Assessing the Targeting Performance of Social Programs: Cape Verde

Angel-Urdinola, Diego and Wodon, Quentin

World Bank

January 2008

CHAPTER 13

Assessing the Targeting Performance of Social Programs

Cape Verde

Diego Angel-Urdinola and Quentin Wodon

Budget constraints faced by governments in developing countries imply that effectively targeting performance of public subsidies and social programs (whether the subsidies are provided in cash or in kind) is important in reducing poverty. There are three main advantages to effective targeting. First, for programs not intended to offer universal coverage, better targeting helps reduce program outlay because there are fewer beneficiaries. Second, for any given level of outlay, better targeting suggests that the share of public expenditure that accrues to poor people typically will be higher and so will enable the programs to have a larger impact on poverty. Third, targeting may help reduce the potential negative incentive effects or distortions in economic behavior associated with transfers if fewer households are affected by the programs. For example, if fewer households benefit from subsidized water or electricity service, there will be less incentive to consume more than would be consumed normally if the full cost of the service were paid by the household. Too much targeting, however, can produce negative incentive effects. In some industrial countries, transfers may lead to poverty traps whereby the incentives for some households to emerge from poverty are lessened by high implicit taxation rates associated with increased income and decreased transfers.

In this chapter, our objective is not to discuss the incentive effects associated with social programs; rather, we intend to document the incidence or distributional properties of the programs under way in Cape Verde, a group of islands off the West African coast in the North Atlantic Ocean, and to analyze whether some systems of targeting could help improve targeting performance.[1]

According to the Cape Verde poverty report prepared by the World Bank (2005), public transfers in Cape Verde represent, on average, between 5 percent and 13 percent of household income, depending on the consumption quintile to which a household belongs. Most social public spending is invested for education, health care, and pensions. As a result, school enrollment rates are high and the country has been successful in eradicating most communicable diseases and in achieving the best performance levels for basic indicators among sub-Saharan African countries.[2]

Cape Verde, however, needs to improve the efficiency of its spending because of budget constraints. The demands for education and health care have increased, with nearly universal access to primary education translating into a higher demand for secondary and tertiary education. Unit costs per student in primary school increased from $60 in 1993 to $128 in 2000. The increase at the secondary level was even larger, from $125 in 1993 to $334 in 2000 (World Bank 2005). Estimates suggest that the annual unit cost for a student in tertiary education circa 2004–05 could be as high as $2,000 (because of investment in new university facilities and study-abroad programs promoted by the government).

Because overall life expectancy is high, the health care system faces the challenge of providing subsidized and affordable medical care to a growing and aging population in need of expensive and complicated treatments. Government expenditures on pensions also are substantial and the financial situation of the contributory pension system is not sustainable in the long run (see World Bank 2007).

Beyond an analysis of the incidence of public spending in Cape Verde, we also provide a framework for analyzing the factors that determine the targeting performance of social programs and transfers. Whereas most indicators of benefit incidence are silent as to why subsidies are targeted the way they are (that is, the indicators give only an idea of subsidies' targeting performance),[3] we develop a simple decomposition that enables an analysis of both "access" and "subsidy design" factors that affect subsidies' overall targeting performance. Finally, we explore the potential for more effective targeting of social programs in Cape Verde by comparing the targeting performance that could be achieved either under a proxy means-testing system or under a geographic targeting system based on a poverty map recently completed.

To sum up, to increase efficiency and limit costs, efforts must be made to allocate resources to those segments of the population that most need them. In this chapter, we analyze how public transfers are targeted using data from a 2001–02 national household survey, and study the incidence and coverage of public transfers. Because incidence analysis does not explain the rationale behind resource allocation, we look at the determinants of the system's targeting performance following a framework developed by Angel-Urdinola and Wodon (2007). We also discuss alternative targeting mechanisms to improve performance.

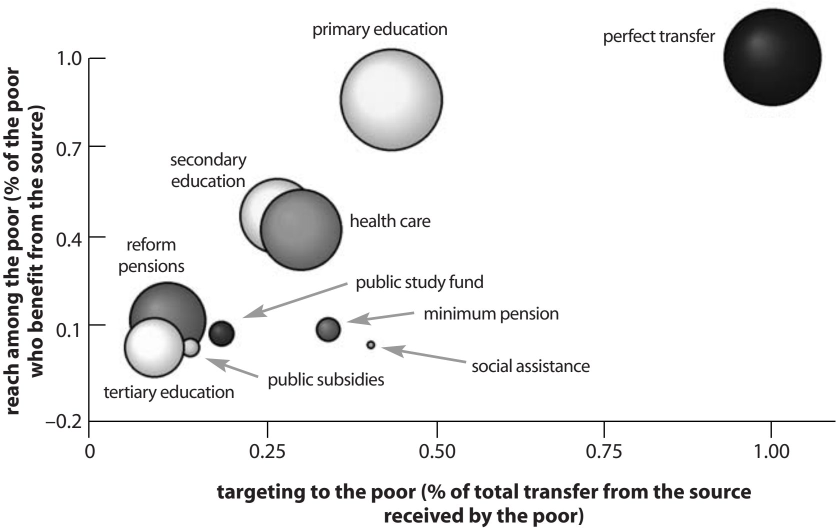
Incidence of Public Transfers and Targeting Performance

This section provides an analysis of the incidence and coverage of public transfers in Cape Verde, using data from the *Inequérito às Despensas e Receitas Familiares* household survey conducted by Cape Verde's Ministry of Finance and the National Institute for Statistics during the last trimester of 2001 and the first trimester of 2002. The survey collected general information on households and individuals (including data on demographics, education, assets, and health) and comprehensive information on income and expenditures. The stratified sample included 4,584 households (44 percent from rural areas) and was representative of the total population (approximately 95,257 households).

