WPS4724

Policy Research Working Paper 4724

Simulating the Impact of Geographic Targeting on Poverty Alleviation in Morocco:

What Are the Gains from Disaggregation?

Mohammed Douidich
Abdeljouad Ezzrari
Peter Lanjouw

The World Bank
Development Research Group
Poverty Team
September 2008

Policy Research Working Paper 4724

Abstract

The authors employ the recently completed "poverty map" for Morocco, referring to the year 2004, as a tool for an ex-ante evaluation of the distributional incidence of geographic targeting of public resources. They 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. In both rural and urban areas, the findings reveal large gains from targeting smaller administrative units, such as communes or districts. 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. The results indicate that a useful way forward might be to combine fine geographic targeting using a poverty map with within-community targeting mechanisms.

This paper—a product of the Poverty Team, Development Research Group—is part of a larger effort in the department to develop and apply tools for the analysis fo poverty and income distribution. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at planjouw@worldbank.org.

Simulating the Impact of Geographic Targeting on Poverty Alleviation in Morocco: What Are the Gains from Disaggregation?

Mohammed Douidich, Abdeljouad Ezzrari and Peter Lanjouw[1]

Key Words: Targeting, Poverty, Poverty Maps.

JEL Classification Numbers: C15, I32, H53.

[1] Douidich and Ezrzrari are at the Observatoire sur les Conditions de Vie, Haut Commisariat au Plan, Morocco, and Lanjouw is at the World Bank We are very grateful to Ruslan Yemtsov detailed comments and suggestions. These are the views of the authors and should not be attributed to the Government of Morocco, the World Bank or any affiliated organization. Address for correspondence: planjouw@worldbank.org.

I. Introduction

Public policies in developing countries are often articulated in terms of poverty reduction objectives. In Morocco, a long-standing approach has been to provide assistance in the form of social transfers, food subsidies, and public investments. Recent years have seen a growing appreciation that a significant fraction of such public expenditures has gone disproportionately to the non-poor segments of society. For example, calculations by the Moroccan Planning Commission (Haut-Commissariat au Plan, HCP) indicate that the top quintile in the consumption distribution has received more than 40% of total food subsidies and more than half of the government's subsidies to secondary and tertiary education.

In 2005 the Government of Morocco launched the "Initiative Nationale Pour Le Développement Humain (INDH)" (National Initiative for Human Development). This broad strategy for combating poverty in Morocco aims explicitly to correct for social distortions brought about by mis-targeting of public resources. To this end there has been considerable attention paid to the scope for, and potential benefits from, targeting of poor communities. However, despite their intuitive appeal, transfer schemes targeting poor communities are 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 proxy indicators are used for targeting rather than direct estimates of poverty, mis-targeting can result due to problems with the proxy welfare index at the community level.[2]

[2] For further discussion of the latter problem see Hentschel, Lanjouw, Lanjouw and Poggi (2000).

In recent years there has been growing experience with the development of "poverty maps" that combine household survey with population census data, so as to impute income or consumption to each household in the census.[3] 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 reliable estimates of welfare at the local level. In an attempt to inform the design of policies under the INDH, the HCP developed a poverty map based on census data from 2004 and household survey data from 2002, applying a methodology developed by Elbers, Lanjouw and Lanjouw (2003) under the auspices of the World Bank. Such a poverty map can be used to assess the potential gains in targeting efficiency from geographic targeting.

This paper asks how much the high degree of spatial disaggregation offered by the Moroccan poverty map can help to improve targeting schemes aimed at reducing poverty in the country. The paper builds on the earlier analysis in Ravallion (1993) who finds that spatial disaggregation to 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. Similarly, in a companion study to the present one, Elbers, Fujii, Lanjouw, Özler, and Yin (2007) find that fine geographic targeting offers significant benefits over broad targeting in Ecuador, Madagascar and Cambodia.. As in Ravallion (1993) and Elbers et al (2007), we consider here the distribution of a hypothetical budget to the population of Morocco. 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. 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

[3] See Elbers, Lanjouw and Lanjouw (2002, 2003) and Demombynes, Elbers, Lanjouw, Lanjouw, Mistiaen and Ozler (2002).

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 about poverty outcomes across localities can be incorporated into the design of a transfer scheme so as 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. The schemes span the range between the simplest, most intuitive transfer scheme to one where expected poverty at the national level is minimized subject to information and budget constraints. We compare performance across schemes, and also consider their relative performance at alternative levels of disaggregation. We focus on the squared poverty gap – a measure of poverty that is particularly sensitive to the distance between a poor person's income level and the poverty line.[4] We specify a poverty line that accords with a poverty rate of around 20% nationally, and we postulate a modest hypothetical budget that would be insufficient, in and of itself, to eliminate all poverty, even when perfectly targeted.[5] Finally, we ask how close "optimal geographic targeting" in combination with a poverty map, comes to the hypothetical scenario of "perfect targeting". From this we can get a sense of the potential benefit from combining detailed geographic targeting with additional targeting mechanisms such as means-testing or self-selection targeting mechanisms within communities.

We find that there are potentially large gains in targeting performance from disaggregating to the local level. The benefits become increasingly evident as one makes use

[4] 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 α=0) welfare 'optimization' is not well defined and the approach taken here is thus less obviously applicable (see for example Ray, 1998, pg 254-255).

