Simulating farm household poverty: from passive victims to adaptive agents

Pepijn Schreinemachers*

Josef G. Knoll Visiting Professorship for Development Research, University of Hohenheim, Germany (pepijn@uni-hohenheim.de)

Thomas Berger

Josef G. Knoll Visiting Professorship for Development Research, University of Hohenheim, Germany (490e@uni-hohenheim.de)

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* Corresponding author

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Abstract

Existing microeconomic models for simulating poverty heavily rely on static projection from statistical inference. When used for simulation these models tend to conceive farm households as passive victims and thereby underestimate their resilience and adaptive capacity. Farming systems research has much to contribute to the research on poverty by bringing in a detailed understanding of farm household decision-making, which directly relates to their adaptive capacity.

This paper presents a novel methodology to simulate poverty dynamics using a farming systems approach. The methodology is based on mathematical programming of farm households but adds three innovations: First, poverty levels are quantified by including a three-step budgeting system, including a savings model, a Working-Leser model, and an Almost Ideal Demand System. Second, the model is extended with a disinvestment model to simulate farm household coping strategies to food insecurity. Third, multi-agent systems are used to tailor each mathematical program to a real-world household and so to capture the heterogeneity of opportunities and constraints at the farm level as well as to quantify the distributional effects of change. An empirical application to Uganda illustrates the methodology. The method opens exciting new prospects for applying farming systems research and multi-agent systems to poverty analysis and the *ex ant*e assessment of alternative policy interventions.

Keywords: food security, inequality, farming systems, multi-agent systems

1 Introduction

Poor people in developing countries are food insecure and have unequal opportunities to pursue the life of their choosing (The World Bank 2000, 2005). Most of these poor people are members of farm households managing agricultural fields for their sustenance. Although their poverty has much to do with factors that go far beyond their agricultural fields—such as markets, governments, and climate—it is the management of these fields that is their main safety net.

Most microeconomic analyses of poverty have paid little attention to how poor people engage in agriculture. Instead, these analyses have sought to identify underlying determinants of poverty by regressing a large number of exogenous variables (such as age, education, household size, and land ownership) on a measure of poverty (e.g., Feleke et al. 2005). This approach is also recommended in the World Bank's *Sourcebook for Poverty Reduction Strategies* (Coudouel et al. 2002). Pyatt (2003) labels it the 'statistical approach' for its reliance on statistical inference and to distinguish it from the 'structuralist approach' that seeks to understand the linkages. Although the statistical approach is useful for identifying variables that are important for poverty reduction, it has two main drawbacks:

First, the statistical approach does not reveal details about the opportunities and constraints of poor people to improve their lot and therefore yields limited information for policy implementation. Datt and Jolliffe (2005), for instance, find that one additional average year of schooling in Egypt would reduce poverty levels by ten percent. This underlines the importance of education but efficient policy implementation requires more information about the underlying linkage between education and poverty. For example,

does education reduce poverty because better-educated farmers have fewer children, because they adopt improved technologies, or is it because they leave agriculture? Imagine that the main linkage would be the adoption of technologies: imposing one extra year of schooling on every Egyptian pupil would then be a particular inefficient policy implementation.

Second, when used for simulation the statistical approach treats farm households too much as passive victims and too little as adaptive (but sometimes failing) agents. This is because the *ceteris paribus* condition leads to a static projection of one variable, which underestimates the resilience and adaptive capacity of farm households to changing conditions. For instance, Datt and Jolliffe (2005) simulated a six percent decrease in rural poverty when distributing about 14 percent of the land from the largest landowners to households with the least land and the lowest levels of education. Yet, their assumption that the productivity of small and large farms will be unaffected by this dramatic shift in resources is unlikely to hold.

Agricultural economics has much to contribute to poverty research because of its in-depth understanding of farm household decision-making. Farming systems research (FSR) in particular can complement the statistical approach with a better understanding of the opportunities and constraints of the natural and socioeconomic system that underlies the revealed statistical relationships. It has also a standard tool—mathematical programming of the farm household—to model the drivers of the system, to incorporate economic trade-offs, and to simulate adaptation to changing conditions.