Our analysis covers all public transfers that could be identified in the household survey. Public spending for primary, secondary, and tertiary education is considered, as are outlays for public pensions (that is, reform pensions, which are traditional pensions, and minimum pensions, which target poor people).[4] The survey also included information on school stipends (*bolsas de estudo*), other public subsidies (*abonoes e subsídios diversos*), and social assistance (*prestações de assistência social pelas administrações publicas em género*).

Many assumptions have been made in using the survey data. One assumption is that the unit cost of providing basic in-kind public services—say, in education and health—is similar across geographic areas or household categories that use these services. As noted by Wodon and Ye (2006)

Figure 13.1. Incidence and Coverage of Remittances/Private Transfers, 2001–2002



Source: Authors' estimates.

in the case of Sierra Leone, when this assumption is not verified, it typically is because poor people benefit more than nonpoor people from lower-cost (and lower-quality) services. This means that the estimates of in-kind benefits accruing to the poor from the use of publicly provided services, as presented here, are probably overstated.

To present and visualize our results on the incidence of public transfers, we first rely on a diagram that provides three sources of information at once (figure 13.1). The three indicators are the percentage of the poor population that benefits from any given income source, the percentage of the total income from a source that is received by the poor, and the size of the income source (that is, the total income from the source obtained by the population as a whole). Here are the key results portrayed in the figure:

- *Sizes of various transfers:* Primary, secondary, and tertiary education; health care; and reform pensions all represent large public transfers to households (pensions are not purely public transfers, however; they are partly private contributions because workers have contributed to the pension scheme). Outlays for minimum pensions, school stipends, social assistance, and other public subsidies are much smaller.

- *Coverage:* For primary and secondary education and for health services, coverage levels are fairly high. For other transfers, coverage levels are in the 10–15 percent range or even lower. For example, coverage of tertiary education among the poor is virtually zero.
- *Targeting:* Given that poor people represent 36.7 percent of the country's population,[5] a lower share than 36.7 percent would mean that, relative to their population size, poor people benefit less from transfers than does the population as a whole. As expected, the targeting indicators are more favorable for primary education than for secondary education and health, with virtually none of the spending on tertiary education benefiting the poor. The share of reform pension outlays that reaches the poor also is minimal. About a third of the outlays for the minimum pension schemes do reach the poor, but poor people still receive a lower share of these outlays relative to their proportion of the total population. That suggests weaknesses in the targeting system for these pensions. About 40 percent of social assistance outlays reach the poor, but the targeting indicator is lower for other public subsidies and schooling stipends.
- *Eradication of poverty:* The large bubble on the upper right corner on Figure 13.1 represents the size of a perfectly targeted transfer that would be sufficient to eradicate poverty (the coverage among the poor would be 100 percent, as would be the targeting among the poor, since the transfer would provide to each poor household exactly what is needed to lift the household to the poverty line). Pooling the resources from various types of cash transfers could go a long way in reducing poverty if all these resources were better targeted to the poor. Aiming for perfectly targeted transfers is obviously difficult in most cases (such as reform pensions, which are meant to replace income lost by retirement), and we do not recommend it because many of the transfers are meant to cover a larger population than the poor. Still, overall, only a small portion of the transfers typically reach poor people so the effect of those transfers on the reduction of poverty is relatively limited.

Following Angel-Urdinola and Wodon (2007), another way to look at benefit incidence is to define a simple indicator of targeting performance, Ω, which is the share of the subsidy benefits received by the poor (S_P / S_H, where S_P denotes the value of all subsidies accruing to the poor and S_H denotes the total value of the benefits received by the population as a whole) divided by the proportion of the population in poverty (P/H, where P denotes the number of poor households or individuals and H denotes the number of households in the overall population. In mathematical notation, we have

$$\Omega = \frac{S_p}{P} \Big/ \frac{S_h}{H}. \tag{13.1}$$

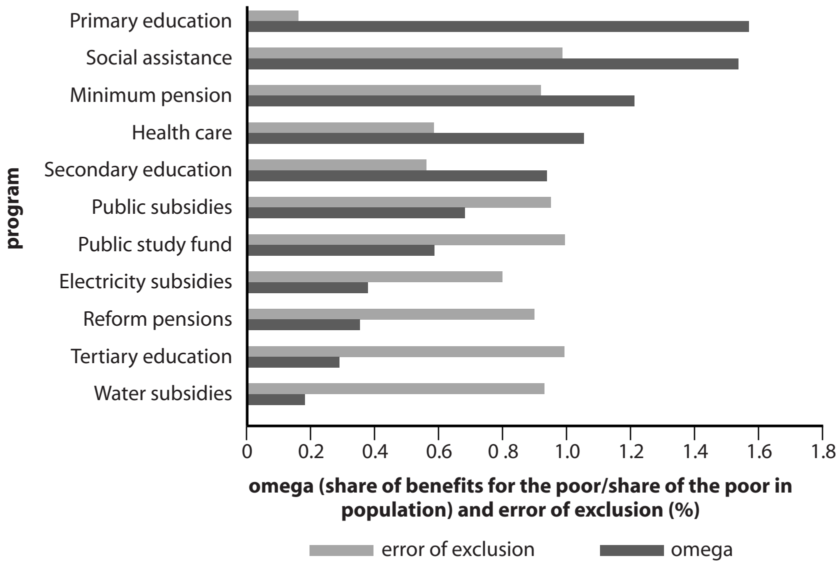
A value of 1.00 for Ω implies that the subsidy distribution is neutral, with the share of benefits going to the poor proportional to their population share. A value above (below) 1.00 for Ω implies that the subsidy distribution is progressive (regressive): the poor receive a larger (smaller) share of the benefits than their population share. The smaller the number, the more regressive it is—and vice versa.