[5] We have tried more poverty lines and budget sizes, but for reasons of brevity do not present them in this paper. In a companion paper, Elbers, Fujii, Lanjouw, Ozler and Yin (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, Makdissi, and Wodon (2003).

of more and more disaggregated data on poverty. We show that a given impact on poverty can be achieved at considerably less expense with detailed spatial targeting than with a uniform transfer. The gains are generally more muted when the targeting scheme makes only crude use of the local level poverty estimates. However, we find that overall targeting performance with fine geographic targeting, remains far from the ideal of perfect targeting. 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 Morocco. We emphasize that these spatially disaggregated data are estimates, with confidence bounds, rather than actual measures of poverty. Section III 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. Section IV describes the simulation procedures and presents results, and Section V discusses budget allocations across provinces. Section VI provides a concluding discussion.

II. Producing Local Estimates of Poverty

We employ a methodology for producing local-level estimates of poverty that has been described in detail in Elbers, Lanjouw and Lanjouw (2002, 2003).[6] 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 also occur at the household

[6] Elbers, Lanjouw and Leite (2008) present evidence for Minas Gerais, Brazil, in support of the underlying assumptions of the methodology.

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. A general rule of thumb is that welfare estimates obtained on this basis will be estimated fairly precisely as long as the target population comprises at least 1,000-5,000 households. [7]

The first-stage estimation is carried out using household survey data.[8] The empirical models of household consumption allow for an intra-cluster correlation in the disturbances (see Elbers, Lanjouw and Lanjouw, 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 household 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. Since predicted household-level per capita consumption in

[7] 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's 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).

[8] 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.

the census is a function not only of 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, we do not produce just one predicted consumption level per household in the census. Rather, *r* predicted expenditures are simulated for each household (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.[9] The data used in this study consist of the pairing of the 2002 household survey with the 2004 population census.

III. Transfer Schemes

As described in Section I, our main objective in this paper is to see to what extent the availability of poverty estimates for different geographic locations can help to improve the poverty impact of distributing a given budget. We postulate that the government has a budget, *S*, available for distribution and wishes to transfer this budget in such a way as to reduce poverty. We specify a baseline case in which the government is assumed to have no

[9] 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

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. [10]

The analysis in this paper is modeled closely on the approach laid out in Elbers, Fujii, Lanjouw, Özler and Yin (2007), in which the gains from geographic targeting at different levels of geographic disaggregation are assessed in Ecuador, Madagascar and Cambodia. Optimal use of geographically disaggregated information on poverty has been further investigated by Kanbur (1987), Ravallion and Chao (1988), Glewwe (1991), Ravallion (1993), and Baker & Grosh (1994). Kanbur (1987) formalized the theoretical problem of policy design under imperfect information, while Ravallion & Chao (1988) demonstrated how this general targeting problem can be solved in a computationally feasible way.[11] 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(α-1) should be targeted on the margin.[12] Hence, to minimize the squared poverty gap (equal to a poverty measure from the FGT class with α=2), target populations should be ranked by the poverty gap (FGT with α=1) and lump-sum transfers made until the poverty gap of the poorest locality becomes equal

estimates, over the *r* replications, yields the estimated poverty rate in community *c*, and the standard deviation yields the associated estimated standard error.

[10] 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 distributed in a way that mirrored pre-existing inequality. 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.

[11] 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.

[12] Following Foster, Greer and Thorbecke (1984) the FGT class of poverty measures take the following form:

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

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).

to that in the next poorest one, and so on, until the budget is exhausted.[13] Note that although our analysis is undertaken on the basis of the FGT(2) poverty measure, 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.

The second targeting scheme that we compare against our benchmark case assumes some 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.

Of course, countless alternative "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.[14] Indeed, the specific scheme implemented here has the virtue of not only being simple but also surprisingly effective at times.

Our "naïve" scheme takes the following form. We first rank geographic areas by estimated poverty. If our interest was to gauge the impact of our scheme on the headcount rate, we would rank areas by the headcount. But as we wish, in this paper, to assess the impact on the squared poverty gap we rank by those estimates. We have an assessment of overall poverty

[13] Elbers et al (2004) provide a formal statement of this result.
[14] See Elbers et al (2004) for more detail.

in the 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. [15]

Budget and Poverty Lines

As has been mentioned in Section I, 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 this study we employ a number of different budget levels in order to assess the performance of geographic targeting mechanisms under different financial scenarios. As a benchmark, we identify the per capita consumption value of the 25th percentile of the consumption distribution.[16] We scale this consumption value by the total population. Our benchmark

[15] We experimented also with a "constrained" optimal scheme that combined simplicity with a limited degree of optimization. In this secheme, 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.

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

budget is set to equal 5% of this total value. We treat rural and urban areas separately and thus calculate this budget separately in rural and urban areas, respectively.

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 this study, we select as benchmark the official poverty line of 3098 DH in rural areas and 3421 DH in urban areas.. This line yields a rural poverty rate of 23% and urban poverty rate of 8% in 2004.

IV. Simulation Procedures and Results

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.

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:

(7) $$G_c(a_c) = \int_0^z (z - y - a_c)^+ dF_c(y),$$

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:

(8) $$\sum_c N_c a_c = S,$$

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.