The actual contribution to poverty research of agricultural economics in general and FSR in particular has, however, been limited (*cf.* von Braun 2003; Johnson et al. 2003). One

reason is that FSR has focused too much on the production side and has relatively neglected the consumption side of the farm household: The consumption side was usually only included when the separability assumption of production and consumption decisions was indefensible. Many researchers have tackled the problem of inseparability by including some sort of demand equation in the model such as minimum consumption requirements or simple Engel equations (e.g., Holden and Shiferaw 2004). Such models often quantify 'food security' as mere food production. Yet, when using these models for poverty analysis, a detailed expenditure model is needed that can quantify poverty levels in terms of monetary or food energy consumption.

A further constraint to FSR is its limited representation of heterogeneity and interaction, which is essential for understanding poverty and the distributional effects of policies combating it. Most modelers have rather arbitrarily decided on a limited number of representative farm households (typically four) based on *a priori* knowledge or statistical analysis, which gives only a limited representation of heterogeneity. Balmann (1997), Berger (2001), and Happe (2004) show that heterogeneity and interaction in agriculture can be successfully modeled by a combination of mathematical programming (MP) and multi-agent systems (MAS). This paper is a first attempt to apply this potential of MP-MAS to poverty analysis.

The paper outlines a novel methodology for simulating poverty that builds on MP of farm households but adds three dimensions:

1. <u>To quantify poverty</u>, a three-step budgeting system of savings, total food expenditures, and expenditures on specific food categories is included in a MP model of the farm household.

2. To simulate farm household coping strategies to food insecurity, a disinvestment model is included.

3. To capture heterogeneity and distributional effects, MAS is used to tailor each MP to a real-world farm household.

The remainder of this paper is structured as follows. Section 2 explains the use of multi-agent systems as a framework to generate agent-specific programming models and interactions. Section 3 lays out the three-step budgeting system and Section 4 extends this to include coping strategies. The method is illustrated by an empirical application to Uganda in Section 5. Finally, Section 6 concludes.

2 Multi-agent systems

Multi-agent systems (MAS) of land use decisions have two main components: a spatial component representing the physical landscape under study and an agent-based component representing human decision-making and interaction (Parker et al. 2002). For the present purpose, the term 'agent' denotes a model representation of a real-world farm household.

MAS have a one-to-one representation of real-world farm households and computational agents, which eliminates the need to define a limited number of representative farm households and makes MAS highly suitable for representing heterogeneity in both socioeconomic and biophysical terms. Agent interaction can be simulated in MAS. For instance, Berger (2001) implemented networks for technology diffusion and local land and water markets.

Empirical MAS can be parameterized from farm household survey data (Berger and Schreinemachers 2006). Statistically estimated models, such as production functions and expenditure systems, are very suitable for MAS as they both thrive on and represent heterogeneity (Schreinemachers and Berger 2006). More details on how MAS can be used to simulate poverty follow.

3 A three-step budgeting system

In a developing country context, poverty is best quantified in terms of food energy consumption (Coudouel et al. 2003). This section describes how a MP model of the farm household can quantify poverty by including well-established expenditure models.

It is assumed that agents maximize a three dimensional utility function consisting of: (1) cash income generated from selling farm products; (2) home consumption of own produce; and (3) future income from investments discounted as an annuity. Agents engage in farm and non-farm activities. Because of space limitations, only the consumption side is described while the reader can consult Schreinemachers (2006) for the complete model.

Assuming 'weak separability' in consumer decision-making, the expenditure decisions can be conceptualized as a stepwise budgeting process as shown in **Figure 1** and separate models can be estimated at each step (Sadoulet and de Janvry 1995: 36).

>> FIGURE 1 <<

Step 1: Savings and expenditures

In the first step, agents decide how much of their income to expend and how much to save. Let the variable SAV be the savings and INC the disposable income, H the household size measured in an equivalence scale (joules), D a matrix of locational dummies, and α_0 a constant term. The amount of savings can be specified as a quadratic function of disposable income:

(1) $$SAV = \alpha_0 + \alpha_1 INC + \alpha_2 INC^2 + \alpha_3 H + \sum_{i=1}^{n-1} \alpha_{4,i} D_i \qquad \text{with } \alpha_2 > 0$$

in which the *alfas* are the parameters to be estimated. Micro-economic theory suggests that the share of savings increases with income, which is the case if α_2 is positive. If income and savings are known then the total expenditure (TEX) can be derived from the income identity:

(2) $$INC = SAV + TEX$$

Step 2: Food and non-food expenditures

In the second step, agents decide how much of this total expenditure to allocate to food (FEX) and non-food items (NEX). A modified version of the Working-Leser model can quantify this relationship (Hazell and Roell 1983):

(3) $$v = \beta_0 + \beta_1 \ln TEX + \beta_2 H + \sum_{n=1}^{40} \beta_3 D_i$$

in which *v* is the expenditure share on food and the *betas* are parameters to be estimated. It follows that the value of food expenditures (FEX) equals TEX**v*/100 while NEX can be derived from the parameter estimates using the properties of symmetry and adding up.