In our analysis, we also provide data on the public transfer allocations' errors of exclusion. An error of exclusion occurs when a poor household does not benefit from a subsidy. Denoting by B_p the proportion of households who get the public transfer (that is, the beneficiary incidence or coverage level among the poor mentioned in the discussion of figure 13.1), the share of poor households excluded from the subsidy is

$$\text{Error of exclusion} = 1 - B_p. \tag{13.2}$$

Figure 13.2 displays the value of the targeting performance indicator, Ω, as well as the errors of exclusion for the public transfers described above and for subsidies for the consumption of water and electricity (these values are obtained from Angel-Urdinola and Wodon 2007). As before, the results suggest that public transfers related to primary education, social assistance, minimum pensions, and health care are the most pro-poor (that is, the value of Ω is greater than 1). With the exception of primary education and, to some extent, health care, however, program coverage is very limited because the errors of exclusion are often high. Other public transfers (secondary education, the public study fund that provides grants for schooling, electricity and water subsidies, reform pensions, and tertiary education) display values of Ω lower than 1, suggesting that resources are allocated more heavily to nonpoor households than to poor households. Most of the programs with low values for Ω also have very limited coverage, as suggested by their high errors of exclusion.

Figure 13.2. Indicators of Targeting Performance



Source: Authors' calculations.

Factors That Determine Targeting Performance

The data presented above suggest that many poor households in Cape Verde do not receive a range of public transfers and that the values of the targeting performance indicators Ω are often lower than 1. As Angel-Urdinola and Wodon (2007) described in detail for the case of water and electricity subsidies, there may be both "access" and "subsidy design" factors that contribute to low targeting performance and poor coverage.

Access factors can de divided into physical access (A) and usage or "take up" of subsidies or services (U). Let A_H represent the share of all households having physical access to (or being eligible for) a transfer or service. For example, access to primary education is available only in communities or geographic areas where there are schools. Given access, let $U_{H|A}$ be the share of households who have physical access to a public transfer or service and choose to use it or are eligible for it (this could not occur, for instance, if parents do not send their children to school because they can't afford the fees or if eligible households do not receive a cash transfer to which they are entitled because they lack information about the program).

Subsidy design factors are those that determine the final distributional incidence of the transfer, once we know who could benefit from the subsidy or transfer because the household has access to it and is using the service. A first subsidy design factor is the targeting mechanism used. $T_{H|U}$ is defined as the share of households among those using a service that actually get the public transfer (that is, the beneficiary population among the population that potentially can benefit from the transfer because it has access and is using the service).

A second subsidy design factor is the rate of subsidization, *R*. Denote the average unit cost of the service by C (such as the average annual unit cost per student in primary school). C is assumed to be constant across all households. The total cost of serving a customer is a function of C and of the quantity consumed (or the number of beneficiaries using the service), denoted by Q. If the average quantity consumed by *subsidy recipients* is $Q_{H|T}$, and the average private expenditure on the good (such as co-payments for health care or education) is denoted by $E_{H|T}$, then the average rate of subsidization is $R_{H|T} = 1 - E_{H|T} / (Q_{H|T} * C)$. As shown in Angel-Urdinola and Wodon (2007), the parameter Ω can be described as a product of five ratios, as follows (denoting by *P* the poor):

$$\Omega = \frac{A_P}{A_H} \times \frac{U_{P|A}}{U_{H|A}} \times \frac{T_{P|U}}{T_{H|U}} \times \frac{R_{P|T}}{R_{H|T}} \times \frac{Q_{P|T}}{Q_{H|T}}. \tag{13.3}$$

The first two ratios represent the service access rate among the poor divided by the access rate among the population as a whole, followed by the usage rate for a service (given access) for the poor compared with the rate for the population as a whole. Typically, one would expect that the ratio of access rates (*A*) would be lower than 1 because the poor tend to live in areas with lower access to public transfers and services than the population as a whole. Similarly, one would expect that the ratio of the usage rates for transfers and services (*U*) would be lower than 1 because a lack of information and, perhaps, a lack of funds makes poor people less likely to use public services than is the population as a whole where there is access. This "access-factors handicap" can be expected to work against the targeting of public transfers to the poor. Subsidy design factors will need to overcome the access handicap if the distribution of transfers is to be progressive, so that the value of Ω is larger than 1. This result could be observed among others if targeting is good (among those using the service, the poor are more likely to receive the public transfer than is the population as a whole), if the unit reduction in price versus full cost received by the poor is larger than for the nonpoor, or if the poor are likely to consume more of the good than is the population as a whole when they have been found eligible for the transfer (for example, the poor may have more children enrolled in public schools than does the total population).

