. We specify a baseline case in which the government is assumed to have no knowledge of who the poor are or where they are located. It is therefore unable to distribute its budget in any manner other than a lump-sum transfer to the entire population of size N. We thus calculate the impact of transferring S/N to the entire population.[7]

Optimal use of geographically disaggregated information on poverty has been investigated by Kanbur (1987), Ravallion and Chao (1988), Glewwe (1992), Ravallion (1993), and Baker and Grosh (1994). Kanbur (1987) formalized the theoretical problem of policy design under imperfect information, while Ravallion and Chao (1988) demonstrated how this general targeting problem can be solved in a computationally feasible way.[8] Kanbur (1987) shows that to minimize poverty summarized by the Foster–Greer–Thorbecke (FGT) class of poverty measures with parameter value $\alpha > 1$, the group with the higher FGT($\alpha - 1$) should be targeted on the margin.[9] Hence, to minimize the squared poverty gap (equal to a poverty measure from the FGT class with $\alpha = 2$), target populations should be ranked by the poverty gap (FGT with $\alpha = 1$) and lump-sum transfers made until the poverty gap of the poorest locality becomes equal to that in the next poorest one, and so on, until the budget is exhausted.[10]

The second targeting scheme that we compare against our benchmark case assumes the same knowledge of the spatial distribution of poverty, but does not make use of this knowledge in any particularly scientific or systematic way. This "naïve" targeting scheme was selected in order to contrast with the "optimal" scheme described above. Implementation of an "optimal" scheme might be difficult in practice. Governments often need to be able to communicate in a very clear and simple way how resources will be targeted, and this may preclude the fine-tuning needed for an optimal scheme. Our naïve scheme attempts to assess how detailed geographic targeting improves efficiency conditional on the types of constraints that governments may typically face in practice.

Our "naïve" scheme takes the following form.[11] We first rank geographic areas by their estimated poverty gap squared measures. We have an ex ante assessment of overall poverty in the

---

[7] It could be argued that our benchmark scenario is not terribly realistic. Perhaps more likely would be a situation where absence of detailed information on the extent and distribution of poverty, and absent any specific effort to target the poor, would result in a default situation of resources being appropriated by the non-poor (see the discussion in Campante and Ferreira, 2004). To the extent that this is true our estimates of the gains from targeting, once we assume some information on the distribution of poverty, might be seen as conservative estimates of the true benefits.

[8] As we use predicted expenditures from census data unlike Ravallion and Chao (1988), who use observed income data from household surveys, we utilize a different algorithm to solve the optimization problem. Applying their algorithm to our setting would yield the same results.

[9] Following Foster et al. (1984) the FGT class of poverty measures take the following form:

$$\mathrm{FGT}(\alpha) = \left(\frac{1}{\sum w_i}\right) \sum w_i (1-(x_i/z))^{\alpha}$$

where x_i is per capita expenditure for those individuals with weight w_i who are below the poverty line and zero for those above, z is the poverty line and $\sum w_i$ is total population size. α takes a value of 0 for the Headcount Index, 1 for the Poverty Gap and 2 for the Squared Poverty Gap. For further discussion, see Ravallion (1994).

[10] Elbers et al. (2004) provide a formal statement of this result.

[11] Of course, virtually an infinite number of "naïve" schemes could be implemented. We explore here one, particularly straightforward, example. Experimentation with alternative schemes has not yielded any that is obviously more effective. Indeed, the specific scheme implemented here has the virtue of not only being simple, but also surprisingly effective given the budget and poverty line used in this paper. See Elbers et al. (2004) for more detail.

country. We take our budget S and divide it by the total number of poor persons in the country, N_p. Our budget divided by the total number of poor persons yields the transfer a that will be distributed to each person. We select the poorest geographic area and transfer a to all persons in that area. If the budget has not been exhausted in the first region, we move to the next poorest region and transfer a to all persons in this second region. We continue until the budget is exhausted. In the marginal region – that in which the budget is exhausted – we do not transfer a, but transfer an equal share of whatever remains in the budget to the population of that last region. Note that this scheme does not guarantee some amount of transfer to all regions. The scheme also implies that households will be receiving differing amounts according to their overall size.[12]

