Chapter 3

Generating a System for Targeting Unconditional Cash Transfers in Cameroon

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Cameroon has seen robust recent economic growth and is one of the better-off countries in Sub-Saharan Africa. Yet its poverty level has remained persistently high and geographically concentrated in the northern—rural—parts of the country.

Social assistance has been largely reactionary, subsidizing food and fuel prices in response to a crisis, and the results have been regressive (World Bank 2011a). Safety net programs have suffered from limited resources, weak coverage, and poor targeting; excluding subsidies, they account for only 0.23 percent of gross domestic product (GDP), which ranks Cameroon's safety net allocations among the lowest in Sub-Saharan Africa. For these reasons, the government is dedicating a large part of social assistance spending to a unified safety net, moving toward unconditional cash transfers (UCTs) targeted to the poor.

This case study presents an improved mechanism for targeting assistance to poor and vulnerable households in Cameroon. It is based on the work done since 2009 to review the safety net system and draws on documents that describe efforts to identify and target poor and vulnerable households (Nguetse-Tegoum 2011; World Bank 2011a, 2011b; Nguetse-Tegoum and Stoeffler 2012). At present, the outcomes are being piloted in two of the poorest regions, the north and far north.

This case study is organized as follows. First, it presents an overview of poverty and vulnerability in Cameroon as well as current safety net programs. Second, it explains the targeting method employed in Cameroon and the proxy means testing formula generated. Third, it presents ex ante targeting results and details a design for the ex post evaluation of the targeting mechanisms. A final section concludes with lessons learned.

Poverty, Vulnerability, and Social Assistance Response

Cameroon is divided into 10 administrative regions and 58 *départements*, followed by *communes* in rural areas and *arrondissements* in urban areas. Although the country has had strong economic growth in the last decade, the gains have been split largely on a north-south axis, and the incidence of poverty has remained high in the northern half.

Between 2001 and 2007, the poverty rate was virtually constant, at approximately 40 percent of the population. This means that the number of poor increased by 1.1 million as the population grew. In 2007, out of a population of 17.9 million people, 7.1 million were poor.[1] The results are striking when poverty is deconstructed by taking into account the variability in future expected consumption based on the current characteristics of households (Chaudhuri and Datt 2001).

Of the total population, 4.7 million people (26.1 percent) are chronically poor, in that based on their current assets they are expected to be poor in the future (Nguetse-Tegoum 2011). Among the remaining poor, 9.9 percent are transient poor and 4 percent are progressive poor, which means that they are progressing quickly out of poverty.

Chronic poverty is mainly a rural phenomenon: 95.6 percent of the chronic poor live in rural areas, and almost 40 percent of the rural population reside in chronic poverty. In addition, poverty is concentrated in the five northern regions of Cameroon, where 80 percent of the chronic poor are located (and 46.2 percent of the population live). These regions are Adamaoua, the east, northwest, north, and far north. In these last two, the rate of chronic poverty is above 50 percent.

Characteristics of Chronically Poor Households

Table 3.1 shows the characteristics of chronically poor households compared to the entire population for rural areas, urban areas, and five regions selected for a cash transfer project. Poor households tend to have common socioeconomic characteristics with respect to gender of the household head, level of education, labor market attachment, and household size. Chronic poverty increases with the age of the household head and clearly decreases with education level. Since education level and primary activity are related, it is not surprising that being a farmer is strongly correlated with chronic poverty, even in urban areas. Polygamist households have a higher incidence of chronic poverty, and single men and women have a lower incidence of chronic poverty than monogamist married households. Larger household size is also related to a higher rate of chronic poverty.

Chronic poverty also is correlated with lack of access to basic necessities. On the one hand, households with no access to electricity, no toilet in the house,

Table 3.1 Characteristics of Chronically Poor Households in Cameroon
share of the category unless otherwise noted

	Rural areas		Urban areas		Five project regions, rural areas	
Characteristic	All	Chronic poor	All	Chronic poor	All	Chronic poor
Household region						
Adamaoua	0.062	0.061	0.032	0.053	0.10	0.075
Far north	0.24	0.37	0.067	0.14	0.40	0.45
North	0.12	0.18	0.056	0.15	0.20	0.22
Northwest	0.13	0.15	0.054	0.10	0.21	0.18
East	0.061	0.065	0.019	0.021	0.100	0.079
Douala	n.a.	n.a.	0.28	0.088	n.a.	n.a.
Yaoundé	n.a.	n.a.	0.27	0.048	n.a.	n.a.
Center	0.11	0.061	0.020	0.041	n.a.	n.a.
Littoral	0.030	0.011	0.044	0.15	n.a.	n.a.
West	0.11	0.047	0.096	0.19	n.a.	n.a.
South	0.046	0.020	0.0080	0.0061	n.a.	n.a.
Southwest	0.090	0.046	0.050	0.017	n.a.	n.a.
Household head characteristics						
Has no education	0.40	0.55	0.12	0.32	0.57	0.63
Primary school education	0.37	0.34	0.29	0.45	0.31	0.30
Secondary 1 education	0.14	0.083	0.25	0.18	0.079	0.058
Secondary 2 education	0.063	0.021	0.21	0.049	0.031	0.010
Polygamist	0.23	0.29	0.083	0.16	0.29	0.32
Widow	0.11	0.099	0.099	0.16	0.076	0.074
Handicapped	0.064	0.069	0.054	0.061	0.061	0.067
Male household head	0.80	0.84	0.77	0.73	0.85	0.87
Age (years)	45.2	46.9	42.7	48.5	45.0	46.6
Number of household members by age category						
0–4 years old	1.26	1.54	0.93	1.31	1.44	1.61
5–14 years old	2.21	2.96	1.64	2.79	2.49	3.07
15–59 years old	2.95	3.32	3.45	4.11	3.10	3.33
60 years old and older	0.31	0.33	0.18	0.40	0.31	0.33
Household head occupation						
Public sector	0.050	0.018	0.15	0.029	0.036	0.013
Private sector, formal	0.028	0.0076	0.13	0.032	0.013	0.0047
Informal sector	0.15	0.097	0.50	0.49	0.13	0.096

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Table 3.1 (continued)