Table 13.1 provides the results of the above Ω decomposition to explain in more detail the key determinants of targeting performance for the various public transfers observed in Cape Verde's household survey. For primary education and health care, which present values of Ω greater than 1, access generally is high among the poor (that is, A_P is close to 1 in both cases), and usage rates are larger among the poor (that is, $U_{P|A} > U_{H|A}$). The latter finding probably arises because richer households can afford to choose to use private services for either education or health care. We find, for instance, that usage rates for primary education are 10 percentage points higher than average among poor households, and rates for health care are 3 percentage points higher. As expected, overall usage rates for education are higher than for health care (78–87 percent versus 35–38 percent) because households are more likely to have children in the education system than to have a member (presumably sick) actively using health services. In terms of quantity consumed, we find that the Q ratios for primary education and health care are close to 1. For education, the Q ratio is slightly above 1 for education because, on average, poor households are larger and thus more likely to have more children using education services on a yearly basis (thus, $Q_{P|T} = 2.03 > Q_{H|T} = 1.75$). For health care, the ratio is slightly below 1, which is not surprising because richer households usually have a higher average of effective health consultations per household each year ($Q_{P|T} = 33.6 < Q_{H|T} = 34.22$; these values are high because the number of recent visits is annualized). For secondary education, the value of Ω is also slightly lower than 1, mainly stemming from a high Q ratio ($Q_{H|T} = 1.6 > Q_{P|T} = 1.5$), which results from nonpoor households tending to have more children in secondary school. Users of minimum pensions and social assistance programs, which also display a value for Ω greater than 1, generally are poor households, and thus $A_P * U_P > A_H * U_H$. Q ratios for these two programs, on the contrary, are usually lower than 1, which suggests that, on average, richer households receive larger nominal benefits than do poor households.

Other programs (public subsidies, public study funds, and social assistance programs) display Ω values below 1. For example, it is striking to see that social assistance programs are not well targeted, and it would be

Table 13.1. Decomposition of Determinants of Public Transfers Performance

Program	*Ratio of share of households with community access to service (A)*	*Ratio of share of households with access who use service (U|A)*	*Ratio of share of users who receive subsidy (T|U)*	*Ratio of subsidization (R|T)*	*Ratio of average quantity consumed (Q|T)*	*Unit cost (CVEsc) (C)*
Water subsidies						
Poor households	0.52	0.20	1.00	0.40	3.36	350
All households	0.65	0.41	1.00	0.33	6.37	350
Ratio	0.79	0.49	1.00	1.19	0.53	350
Electricity subsidies						
Poor households	0.72	0.34	1.00	0.11	56.83	20.5
All households	0.82	0.54	1.00	0.06	111.72	20.5
Ratio	0.88	0.63	1.00	1.70	0.51	20.5
Primary education						
Poor households	1.000	0.877	1.000	1.000	2.032	31,370
All households	1.000	0.780	1.000	1.000	1.751	31,370
Ratio	1.000	1.124	1.000	1.000	1.160	31,370
Secondary education						
Poor households	0.984	0.399	1.000	1.000	1.514	27,552
All households	0.993	0.408	1.000	1.000	1.581	27,552
Ratio	0.991	0.978	1.000	1.000	0.958	27,552
Tertiary education						
Poor households	0.163	0.034	1.000	1.000	1.432	412,386
All households	0.272	0.091	1.000	1.000	1.106	412,386
Ratio	0.599	0.374	1.000	1.000	1.295	412,386

Health care						
Poor households	0.993	0.388	1.000	1.000	33.640	1,743
All households	0.994	0.358	1.000	1.000	34.215	1,743
Ratio	0.999	1.085	1.000	1.000	0.983	1,743

Program	*(A x U)*	*(T|U)*	*(R|T)*	*(QC|T)*
Reform pensions				
Poor households	0.097	1.000	1.000	65,269.64
All households	0.102	1.000	1.000	175,155.30
Ratio	0.954	1.000	1.000	0.373
Subsidies				
Poor households	0.049	1.000	1.000	28,892.04
All households	0.071	1.000	1.000	29,415.58
Ratio	0.690	1.000	1.000	0.982
Public study fund				
Poor households	0.006	1.000	1.000	115,597.60
All households	0.010	1.000	1.000	126,327.50
Ratio	0.638	1.000	1.000	0.915
Social assistance				
Poor households	0.013	1.000	1.000	24,545.98
All households	0.006	1.000	1.000	32,721.84
Ratio	2.039	1.000	1.000	0.750
Minimum pension				
Poor households	0.070	1.000	1.000	31,734.90
All households	0.047	1.000	1.000	38,888.40
Ratio	1.486	1.000	1.000	0.816

Source: Authors' calculations.

useful to learn why this is true by examining the various subprograms in this category.[6] In any case, contrary to what we observed for minimum pensions, users of these various programs and transfers are more likely to be nonpoor households and thereby $AP * UP < AH * UH$). Furthermore, Q ratios for these programs are lower than 1, which suggests that richer households receive greater benefits, on average. As for utility services, low Ω values for electricity and water subsidies result from a combination of different subsidy rates and quantities consumed by poor and nonpoor households. Although the rate of subsidization is greater for poor households than for all households ($R_{P|T} = 0.11$ versus $R_{H|T} = 0.06$), the average quantity (in kilowatt hours) consumed per month by poor households connected to the network is less than half the quantity consumed in the population as a whole ($Q_{P|T} = 49.31$ versus $Q_{H|T} = 111.72$). Indeed, because the system provides greater subsidies to households that consume less (the country implemented an inverted block tariffs scheme), this difference in consumption levels explains why the energy bills of poor households are more discounted than bills of other households. However, nonpoor households still receive a larger subsidy each month than do the poor households because they consume more electricity and almost all of their consumption is subsidized to some degree: the product of $R_{P|T} / R_{N|T} * Q_{P|T} / Q_{N|T}$ is 0.81.[7]

Improving Targeting Performance

Targeting is a relevant subsidy factor for improving the allocation of resources so that they become more beneficial for poor people. There are several targeting mechanisms that policy makers can design to define criteria for public transfer eligibility. Some of the more widely used mechanisms are geographic targeting (whereby benefits are allocated in localities with high concentrations of poverty), quantity targeting (through which benefits are allocated to users who consume smaller quantities of service), and proxy means testing (whereby benefit allocations are based on the prediction of a household's poverty level, reflected by certain visible characteristics). Targeting mechanisms are well designed to the extent they provide more accurate predictions of which households are poorer (and therefore in greater need of public transfers). In this section, we analyze the predictive power of means-testing and geographic mechanisms.