Table 1 presents the basic results from our simulations. There are a number of conclusions to be drawn. First, the availability of disaggregated data on poverty can help to improve on a uniform lump-sum transfer across the entire population. Targeting transfers to poor localities, in accordance with the optimization scheme outlined above, yields lower values of the national FGT2 than when the budget is transferred as a uniform lump-sum transfer to the entire population. Second, the more disaggregated the poverty map, the greater the improvement over the uniform lump-sum transfer. Traditionally, household survey data in Morocco are generally able, at best, to provide estimates of poverty at the regional level. The simulations here suggest that with estimates of poverty at the province, commune and district levels, further improvements in terms of impact on the FGT2 with a given budget are attainable, and are non-negligible.[17] Third, while the general patterns we observe are similar across our different budget and poverty line scenarios, they are not identical. We see for example, that the gains from optimal targeting at the district level in rural areas are most striking when an extreme poverty line of 75% of the official poverty line is assumed to hold. In this case a given budget can yield a FGT2 measure that is just over one third (34%) of the FGT2 that would obtain if the budget had been allocated uniformly across the population. Similarly, in urban areas, district level targeting and an extreme poverty line that is 75% of the official poverty line yield an FGT2 measure that is less than one-fifth the value of the FGT2 that would have obtained with a uniform transfer. As is intuitively clear, the lower the poverty line the greater the scope for errors of inclusion with a uniform transfer. Finally, fourth, even though our base-case low budget represents a considerable resource envelope (as evidenced by the sizable impact on poverty of even a uniform lump-sum transfer) it is clear that optimal targeting at the lowest possible level of disaggregation is far from sufficient to eliminate poverty altogether (see further below).[18]

Table 2 repeats the simulations presented in Table 1 but focuses now on the headcount, or FGT0, measure of poverty. As mentioned above the optimization procedure outlined in Kanbur (1987) applies to the squared poverty gap or FGT2 measure. There is no analogous optimization algorithm for the FGT0 measure. We report in Table 2, however, the resulting FGT0 estimates from having applied the procedure to allocate our budget in such a way as to minimize the resulting FGT2 measure. Table 2 reveals that the gains in terms of the FGT0 of

[17] In urban areas, the lowest level of government administration is at the commune level. Urban communes are often very large agglomerations. We apply the census concept of a district in urban areas to explore the potential gains from targeting within communes, but note that such districts do not have an obvious analogue in terms of local administration or government.

[18] 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 optimal transfer simulations and estimating not FGT2 values, but rather the

geographic targeting are far less marked than was observed when the FGT2 measure was our reference measure. In the baseline case, targeting at the district level in rural areas can be expected to achieve a nine percentage point further decline of the headcount rate over the uniform transfer – with commune level targeting the new FGT0 is 91% the value of the FGT0 that would have obtained had the budget been allocated uniformly across the rural population. In urban areas, the gains are more impressive: the new FGT0 is 65% of the value from a uniform allocation across the urban population. Again, when a particularly austere poverty line is selected (column 3) the gains from geographic targeting over uniform targeting are most pronounced.

Calculating "Equivalent Gains"

In thinking about the "performance" of the transfer scheme we are interested not only in the poverty impact of a specific scheme, but also in how much more "expensive" a given poverty reduction would be without, as opposed to with, geographic targeting. To explore the latter we apply a variant on the simulation procedures described above whereby we calculate how much smaller the overall budget *S* could be in order to achieve the same impact on the FGT2 measure with optimal targeting as with the untargeted uniform lump-sum transfer.

Table 3 demonstrates that in rural Morocco even a poverty map at the regional level would have permitted the same reduction in the FGT2 as the uniform transfer at only 76% of the cost of the uniform transfer. With a more detailed rural poverty map that allows for disaggregation down to the district level, the same impact could have been achieved at only 28% of the cost of the uniform transfer. In urban areas, with district level targeting, the same

---

difference in the estimated FGT2 based on optimal targeting at the 3rd administrative level vis-à-vis targeting at the uniform, 1st and 2nd administrative levels. In all cases, these differences are strongly significant.

impact as a uniform transfer can be achieved at 23% of the cost (Table 3). These results confirm that not only are there gains from spatial targeting, but they can be of considerable magnitude.

Simulating the Impact of "Naïve" Geographic Targeting

The optimization scheme implemented above is intuitively straightforward. But it is not always easy to describe and explain in non-technical terms exactly how much each commune should receive under this scheme. 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 combined with simplistic, non-optimal, transfer schemes.

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 Morocco. On the basis of the poverty map we identify the localities that will receive priority in the targeting scheme (we consider initially regions, then provinces, then communes, then districts 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*, 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 be compared to the original estimate of national poverty from the poverty map, and to the estimate of the poverty associated with an untargeted lump-sum transfer.

Table 4 presents results of transferring our given budget on the basis of our naïve scheme. It is striking that the reduction in the FGT2 achievable in rural areas with a naïve scheme, applied at the most disaggregated level possible in the poverty map, is fairly sizeable. Broadly, the reduction in the rural FGT2 on the basis of this scheme is only a few percentage points behind the impact with the optimal scheme. For example, in the baseline case with naïve district level targeting (column 1) the new FGT2 is less than half as much (47%) as it was prior to the transfer. This compares with a new FGT2 of 42% of the original FGT2 measure if targeting had been carried out optimally.