3.1. Budget and poverty line[13]

We assume that the budget available for distribution has been exogenously set. As is intuitively clear, the potential benefits from targeting will vary with the overall size of budget. In the limit, as the budget goes to infinity, there is no need for targeting, as even a uniform transfer will eliminate poverty. In each of the three countries examined here, we identify the per-capita consumption value of the 25th percentile of the consumption distribution.[14] We scale this consumption value by the total population. Our benchmark budget is set to equal 5% of this total value.[15]

Gains from targeting also vary with the choice of poverty line. The higher the poverty line, the less need for targeting, as leakage to the non-poor diminishes to zero in the limit. In this study, we select as benchmark a conservative poverty line, that line which yields a 20% headcount rate in each of our three countries.[16] We focus on the squared poverty gap – a measure of poverty that is particularly sensitive to the distance between a poor

[12] We experimented also with a "constrained" optimal scheme that combined simplicity with a limited degree of optimization. In this scheme, a uniform benefit is offered in all areas that the scheme operates in and no benefits are provided elsewhere. The optimal list of areas is then solved for, conditional on the benefit being the same everywhere. This scheme resembles the naïve scheme described above, but the benefit size allocated is also optimal, rather than determined arbitrarily. Unsurprisingly we find that this scheme performs a bit better than our naïve scheme, but the improvement is only slight, and it comes at a cost of being somewhat more complicated to explain. We are grateful to a referee for this suggestion.

[13] We have tried other poverty lines and budget sizes than the ones described in this sub-section, but for reasons of brevity we do not present them here. In a companion paper, Elbers et al. (2004) we provide results for a wider set of poverty lines and budgets. For a formal discussion of using "program dominance curves" to assess the poverty impact of different programs, see Duclos et al. (2003).

[14] The consumption distribution is constructed based on the average, across r replications, of household-level predicted per-capita consumption in the population census.

[15] See Elbers et al. (2004) for additional simulation results based on a budget equal to 10% of this value. This analysis confirms the Ravallion (1993) finding that as the available budget increases, the incremental gain from geographic targeting over uniform transfers is attenuated.

[16] Within each replication r, the predicted per-capita consumption level associated with a 20% headcount rate is identified. The average across the r replications of this predicted consumption level is then taken as poverty line. It is clear that this poverty line will not necessarily yield a 20% headcount rate within each replication, nor would it yield such a rate for average per capita consumption at the household level (averaging across r replications). Elbers et al. (2004) repeat simulations also for a poverty line yielding an overall poverty rate of 40% and show that as the poverty line increases, the gains from spatial disaggregation and geographic targeting become less marked.

person's income level and the poverty line.[17] Note that although our analysis is undertaken based on the squared poverty gap, a similar approach could also have used some more conventional measure of social welfare; one that does allow incomes above the poverty line to also receive some positive social weight. We have found that the broad conclusions from our analysis are not affected by such a change in set-up.

4. Simulation procedures and results

4.1. Simulating the impact of uniform transfers

Our policy simulation in the case of uniform transfers is calculated in a very straightforward manner. Budget S is divided by total population N. The resulting transfer a is added to each predicted expenditure in our database, to yield $y_{ch}^{(r)}+a$. For each replication r we estimate post-transfer national poverty. The average across the r replications of the estimated post-transfer poverty rates yields our expected poverty rate associated with the benchmark, untargeted lump-sum transfer scheme. This new estimated poverty rate can be compared to the original national-level poverty estimate from the poverty map to gauge the impact of the transfer.