Proxy Means Testing to Predict Household Poverty

Proxy means-testing mechanisms rely on a method of predicting household welfare based on visible characteristics. Like the other targeting methods, proxy means testing may be used in combination with quantity targeting or may be the sole basis for identifying subsidy beneficiaries.

To design a proxy means-testing mechanism, we relied on linear regressions to predict household welfare. In particular, we used the natural log of per capita expenditure as the dependent variable, and we controlled for household characteristics that may predict per capita consumption and that are easily verifiable by a social worker. These household-level variables include the log of the household size (to allow for nonlinearity), whether the household head is female, the age of the head and the age squared, the literacy and education levels of the head (the excluded category is a household head who has no education), and other infrastructure variables (for example, household access to electricity, piped water, and a toilet; and a household dwelling's type of walls, floor, and ceiling). We also included a vector of geographic variables (a set of geographic dummies for every island) and dummies reflecting whether households possess a series of assets (television, radio, telephone, oven, refrigerator, washing machine, bicycle, motorcycle, and other motor vehicles). To maximize the predictive power of our regression, we relied on stepwise estimation. This method ensures that the set of available variables included in our model provides the highest possible fit as measured by the R^2. When the model was estimated, we generated a predictor of the dependent variable. Additionally, we created a dummy variable (*poor*) that takes the value of 1 if the "observed" value of household per capita consumption is below the official poverty line (equivalent to CVEsc 43,249.8 per capita annually), and a second dummy (*predicted poor*) that equals 1 if the "predicted" value of the household's per capita consumption fulfills the same condition.

Regression results are available on request. In general, when making statistical predictions based on linear regressions, two errors arise (Type I and Type II errors). In our case, the Type I error (error of exclusion) would consist of excluding from a targeted program households that are poor but are predicted to be nonpoor on the basis of the proxy means-testing mechanism; and the Type II error (error of inclusion) would consist of allocating program benefits to households that are nonpoor. Findings of how well our model predicts poverty (and the size of the Type I and Type II errors) are presented in table 13.2.

Table 13.2. Errors of Exclusion and Inclusion in a Proxy Means-Testing Model

	All households		
Targeting indicator	*National*	*Urban*	*Rural*
Poor, predicted poor	0.175	0.095	0.295
Poor, predicted nonpoor	0.106	0.080	0.125
Error of exclusion	0.377	0.459	0.298
Nonpoor, predicted nonpoor	0.651	0.793	0.451
Nonpoor, predicted poor	0.069	0.032	0.129
Error of inclusion	0.095	0.039	0.222
Sample size (number of households)	4,583	2,463	2,120
Weighted sample size	95,237	54,283	40,954

Source: Authors' calculations.

In Cape Verde, 28.1 percent of all households are poor. As shown in table 13.2, our model rightly predicted as "poor" 17.5 percent of the actual 28.1 percent, and it wrongly predicted the remaining 10.6 percent (therefore, the Type I error is equivalent to approximately 38 percent, as a share of the predicted poor). Table 13.2 presents similar results for urban and rural areas. The Type I error is 46 percent in urban areas and 30 percent in rural areas. Although the share of incorrectly predicted poor households is somewhat high, more information should be collected before making a judgment of the model. In particular, the model still could be considered a good one to the extent that most of the households mispredicted as poor are borderline nonpoor households (that is, they are only marginally above the poverty line). Furthermore, by changing the poverty line, the magnitude of the errors also change. We will conduct more detailed analyses of this issue below. The Type II error of the model, measured by the poor households predicted to be nonpoor, is approximately 10 percent nationwide (4 percent in urban and 22 percent in rural areas).

We provide a more detailed analysis of the errors of inclusion and exclusion by using a prediction matrix based on population decile (rather than on household decile) of per capita consumption (table 13.3). Cape Verde's 28.1 percent poor households are equivalent to 36.7 percent of the population (25 percent urban and 51 percent rural). For simplicity's sake in identifying the poor population, we used the third, fourth, and fifth deciles of per capita consumption (weighted by the population weights) as our new poverty lines at the urban, national, and rural levels, respectively. According to the matrix, errors of exclusion are 10.0 per-