	Rural areas		Urban areas		Five project regions, rural areas	
Characteristic	**All**	**Chronic poor**	**All**	**Chronic poor**	**All**	**Chronic poor**
Informal, agriculture	0.74	0.85	0.10	0.32	0.79	0.87
No occupation	0.038	0.030	0.12	0.13	0.029	0.020
Housing characteristics						
Owner of the house	0.81	0.91	0.48	0.75	0.90	0.95
Lighting: oil	0.66	0.72	0.094	0.37	0.73	0.73
Lighting: electricity	0.23	0.092	0.90	0.59	0.098	0.039
Cooking fuel: bought wood	0.12	0.063	0.38	0.55	0.14	0.068
Cooking fuel: picked-up wood	0.83	0.93	0.11	0.39	0.84	0.93
Cooking fuel: natural gas	0.028	0.0028	0.39	0.012	0.0063	0.0013
Source of water: forage	0.33	0.32	0.20	0.34	0.32	0.32
Has solid wall	0.12	0.061	0.58	0.28	0.064	0.043
Has solid roof	0.61	0.41	0.99	0.94	0.41	0.30
Has solid floor	0.27	0.13	0.87	0.63	0.17	0.092
Flush toilets	0.0074	0	0.18	0.00062	0.0024	0
Improved latrines	0.12	0.057	0.48	0.29	0.059	0.037
Unimproved latrines	0.71	0.70	0.34	0.69	0.72	0.69
No toilets	0.16	0.24	0.0071	0.029	0.22	0.28
Physical assets						
Phone	0.26	0.11	0.84	0.44	0.16	0.078
Radio	0.48	0.36	0.64	0.50	0.41	0.34
Television	0.13	0.035	0.69	0.29	0.054	0.018
Motorcycle	0.089	0.053	0.087	0.033	0.095	0.051
Bike	0.21	0.27	0.054	0.11	0.30	0.31
Number of observations	5,026	1,240	6,365	345	2,702	951

Source: Calculations based on ECAM3 data.
Note: n.a. = not applicable. Descriptive statistics for households in Cameroon by living areas and poverty status, expressed as a share of the population in the column (unless noted otherwise). Household size and sample weights are used to obtain nationally representative figures in terms of individuals. Chronically poor households are defined as those below 80 percent of the national poverty line.

and less durable housing construction materials are more likely to be chronically poor. On the other hand, households owning a mobile phone are rarely chronically poor.

Table 3.1 also confirms that the chronic poor are concentrated in rural areas, in particular in the five project regions. For instance, in the entire rural population, 12 and 24 percent of households live in the north and far north regions, respectively, but 18 and 37 percent of the rural chronically poor households live in these regions, indicating that the chronic poor are overrepresented in the two northern regions. As expected, the chronic poor possess lower levels of several physical assets: 3.5 percent of them have a television in rural areas (29 percent in urban areas) compared with 13 percent of the whole rural population (69 percent in urban areas). Poor households also have lower levels of human capital: 55 percent of the poor never went to school (no education), but this number rises to 63 percent in the five project regions. Poor households are underrepresented in the public sector (2.9 percent in urban areas) and the formal private sector (3.2 percent in urban areas) compared with the entire population (15 and 13 percent, respectively) and are overrepresented in the agricultural informal sector even in urban areas (32 percent in urban areas compared with 9.8 percent of the entire urban population). They live in larger households on average (more household members in each age category for all areas), and their houses tend to lack equipment and solid material: in urban areas, only 28 percent of the poor have solid walls, compared with 58 percent of the whole urban population.

Differences between rural and urban poverty are also found, with the urban poor having older members and more household heads who are widows, for instance, compared with the rural poor. These differences between poor and nonpoor households, in each living area, can be exploited to design the proxy means testing formula.

Shocks Affecting Households

Cameroonian households are vulnerable to environmental, macroeconomic, and social covariate shocks, in addition to idiosyncratic shocks to employment and health. Climatic risks are the primary source of environmental shocks because they have a direct impact on the livelihoods of the 45 percent of the population engaged in subsistence agriculture. Since climatic events also affect the regional food supply, they affect the food security of the general population. Among these risks, flooding, drought, and desertification are frequent in the poorest provinces (north and far north).

Macroeconomic risks include inflation, exchange rate fluctuations, export price volatility, depressed export demand, and lower remittances and foreign direct investment. All of these have been important shocks in past years. Recently, the fuel and food price crises as well as the financial crisis have been major shocks in Cameroon. Macroeconomic risks are exacerbated by the high reliance of the Cameroonian economy on unprocessed primary goods that are subject to price volatility, by limited diversification of export commodities, and by low agricultural productivity that generates import dependency.

Social covariate risks mainly affect women and children. They include early arranged marriage, human trafficking, and genital mutilation (prevalence rate of 1.4 percent). More broadly, they can include political upheaval and ethnic strife.

Idiosyncratic shocks affect several aspects of household well-being. The largest health shock is death of a household member; disease and disability also influence household well-being. Other idiosyncratic shocks include theft or loss of employment, although the latter probably has a limited impact in rural areas.

Additional information on the frequency of shocks is needed to provide a comprehensive picture of the importance of exposure to shocks for the economic well-being of households. Collection of this information represents an important area for future investment.

Current Social Assistance Programs to Address Short- and Long-Term Needs: Insufficient Scope and Coverage

The number of existing safety net programs is small in Cameroon, and their scope and coverage are limited. The seven safety nets and the principal actors—donors—are presented in table 3.2. Except for price subsidies, the coverage of each program is just above 1 percent of the population and only about two-thirds of the targeted population.

Within the social sector, health and education accounted for 96 percent of total spending or 24 percent of the government budget between 2006 and 2010 (World Bank 2011a). Safety nets accounted for only 0.76 percent of the government budget (0.23 percent of GDP) without including food and fuel subsidies. This compares to an average of 1.9 percent of GDP in developing countries; in Sub-Saharan Africa, Burkina Faso (0.6 percent), Mali (0.5 percent), and Tanzania (0.3 percent) have higher expenditures as a share of GDP than Cameroon. In Ethiopia and Malawi, spending levels are around 4.5 percent of GDP, and Mauritius and South Africa (two countries with higher per capita income than Cameroon) also have higher shares of safety net spending.

Table 3.2 summarizes expenditures of the safety net system in Cameroon by type of program for 2008, 2009, and 2010. As the table shows, when we include universal price subsidies, safety net spending rises to 7.4 percent of the government budget or 1.6 percent of GDP (World Bank 2011a). Indeed, these subsidies are particularly expensive, and costs have risen far above expectations. Further, the subsidies are regressive, because the poor have a lower overall consumption of many of the subsidized products.

Table 3.3 presents details on the targeting criteria (including geographic area), coverage, and costs per beneficiary. In addition to limited scope and coverage, coordination between programs is scant, and response to shocks consists mostly of ad hoc emergency interventions. Targeting is relatively poor overall and is even regressive for universal subsidies, which have represented most of the budget for social protection since 2007.