4.2. Simulating the impact of "optimal" geographic targeting

Simulating the impact of the "optimal" targeting scheme is a bit more complicated. Following Kanbur (1987), we want to equalize the following expression across the poorest locations of a country:

$$G_c(a_c) = \int_0^z (z-y-a_c)^+ \mathrm{d}F_c(y), \tag{1}$$

which is z times the poverty gap in location c, after every person in the location has received a transfer a_c. $F_c(y)$ is the average of the R simulated expenditure distributions of c. The function $(x)^+$ gives the 'positive part' of its argument, i.e. $(x)^+=x$, if x is positive, otherwise 0. Transfers a_c (which must be nonnegative) add up to a given budget S:

$$\sum_c N_c a_c = S, \tag{2}$$

where N_c is the population size of location c. After transfers there is a group of locations all sharing the same (maximum) poverty gap rate in the country. These are the only locations receiving transfers. We describe in the Appendix how this problem is solved given that we are working with a database of incomes for every household in the population census in each of our three countries.

Table 2 presents the results from our simulations with the optimal targeting scheme in Ecuador, Madagascar and Cambodia. This table depicts how much "cheaper" a given level of poverty

[17] We focus on the squared poverty gap because of its appealing properties from both a conceptual and technical point of view. The basic approach explored here would also work for other poverty measures, particularly FGT measures with values of parameter α greater than 1. However, with the headcount measure (the FGT measure with $\alpha=0$) welfare 'optimization' is not well defined and the approach taken here is thus less obviously applicable (see for example Ray, 1998, pp. 254–255).

Table 2
Cost of reducing poverty to the same level achieved by uniform transfers using the "optimal" targeting scheme

	Ecuador (rural)	Madagascar (urban and rural)	Cambodia (urban and rural)
Uniform transfer	100	100	100
Optimal targeting (1st administrative level)	76.0	60.7	54.5
Optimal targeting (2nd administrative level)	66.7	46.4	41.4
Optimal targeting (3rd administrative level)	58.4	37.6	30.8

See Table 1 for details on the number and average size of the administrative units in each country. We use poverty gap squared (FGT_2) as our measure of poverty. In each country, we first distribute the fixed, exogenous budget *uniformly* across the entire population and calculate the post-transfer FGT_2. Then, we calculate how much it would cost to achieve the same reduction in poverty if we distributed the funds *optimally* across geographic units. Each cell reports this amount as a percentage of the total budget available for that country.

reduction can be attained with optimal geographic targeting as opposed to no targeting. We apply a variant of the simulation procedures described above, whereby we calculate how much smaller the overall budget S could be in order to achieve the same poverty impact with optimal targeting as with the untargeted uniform lump-sum transfer. In all three countries, our calculations indicate large savings from optimal geographic targeting. In Ecuador, the gains from targeting at the local level are large but somewhat more muted than in Madagascar and Cambodia, most likely because our focus is only on rural areas, and as a result finer disaggregation does not lead to separating urban districts from rural ones. In Madagascar, and Cambodia the savings are particularly striking. For example, in these two countries one would need, respectively, only 38% and 31% of the uniform transfer budget to achieve the same reduction in the FGT_2 with optimal targeting at the firaisana and commune-level.

4.3. Simulating the impact of "naïve" geographic targeting

The optimization scheme described above is intuitively straightforward. But the process behind the decision as to the exact amount each community will receive is not always easy to describe. Given that the design and implementation of targeting schemes is often part of a political process, and that there is generally a need to be able to explain allocations in a simple and clear manner, it is of some interest to ask whether gains from spatially disaggregated geographic targeting are also significant when the poverty map is used to implement simpler, non-optimal, transfer schemes.[18]

To simulate the impact of the "naïve" transfer scheme we start by taking our poverty map as the basic statement on the distribution of poverty in the country. Based on the poverty map we identify the localities that will receive priority in the targeting scheme (we consider initially regions, then provinces, then communities, etc.). We calculate the amount a that will be targeted to all persons in the priority regions (budget S divided by the total number of poor people in the country, N_p). We simulate the targeting scheme in turn for each replication r by allocating a to all persons in our priority regions (irrespective of whether, in replication r,

[18] Optimal geographic transfers also allocate different amounts to different communities, something a government may find hard to implement, either for administrative difficulties or political reasons. Simpler schemes that allocate a uniform or a per-capita amount to eligible units may be more palatable under such circumstances.