Table 13.3. Welfare Prediction Matrix

Per capita expenditure decile	100										Error of inclusion
	1	2	3	4	5	6	7	8	9	10	
National											
1	4.48	2.54	1.73	0.70	0.35	0.14	0.05	0.02	0.01	0.00	0.57
2	2.52	2.43	1.99	1.36	1.04	0.46	0.15	0.04	0.00	0.00	1.69
3	1.46	1.67	1.90	2.22	1.18	0.84	0.42	0.28	0.01	0.00	2.73
4	0.38	1.07	1.52	1.99	1.63	1.57	1.27	0.45	0.13	0.00	5.05
5	0.57	0.89	1.26	1.53	1.78	1.69	0.93	1.03	0.25	0.03	0.00
6	0.42	0.70	0.67	0.92	1.67	1.76	2.15	0.99	0.71	0.03	0.00
7	0.13	0.20	0.37	0.67	0.98	1.77	1.63	2.21	1.68	0.35	0.00
8	0.03	0.37	0.31	0.38	0.94	0.95	1.96	2.18	2.14	0.73	0.00
9	0.00	0.10	0.16	0.15	0.31	0.39	1.15	2.11	3.41	2.24	0.00
10	0.00	0.02	0.10	0.08	0.14	0.41	0.29	0.68	1.66	6.60	0.00
Error of exclusion	1.15	2.28	2.87	3.73	0.00	0.00	0.00	0.00	0.00	0.00	
Urban areas											
1	5.93	2.55	0.96	0.48	0.26	0.00	0.01	0.01	0.00	0.00	0.76
2	2.38	2.84	2.29	1.13	0.74	0.31	0.17	0.00	0.00	0.00	2.35
3	0.50	2.11	1.97	2.36	1.59	0.92	0.31	0.10	0.06	0.00	5.34
4	0.77	0.98	2.04	1.74	1.35	1.79	0.96	0.34	0.08	0.00	0.00
5	0.16	0.91	1.13	1.29	2.03	1.53	1.69	0.92	0.31	0.00	0.00
6	0.20	0.10	0.85	1.24	1.21	1.70	1.91	1.92	0.78	0.15	0.00
7	0.10	0.38	0.44	1.01	1.36	1.61	2.01	1.67	1.17	0.15	0.00

continued on next page

Table 13.3, *continued*

	100										
Per capita expenditure decile	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*Error of inclusion*
					Urban areas						
8	0.00	0.12	0.16	0.40	0.77	1.65	1.43	2.86	1.98	0.64	0.00
9	0.00	0.00	0.14	0.24	0.43	0.43	1.09	1.78	3.52	2.38	0.00
10	0.00	0.00	0.00	0.11	0.27	0.04	0.45	0.39	2.14	6.61	0.00
Error of exclusion	1.23	2.49	4.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
					Rural areas						
1	4.20	1.86	1.35	0.87	0.94	0.37	0.23	0.17	0.02	0.04	0.83
2	2.11	1.54	1.88	1.41	1.32	0.71	0.58	0.40	0.00	0.02	1.71
3	1.79	1.51	1.88	1.24	0.94	1.29	0.67	0.51	0.14	0.06	2.67
4	0.87	1.34	1.70	1.15	1.38	1.29	0.85	0.63	0.55	0.22	3.54
5	0.38	1.11	0.94	1.29	1.56	1.40	1.31	1.39	0.46	0.22	4.78
6	0.48	0.95	0.91	0.97	1.28	1.46	1.48	1.05	1.20	0.21	0.00
7	0.24	0.95	0.53	0.89	0.82	1.24	1.32	1.66	1.70	0.59	0.00
8	0.00	0.56	0.63	1.08	0.62	0.75	1.44	1.48	2.08	1.37	0.00
9	0.00	0.12	0.11	0.55	0.83	0.90	1.58	1.88	2.14	1.90	0.00
10	0.00	0.00	0.14	0.49	0.28	0.59	0.56	0.82	1.76	5.32	0.00
Error of exclusion	0.72	2.58	2.32	3.98	3.83	0.00	0.00	0.00	0.00	0.00	

Source: Authors' estimates.
Note: Values in cells indicate share of the total population. The shaded areas in the matrix account for the errors of inclusion or exclusion.

cent, 8.5 percent, and 13.5 percent at the national, urban, and rural levels, respectively. Almost half of the individuals excluded (poor but predicted nonpoor) are borderline poor. The magnitude of the errors of inclusion is similar to that of the errors of exclusion. Most of the nonpoor households "wrongly" predicted are also borderline nonpoor (that is, they are only a little above the poverty line).

Now we turn to exploring how sensitive the prediction model is to the choice of poverty line. To do so, we ranked our welfare predictor from the lowest to the highest. Using household weights and size (and conserving the ranking), we calculated the share of the total population represented by each household in the survey. We defined as "predicted poor" all households below our choice of poverty line (we used 20, 30, 40, and 50 percent of the cumulative population distribution of the predictor, respectively). The real "poor" (approximately 37 percent) are those households with observed per capita incomes below the official poverty line—that is, below CVEsc 43,249.8 per capita annually. Our results are summarized in table 13.4.

Table 13.4. Means-testing Performance under Different Poverty Lines

	All households			
Sample considered poor (%)	*Poor, predicted poor (%)*	*Poor, predicted nonpoor (%)*	*Nonpoor, predicted poor (%)*	*Nonpoor, predicted nonpoor (%)*
National				
20.00	16.00	20.69	3.98	59.32
30.00	22.69	14.01	7.29	56.01
40.00	28.39	8.31	11.59	51.72
50.00	32.06	4.64	17.91	45.39
Urban				
20.00	15.17	9.81	4.81	70.20
30.00	19.44	5.55	10.52	64.50
40.00	22.23	2.75	17.76	57.26
50.00	24.02	0.96	25.96	49.06
Rural				
20.00	16.65	34.42	3.31	45.62
30.00	24.48	26.59	5.51	43.42
40.00	30.66	20.41	9.33	39.60
50.00	36.97	14.10	12.94	35.99

Source: Authors' calculations.

As suggested in table 13.4, using a cutoff point of 40 percent of the predicted poor (the benchmark case because the actual poverty rate is 37 percent), the model gives a good prediction of poor households, especially in urban areas. Urban poverty predictions are more accurate mainly because urban households show a larger dispersion in terms of consumption as well as asset levels than do rural households, which increases the power of the proxy means-testing mechanism. Using higher (lower) cut-off points results in a higher (lower) share of the actual "poor" being predicted poor, especially in urban areas. Of course, a higher (lower) cut-off point increases (decreases) the probability that the model fails to exclude nonpoor households from the targeted program. That may contribute to an overinvestment (underinvestment) of social funds because the percentage of nonpoor households predicted to be poor becomes larger (smaller).