Step 3: Expenditures on specific food categories

In the final step, agents decide to spend their food budget on broad categories of food products. The use of categories instead of individual items gives agents more scope for substituting between food items. The third step can be quantified using a linear approximation of the Almost Ideal Demand System (LA/AIDS) (Deaton and Muellbauer 1980):

$$(4) \qquad w_k = \delta_{0,k} + \sum_k \delta_{1,k,l} \ln p_l + \delta_{2,k} \ln(M/P^*) + \delta_{3,k} H + \sum_{n=1}^{40} \delta_{4,k} D_i$$

where the subscripts *k* and *l* denote individual food categories of a total of *n* categories (*k,l*=1,2,..,*n*) and the *gammas* denote parameters to be estimated. The variable w_k is the share of category *k* in the total food budget; M is the per capita food expenditure measured in an equivalence scale for household size. P^* is an index of prices, which in the original (non-linear) version has a translog functional form but in its linear version can be replaced by the logarithm of the Stone geometric price index (Deaton and Muellbauer 1980):

$$(5) \qquad \ln P^* = \sum_k w_k \ln p_k$$

Food energy needs and supply

The value of expenditures on the k-th food category is estimated as w_k*FEX. To quantify food consumption in joules, each value can be divided by its unit value to get a physical quantity and then multiplied by an energy weight as shown in **Figure 1**. Standard conversion tables (e.g., Latham 1997) can be used to express each food product into energy units, while survey estimates can be used to compute the average energy contents and unit values of food categories.

To quantify consumption poverty for each agent, the estimated energy intake from the three-step budgeting system is compared to the agent's food energy needs. James and Schofield (1990) suggested estimating age and sex-specific energy needs from basal metabolic requirements and physical activity related requirements. This method can also be used to construct an equivalence scale of household size in joules.

Implementation of the three-step budgeting system in a MP model

Steps 2 and 3 are cost-minimization problems because consumption absorbs own produce that could have been sold, and absorbs revenues that could have been re-invested. This makes step 1 a maximization problem as savings reduce the need for consumption. The minimization of concave and the maximization of convex functions requires either a piecewise linear approximation with binary variables or (Type 2) Special Ordered Sets to ensure that the segments enter the optimal solution in the correct order (Hazell and Norton 1986). The first option is shown here as not all solver software allows for the second option.

>> TABLE 1 <<

Table 1 shows how to implement the three-step budget system in a MP model. The frequent occurrence of interaction terms poses no problem as long as there is not more than one endogenous variable. Equations (1), (3), and (4) can be found in rows 4, 8, and 16. The appendix explains each coefficient in detail, so that the method can be replicated.

Many coefficients are agent-specific as they depend on household size, these are printed in bold in the table. The MAS software takes care of updating these coefficients for every agent, passes the updated matrix to a solver, and then stores the solution vector for each problem for later analyses.

4 Disinvestment as a coping strategy

Farm households are food secure if they have strategies to smooth consumption in the event of disaster. One such commonly observed strategy in African farming systems is keeping livestock (Kristjanson et al. 2004). Farm households buy and maintain animals in good years, when yields or prices are high, and sell them in bad years, when yields or prices are low. By investing and disinvesting in livestock, households smooth their income and consumption between years.

The difference between a good and a bad year can be conceptualized as a food energy balance. For instance, a bad year is when income is not enough to satisfy 90 percent of the food energy needs. This level is arbitrary and one should ideally base it on in-depth interviews. **Figure 2** shows the theoretical model for this disinvestment process. The upper diagram shows that savings increase (the solid line) and expenditures decrease (the dashed line) as a share of income. The lower diagram shows food energy as a function of

income with the horizontal line depicting the food energy level at 90 percent (E_{90}) fulfillment of the (physical) needs; the income level where both functions intersect is denoted as Y_0.

>> FIGURE 2 <<

Agents try to avoid poverty by keeping their income above level Y_0. Yet, if income would fall below Y_0, then an agent has two options: (1) add savings to the disposable income; and/or (2) sell livestock and add the returns to the disposable income. Both options entail the substitution of current consumption for future income. Agents continue their disinvestment until their food energy needs are satisfied for at least 90 percent, which is when the level of income equals Y_0.