The proposal to improve the current social protection system by creating an unconditional cash transfer program aims both to expand the coverage and improve the targeting of poor households in a more systematic way.

Table 3.2 Expenditure on Safety Net Programs in Cameroon, 2008–10
CFAF, millions

Program and type of expenditure	Funder	2008	2009	2010
School feeding programs				
School feeding	MINEDUB	50	55	50
School feeding	WFP	1,746	1,746	1,746
Fee waiver programs				
Hospital fees	MINSANTE	4,400	1,600	1,600
School fees	MINEDUB	—	4,800	4,800
Cash transfer programs				
Indigents and street children	MINAS	50	50	50
Price subsidies				
Energy products subsidy	MINFI	136,900	22,500	112,500
Food price subsidies	MINFI	73,000	51,000	51,000
Transport subsidies	MINFI	3,200	3,200	3,200
Public works programs				
Food-for-work	WFP	—	196	196
Yaoundé Sanitation Project (PAD-Y)	MINEPAT	—	600	600
PAD-Y	AfDB	—	2,400	2,400
Emergency				
Cereal stocks	WFP	396	196	196
Emergency, refugees	WFP, UNICEF	25,713	6,354	14,597
Cereal stocks	BID, MINADER	—	215	100
Nutritional support programs				
OVC	UNICEF	47	47	47
OVC	NGOs	100	100	100
Total government of Cameroon		217,600	83,805	173,800
Total government of Cameroon (without subsidies)		1,762	4,500	2,305
Total donors or partners		27,999	11,255	19,383
Total		245,599	95,060	193,183
Total (without subsidies)		32,499	13,560	21,683

Source: World Bank 2011a.
Note: — = not available. MINEDUB = Ministry of Basic Education; WFP = World Food Program; MINSANTE = Ministry of Public Health; MINAS = Ministry of Social Affairs; MINFI = Ministry of Finance; MINEPAT = Ministry of Economy, Planning, and Regional Development; AfDB = African Development Bank; UNICEF = United Nations Children's Fund; BID = Islamic Development Bank; MINADER = Ministry of Agriculture and Rural Development; OVC = orphans and vulnerable children; NGO = nongovernmental organization.

Table 3.3 Existing Assistance Programs in Cameroon

Type of program	Targeting criteria	Geographic area	Coverage	Cost per beneficiary
School feeding programs				
WFP and MINEDUB	Provinces with low school attainment and high food insecurity	Adamaoua, far north, north	55,366 students (7,180 girls taking home rations) in 367 targeted schools	CFAF 35,000
Nutrition programs				
WFP village granaries		Northern provinces	300,000 people through 410 granaries	
WFP for refugees		North, east, Adamaoua (mostly)	210,000 people with food programs for refugees	
UNICEF Survie (health, nutrition, and WASH)		Far north and north	60,695 people in 60 villages	
UNICEF and NGOs, OVCs	OVCs (micro-credit loans)	All provinces except in the north and far north regions	2,614 children	CFAF 16,190 per child
CARE, assistance to OVCs	Health status of the children and economic status of the family		20,000 people, including 3,000 OVCs	
CRS, assistance program		Mostly northwestern regions	7,500 children countrywide	
Labor-intensive public works programs				
Projet d'Assainissement de Yaoundé	Self-selection (inefficient because of high wage)	Yaoundé	6,000 employees	CFAF 22.3 billion total: daily rate of CFAF 2,400
WFP food-for-work programs	Self-selection	Far north and north regions	16,590 families	Wage equivalent of CFAF 3,147 in cereals monthly
Emergency response initiatives				
WFP and MINADER, village cereal stocks	Area and periods of droughts, food crises, and emergency situations	Northern and western provinces	133 cereal stocks in villages	
WFP assistance to refugees		Eastern borders and Adamaoua	760,940 refugees in 2008 and 227,655 in 2009 in 72 sites	
WFP emergency response to droughts		Far north and north regions	565,400 beneficiaries in 2008 and 94,457 in 2009	

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Table 3.3 (continued)

Type of program	Targeting criteria	Geographic area	Coverage	Cost per beneficiary
Universal price subsidies				
	Universal (proved regressive)	Entire country	Entire population	6.92% of government budget in 2009
Unconditional cash transfers				
MINAS	Specific vulnerable groups (street children, disabled, elderly)			Total estimated around US$10 million
Fee-waiver programs for basic services (by each ministry)				
MINEDUB and MINESUP	Disadvantaged primary school students, disabled university students	Northern and western provinces	69,429 children and 60,000 university students	

Source: World Bank 2011a.
Note: WFP = World Food Program; MINEDUB = Ministry of Basic Education; UNICEF = United Nations Children's Fund; WASH = water, sanitation, and hygiene; NGO = nongovernmental organization; OVC = orphans and vulnerable children; CARE = Cooperative for Assistance and Relief Everywhere; CRS = Catholic Relief Services; MINADER = Ministry of Agriculture and Rural Development; MINAS = Ministry of Social Affairs; and MINESUP = Ministry of Higher Education.

A pilot that employs the targeting method presented here is currently being implemented in the rural *commune* of Soulédé-Roua in far north region and the urban *arrondissement* of Ndop in the northwest region. Different data sets—ECAM3 and General Population and Housing Census (GPHC)—can be used to refine the geographic targeting at the *département* or even *commune* level. For instance, five *départements* (out of 58 in Cameroon) contain about 1.8 million chronic poor, or 49 percent of the total for the country. This pilot will be extended to the five regions where chronic poverty is concentrated—Adamaoua, the east, far north, north, and northwest—and will, given resource constraints and high poverty incidence, target only chronically poor households.

The remainder of the case study provides details on the targeting method generated for this UCT program.

Targeting Methodology Employed in Cameroon

In order to increase both coverage and targeting of the current social protection system, a proxy means test (PMT) formula was developed. In the UCT pilot, the PMT formula is coupled with geographic and community targeting. We first present the PMT formula and then describe how it is combined with two other targeting methods in the pilot.