Geographic Targeting to Predict Household Poverty

Using census data and the Cape Verde poverty map (which predicts per capita expenditure for all households included in the census), we ranked all districts in the country, from the one with the highest average poverty rate to the one with the lowest rate. We then calculated the overall population share in every district. Keeping the rank constant, we calculated the cumulative population distribution. All households belonging to the provinces below 20, 30, 40, and 50 percent of the population distribution were predicted as "geographically poor."

As suggested by table 13.5, geographic targeting, like proxy means testing, has a better predictive power in urban than in rural areas. By implementing this method and assuming poverty rates of 20, 30, 40, and 50 percent of the population, respectively, we could predict correctly only 28 percent of the poor households in rural areas (versus 47 percent in urban areas), 40 percent (versus 61 percent), 51 percent (versus 72 percent), and 62 percent (versus 82 percent). This result is not surprising because the urban poor population usually is concentrated in slum districts, whereas poor households are more widely dispersed in rural districts.

As table 13.6 suggests, proxy means testing offers a better targeting mechanism than does geographical targeting at the national, urban, and rural levels when all households in the survey and census are included in the analysis. This is true because both the errors of inclusion and the errors of exclusion are smaller using proxy means-testing mechanisms than using geographic targeting methods in all scenarios. This is to be expected

Table 13.5. Geographic Targeting Using Census Data

	All households			
Sample considered poor (%)	*Poor, predicted poor (%)*	*Poor, predicted nonpoor (%)*	*Nonpoor, predicted poor (%)*	*Nonpoor, predicted nonpoor (%)*
National				
20.00	14.26	21.91	5.72	58.11
30.00	20.01	16.16	9.89	53.93
40.00	24.96	11.22	14.88	48.95
50.00	28.92	7.26	20.94	42.89
Urban areas				
20.00	8.88	10.10	11.00	70.03
30.00	11.54	7.44	18.28	62.75
40.00	13.77	5.21	26.02	55.01
50.00	15.55	3.42	15.55	46.84
Rural areas				
20.00	15.47	40.55	4.52	39.46
30.00	22.21	33.82	7.68	36.30
40.00	28.59	27.43	11.30	32.67
50.00	34.55	21.48	15.34	28.63

Source: Authors' calculations.
Note: The actual "poor" are defined as those households having annual consumption below CVEsc 43,249.8 per capita (the official poverty line).

because the proxy means-testing model controls not only for locality factors but also for other variables that predict welfare, such as type of housing characteristics and demographics.

Conclusion

Cape Verde spends heavily on public transfers, especially for health care, education, and pensions. Although large government spending in the social sectors has made the country one of the best performers in West Africa regarding the delivery of services in those sectors, the system needs to improve the efficiency of its spending to ensure its sustainability. The country's expenditures on primary education and health care constitute a large share of overall public transfers in nominal terms, and they are quite pro-poor. However, other components of the social protection network (such as pensions, public subsidies, public study funding, utility subsidies, and higher education) are not reaching the poor adequately.

Table 13.6. Geographical Targeting Versus Proxy Means Testing

	Geographical targeting using census		Proxy means testing using survey	
Share of the sample considered poor (%)	*Error of inclusion (%)*	*Error of exclusion (%)*	*Error of inclusion (%)*	*Error of exclusion (%)*
	Full sample		Full sample	
National				
20	28.63	27.38	19.92	25.86
30	33.08	23.06	24.32	20.01
40	37.35	18.65	28.99	13.84
50	42.00	14.48	35.84	9.27
Urban areas				
20	55.33	12.60	24.07	12.26
30	61.30	10.60	35.11	7.92
40	65.39	8.65	44.41	4.58
50	50.00	6.80	51.94	1.92
Rural areas				
20	22.61	50.68	16.58	43.00
30	25.69	48.23	18.37	37.98
40	28.33	45.64	23.33	34.01
50	30.75	42.87	25.93	28.15

Source: Authors' estimation.
Note: The actual "poor" under means testing are defined as those households having per capita consumption below CVEsc 43,249.8 annually (the official poverty line).

The targeting performance of public transfers in Cape Verde has a natural distributional handicap because poor households usually have an access disadvantage: they are limited in access to infrastructure and information, and they still cannot afford the services. To overcome this handicap, policy makers must pay attention to the performance of subsidy-design factors (such as targeting mechanisms and rates of subsidization). Results for Cape Verde indicate that, apart from primary education and health care (services with high rates of access and use among poor people), public transfers are not being allocated in a pro-poor manner because of a combination of disadvantageous access factors among the poor and poorly performing design factors (especially involving targeting mechanisms).