Table 3
Impact of cash transfers to different administrative levels on poverty reduction using the "optimal" vs. the "naïve" targeting schemes

	Ecuador (rural)		Madagascar (urban and rural)		Cambodia (urban and rural)	
	Optimal	Naïve	Optimal	Naïve	Optimal	Naïve
Pre-transfer FGT_2	100	100	100	100	100	100
Post-uniform transfer FGT_2	71.4	71.4	70.3	70.3	73.7	73.7
Post-targeting FGT_2 (1st administrative level)	65.7	71.8	57.0	63.7	57.9	63.2
Post-targeting FGT_2 (2nd administrative level)	63.2	67.1	51.1	54.8	52.6	57.9
Post-targeting FGT_2 (3rd administrative level)	59.6	63.6	46.7	50.0	47.4	52.6

See Table 1 for details on the number and average size of the administrative units in each country. We use poverty gap squared (FGT_2) as our measure of poverty. In each country, the FGT_2 has been normalized to 100 for easy comparison of our results across countries.

those regions are particularly poor or not) until the budget is exhausted. We re-calculate the post-transfer national poverty rate in replication *r*. The average post-transfer national poverty rate across all replications provides our estimate of how poverty will have changed as a result of the transfer scheme. This expected poverty rate can then be compared to the pre-transfer estimate of national poverty, to the estimate of post-transfer poverty associated with the untargeted lump-sum transfer, and to that after the optimal transfer. Table 3 presents these results.[19]

It is striking that in all three countries, the reduction in the FGT_2 achievable with a naïve scheme, applied at the most disaggregated level possible in the poverty map, is sizeable. Broadly, the reduction in the FGT_2 based on this scheme is similar to the impact with the optimal scheme at one level of aggregation higher. For example, in Ecuador, targeting at the 3rd administrative-level using our naïve scheme yields an estimated FGT_2 that is 63.6% the value of the pre-transfer FGT_2, roughly the same as the 63.2% attainable with optimal targeting at the 2nd administrative-level. Similarly, in Madagascar and Cambodia, 3rd administrative-level targeting with the naïve scheme yields national FGT_2 estimates, each of which is approximately half as high as the respective pre-transfer poverty rate, remarkably comparable to the figures using optimal targeting at the 2nd administrative-level in each country.

Elbers et al. (2004) show that the relative performance of our "naïve" scheme varies significantly when a higher budget or a higher poverty line is used. Indeed, there are cases where giving every individual the same amount of money would have a higher impact on poverty reduction than using the naïve scheme described here. It is also difficult to know in advance how other similar, non-optimal, targeting schemes would perform in a certain country. The point to emphasize is that poverty maps of the kind developed here can be utilized to devise targeting schemes that are intuitive and transparent, and that perform nearly as well as the optimal geographic targeting scheme.

[19] Elbers et al. (2004) assess the statistical precision of comparisons of poverty across scenarios. The statistical significance of poverty differences is ascertained by returning to the transfer simulations and estimating not FGT2 values, but rather the difference in the estimated FGT2 based on a specific targeting scheme at the 3rd administrative level vis-à-vis targeting at the uniform, 1st and 2nd administrative levels using the same targeting scheme. In all cases, these differences are strongly statistically significant.

Table 4
Distance between "optimal" targeting and "perfect" targeting in Cambodia

	FGT_2 (*100)	% Spent on non-poor	% Reduction in FGT_2
Budget = total poverty gap associated with 20% overall poverty rate			
Level of targeting			
Pre-transfer	1.93		
Lump-sum transfer	1.47	81.2	23.9
Province * Urban / Rural (44)	1.23	71.2	36.4
District (180)	1.12	67.0	41.9
Commune (1594)	0.99	62.5	48.7
Household (2 130 544)	0.00	0.00	100.0

The numbers in parentheses reflect the number of units targeted.