PMT Formula

In order to implement the program efficiently and with low administrative cost, the number of variables in the PMT formula has to be limited and the accuracy of the responses has to be easy to verify. The variables include sociodemographic characteristics of the household head, demographic composition of the household, housing construction materials, and household equipment and assets. They attempt to cover the maximal dimensions of poverty and correspond to the characteristics of the chronic poor outlined in the previous section. The ECAM3 data were used to select variables associated with chronic poverty and to estimate weights for them. For the PMT formula presented here, chronically poor households are defined as those where adult-equivalent expenditures are below 0.8 of the poverty line, or CFAF 215,554.[2]

We used an ordinary least squares (OLS) regression in order to select the variables and to assign weights, with adult-equivalent expenditures as the dependent variable. In this context, the usual sources of potential parameter bias (omitted variables and endogeneity) are not a concern, since the goal of the PMT is not to determine causality but to establish a correlation between chronic poverty and characteristics of the households. Moreover, we focus on the predictive capacity of the model. Thus the main criteria used to design the formula are the errors of inclusion and exclusion generated by the model. To test the formula in a robust manner, two-thirds of the sample were randomly selected and used for the OLS regression, while the last third was retained to test the formula and compute the errors of inclusion and exclusion.[3] The PMT formula is presented in table 3.4.

When the household's level of well-being increases, the PMT score increases, which means that the household is less likely to be a beneficiary of the program. The demographic composition of the household has a significant effect on its eligibility status, since the weights associated with larger household size are negative. Being a male, uneducated, or an older household head (negative coefficients) also increase(s) the likelihood of eligibility. The PMT score increases—decreasing the likelihood of program eligibility—when a household has access to goods such as electricity or fuel and owns assets like a radio or cart. Some measures of household assets are particularly indicative: refrigerator, motorcycle, and television (positive) or lack of a proper latrine (negative). The R^2 of 0.615 indicates that the model explains 61.5 percent of the variation in the adult-equivalent expenditures.

Table 3.4 PMT Formula for Rural Areas of Cameroon

Variable	Response	Weight
Household head gender	Man	–99
	Woman	0
Household head age	Less than 34 years old	0
	35–49 years old	–100
	50 years old and older	–61
Household head education	No education	–312
	Primary and secondary 1	–291
	Secondary 2 and more	–202
Household head religion	Muslim	144
	Christian	0
	No religion	0
Household head marital status	Monogamist	85
	Polygamist	115
	Other (single)	0
Household head occupational category	Formal sector (public or private)	0
	Nonagricultural informal	0
	Agriculture	–72
	Unemployed	–96
Household size	1 member	0
	2–3 members	–367
	4–5 members	–684
	6–7 members	–794
	8 members and more	–894
Household composition	Members between 0 and 4 years old	23
	Members between 5 and 14 years old	–30
	Members between 15 and 59 years old	–40
	Members 60 years old and older	–43
Size of the house	Small: less than 25 square meters	–90
	Medium: from 25 to 50 square meters	–33
	Large: from 50 to 95 square meters	–22
	Very large: 96 square meters and more	0
Lighting source	AES-SONEL electricity	280
	Oil	185
	Other (natural gas, generator)	0
Main energy source for cooking	Picked-up wood	–150
	Other (bought wood, natural gas, oil, sawdust, coal)	0

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Table 3.4 (continued)

Variable	Response	Weight
Bathroom facility	Equipped latrine	–240
	Unequipped latrine, no latrine	–260
	Flush toilet	0
Main roof material	Cement, sheet metal, tile	51
	Other	0
Main floor material	Soil	–62
	Other	0
Own radio	Yes	67
	No	0
Television or satellite network	Yes	40
	No	0
Own television	Yes	171
	No	0
Own motorcycle	Yes	285
	No	0
Own cart	Yes	117
	No	0
Own refrigerator	Yes	415
	No	0
Own unfarmed land	Yes	46
	No	0
Own house not used by a household member	Yes	105
	No	0
Constant		13,787
Number of observations	1,752	
R^2	0.615	

Source: Nguetse-Tegoum and Stoeffler 2012.

Short-Term Targeting and Data Constraints

The PMT formula presented above does not include a short-term component that would allow programs to address vulnerability by including households affected by temporary adverse shocks. However, adding a short-term component to the PMT targeting is constrained by data limitations. The questionnaires from ECAM3 ask limited questions about shocks faced by the household. Ideally, information would be available on idiosyncratic shocks affecting health (disease and death), loss of employment, and theft, for instance, and on covariate shocks such as agricultural or climatic shocks (pests, floods, storms, and droughts). Further, because of the endogeneity of shocks, data at the individual level and at the community (or regional) level are desirable.

In the absence of such information, we used geo-referenced meteorological data from the National Aeronautics and Space Administration (NASA) on rainfall[4] between 1997 and 2006 to construct long-term rainfall averages and data on the range of rainfall in 2007 to compute the deviation from long-term averages. We also created a dummy variable "drought" for each of our *départements* and included it in our PMT formula estimation to give it a weight. The variable has a coefficient estimate of –0.094 with standard deviations of 0.020; this means that living in an area affected by such a "drought" is associated with 9 percent lower predicted consumption, on average. The weight in the PMT is, for instance, about the same as for being unemployed. The addition of the "drought" variable to the formula does not cause a large change in any of the coefficients presented in table 3.4. Specifically, the weights associated with the variables keep the same magnitude overall, and none of the signs changes.

This "drought" variable, however, has serious limitations. The scale used (*département*) is too large to take into account local variations (real rainfall). Further, 2007, the year of ECAM3, was overall a "good" year with no major drought or flood. Finally, there are no data on household exposure in ECAM3 to combine with this "drought" variable in order to compute an endogenous treatment effect. Thus the impact of "drought" has to be the same for all households in a "drought" area in our model.

Collecting information on covariate and idiosyncratic shocks at the household level is increasingly imperative in order to improve PMT formulas and develop a short-term targeting component. Despite the limitations encountered, our simple "drought" variable provides encouraging results, which are discussed in the next section along with other targeting results.

Urban Formula: Lower Poverty Rates and More Difficult Discrimination

Finding an efficient PMT formula for urban households is a more delicate exercise than working on the rural formula. The urban poverty rate is much lower than the rural rate in Cameroon; the poverty incidence is 55 percent in rural areas and only 12.2 percent in urban areas (Nguetse-Tegoum 2011). In addition, urban poverty might be more diverse in its causes and manifestations than rural poverty. All potential PMT formulas perform poorly in urban areas, particularly in terms of exclusion errors using the ECAM3 data set. Conducting specific research on poor urban households erroneously excluded by the PMT formula would help to identify their attributes.

