POLICY RESEARCH WORKING PAPER 2847

The Nature and Dynamics of Poverty Determinants in Burkina Faso in the 1990s

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The World Bank
Africa Technical Families
Macroeconomics 3
May 2002

POLICY RESEARCH WORKING PAPER 2847

Abstract

Fofack investigates the determinants and dynamics of poverty during the five-year growth period that followed the 1994 CFA franc devaluation in Burkina Faso. Results show that the nature and dynamics of poverty determinants are influenced by the spatial location of households and that the post-devaluation growth period did not significantly alter the pattern of poverty determinants. The most significant determinants of poverty over the growth period include the burden of age dependency, human and physical assets, household amenities, and spatial location. Though consistently significant at the national level, the direction of association between these determinants and welfare depends on their nature. While the burden of age dependency is consistently negatively associated with welfare, asset ownership is positively associated. The probability of being poor declines with increasing share of household assets and increases with the burden of age dependency. There are some variations at the regional level, however, shown by the difference in the scope of significance of these determinants. While the ratio of age dependency remains the most significant determinant of rural poverty, its explanatory power decreases considerably in urban areas where its marginal effect on the probability of being poor is relatively low over the two reference periods, despite the significance of the probit coefficient and the relatively low asymptotic standard error.

This paper—a product of Macroeconomics 3, Africa Technical Families—is part of a larger effort in the region to better understand the determinants of growth and poverty in Sub-Saharan Africa. Copies of the paper are available free from the World Bank, 1818 H Street NW, Washington, DC 20433. Please contact Paula White, room J7-270, telephone 202-458-1131, fax 202-473-8466, email address pwhite2@worldbank.org. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at hfofack@worldbank.org. May 2002. (26 pages)

The Nature and Dynamics of Poverty Determinants in Burkina Faso in the 1990s

By

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JEL classifications: *C25; D31; I32; R12*

Keywords: univariate probit models, poverty determinants, dynamics of poverty determinants, marginal effects, spatial effects, binary responses outcome, probability of being poor, standards normal cdf.

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I. Introduction

Poverty is widespread in Burkina Faso and persisted over the nineties, up to and including the post-devaluation growth period.[2] This growth period was characterized by a relative increase of GDP per capita, largely attributed to improved terms of trade, mainly in the export crop sector. In constant 1995 dollars, the GDP per capita increased from US$235 to US$260 between 1993 and 1998 (World Bank, 2000; Burkina Faso, 2001). Yet despite this post-devaluation growth performance, the incidence of poverty remained high over the period, above 45 percent, and even increased in a number of regions and socioeconomic groups. It increased from 51 to 56 percent, and the poverty gap increased from 15 to 20 percent in the Centre-Sud region.[3] Across socioeconomic groups, the "Other Active" category recorded the largest increase in poverty incidence, which rose to 29 percent, from 19; the poverty gap remained constant at 7 percent.[4] The same pattern was observed among the subsistence farmers, the largest socioeconomic group, accounting for over 75 percent of the active labor force: while the poverty gap in this group remained constant, the incidence of poverty increased from 51 to 54 percent (Fofack, Monga and Tuluy, 2001).

The persistence of poverty, particularly in the midst of growth, is stressed in the "Poverty Reduction Strategy Paper for Burkina Faso" (World Bank, 2000). This document also provides trends in welfare and poverty, as well as constraints on poverty reduction. Some of these constraints are further investigated in Fofack, Monga and Tuluy (2001). These two studies do not go so far as investigating the determinants of poverty. However, understanding the poverty determinants and their changes over time are critical for policy analysis, including the design of effective poverty reduction strategies (Glewwe, 1991). Understanding the nature and dynamics of these determinants may be critical in the identification of factors driving the changes in household income and consumption behaviors. The object of this paper is to investigate the nature and dynamics of poverty determinants in Burkina Faso in the post-devaluation growth period.

In the past, few studies have attempted to investigate the determinants of poverty in Sub-Saharan African countries (House, 1991; Glewwe, 1991; Coulombe and McKay, 1996). Investigating the determinants of welfare among peasant households in Sudan, House (1991) identified lack of diversification of production and limited income-generating opportunities as key determinants of rural poverty. Glewwe (1991) found the availability of medical services, among other factors, to be a strong determinant of welfare in Côte d'Ivoire, similarly to return to education which appeared to be particularly high in urban Côte d'Ivoire. The welfare effects of agricultural extension services in rural Côte d'Ivoire appeared to be limited, however. In a related study on Mauritania, Coulombe and McKay (1996) found the determinants of welfare to be variable across regions and socioeconomic groups, with education appearing as a strong predictor of

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[2] In January 1994, former French colonies in Central and West Africa devalued their currency, the CFA Franc, for the first time in over 30 years. The CFA Franc is pegged to the French Franc at the rate of CFA Franc 100 for French Franc 1. Before the devaluation, this rate was CFA Franc 50.