Note, however, that there is no guarantee that a naïve targeting procedure as applied here will, indeed, yield such good results. For example, in urban areas, naïve district level targeting leads to a new FGT2 that is 49% of original measure. This compares with an FGT2 that was just 19% of the original FGT2 when the optimal targeting scheme had been applied (Table 3). Moreover, in column 3 of Table 4 – referring to the baseline budget in combination with a particularly austere poverty line - we can see that naïve targeting at the regional level even in rural areas achieves *less* reduction in overall poverty than is the case with uniform targeting (a post-transfer FGT2 of 69% of the original with naïve targeting versus a post-transfer FGT2 of 61% of the original with uniform targeting). Again in urban areas this is even more clearly seen: naïve targeting at any geographic level higher than the district always leads to a post-transfer FGT2 that is higher than the FGT2 that would obtain with a uniform transfer. And when the poverty line is set at 75% of the official line, even district level targeting under the naïve scheme is less successful than a uniform transfer. The intuition for this finding is straightforward: in urban areas, overall poverty is low and so the transfer *a* being offered to all persons in the priority regions is large (S/N_p). This is rapidly depletes the available budget while benefiting only relatively few poor people (and many non-poor people). After only a few priority regions have been targeted the budget is depleted and poor persons in the other regions receive no transfer. In the contrasting case of the uniform transfer all people in all regions receive a (much smaller) transfer. If the poor are generally located close to the poverty line then even a small transfer might suffice for a large number of them to cross the poverty line, and in this way more poverty reduction can be achieved with a uniform transfer than via our "naïve" scheme. It is clear that in urban areas, the choice of targeting scheme is far from innocuous – with major benefits from applying an optimal targeting scheme, and no gains from applying a naive transfer scheme.

V. Budget Allocations across Provinces

Our discussion above, exploring the gains from geographic targeting in a country such as Morocco, has been essentially hypothetical. We have explored what might have been the impact on measured poverty from distributing a given budget via cash transfer payments, under a variety of transfer rules. A number of principles have emerged from this analysis, the most significant of which is that there are potentially appreciable benefits from fine geographic targeting over a uniform transfer. While these general principles are useful to bear in mind in the design of anti-poverty strategies, they do not directly address the specific details of Morocco's poverty reduction efforts and cannot be used to directly assess or evaluate these efforts.

As was stated in the introduction, in May 2005 King Mohammed VI of Morocco launched the National Human Development Initiative (INDH) and underscored his desire to have this initiative represent a cornerstone of his reign. This initiative builds on previous efforts in Morocco to encourage decentralization and to improve the government's efforts to respond to local needs. The initiative was allocated an initial resource envelope of the equivalent of US$1 billion for the period 2006 to 2010, and these resources are devoted evenly to four broad components: a rural component that targets 403 of the poorest rural communes, an urban component targeting 264 of the poorest urban neighborhoods, a component that focuses specifically on the reduction of vulnerability, and a cross-cutting component aimed at building capacity, information exchange and communication. The rural component aims to finance activities that support access to basic services, development of economic and social infrastructure and income-generating activities. The design of the project is explicitly not an income transfer scheme, but rather one that aims to galvanize the economic and social environment in the poorest rural communities. The selection of the targeted communes in this rural component was based on a number of criteria including their estimated poverty rates – based on the poverty map that was developed with the 1994 census and 1998 survey data.

It is clear that the analysis in the present study cannot be used directly to assess the design and operation of the rural component of the INDH. There are too many ways in which the stylized anti-poverty strategy considered in this study differs from the INDH. However, it may remain of interest to examine how a given budget would be distributed across the provinces of Morocco if an optimal commune-level targeting of income transfers were to be implemented. This budget distribution could be compared against the provincial distribution of the current INDH program. While there is no presumption that the current INDH provincial distribution should be the same as that of the hypothetical anti-poverty scheme examined here, it may be helpful to the authorities if it were observed that there were marked inconsistencies across the actual INDH provincial distribution and the “optimal” distribution.

Tables 5 and 6 provide a breakdown of the hypothetical budget considered in this study if resources were targeted to the poorest districts (Table 5 for rural areas and Table 6 for urban areas) from the 2004 poverty map, and the program was designed to transfer resources uniformly across all individuals in a given commune (but with different amounts across communes) in such a way as to minimize the national FGT2 for rural areas. Column 1 of Table 5 reveals that in the case of the baseline budget and poverty line the five rural provinces of Erachidia (10.67%), Essaouira (7.8%), Ouarzazate (6.6%), Taroudannt (5.2%) and Taza (5.17%) would be allocated a little under two-fifths of the entire budget to be transferred, in order to achieve the more than halving of the overall rural FGT2 that could be achieved with optimal district-level targeting (see Table 1). The remaining 60% of the budget would be distributed broadly across another 45 provinces. It is interesting to note, however, that in the case where the budget available for distribution was only half as much (column 2) these five provinces would account for a larger fraction of the budget (42%), and when the budget is set at the baseline level, but the poverty line is set at only 75% of the baseline case, these five provinces would account for only one-third of the budget to be allocated. Again, this reveals that while the broad priority to be attached to these five provinces seems robust, the specific budget shares that should be devoted to these provinces is not invariant to the location of the poverty line and the overall budgetary envelope that is available for distribution.