In light of these difficulties, we adopted a quantile regression (QR) methodology to design the urban PMT formula. Quantile regressions offer three advantages compared to OLS.[5] First, they are less sensitive to outliers, which can be an advantage in urban areas. Second, they allow us to focus on limiting errors at the bottom end of the expenditure distribution; that is, to limit exclusion errors by ensuring that the formula effectively models expenditures of the poorest households—without caring about the imprecision in the formula above the poverty threshold needed for the program. Third, QRs allow us to change easily the threshold used, depending on the needs of the program, such as the number of total beneficiaries or trade-off between inclusion and exclusion errors. For these reasons, the QR model performed much better than the OLS specifications tried for urban areas.

We chose a quantile level of 0.1 for the QR of the urban model (which can be adjusted to reflect the program needs) to reflect the poverty level in urban areas (12.2 percent). The PMT formula for urban areas is presented in table 3.5. This urban formula does not reveal any surprise in terms of signs of the weights associated with each variable. Since the QR minimizes errors at the bottom of the distribution, the PMT weights generated overall are smaller than those of the OLS rural model. Education is not as important in the urban formula, but family composition continues to weigh heavily in the score, with larger households associated with lower expenditures. The urban formula also enables the introduction of new types of assets: cars, compact disk players, and digital video disk players.

Targeting Process: Geography, PMT, and the Community

Proxy means testing is only one component of the information used in the targeting process developed for Cameroon. Here we describe how the geography, the community, and the PMT are combined in the targeting process. The main steps are shown in figure 3.1. After defining the geographic area where the program will be implemented, the community selects potential beneficiaries (that is, those considered as poor by the community). Those households designated by the community then answer a short survey containing all the variables included in the PMT formula (table 3.5). The data set obtained is used to compute the PMT scores. Households with a score below the threshold (12,281 with this formula) are placed on a list for cash transfers. The list is then validated by the community.

For the pilot in Soulédé-Roua, in particular, community targeting was an important feature. After Soulédé-Roua was geographically targeted, the 15 poorest villages (among the 34 villages of the *commune*) were selected with the community, based on poverty criteria such as poor infrastructure and lack of arable land. In selected villages, the community conducted the first round of a household-level selection, with the aim of keeping around 70 percent of the households as potentially eligible. The selection protocol was established by the pilot project team in collaboration with the community. Selection committees

Table 3.5 PMT Formula for Urban Areas of Cameroon

Variable	Response	Weight
Household head gender	Man	0
	Woman	213
Household head age	Age	11
	Squared age	–0.5
Household head education	No education	–110
	Primary	–136
	Secondary 1	–104
	Secondary 2	–100
	Higher education	0
Household head marital status	Married or union	131
	Single, divorced, or separated	0
Household head occupational category	Public sector	77
	Formal private sector	80
	Nonagricultural informal	15
	Unemployed	24
	Informal agriculture	0
Household size	1 member	0
	2–3 members	–339
	4–5 members	–566
	6–7 members	–634
	8 members and more	–691
Household composition	Members between 0 and 14 years old	–51
	Members between 15 and 59 years old	–49
	Members 60 years old and more	–3
Housing type	Isolated house	0
	House with several housing units	60
	Compound, *saré*	98
	Modern villa, building with apartments	145
Housing occupation status	Free housing (provided by the employer or by family)	–21
	Tenant	–6
	Owner	0
Size of the house	Small: less than 25 square meters	0
	Medium: from 25 to 50 square meters	12
	Large: from 50 to 99 square meters	42
	Very large: 100 square meters and more	47
Main source of drinking water	Tap or drilling	53
	Other (well, equipped spring, river, rainfall)	0

(continued next page)

Table 3.5 (continued)

Variable	Response	Weight
Lighting source	AES-SONEL electricity	60
	Other (natural gas, generator)	0
Main energy source for cooking	Other (does not cook, sawdust)	0
	Natural gas, electricity	73
	Oil	–16
	Picked-up wood	–133
	Bought wood	–23
Bathroom facility	Flush toilet	280
	Equipped latrine	138
	Unequipped latrine	102
	No bathroom facility	0
Main wall material	Concrete, baked brick, stone	11
	Other (terracotta, simple brick, plank)	0
Main roof material	Cement, sheet metal, tile	137
	Other	0
Main floor material	Cement or tile	45
	Other	0
Own mobile or home phone	Yes	189
	No	0
Own radio	Yes	56
	No	0
Own television	Yes	114
	No	0
Own compact disk or digital video disk player	Yes	46
	No	0
Own refrigerator or freezer	Yes	158
	No	0
Own ventilator or air conditioning	Yes	94
	No	0
Own stove or oil portable stove	Yes	51
	No	0
Own motorcycle or a bicycle	Yes	132
	No	0
Own car	Yes	405
	No	0
Own living room or dining room	Yes	6
	No	0

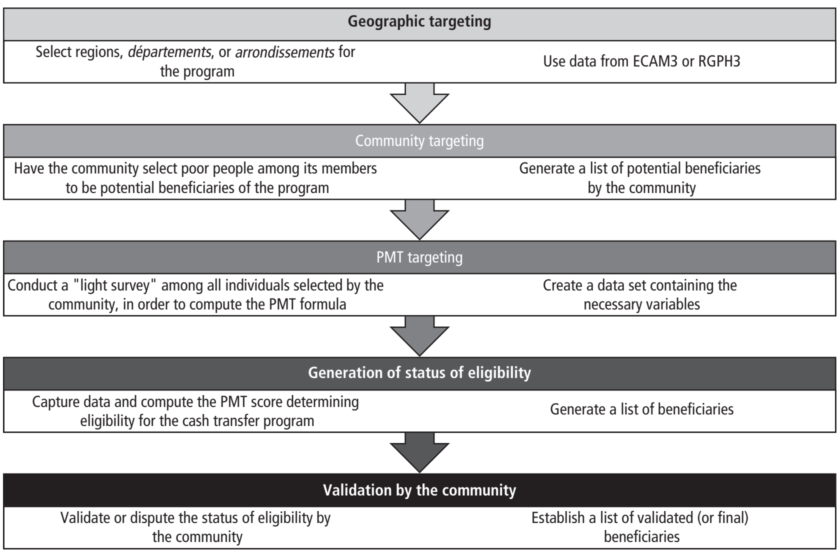
(continued next page)

Table 3.5 **(continued)**

Variable	Response	Weight
Own farmed land	Yes	33
	No	0
Own unfarmed land	Yes	53
	No	0
Own house not used by a household member	Yes	1
	No	0
Constant		12,245

Source: Calculations based on ECAM3 data.
Note: Quantile regression (0.1), dependent variable: adult-equivalent household expenditure (in log).