If the agent is unable to sell assets or consume savings, then it runs into an energy deficit and falls into poverty. **Figure 2** shows that the consumption and (dis-)savings functions are non-smooth below level Y_0, because selling livestock is a discrete rather than a continuous event; a smooth function would, however, represent the consumption of savings, but is not shown here.

At income levels between Y_0 and Y_1, no income is saved: the savings function is flat at the zero level, as all income is consumed. Point Y_1 represents the highest level of income at which agents do not save income and can be derived from the savings equation (see **Appendix**).

Implementation of coping strategies in a MP model

Table 2 shows a simplified matrix implementation of the disinvestment problem. It has an objective function to be maximized in the first equation and nine constraints. Agents have a household size (H, measured in joules) and two resources: savings (SAV) and livestock (LVS). Savings can either be deposited at an interest rate *d* or be consumed. Agents furthermore choose between selling their livestock in a future year at an expected price *c1* or selling their livestock in the present year at price *c2*. If *c1* exceeds *c2*, then the livestock would be maintained. A simple Engel equation (row 6) replaces the more complex budgeting system of **Table 1**; it requires an agent to spend a share α on food with each unit of food adding σ joules to the food energy supply (row 7). Food energy demand equals the agent's household size in joules. Row 8 evaluates the food energy supply and demand: if demand exceeds supply, then the binary activity (column 9) has to be selected, which allows the agent to run into an energy deficit. Yet, for this to happen, the agent must first sell all livestock (row 9) and consume all savings (row 10).

The MAS software keeps track of each agent's livestock and savings endowments, as well as all other agent-specific data. A main function of the MAS is therefore data handling and processing.

>> TABLE 2 <<

5 Empirical application

The purpose of this section is to illustrate the usefulness of the methodology rather than to generate policy recommendations, as space limitations curb the scope of this paper. The methodology was applied to two village communities in southeastern Uganda comprising 520 farm households. The strength of the above methodology ultimately depends on how well farm household incomes are simulated. For this, the model has a very detailed crop and livestock production part; the complete MP model has 2,320 activities, including 50 integers, and 553 constraints; in addition, the model is coupled to a biophysical model that simulates changes in soil nutrients (see Schreinemachers 2006 for details).

The 1999-2000 Uganda National Household Survey was used to estimate the expenditure system. Step 1 and step 2 equations were estimated in unrestricted form using ordinary least squares, while the LA/AIDS was estimated in restricted form using Seemingly Unrelated Regressions.

The simulation results shown in **Figure 3** assess the combined impact of short-term credit and access to technologies (mineral fertilizers and improved maize). The figure overlays two kernel density distributions of poverty levels; one is the average baseline over a 15-year simulation period and the other is the scenario with full access to credit and innovations over the same period. The figure shows that the simulated policy intervention substantially reduced poverty levels, as the bulge of the agents has crossed the poverty line (set at 3.3 billion joules/capita). It also shows that neither the very poorest nor the richest agents would benefit from the policy intervention, as the tails of the distribution

have not moved. This policy intervention would hence not be suitable if the objective were to reach the poorest of the poor.

>> FIGURE 3 <<

6 Conclusion

The statistical approach to poverty analysis provides only limited information for policy implementation, as it reveals neither the opportunities and constraints of poor people nor the dynamics of change and adjustment at the farm level. Agricultural economics has much to contribute to poverty analysis by bringing in a more detailed understanding of decision-making by farm households.

The paper showed that the combination of MP and MAS is a suitable tool for poverty analysis if based on detailed food expenditure systems to quantify poverty. The approach can also accommodate qualitative information on coping strategies. Main strengths of the approach lay in its ability to capture the heterogeneity of farm households, their adaptive capacity, and to assess the distributional effects of policy intervention *ex ante*. We hope that this paper will stimulate agricultural economist to further improve and apply the available methods on poverty analysis.