In urban areas, optimal district level targeting would less markedly concentrate resources in a small subset of provinces (Table 6). The five provinces of Marrakech-Menara (6.9%), Fes Jdid-Dar-Dbibagh (6.3), Kenitra (6.1%), Casablanca (6.0%) and Tanger Assilah (5.4%) together account for about 30% of the entire budgetary outlays – nearly 10 percentage points less than the five most “deserving” rural provinces. This general picture also remains when we consider the scenarios with half the available budget or 75% of the official poverty line.

VI. Discussion

In this paper we have used a "Poverty Map" produced in Morocco to 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 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 large gains from targeting smaller administrative units, such as provinces, communes or districts. 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 apply such schemes in practice. We have considered, therefore, an alternative transfer scheme, based on a naïve, non-optimal use of the poverty map. We have found that while this naïve scheme does not achieve the same success as the optimal targeting scheme, its performance remains surprisingly good in rural areas. On the other hand, we saw that in urban areas, the naïve scheme we implemented can perform less effectively than even a uniform lump-sum transfer. To the extent that policymakers are concerned about issues of communication and transparency, our results suggest that there are conditions under which even simplistic targeting schemes based on the poverty map can yield encouraging results. But simulation analyses of the kind presented here would be needed to help assess when, and which, simpler targeting approaches might be applicable.

We emphasize further that the stylized analysis presented in this study cannot be used to directly evaluate the existing poverty alleviation efforts of the Moroccan government. We suggest that one possible exercise that might inform policymakers' current deliberations is to compare the hypothetical "optimal" provincial budgetary distribution deriving from the present analysis with the actual provincial distribution that is currently in place. There is no presumption that these two should line up exactly. However, it may well be of interest to follow up with further investigation if this exercise reveals glaring inconsistencies.

There are, however, important caveats that attach to the findings in this paper. 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. Second, we assume in this paper 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 might increase with the degree of disaggregation. Fourth, we do not allow for behavioral responses in the population. Fifth, we do not address the possibility that inequalities in power and influence that prevail in a community influence how transfers are allocated. Such factors could result in an overestimation of the impact of the targeting scheme on poverty reduction.

Thus the results in this paper should be viewed as illustrative only. At all times, the gains from targeting should be juxtaposed against the potential costs and political-economy considerations, as well as scrutinized against other possible policy objectives. In practice, a combination of geographic targeting between villages and means-tested targeting within villages may be the best way forward. Policymakers need to assess such programs on a case-by-case basis to determine just how far to rely on fine-geographic targeting as the central element in their poverty alleviation 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 where a first stage model has no predictive power (an extremely low R^2) the resulting community level estimates of poverty from the census will 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 how real welfare is distributed in a country. Even if estimates of poverty at the community level are fairly precise, as they have been found to be in

Morocco, 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 across communities and low levels of inequality in the poorest communities.

We have not pursued in this paper the related question of whether poverty maps could be used to target *individual households*. We have emphasized that household-level estimates of poverty, derived on the basis of 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 policy would not yield the expected outcome. However, even highly imprecise household level poverty estimates can still convey information. And indeed, preliminary calculations with our data suggest that household-level targeting could not only yield significant reductions in expected poverty, but that even the confidence bounds around this expectation might not be too large. However, we would submit that in deciding to shift from geographic targeting of resources to communities, to the targeting of those resources to individual households, 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. 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. It is an important subject for future research.

References

Baker, J., and Grosh, M. (1994). Poverty Reduction Through Geographic Targeting: How Well Does It Work? World Development 22(7): 983-995.

Coady, D. and 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., and Kanbur, R. (2003). Community and Anti-Poverty Targeting. Unpublished manuscript.

De Janvry, A., Sadoulet, E., Calva, L.F., and Solaga, I. (2003). Concept Paper and Terms of Reference for the External Evaluation of SEDESOL's Microregions Program. Unpublished manuscript, Dept. of Agriculture and Resource Economics, UC Berkeley.

Demombynes, G., Elbers, C., Lanjouw, J.O., Lanjouw, P., Mistiaen, J. and Özler, B. (2002) 'Producing an Improved Geographic Profile of Poverty: Methodology and Evidence from Three Developing Countries' in van der Hoeven, R. and Shorrocks, A. (eds) Growth, Inequality and Poverty: Prospects for Pro-Poor Economic Development (Oxford: Oxford University Press).

Duclos, J., Makdissi, P., and Wodon, Q. (2003). Poverty-Efficient Transfer Programs: the Role of Targeting and Allocation Rules. CIRPÉE Working Paper 03-05.

Elbers, C., Lanjouw, J.O. and Lanjouw, P. (2002). Micro-Level Estimation of Welfare. Policy Research Working Paper 2911, Development Research Group, the World Bank, Washington D.C.

Elbers, C., Lanjouw, J.O. and Lanjouw, P. (2003). Micro-Level Estimation of Poverty and Inequality. Econometrica 71(1): 355-64.

Elbers., C., Lanjouw, P. and Leite, P.G. (2008) Brazil within Brazil: Testing the Poverty Mapping Methodology in Minas Gerais, Policy Research Working Paper No. 4513, World Bank, Washington D.C.