4.4. *Distance from perfect targeting*

As has been emphasized in Section 2, the poverty map cannot provide reasonably precise estimates of poverty below some level of aggregation.[20] It remains of interest, however, to ask how much of a further reduction in poverty could be expected if policymakers could actually target individual households perfectly.[21] We can compare optimal geographic targeting to household level targeting by noting that the budget required to eliminate poverty under the assumption of perfect targeting (i.e. it is possible to observe the precise welfare level of every household and to tailor the transfer received by each household perfectly) is provided by the poverty gap (FGT_1) weighted by the poverty line and the total population. Thus, we can calculate from our poverty mapping database the hypothetical cost of eliminating poverty if it were possible to target the poor perfectly (and there were no behavioral responses). We can then take this budget and target it, instead, geographically, at the lowest level of geographic disaggregation that we feel that the poverty map can support. How far are we from having eliminated poverty when our transfer occurs at this geographic level rather than having been tailored to the precise circumstances of each poor household? In rural Ecuador, optimal parroquia-level geographic targeting of this budget reduces the FGT_2 by only 37% points. Table 4 presents the results for Cambodia. Similar results obtain in Madagascar.

Why does optimal geographic targeting based on our detailed poverty maps fall so far short of the ideal? In a companion paper, Elbers et al. (2004) analyze evidence on the variation of inequality levels within poor communities. They show that in three countries, including two of the countries examined here (Ecuador and Madagascar), within-community inequality varies widely across communities. Some communities exhibit levels of inequality as high, or higher, than overall inequality at the national level, while others are significantly more equal. An important conclusion from this study is that there should be no presumption of lower levels of inequality in poor communities. In fact, in the three countries examined in the above-mentioned study, median inequality is highest amongst the bottom quintile of communities

[20] By 'reasonably precise' estimates, we mean ratios of standard error to point estimate that are similar to those that would be obtained from the household survey at the stratum level. As we will see in the next section, this does not imply that there is no useful information contained in poverty estimates for groups smaller than villages, such as neighborhoods or even households. It does mean, however, that one's ability to draw meaningful inferences declines rapidly as the unit of observation becomes smaller than, say, a village.

[21] One could alternatively ask how much of a further benefit could one expect if, rather than being providing lump-sum transfers to poor communities, policymakers were able to combine geographic targeting with, say, means testing within poor communities.

(ranked either in terms of average per-capita consumption or headcount rate of poverty) and this quintile also displays the highest degree of variation of inequality levels across communities. The implication of this finding is that within very poor communities, even small ones with populations of 5000 households or less, there are likely to be both poor and non-poor households. Community level targeting that transfers a uniform amount to all individuals within these small communities is thus likely to continue to suffer from significant leakage. The poverty impact of such targeting will thus fall short of what would have been possible if perfect targeting were available.

5. Discussion

In this paper, we have used "Poverty Maps" produced in Ecuador, Madagascar and Cambodia to simulate the impact on poverty reduction of transferring an exogenously given budget to geographically defined sub-groups of the population according to their relative poverty status. We have asked to what extent effectiveness of targeting in reducing poverty improves as we define these sub-groups at progressively lower levels of spatial disaggregation.

We have found significant gains from targeting smaller administrative units, such as districts or villages. These gains are large and surprisingly similar in three countries at different stages of development, and with entirely different distributions of welfare. We have shown that the benefits from targeting are particularly clearly discerned when expressed in terms of budgetary savings of achieving a given rate of poverty reduction.

Our assessment of targeting performance has been based on an optimal use of estimates from poverty maps. There might be grounds for concern that the design of transfer schemes based on such optimized routines suffers from lack of transparency and would be difficult to describe in simple terms. Governments may consequently not be able to put such schemes into practice. We have considered, therefore, an alternative transfer scheme, based on a simpler, non-optimal use of the poverty map. We have found that while this particular "naïve" scheme does not achieve the same success in our three countries as the optimal targeting scheme, its performance remains surprisingly good given the budget and poverty line employed in this paper. On the other hand, as shown in Elbers et al. (2004), when the budget or the poverty line is higher, the same targeting scheme we implemented can perform worse than even a uniform transfer to individuals.