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Tables and figures

Figure 1: Three-step budgeting system

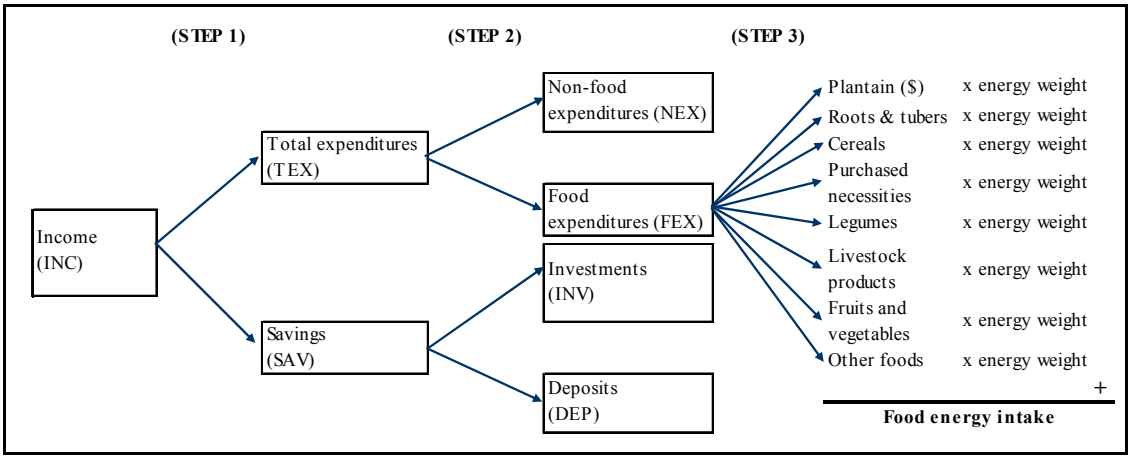


Table 1: Implementation of the three-step budgeting system in a linear program

	1. Sell [kg]	**2. INC**	3. Savings	*4. Segment 1*	*5. Segment 2*	*6. Binary*	**7. TEX**	8. Constant	9. Household size	*10. Segment 1*	*11. Segment 2*	*12. Segment 3*	*13. Binary 1*	*14. Binary 2*	**15. FEX**	16. Constant	17. Household size	18. Price	*19. Segment 1*	*20. Segment 2*	*21. Segment 3*	*22. Binary 1*	*23. Binary 2*	24. Cons. food cat. 1	25. Cons. food cat. 2		
1. Maximize	c_3																							c_1	c_2		
2. Income function	c_3	-1																						c_1	c_2	=	0
3. Savings transfer		1		-1	-1																					=	0
4. Savings function			-1	0	**Φ**																					=	0
5. INC=SAV+TEX		1	-1				-1																			=	0
6. lower bound 1				-1		$\mathbf{S_1}$																				≤	0
7. upper bound 1					1	$-S_2$																				≤	0
8. Food function								β_5	χ	λ_1	λ_2	λ_3			-1											=	0
9. Constant							1	-1																		=	0
10. Household size							1		-1																	=	0
11. TEX							1			-1	-1	-1														=	0
12. lower bound 1										-1			E_1													≤	0
13. lower bound 2											-1			E_2												≤	0
14. upper bound 2											1		$-E_2$													≤	0
15. upper bound 3												1		$-E_3$												≤	0
16. Food category 1																ψ_1	η_1	φ_1	$\zeta_{1,1}$	$\zeta_{1,2}$	$\zeta_{1,3}$			$-c_1$		≤	0
17. Food category 2																ψ_2	η_2	φ_2	$\zeta_{2,1}$	$\zeta_{2,2}$	$\zeta_{2,3}$				$-c_2$	≤	0
18. Constant															1	-1										=	0
19. Household size															1		-1									=	0
20. FEX															1				-1	-1	-1					=	0
21. lower bound 1																			-1			F_1				≤	0
22. lower bound 2																				-1			F_2			≤	0
23. upper bound 2																				1		$-F_2$				≤	0
24. upper bound 3																					1		$-F_3$			≤	0
25. upper bound obj. function				$\mathbf{S_1}$	S_2	1				E_1	E_2	E_3	1	1					F_1	F_2	F_3	1	1			≤	0