Elbers, C., Lanjouw, P., Mistiaen, J., Özler, B., and Simler, K. (2004). Unequal Inequality of Poor Communities. World Bank Economic Review, Vol 18, No. 3 (401-421).

Elbers, C., Fujii, T., Lanjouw, P., Ozler, B. and Yin, W. (2007) 'Poverty Alleviation Through Targeting: How Much Does Disaggregation Help?' *Journal of Development Economics*, 83, 197-213.

Foster, J., Greer, J. and Thorbecke, E. (1984) 'A Class of Decomposable Poverty Measures' *Econometrica* 52, 761-776.

Fujii, T. (2004). 'Commune-level Estimation of Poverty Measures and its Application in Cambodia'. WIDER Research Paper No. 48, World Institute of Development Economics Research, Helsinki, Finland. (available at: http://www.wider.unu.edu/publications/rps/rps2004/rp2004-048.pdf)

Gelbach, J. and Pritchett, L. (2002). Is More for the Poor Less for the Poor? The Politics of Means-Tested Targeting. *Topics in Economic Analysis and Policy*, Vol 2(1).

Glewwe, P. (1992). Targeting Assistance to the Poor. *Journal of Development Economics* 38: 297-321.

Hentschel, J. and Lanjouw, P. (1996). Constructing an Indicator of Consumption for the Analysis of Poverty: Principles and Illustrations with Reference to Ecuador. *LSMS Working Paper* No.124, DECRG-World Bank: Washington DC.

Hentschel, J., Lanjouw, J.O., Lanjouw, P., and 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)147-65.

Kanbur, R. (1987). Measurement and Alleviation of Poverty. *IMF Staff Papers*, 34:60-85.

Mistiaen, J., Özler, B., Razafimanantena, T., and Razafindravonona, J. (2002). Putting Welfare on the Map in Madagascar. Africa Region Working Paper Series 34.

Ravallion, M. and Chao, K. (1988). Targeted Policies for Poverty Alleviation Under Imperfect Information: Algorithms and Applications. *Journal of Policy Modeling* 11: 213-24.

Ravallion, M. (1993). Poverty Alleviation Through Regional Targeting: A Case Study of Indonesia, in *The Economics of Rural Organization: Theory, Practice and Policy*, editors Braverman, A., Hoff, K. and Stiglitz, J. World Bank and Oxford University Press.

Ravallion, M. (1994) Poverty Comparisons (Harwood Press: Chur, Switzerland).

Ray, D. (1998) Development Economics (Princeton: Princeton University Press).

Appendix
Simulating the Impact of "Optimal" Geographic Targeting

As described in Elbers et al (2007) and in the text, given our interest to minimize the FGT2, 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 III 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:

(A.1) $$G = \int_0^z (z - y - a_c)^+ dF_c(y) .$$

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

(A.2) $$G(a) = \int_0^z (z - y - a)^+ dF(y) = \int_0^{z-a} F(y)dy.$$

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 *z k/n*, where *k=0, …,n*. In other words we have a table of *F*(*z k/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.[19]

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,...,n*, b_k as the surface under the (approximated) expenditure distribution between *z-kz/n* and *z*-(*k-1*)*z/n*, divided by *z*:

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

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

(A.4) $$g_k = g_{k-1} - b_k .$$

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.5) $$a_k = kz/n .$$

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

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

[19] 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.

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

This scheme can be implemented using standard spreadsheet software.

Table 1: Impact on FGT2 of Targeting at Different Levels of Geographic Disaggregation Optimal Targeting Scheme

	Rural Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.02036	0.02036	0.00722
% of original FGT2			
Uniform transfer	71% (100%)	85% (100%)	61% (100%)
Region Level	65% (92%)	80% (94%)	51% (84%)
Province Level	58% (82%)	73% (86%)	41% (67%)
Commune Level	45% (63%)	62% (73%)	26% (43%)
District Level	42% (59%)	59% (69%)	21% (34%)

	Urban Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.00681	0.00681	0.00226
% of original FGT2			
Uniform transfer	53% (100%)	74% (100%)	38% (100%)
Region Level	46% (88%)	67% (91%)	31% (80%)
Province Level	44% (83%)	64% (87%)	29% (75%)
Commune Level	40% (75%)	60% (81%)	24% (63%)
District Level	19% (37%)	33% (44%)	7% (19%)

Table 2: Impact on FGT0 of Targeting at Different Levels of Geographic Disaggregation Optimal Targeting Scheme

	Rural Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.2275	0.2275	0.10491
% of original FGT2			
Uniform transfer	85% (100 %)	93% (100%)	78% (100%)
Region Level	84% (99%)	92% (99%)	74% (95%)
Province Level	82% (96%)	91% (98%)	69% (88%)
Commune Level	78% (92%)	89% (96%)	59% (76%)
District Level	77% (91%)	88% (95%)	54% (69%)

	Urban Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.0801	0.0801	0.0330
% of original FGT2			
Uniform transfer	72% (100%)	86% (100%)	59% (100%)
Region Level	68% (94%)	83% (96%)	52% (89%)
Province Level	66% (92%)	81% (95%)	50% (85%)
Commune Level	63% (88%)	79% (92%)	46% (78%)
District Level	47% (65%)	60% (70%)	23% (39%)