Figure 3.1 **Steps Taken in Implementing the Targeting Process**



Note: RGPH3 = Recensement Général de la Population et de l'Habitation 3 survey.

were established, with checks and balances, to work with defined poverty criteria: housing conditions, food security, and access to basic health and education services.

By combining community and PMT selection, this pilot allows comparisons to be made. It is especially helpful for measuring errors of inclusion and exclusion for both methods of targeting, as has been done in other countries (for example, Alatas et al. 2010).

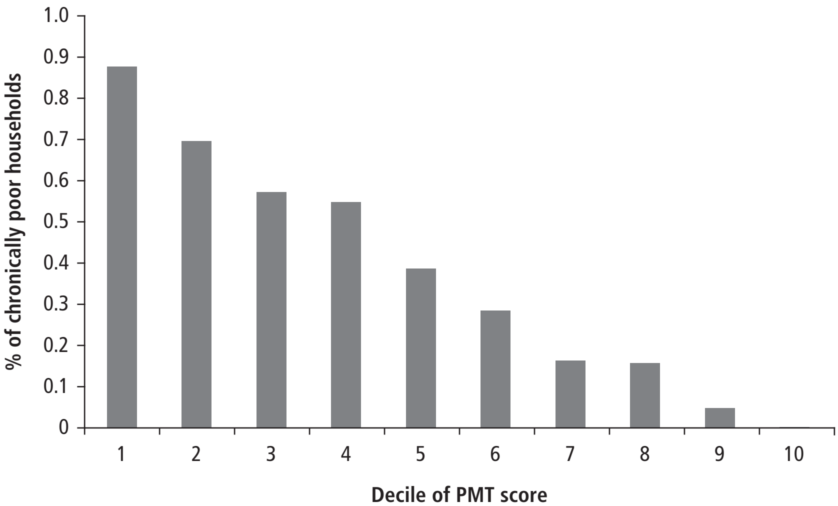
Targeting Results

The main indicators used to assess the efficiency of the targeting formula are errors of inclusion and exclusion. The targeting results are relatively sound compared to similar targeting studies or experiences in other countries: inclusion errors are 24.1 percent, and exclusion errors are 24.8 percent. These results are probably due to the variables employed but also to the relative homogeneity of the geographic area where the targeting takes place. Given the high level of poverty in the area, it is important to minimize exclusion errors even further, for instance, with a mechanism allowing people to dispute their eligibility when they are initially registered as nonbeneficiaries. Unfortunately, the available data (ECAM3) preclude identifying specific groups for which exclusion (or inclusion) errors are especially large. However, the ex post evaluation should allow further investigation of what causes some households to have lower consumption than expected in the PMT.

Figure 3.2 shows the proportion of chronically poor households in each decile of the PMT score. The fact that the lower PMT score deciles are associated with a much higher proportion of the chronic poor demonstrates the efficiency of the targeting mechanism.

Adding the "drought" variable slightly reduces the errors, especially exclusion errors, which decrease by about 1 percentage point; errors of inclusion

Figure 3.2 Proportion of Chronically Poor Households in Cameroon Based on PMT Score



Source: Calculations based on ECAM3 data.

become 23.8 percent and errors of exclusion become 23.9 percent. The results suggest that additional shock variables in general and better meteorological shock variables in particular can improve the efficiency of the targeting. Still, more information is needed on household exposure to shocks.

Errors in the urban formula are also encouraging: 14.5 percent exclusion errors and 35.3 percent inclusion errors. This asymmetry is due to the low quantile level chosen (0.1), which serves to minimize exclusion errors in urban areas.

Ex Ante Performance of the Transfer: A Large Impact on Poverty Indexes

Ex ante simulations were performed, before the start of the pilot, to estimate the potential magnitude of reductions in poverty brought about by unconditional cash transfers in rural areas. The simulations, based on the ECAM3 data, are purely mathematical: the eligibility status of the household is determined using the PMT formula described in the previous section, transfers are added to household consumption, poverty indexes are computed before and after the transfer, and the reduction in poverty is measured. For simplicity, we considered the three Foster-Greer-Thorbecke (FGT) indicators: poverty incidence (headcount ratio), poverty gap, and poverty severity. Since a reduction in poverty incidence only takes into account the number of households crossing a given threshold (the poverty line), it is important to consider the other two indexes (poverty gap and poverty severity) to measure the overall impact on poverty. Here we focus on the impact on chronic poverty—that is, households whose expenditures are below 0.8 of the poverty line.

These simulations also make it possible to compute the Coady-Grosh-Hoddinott (CGH) index, which is an indicator of targeting quality (see Coady, Grosh, and Hoddinott 2004). It measures the part of the transfers actually received by the poorest households, divided by their proportion of the population. Here we consider the part received by the poorest 20 percent of households. Finally, the simulations allow us to estimate the program budget needed when the program is implemented in the entire country.

Different transfer scenarios are considered for the simulations. A usual amount for cash transfer programs (the UCT in Niger) represents 10–20 percent of the beneficiaries' expenditures. According to ECAM3 data, this means monthly transfers per household between CFAF 7,500 and CFAF 15,000. Table 3.6 shows the budget of the transfer depending on the amount per household. For the five targeted regions in Cameroon, this would correspond to a global program budget between CFAF 44.1 billion and CFAF 97.1 billion per year (third column of table 3.6) excluding administrative costs.[6] The last column of table 3.6 shows the reduction in the incidence of chronic poverty (number of households below 0.8 of the poverty line) for each transfer amount, when the PMT presented in table 3.5 is used to target poor households.

Table 3.6 Amount of Transfer per Household and Resulting Global Budget for Cash Transfer Program in Cameroon

CFAF unless otherwise noted

Amount per household per month	Amount per capita per month	Yearly budget of transfer (billions, 2007 data)	Yearly budget of transfer (billions, with projected demographic growth)	Reduction in chronic poverty incidence (%)
7,500	1,000	44.1	49.0	9.15
10,000	1,333	58.8	65.3	13.02
11,250	1,500	66.2	73.4	15.17
12,500	1,667	73.5	81.6	17.64
15,000	2,000	88.2	97.9	21.82
16,500	2,200	97.1	107.7	24.44

Source: Calculations based on ECAM3 data for the 2007 population and RGPH3 data for the projected 2012 population in the target areas.
Note: The budget is based on the number of poor households in Cameroon.

The simulations presented in table 3.6 assume that a fixed amount is transferred to all households below the PMT threshold. However, an alternative is to allocate a different amount to different households. The amount transferred can vary depending on the size of the household, the PMT score, or a combination of these two characteristics.