Figure 2: Theoretical model for coping strategies against food insecurity

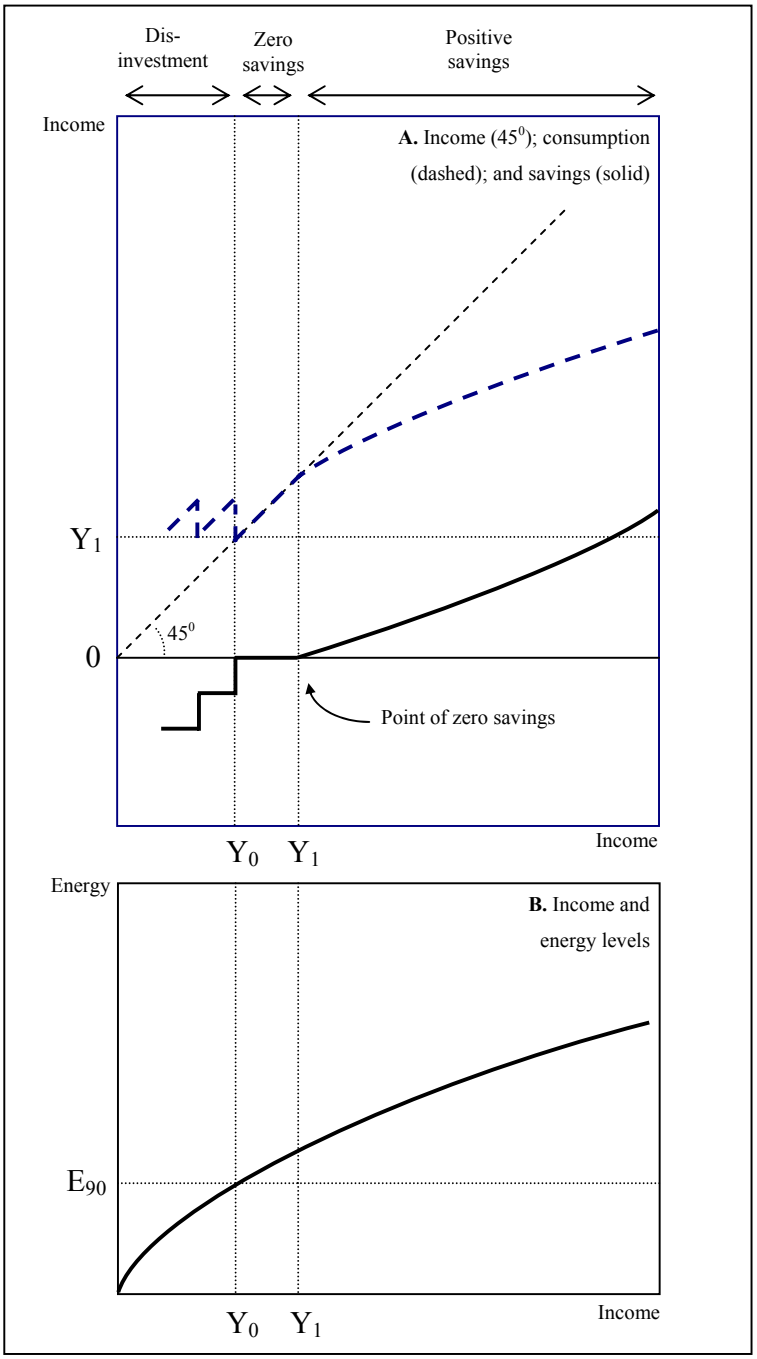
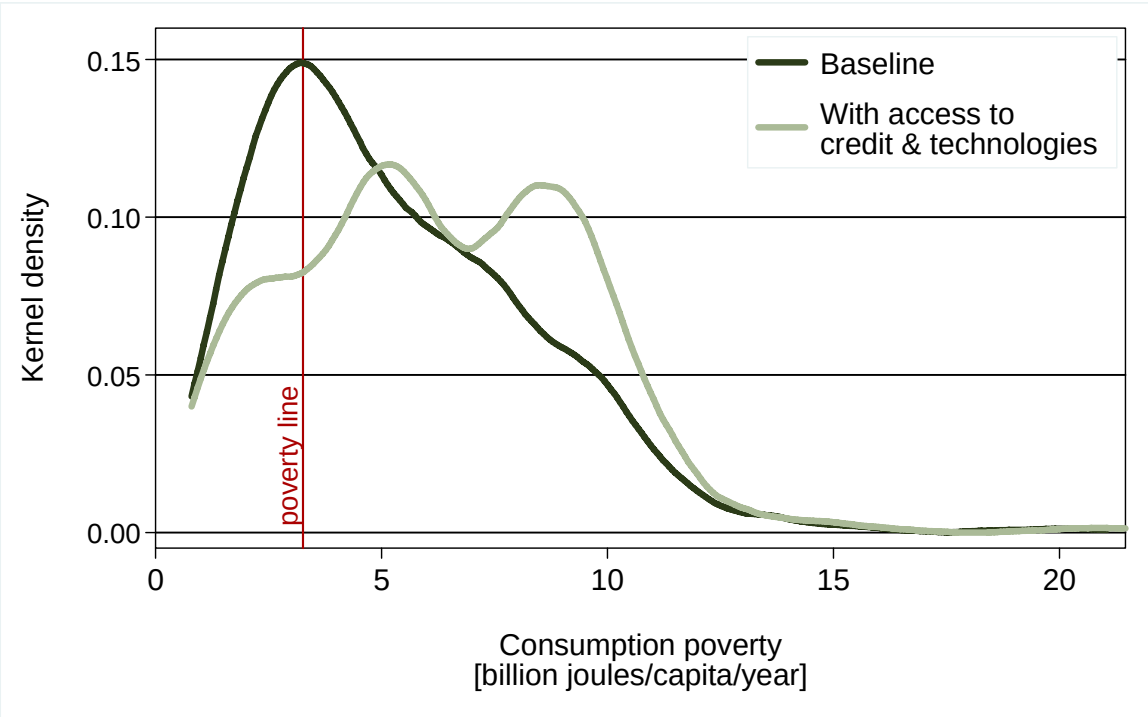