Finally, proxy means testing generally has better predictive power than does geographic targeting, especially in rural areas where poverty is widespread. In urban areas, the predictive advantage of means testing over geographic targeting is lower, probably because urban poverty is concentrated in slums. This poses a natural trade-off because policy makers constrained by tight budgets may choose to implement geographic targeting, even when it sacrifices some predictive power.[8]

Notes

1. There is a large body of literature in this area. Several studies have been devoted to assessing the targeting performance of a wide range of programs in developing and transition economies (for example, Grosh 1994; Subbarao et al. 1997; Braithwaite, Grootaert, and Milanovic 2000; and Coady, Grosh, and Hoddinott 2004). In the case of utilities such as water and electricity, although subsidies are very widespread, it is not clear that they are well targeted (Wodon, Ajwad, and Siaens 2003; Komives et al. 2005; Angel-Urdinola, Cosgrove-Davies, and Wodon 2006; and Angel-Urdinola and Wodon 2007). This finding is problematic given that utility subsidies in developing and transition economies often are more costly than other transfer programs (Alderman 2002).
2. Life expectancy at birth is 70.1 years; child mortality is 42 per 1,000 live births among boys and 30 per 1,000 live births among girls; and the maternal mortality ratio was 150 to 100,000 live births in 2000 (see World Bank 2005 for more details). These figures reflect both the relatively high income per capita in Cape Verde and the high share of public spending devoted to health care.
3. For a good discussion of standard benefit incidence analysis, see Demery (2003).
4. There are two noncontributory social security schemes—one for people in the Food for Work (FAIMO) public works program and one for other elderly or disabled people. FAIMO is a labor-intensive infrastructure works program, financed with food aid counterpart funds, that employs approximately 15,000 to 20,000 people annually. The aim of this program is to provide some income security to the poor, especially those people who live in rural areas and women who are heads of household. In 1992, a noncontributory pension scheme was introduced for workers in FAIMO. All elderly people who have worked at least 10 years in campaigns funded by the government are covered (44 percent of the FAIMO workers have at least 10 years' tenure), and invalidity and old-age pensions are provided. All FAIMO pensioners receive a fixed annual pension equivalent to $300. The Minimum Social Protection (PSM) scheme is a noncontributory, means-tested program set up in 1995 to provide income for people not covered by the other social protection program. The PSM is fully financed with resources from official development assistance. Approximately 7,000 families receive pensions from the PSM, pri-

marily elderly people and families in economic distress who are not covered under other pension schemes.

5. Following the methodology used by the National Institute of Statistics in Cape Verde, a household is considered poor if its annual per capita consumption falls below the official poverty line (equivalent to CVEsc 43,249.8 per capita a year). With that poverty line, 36.7 percent of the population is poor (equivalent to 28.0 percent of households).
6. Unfortunately, the requisite information for such a study is not included in the survey data.
7. For a more detailed discussion on the targeting performance of utility tariffs in Cape Verde, see Wodon et al. (2007).
8. The cost of implementing proxy means testing is usually higher because it requires the involvement of social workers and the use of data processing.

References

Alderman, Harold. 2002. "Subsidies as a Social Safety Net: Effectiveness and Challenges." Social Safety Net Primer Series, Discussion Paper 0224 World Bank, Washington, DC.

Angel-Urdinola, Diego, M. Cosgrove-Davies, and Q. Wodon. 2006. "Rwanda: Electricity Tariff Reform." In *Poverty and Social Impact Analysis of Reforms: Lessons and Examples from Implementation*, ed. Aline Coudouel, A. Dani, and S. Paternostro, 235–56. Washington, DC: World Bank.

Angel-Urdinola, Diego, and Quentin Wodon. 2007. "Do Utility Subsidies Reach the Poor? Framework and Evidence for Cape Verde, Sao Tome, and Rwanda." *Economics Bulletin* 94 (4): 1–7.

Braithwaite, Jeanine, C. Grootaert, and B. Milanovic. 2000. *Poverty and Social Assistance in Transition Countries.* New York: Palgrave Macmillan.

Coady, David, M. Grosh, and J. Hoddinott. 2004. "Targeting Outcomes Redux." *World Bank Research Observer* 19 (1): 61–85.

Demery, Lionel. 2003. "Analyzing the Incidence of Public Spending." In *The Impact of Economic Policies on Poverty and Income Distribution: Evaluation Techniques and Tools,* ed. Françoise Bourguignon and Luis A. Pereira da Silva, 41–68. Washington, DC: World Bank.

Grosh, Margaret. 1994. *Administering Targeted Social Programs in Latin America: From Platitudes to Practice.* Washington, DC: World Bank.

Komives, Kristin, V. Foster, J. Halpern, Q. Wodon, and R. Abdullah. 2005. *Water, Electricity, and the Poor: Who Benefits from Utility Subsidies?* Washington, DC: World Bank.

Subbarao, Kalanidhi, A. Bonnerjee, J. Braithwaite, S. Carvalho, K. Ezemenari, C. Graham, and A. Thompson. 1997. *Safety Net Programs and Poverty Reduction: Lessons from Cross-Country Experience.* Washington, DC: World Bank.

Wodon, Quentin, M. I. Ajwad, and C. Siaens. 2003. "Lifeline or Means Testing? Electric Utility Subsidies in Honduras." In *Infrastructure for the Poor People: Public Policy for Private Provision,* ed. P. Brook and T. Irwin, 277–96. Washington, DC: World Bank.

Wodon, Quentin, D. Angel-Urdinola, D. Echevlin, M. Francisco, and P. Meier. 2007. "Energy Subsidies, Electricity Tariffs, and the Poor in Cape Verde." World Bank, Washington, DC.

Wodon, Quentin, and Xiao Ye. 2006. "Benefit Incidence Analysis Adjusted for Needs and Costs: Assessing the Equity of Public Education Spending in Sierra Leone." World Bank, Washington, DC.

World Bank. 2005. "Cape Verde: Poverty Diagnostic." Report 32826-CV, World Bank, Washington, DC.

———. 2007. "Cape Verde: The Challenge of Increasing Fiscal Space to Meet Future Pressures (Public Expenditure Review)." Report 34523-CV, World Bank, Washington, DC.