The fact that some non-optimal schemes can perform very well under certain circumstances, while others can actually do worse than no targeting in different circumstances points to a useful policy application of the methodology presented here. Given access to similar data for her country, a policy-maker can first evaluate the reduction in poverty using optimal geographic targeting for a given budget. Then, taking into account the political and administrative constraints she faces, she can devise various other transfer schemes that are clear and transparent and choose one that performs reasonably close to optimal targeting (or choose optimal targeting itself, if that is feasible). Hence, such detailed data on poverty can be used as an ex ante evaluation tool for designing a cash transfer scheme that is efficient and realistic.

There are, however, important caveats that attach to these findings. First, we assume that the government is willing to accept that households with equal pre-transfer per-capita consumption levels might enjoy different post-transfer consumption levels.[22] Second, we

[22] This is because two households with the same per capita consumption who live in different communities can receive different transfer amounts under geographic targeting schemes, violating the principle of 'horizontal equity'.

assume that the budget available for distribution is exogenously determined. We abstract away entirely from the question of how the transfers are to be financed. Political economy considerations could influence options for resource mobilization (see for example, Gelbach and Pritchett, 2002). Third, we do not address the very real possibility that the costs of administering a given transfer scheme at the village level may be much higher than at the level of, say, district or province. Fourth, we do not allow for behavioral responses in the population. Finally, we do not address the possibility that inequalities in power and influence that prevail in a community may influence how transfers are allocated. Such factors could result in an overestimation of the impact of the targeting scheme on poverty reduction.[23]

The results in this paper should thus be viewed as illustrative only. The gains from targeting should be juxtaposed against the potential costs and political-economy considerations. In practice, a combination of geographic targeting across villages and some targeting within villages (means-tested or decentralized) may be a more attractive solution. Policymakers need to assess such programs on a case-by-case basis to determine whether fine-geographic targeting is the appropriate strategy.

To conclude, how useful are poverty maps for the purpose of designing geographically targeted poverty alleviation schemes? Our analysis indicates that, in addition to the factors already discussed above, the utility of poverty maps will hinge on two key issues. First is the question of whether the poverty map is able to convincingly distinguish between localities in terms of poverty. This will hinge on the statistical precision of the poverty estimates, which in turn will be largely driven by the accuracy and explanatory power of the consumption models estimated using the household survey data. In the extreme case, if a first stage model had no predictive power (an extremely low R^2) the resulting community level estimates of poverty from the census would all be approximately the same, and confidence intervals around those estimates would be so large as to make it impossible to reject equality of poverty rates across all communities. There would be no gains from geographic targeting over a simple uniform transfer of the available budget.

The second issue concerns the real distribution of wellbeing in a country. Even if estimates of poverty at the community level are fairly precise, as we found them to be in the three countries considered here, simple geographic targeting of resources to communities may not be particularly helpful if variation in living standards *within* communities is pronounced. Geographic targeting will be most effective if the poverty maps reveal both great variation in poverty levels across communities and low levels of inequality in the poorest communities.

One issue that we have not pursued in this paper is the related question of whether poverty maps could be used to target *households* directly. We have emphasized that household-level estimates of poverty, derived based on our methodology, are very imprecise. One might thus expect that household-level targeting using such estimates would yield expected post-transfer poverty rates with very wide confidence intervals, implying considerable risk that the transfer would yield little gains in poverty reduction, but large increases in cost (administrative and

[23] On the other hand, it is also possible that the infusion of transfers into a poor community could increase risk-sharing in that community and thereby contribute to further reductions in poverty. Moreover, Dasgupta and Kanbur (2003) shows that basic results of the targeting literature can change in the presence of community-specific public goods, and that optimal targeting for poverty alleviation can lead to paradoxical results for certain values of the poverty aversion parameter, for example that targeting transfers to the richer community can result in greater welfare gains for the poor (via the increased provision of public goods by the richer segments).

political). However, even highly imprecise household level poverty estimates can still convey some useful information. Indeed, preliminary calculations using the same data employed here suggest that household-level targeting could not only yield significant reductions in expected poverty, but that these gains would be statistically significant.