Table 2: Disinvestment decisions

	1. Deposit savings	2. Consume savings	3. Keep livestock	4. Sell livestock	5. Income transfer	6. Purchase food	7. Energy supply	8. Energy demand	9. Binary		
1. Maximize	***d***		***c1***	***c2***		***-c3***					
2. Savings	1	1								≤	SAV
3. Livestock			1	1						≤	LVS
4. Household size								1		=	H
5. Income transfer	*d*	1	*c1*	*c2*	-1	*-c3*				=	0
6. Food consumption					α	*-c3*				=	0
7. Energy supply						σ	-1			=	0
8. Energy supply=dem.							-1	0.90	-10^3	≤	0
9. Sell livestock				-1					LVS	≤	0
10. Consume savings		-1							SAV	≤	0

Notes: *c*'s are prices, *d* is the interest rate on short-term deposits. SAV is savings, LVS is the herd size, and H is the size of the household in joules. α is the coefficient on income in a demand equation, and σ is the energy equivalent of one unit of consumption.

Figure 3: Distributional effect of policy intervention



Notes: Simulated poverty levels for 520 agents in two scenarios averaged over 15 years. Poverty line is 3.3 billion joules per capita (in male adult equivalents) per year.

Appendix: Explanation of coefficients in Table 1

Step 1: savings model

S_1 The size of the first piecewise linear income segment at which savings are zero and calculated as: $(-\alpha_1 + ((\alpha_1^2) -4 * (\alpha_3 * H + \alpha_5) * \alpha_2)^{0.5}) / (2 * \alpha_2)$ in which α_5 is a composite constant of all relevant dummy variables in the model

S_2 The size of the following segment and should be a sufficiently large number

Φ The average savings coefficient for a piecewise linear segment; calculated as:

$\alpha_1 + \alpha_2 * (S_1 + S_2 / 2)$

Step 2: Working-Leser model

E_i The width of the *i*-th piecewise linear segment of TEX

β_5 A composite constant of the relevant dummy variables in the model

χ The effect of household size (in joules) on food consumption, which is agent-specific and calculated as: $H * \beta_2$

λ_i The average food expenditure coefficient for the *i*-th piecewise linear segment, calculated as: $\beta_1 * \ln((E_{i+1}-E_i) / 2 * 100\% / H)$

Step 3: LA/AIDS

F_j The width of the *j*-th piecewise linear segment of FEX

ψ_k A composite constant of the relevant dummy variables in the model for the *k*-th food category

η_k The effect of household size (in joules) on the consumption of the *k*-th food category, which is agent-specific and calculated as: $H * \delta_3$

φ_k The price effect on the consumption of the *k*-the food category, calculated as: $\varphi_k = \sum_{l=1}^{7} \ln(\delta_{1,k,l} * \frac{p_l}{\bar{p}_l})$ in which p_l stands for the price of food category *l*, which is a weighted function of individual commodity prices.

$\zeta_{k,j}$ The average food item expenditure coefficient for the *k*-th food category and the *j*-th piecewise linear segment, calculated as: $\delta_{2,k} *(\ln (F_j+(F_{j+1}-F_j)/2)-\ln(H)-\ln(P^*))$