Varying transfers according to PMT score can lead to greater reductions in poverty indicators, because poorer households receive more resources, which increases the impact of the project on the poverty gap and on poverty severity. Also, if transfers increase with household size, more resources may be transferred to the poor because larger households show a greater depth of poverty. Moreover, if transfers vary by PMT score, having different levels of transfers may increase the perceived fairness of the program by allocating more resources to the poorest households. This also allows the project to phase out participants as they get closer to the PMT threshold, rather than abruptly cutting the transfer as soon as they cross the threshold.

The drawback is increased administrative complexity with regard to computing the list of beneficiaries, registering beneficiaries, and making payments. Also, beneficiaries may not understand why their level of transfers is different from that of other households or may find this difference unfair. Varying the level of payments may generate additional opportunities for corruption. Ultimately, the choice of fixed or varying levels of payments may depend on the country and project administrative capacities as well as on the evaluation of risk (unfairness, corruption) implied by varying levels of payments.

Scenario 1 simulates a transfer of CFAF 12,500 per month per eligible household, which is the upper median amount based on the PMT scale in table 3.6. The associated reductions in the incidence, depth, and severity of poverty are

Table 3.7 Ex Ante Results of Poverty Simulations for Cameroon

Scenario	Amount of transfer per household per month (CFAF)	Reduction of poverty incidence (%)	Reduction of poverty gap (%)	Reduction of poverty severity (%)	Budget (CFAF, billions)
Scenario 1: Fixed amount per household	12,500	17.64	43.35	54.50	72.0
Scenario 2: Different amount per household	5,000–21,000	16.63	45.09	56.96	72.7
Scenario 3: Different amount by household PMT score	7,500–17,500	17.46	45.65	56.82	74.2
Scenario 4: Different amount by household size and PMT score	1,025–2,250[a]	16.09	47.42	59.02	76.2

Source: Calculations with the ECAM3 data.
Note: The budget is based on the number of eligible households in Cameroon.
a. Per member.

presented in table 3.7. The results show a clear reduction in the incidence of chronic poverty and an even stronger impact on both the poverty gap and poverty severity. The CGH index is 2.51, which indicates very efficient targeting. This scenario serves as the benchmark for comparing poverty reduction with variable transfer amounts.

Scenario 2 simulates a transfer similar to the previous one with regard to the average amount received by each household (CFAF 12,500 per month, budget of CFAF 72.7 billion). This time, five household sizes are created, each of which receives a different amount, ranging from CFAF 5,000 per month for a household with 1–3 members up to CFAF 21,000 per month for a household with 10 members or more. This transfer method is fairer in that it gives a similar amount to each person (and not the household).

The result of this simulation is similar to the first, with a slightly lower impact on the reduction of poverty incidence and a higher impact on the reduction of the poverty gap and severity. The shift in impacts toward reductions in the poverty gap and severity measures stems from the fact that poorer households have more family members on average. The CGH index also is higher in this scenario (2.57) than in scenario 1, suggesting better targeting when the transfer amount varies based on household size.

Scenario 3 divides eligible households into three categories depending on their PMT score. The lower category has PMT scores between 11,589 and 12,047.99, the median category has scores between 12,048 and 12,178.39, and the upper category has scores between 12,178.4 and 12,281. The poorer third receives CFAF 17,500 per month, the median third receives CFAF 12,500 per month, and the higher third receives CFAF 7,500 per month. Under this scenario, the incidence measure recovers to the level seen in scenario 1, while the reductions in the depth and severity of poverty seen in scenario 2 are largely maintained. The CGH index is clearly better in scenario 3 than in scenarios 1 and 2, reaching 2.75 in this simulation, suggesting more efficient targeting.

Scenario 4 essentially combines scenarios 2 and 3. The amount received depends on the number of household members and the PMT score of the household. A household in the lower PMT score category receives CFAF 2,250 per household member, the medium category receives CFAF 1,700 per household, and the higher category receives CFAF 1,025 per household. The impact on poverty indexes is mixed, with a slight decrease in the reduction of poverty incidence associated with the transfers and a larger reduction in the poverty gap and poverty severity measures compared to all other scenarios. In addition, the CGH increases to 2.80, suggesting further gains in targeting efficiency.

Overall, these four simulations indicate a high potential reduction of poverty, especially regarding the poverty gap and poverty severity, compared to similar simulations in other contexts (see, for instance, Narayan and Yoshida 2005). The fact that the depth and severity indexes see a larger reduction than the poverty incidence index indicates that the transfers efficiently target the poorer among the poor. The impact also varies by region and is higher in the provinces with the highest chronic poverty rates. A CGH index between 2.5 and 2.8 would rank this transfer program among the most efficient worldwide (see Castañeda et al. 2005). While it is clear that the targeting is more efficient when the transfer amount varies per household, the difference might not justify the increased administrative complexity, as discussed above.

The ex ante simulations suggest the potential for promising gains in terms of poverty reduction. However, the magnitude of the gains can only be captured through an ex post evaluation. The design for such an ex post evaluation is presented in the next subsection.

Design for an Ex Post Evaluation: Further Learning from the Program

A comprehensive evaluation of the unconditional cash transfer program in Cameroon is needed both to generate political support to sustain the program at the national level and to create empirical evidence regarding the economic impact of the transfer. The evaluation would generate knowledge spillovers far beyond the Cameroon project itself, a fact observed in the evaluation literature (Behrman 2007; Rawlings and Rubio 2005). It would also add to the base of knowledge on the design and implementation of safety net programs in Sub-Saharan Africa.[7]

The impact evaluation would focus on the following issues:

- *Is the targeting efficient?* Simple indicators would allow us to answer this question: inclusion and exclusion errors measured after eligibility is determined, but before the first transfer; coverage in terms of the number of beneficiaries and food as a proportion of expenditures of these beneficiaries; and impact on poverty indexes (FGT). These indicators can be compared to the ex ante ones presented above to evaluate the accuracy of ex ante measures as predictors of ex post performance.

- *What is the impact of transfers on short-term consumption and shock-smoothing?* Short-term measurement of expenditures and food consumption would provide a first answer. Variables regarding risk management by the household (ex ante and ex post) would add further insight into the impacts of transfers on household ability to manage shocks.
- *What is the short-term (permanent) impact on asset accumulation and revenue generation?* Data collection on the use of transfers would increase understanding of the impact of transfers on investment and income-generation activities. Variables collected would include changes in assets, changes in agricultural and nonagricultural activity, and changes in marketing behavior, among others.
- *What is the medium- and long-term impact on education, health, and social indicators?* Most of the impact on health and education occurs in the medium or long run. Data would be collected on variables such as diseases, health visits, nutrition, school attendance, and social variables like early marriage of girls or child employment.