However, before using this finding to call for a shift from geographic targeting of resources to communities, to the targeting of those resources to individual households, one should acknowledge that there are a whole host of additional issues which come to the fore. These issues extend well beyond statistical considerations. For example, targeting individual households is likely to have quite a different, and generally more pronounced, effect on incentives and household behavior. Implementation of a national targeting scheme to individual households may also be much more difficult to administer than a community-level approach. And there are also ethical concerns that are associated with the fact that average gains in expected poverty reduction would come with large targeting errors at the household level. After all, an empirical study documenting that a particular health treatment would lead, *on average*, to society-wide improvements in health status does not necessarily provide adequate justification for doctors to prescribe that specific treatment to individual patients. The cost of misdiagnosis at the level of the patient might be prohibitively high. An assessment of the merits of household-level targeting against community level targeting requires a broader perspective than what has been possible in this paper. But it is an important subject for future research.

Appendix A. Simulating the impact of "optimal" geographic targeting

As described in the text, given our interest to minimize the FGT_2, optimal geographic targeting implies that after transfers there is a group of locations all sharing the same (maximum) poverty gap in the country. We determine the level of transfers going to each location by first solving a different problem. Following the notation introduced in Section 4 consider the minimum budget $S(G)$ needed to bring down all locations' poverty gaps to at most the level G/z. This amounts to transferring an amount $a_c(G)$ to locations with before-transfer poverty gaps above G/z, such that $G_c(a_c(G))=G$. Once we know how to compute $S(G)$, we simply adjust G until $S(G)$ equals the originally given budget for transfers S. To implement this scheme we must solve the following equation for a_c:

$$G = \int_0^z (z-y-a_c)^+ \mathrm{d}F_c(y). \tag{A.1}$$

In what follows we drop the location index c for ease of notation. Using integration by parts, it can be shown that

$$G(a) = \int_0^z (z-y-a)^+ \mathrm{d}F(y) = \int_0^{z-a} F(y)\mathrm{d}y. \tag{A.2}$$

In other words we need to compute the surface under the expenditure distribution between expenditure levels $y=0$ and $y=z-t$, for values of t up to z. Instead of computing $G(t)$ exactly, we use a simple approximation. For this to work, we split the interval $[0,z]$ in n equal segments and assume that the 'poverty mapping' software has generated expected headcounts for poverty lines zk/n, where $k=0, \ldots, n$. In other words we have a table of $F(zk/n)$. Using the table we approximate $F(y)$ by linear interpolation for y between table values. With the approximated expenditure distribution, it is easy to solve for transfers as a function of G (see below). In practice, we find that $n=20$ gives sufficiently precise results.[24]

The computational set-up is as follows (note that the numbering we adopt means going from z in the direction of 0 rather than the other way around). Define $b_0=0$, and for $k=1,\ldots, n$, b_k as the surface under the (approximated) expenditure distribution between $z-kz/n$ and $z-(k-1)z/n$, divided by z:

$$b_k = \frac{1}{2n}(F(z-kz/n) + F(z-(k-1)z/n)). \tag{A.3}$$

Let g_0 be the original poverty gap, or in terms of the discussion above, $g_0=G(0)/z$. For $k=1, \ldots, n$, put

$$g_k = g_{k-1} - b_k. \tag{A.4}$$

The g_k are the poverty gaps of the approximated expenditure distribution for successively lower poverty lines $z-kz/n$. Let a_k be the per-capita transfer needed to bring down the poverty line to $z-kz/n$:

$$a_k = kz/n. \tag{A.5}$$

We can now solve for per-capita transfers as a function of the intended poverty gap $g<g_0$:

1. Find k such that $g_{k+1} \leq g < g_k$.
2. The per-capita transfers resulting in poverty gap g are

$$a(g) = a_k + \frac{g_k - g}{g_k - g_{k+1}} \cdot \frac{z}{n}. \tag{A.6}$$

This scheme can be implemented using standard spreadsheet software.