Table 3 Cost of Achieving the Uniform Transfer Impact When Using Optimal Targeting Expressed as a Percentage of Uniform Transfer Outlay

	Rural Areas	Urban Areas
Uniform transfer	100%	100%
Region Level	76.1%	82.0%.
Province Level	57.1%	73.4%
Commune Level	31.4%	64.5%
District Level	27.7%	23.0%

Table 4: Impact on FGT2 of Targeting at Different Levels of Geographic Disaggregation "Naïve" Targeting Scheme

	Rural Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.02036	0.02036	0.00722
% of original FGT2			
Uniform transfer	71%	85%	61%
Region Level	68%	81%	69%
Province Level	62%	76%	59%
Commune Level	51%	69%	44%
District Level	47%	66%	39%

	Urban Areas 2004		
	Baseline Budget Basline Poverty Line	50% of Budget Baseline Poverty Line	Baseline Budget 75% Poverty Line
Original FGT2	0.00681	0.00681	0.00226
% of original FGT2			
Uniform transfer	53%	74%	38%
Region Level	76%	78%	86%
Province Level	78%	79%	83%
Commune Level	76%	76%	81%
District Level	49%	49%	57%

Table 5: Provincial Distribution of Budgetary Resources with "Optimal" District-Level Targeting.

Rural Areas, 2004

Region	Province	Baseline Budget/ Baseline Poverty Line	50% of Budget/ Baseline Poverty Line	Baseline Budget/ 75% of Baseline Poverty Line
		% of Budget		
Oued Ed-Dahab-Lagouira	Aousserd	0,0021	0,0014	0,0013
	Oued Ed-Dahab	0,0015	0,0000	0,0008
Laayoune-Boujda-Sakia El Hamra	Boujdour	0,0000	0,0000	0,0000
	Laayoune	0,0000	0,0000	0,0000
Région	Assa-Zag	0,1048	0,1221	0,0904
	Es-Semara	0,0046	0,0000	0,0081
	Guelmim	0,6691	1,0574	0,5798
	Tan-Tan	0,0502	0,0655	0,0416
	Tata	0,6663	0,5749	0,6754
Souss –Massa-Draa	Agadir-Ida ou Tanane	0,1476	0,0302	0,2229
	Chtouka Ait Baha	1,5854	1,5109	1,5805
	Inezgane Ail Melloul	0,1660	0,0697	0,1653
	Ouarzazate	6,6297	8,1895	5,7310
	Taroudannt	5,1833	4,6297	4,8425
	Tiznit	1,9956	1,4573	2,1687
	Zagora	2,0899	1,5645	1,8815
Gharb-Chrarda-Béni Hssen	Kenitra	5,1251	4,1464	5,6199
	Sidi Kacem	4,2732	3,3046	4,9088
Chaouia-Ouardigha	Benslimane	0,7984	0,6638	1,1586
	Khouribga	1,2524	0,8857	1,6306
	Settat	0,8426	0,2151	1,5393
MarrakechTensift-Al-Haouz	Al Haouz	0,9319	0,5432	0,8621
	Chichaoua	3,0240	2,9484	2,5675
	El Kelaa des Sraghna	4,0929	2,7147	3,5097
	Essaouira	7,8308	9,9106	6,3503
	Marrakech-Menara	0,0897	0,0092	0,2284
Oriental	Berkane	0,5150	0,4509	0,5748
	Figuig	2,2377	3,8629	1,8640
	Jerada	1,3127	2,0763	0,9614
	Nador	1,6573	1,7560	2,0401
	Oujda-Angad	0,2411	0,0511	0,4220
	Taourirt	2,1741	2,8025	2,1357
Grand Casablanca	Casablanca	-	-	-
	Médiouna	0,0001	0,0000	0,0217
	Mohammadia	0,0085	0,0000	0,0679
	Nouaceur	0,0094	0,0000	0,0545
Rabat-Salé-	Khemisset	1,1911	0,6946	2,1192

Region	Province	Baseline Budget/ Baseline Poverty Line	50% of Budget/ Baseline Poverty Line	Baseline Budget/ 75% of Baseline Poverty Line
		% of Budget		
Zemmour-Zaer	Rabat	-	-	-
	Salé	0,4641	0,2781	0,6625
	Skhirate-Temara	0,0660	0,0174	0,2208
Doukkala-Abda	El Jadida	3,2497	2,3924	2,8270
	Safi	2,6672	1,2749	2,1604
Tadla-Azilal	Azilal	2,4093	1,9930	1,9503
	Beni Mellal	0,2347	0,1916	0,1862
Meknes-Tafilalet	Al Ismailia	1,8856	1,9801	1,9634
	El Hajeb	0,1475	0,0306	0,2787
	Errachidia	10,6089	14,6572	9,8554
	Ifrane	0,0365	0,0098	0,0312
	Khenifra	4,0114	4,4967	4,1413
Fes-Boulemane	Boulemane	1,9444	1,9704	2,2005
	Fes Jdid-Dar-Dbibagh	0,0000	0,0000	0,0013
	Sefrou	1,1020	1,4366	1,0563
	Zouagha Moualay Yacoub	1,3953	1,6551	1,4645
Taza-Al Hoceima-Taounate	Al Hoceima	0,5423	0,3089	0,7407
	Taounate	0,6289	0,2132	1,0241
	Taza	5,1707	5,2289	5,3820
Tanger-Tetouane	Chefchaouen	1,6523	0,7983	2,0153
	Fahs-Bni-Makada	1,8232	2,2499	1,7610
	Larache	1,3389	1,0188	1,5781
	Tange Assilah	0,2786	0,1526	0,3366
	Tétouan	1,4382	1,3368	1,5362
TOTAL		100 %	100 %	100 %

Note: The provinces of Casablanca and Rabat do not contain any rural areas.