A serious evaluation of the UCT pilot and its impact requires a counterfactual using an experimental design with untreated villages (Rawlings and Rubio 2005). Thus it is necessary to collect data in villages where the pilot is being conducted (treatment villages) and in similar villages not included in the pilot cash transfer (control villages) for the evaluation. The literature (Angelucci and de Giorgi 2009; Katayama 2010) recommends using this design rather than using control households in the same community as treatment households because of the indirect effect on ineligible households within a community. The design also would allow us to measure the spillover effect of the transfers. Of course, a qualitative analysis needs to complement this rigorous quantitative evaluation in order to evaluate the full effect of the transfers (Kanbur 2002; Ravallion 2009).

Conclusion: What We Have Learned?

The experience gathered in preparing this unconditional cash transfer suggests that chronic poverty can be effectively targeted for social assistance in Cameroon. Because of the concentration of poverty in the northern provinces and in rural areas, geographic targeting is a crucial component of any targeting mechanism. When geographic targeting is combined with a proxy means testing formula in rural areas, the targeting mechanism generates inclusion and exclusion errors both under 25 percent. Community targeting will be added in the pilot to improve targeting efficiency and community acceptance. An efficient targeting mechanism is harder to find for urban areas, where the incidence of chronic poverty is lower and inclusion errors are considerably higher. However, quantile regression methods have allowed us to overcome some of this difficulty. Current data regarding shocks affecting households are insufficient to assist in program targeting for short-term needs, even in rural areas where covariant shocks have major impacts on household well-being.

The next steps in implementing the targeted UCT in Cameroon are twofold. First, better information regarding risks and shocks has to be collected in order to elaborate a PMTplus targeting approach, which can be employed to scale up assistance programs rapidly in the face of adverse shocks. Second, the UCT pilot has to be evaluated rigorously in order to assess the efficiency of the main (long-term) UCT component.

Annex 3A Detailed Results

Table 3A.1 PMT Formula for in a Pilot Program in Rural Areas of Cameroon

Variable	Response	Weight
Household head gender	Man	1,569
	Woman	0
Household head age	Age	69
	Squared age	–0.5
Household head education	No education	3,647
	Primary	4,103
	Secondary 1	2,826
	Secondary 2 and more	0
Household head religion	Muslim	–423
	Christian and other	0
Household head occupational category	Formal sector (public or private)	0
	Nonagricultural informal	2,408
	Agriculture	4,953
	Unemployed	2,590
Household size	1–3 members	0
	4–5 members	2,646
	6–7 members	4,520
	8 members and more	6,371

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Table 3A.1 (continued)

Variable	Response	Weight
Household composition	Members, 0–4 years old	204
	Members, 5–14 years old	2,084
	Members, 15–59 years old	921
	Members, 60 years old and older	1,000
Housing type	Compound, *saré*	–679
	Other	0
Housing occupation status	Owner	1,819
	Not owner	0
Main source of drinking water	Tap, drilling	–246
	Other (well, equipped spring, river, rainfall)	0
Main lighting source	AES-SONEL electricity	–3,872
	Other (natural gas, generator)	0
Main energy source for cooking	Bought wood	3,229
	Picked-up wood	6,033
	Other (natural gas, oil, sawdust, coal)	0
Bathroom facility	Equipped latrine, flush toilet	0
	Unequipped latrine	1,851
	No bathroom facility	4,613
Main wall material	Concrete, baked brick, stone	–1,149
	Other (terracotta, simple brick, plank)	0
Main roof material	Cement, sheet metal, tile	–3,210
	Other	0
Main floor material	Cement, tile	–1,377
	Other	0
Own radio	Yes	–844
	No	0
Own television	Yes	–2,686
	No	0
Own car, motorcycle, bicycle	Yes	–506
	No	0
Own farmed land	Yes	–883
	No	0
Own unfarmed land	Yes	–1,595
	No	0
Own house not used by a household member	Yes	–2,522
	No	0
Own a cart or wheelbarrow	Yes	–296
	No	0

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Table 3A.1 (continued)

Variable	Response	Weight
Own cow(s)	Yes	−3,347
	No	0
Own horse(s) or donkey(s)	Yes	−1,656
	No	0
Own sheep(s) or goat(s)	5 and more	−596
	Less than 5	0
Own chicken or poultry	15 and more	−346
	Less than 15	0
Constant		−27,136

Source: Calculations based on ECAM3 data.
Note: Probit regression, dependent variable: "chronic" (status of chronic poverty of the household, as defined in Nguetse-Tegoum 2011).

Notes

1. These rates come from studies using data from the *Enquête Camerounaise auprès des Ménages 2* and *3* (ECAM2 and ECAM3), where the poverty line is established at CFAF 738 (US$1.64) per day (Cameroon's currency is the African Financial Community franc; Nguetse-Tegoum 2011).
2. This threshold is close to the extreme poverty line—US$1.25 per day—and is used in the PMT for econometric reasons. Adult-equivalent consumption levels are defined based on recommended dietary allowances from the National Research Council (1989).
3. A common PMT formula is used in rural areas across the five project regions rather than estimating five different formulas. See table 3A.1 in the annex to this chapter. The reasons include improving project administration by increasing the simplicity and design (and testing) of the formula with a greater number of observations. Including regions (using dummy variables) in the formula does not increase its ex ante targeting efficiency.
4. These data were obtained from the NASA Langley Research Center POWER Project, which is funded through the NASA Earth Science Directorate Applied Science Program.
5. In all our attempts to generate an efficient urban formula, QR produced much lower targeting error rates than OLS, even when OLS was performed on a subsample containing only the poorest households or when PMT variables were regressed on a simple indicator of being above or below the poverty threshold.
6. Taking into account demographic growth, this amount would be between CFAF 49 billion and CFAF 107.7 billion. Administrative costs usually represent 10–20 percent of the budget for this type of program.
7. Several impact evaluations of *conditional* cash transfer programs have been conducted in the last 15 years, regarding indicators of human capital (Behrman and

Hoddinott 2005; Gertler 2004) or production (Gertler, Martinez, and Rubio-Codina 2012). For a comprehensive review of the literature, see Fiszbein and Schady (2009). However, we lack evidence regarding programs in Sub-Saharan Africa, especially unconditional cash transfer programs (Devereux 2006).

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