References

Baker, J., Grosh, M., 1994. Poverty reduction through geographic targeting: how well does it work? World Development 22 (7), 983–995.

Campante, F., Ferreira, F. 2004. Inefficient Lobbying, Populism and Oligarchy, Policy Research Working Paper No. 3240, Development Economics Research Group, the World Bank.

Coady, D., Morley, S., 2003. From Social Assistance to Social Development: Targeted Education Subsidies in Developing Countries. Center for Global Development and International Food Policy Research Institute.

Dasgupta, I., Kanbur, R. 2003. Community and anti-poverty targeting. Unpublished manuscript.

Demombynes, G., Elbers, C., Lanjouw, J.O., Lanjouw, P., Mistiaen, J., Özler, B., 2002. Producing an improved geographic profile of poverty: methodology and evidence from three developing countries. In: van der Hoeven, R., Shorrocks, A. (Eds.), Growth, Inequality and Poverty: Prospects for Pro-Poor Economic Development. Oxford University Press, Oxford.

Duclos, J., Makdissi, P., Wodon, Q., 2003. Poverty-efficient transfer programs: the role of targeting and allocation rules. CIRPÉE Working Paper 03–05.

[24] Other interpolation schemes are possible. For instance, if the *poverty gap* is given at table values zk/n an even simpler computation presents itself. Often the poverty mapping software will give percentiles of the expenditure distribution. These can also be used for interpolation, but the formulas are more cumbersome, since the percentiles are not equally spaced.

Elbers, C., Lanjouw, J.O., Lanjouw, P., 2002. Micro-level estimation of welfare. Policy Research Working Papers, vol. 2911. Development Research Group, the World Bank, Washington, DC.
Elbers, C., Lanjouw, J.O., Lanjouw, P., 2003. Micro-level estimation of poverty and inequality. Econometrica 71 (1), 355–364.
Elbers, C., Lanjouw, P., Mistiaen, J., Özler, B., Simler, K., 2004. Unequal inequality of poor communities. World Bank Economic Review 18 (3), 401–421.
Foster, J., Greer, J., Thorbecke, E., 1984. A class of decomposable poverty measures. Econometrica 52, 761–776.
Fujii, T., 2006. Commune-level estimation of poverty measures and its application in Cambodia. In: Kanbur, R., Venables, A., Wan, G. (Eds.), Spatial Disparities in Human Development: Perspectives from Asia. United Nations University Press, Tokyo.
Gelbach, J., Pritchett, L., 2002. Is more for the poor less for the poor? The politics of means-tested targeting. Topics in Economic Analysis and Policy 2 (1).
Glewwe, P., 1992. Targeting assistance to the poor. Journal of Development Economics 38, 297–321.
Hentschel, J., Lanjouw, P., 1996. Constructing an indicator of consumption for the analysis of poverty: principles and illustrations with reference to Ecuador. LSMS Working Paper, vol. 124. DECRG-World Bank, Washington, DC.
Hentschel, J., Lanjouw, J.O., Lanjouw, P., Poggi, J., 2000. Combining census and survey data to trace the spatial dimensions of poverty: a case study of Ecuador. World Bank Economic Review 14 (1), 147–165.
Kanbur, R., 1987. Measurement and alleviation of poverty. IMF Staff Papers 34, 60–85.
Mistiaen, J., Özler, B., Razafimanantena, T., Razafindravonona, J., 2002. Putting welfare on the map in Madagascar. Africa Region Working Paper Series 34.
Ravallion, M., 1993. Poverty alleviation through regional targeting: a case study of Indonesia. In: Braverman, A., Hoff, K., Stiglitz, J. (eds.). The Economics of Rural Organization: Theory, Practice and Policy, World Bank and Oxford University Press.
Ravallion, M., 1994. Poverty Comparisons. Harwood Press, Chur, Switzerland.
Ravallion, M., Chao, K., 1988. Targeted policies for poverty alleviation under imperfect information: algorithms and applications. Journal of Policy Modeling 11, 213–224.
Ray, D., 1998. Development Economics. Princeton University Press, Princeton.