Table 6: Provincial Distribution of Budgetary Resources with "Optimal" District-Level Targeting.

Urban Areas, 2004

Region	Province	Baseline Budget/ Baseline Poverty Line	50% of Baseline Budget/ Baseline Poverty Line	Baseline Budet/ 75% of Baseline Poverty Line
		% of Budget		
Oued Ed-Dahab-Lagouira	Aousserd	0.0000	0.0000	0.0000
	Oued Ed-Dahab	0.0628	0.0499	0.0312
Laayoune-Boujda-Sakia El Hamra	Boujdour	0.1035	0.0063	0.1358
	Laayoune	0.4988	0.5925	0.5032
Guelmim-Es-Semara	Assa-Zag	0.1385	0.0623	0.1636
	Es-Semara	0.2383	0.3263	0.2085
	Guelmim	1.1034	1.1150	1.0998
	Tan-Tan	0.4321	0.2567	0.4874
	Tata	0.4411	0.4683	0.4241
Souss –Massa-Draa	Añadir-Ida ou Fanane	1.9032	2.2281	1.8562
	Chtouka Ait Baha	0.2059	0.1090	0.2259
	Inezgane Ail Melloul	2.2009	1.7281	2.3768
	Ouarzazate	0.8493	0.6565	0.8634
	Taroudannt	1.3122	1.1445	1.3506
	Tiznit	0.2044	0.1638	0.2219
	Zagora	0.3690	0.2655	0.3899
Gharb-Chrarda-Beni-Hssen	Kenitra	6.1400	8.3391	5.5691
	Sidi Kacem	2.0688	2.0639	2.1079
Chaouia-Ouardigha	Benslimane	0.3554	0.2907	0.3840
	Khouribga	2.3024	2.1935	2.3351
	Settat	2.0087	1.7074	2.0406
MarrakechTensift-Al-Haouz	Al Haouz	0.6078	0.5754	0.6109
	Chichaoua	0.7756	1.0475	0.6916
	El Kelaa des Sraghna	2.7374	3.2991	2.5384
	Essaouira	1.2450	1.4229	1.1611
	Marrakech-Menara	6.9347	6.5466	7.0183
Oriental	Berkane	1.1301	1.0140	1.1629
	Figuig	0.4755	0.4340	0.4623
	Jerada	0.6734	0.6635	0.6427
	Nador	3.1112	2.9897	3.1753
	Oujda-Angad	2.6137	2.4994	2.6775
	Taourirt	1.8877	2.4671	1.7246
Grand Casablanca	Casablanca	5.9665	6.1023	6.3198
	Mediouna	0.7966	0.9403	0.7341
	Mohammadia	1.1408	1.3647	1.0618
	Nouaceur	0.3118	0.3022	0.3016
Rabat-Sale-Zemmour-Zaer	Khemisset	1.8439	1.8463	1.8263
	Rabat	1.4966	1.5203	1.5059
	Sale	3.8160	3.5303	3.7849
	Skhirate-Temara	2.9060	4.0686	2.5357

		Baseline Budget/ Baseline Poverty Line	50% of Baseline Budget/ Baseline Poverty Line	Baseline Budet/ 75% of Baseline Poverty Line
Doukkala-Abda	El Jadida	2.0346	2.1450	2.0620
	Safi	2.6404	2.5051	2.6893
Tadla-Azilal	Azilal	0.4346	0.2725	0.4674
	Beni Mellal	2.9335	2.3660	3.1029
Meknes-Tafilalet	Al Ismailia	3.5821	3.1393	3.6557
	El Hajeb	0.9420	0.9924	0.9199
	Errachidia	1.2955	1.0270	1.2787
	Ifrane	0.5528	0.4978	0.5734
	Khenifra	2.7196	2.7002	2.6773
Fes-Boulemane	Boulemane	0.5430	0.5935	0.5032
	Fes Jdid-Dar-Dbibagh	6.3347	4.7654	6.5880
	Sefrou	0.9824	0.9408	1.0007
	Zouagha Moualay Yacoub	0.0478	0.0526	0.0413
Taza-Al Hoceima-Taounate	Al Hoceima	0.4493	0.3468	0.4936
	Taounate	0.3270	0.2574	0.3603
	Taza	1.1600	1.1954	1.1777
Tanger-Tetouane	Chefchaouen	0.2410	0.1823	0.2533
	Fahs-Bni-Makada	-	-	-
	Larache	1.7916	2.0704	1.7474
	Tange Assilah	5.3503	5.4818	5.3899
	Tetouan	2.2289	2.0663	2.3077
TOTAL		100%	100%	100%