[3] A poverty gap this high is an illustration of a relatively low level of household income and a high degree of vulnerability of poor households to macroeconomic and exogenous shocks.

[4] This group includes all active workers employed in all but the private and public sectors, export and subsistence agriculture, commerce and artisans.

welfare. These studies are based on one sample survey and do not allow assessment of the dynamics of poverty determinants, or their stability over time, however. Understanding the dynamics of poverty determinants may be useful in explaining the apparent anomaly and contrast between the relatively strong economic growth in the post-devaluation period and persistence of widespread poverty in Burkina Faso.

This paper uses a probit model to infer the nature and dynamics of poverty determinants. The results suggest the burden of age dependency, asset ownership, education and literacy, spatial distribution of welfare and income sources as key poverty determinants in Burkina Faso. At the national level, education and female literacy are significant with negative coefficient, suggesting that the probability of being poor decreases with increasing level of education and literacy. The direction of association is similar for household asset ownership and spatial location of households. On the other hand, the burden of age dependency, which is also significant, has a coefficient with a positive sign. This suggests that the probability of being poor increases with the number of dependents. While the sign of the coefficient and direction of association is stable over time, the magnitude and scope of probability is less so. The size and scope of the probit coefficients are different between the two reference periods at the national level. Also, the nature of poverty determinants is more variable between urban and rural areas. Male literacy is significant in urban areas, whereas spatial effects are more robust in explaining rural poverty.

The remainder of the paper is organized as follows. Section II provides a description of the data sets. Section III focuses on model selection and estimation procedures. Section IV provides empirical results. Section V provides concluding remarks and policy implications.

II. The Data

The study is based on two priority surveys, Enquête Prioritaire I (EPI) and Enquête Prioritaire II (EPII), undertaken by the Burkina Faso "Institut National de la Statistique et de la Démographie" (INSD) in 1994 and 1998. These surveys are very similar in the scope of data collection, sampling design and coverage: they are nationally representative and the sample selection uses a two-stage stratified random sampling in both designs. Individual and household level information is collected on a relatively large sample: about 8,600 households in the first and about 8,500 in the second round.[5] This relatively large coverage is useful for spatial inference on welfare.

These surveys collect information on household and individual characteristics, including household amenities, access to health and education facilities, literacy and education levels of household members, other individual characteristics, and household income and expenditures. Although these surveys collect information on both household income and expenditures, real per capita household expenditures rather than income is used as the response variable to investigate the determinants of household welfare. This choice is guided by the relatively high rate of under-reporting of income, which biases reported household income aggregate (Deaton and Muellbauer, 1980; Fofack, 2000).

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[5] An assessment of the data by INSD concludes that the data is of high quality, consistent, with high response rates and low sampling and non sampling errors; for further details on sampling methods, see Fofack, Monga and Tuluy (2001).

The response variable initially expressed in nominal terms is corrected for inflation over time and over space.[6] The price effects over time are captured by changes in the nominal prices of consumption items— reflected by variations in the level of household expenses between 1994 and 1998— and the adjustment to the 1994 poverty line to reflect the revised household consumption baskets and inflation effects, following either adjustment in the costs of living at the regional levels, or shifts in the consumption baskets of the poor, depending on the degree of substitution between the different consumer goods, and price demand elasticity. This study uses the absolute poverty line for inference on welfare. This line was established at CFA Franc 41,099 in 1994, and CFA Franc 72,690 in 1998, and corresponds to the minimum amount required to satisfy individual basic needs on food and non-food items.[7]

A correlation analysis between the response and the poverty correlates shows a positive association between household asset ownership structure and improved level of welfare expressed by real per capita expenditures across expenditures decile. The correlation coefficient is relatively high. Over 80 percent of proportional variance across income groups is explained by dispersion in asset ownership structure. The magnitude of correlation is relatively stable over time, however. The average number of key assets owed by households increases proportionately with the average income across expenditure decile which is non decreasing (Table 1 in Annex).[8]

A similar pattern is observed for education of household head, where increased level of education is associated with high per capita expenditure decile. Dispersion in the education of these persons explains about 75 percent of proportional variance across income groups, ceteris paribus. On the average, poor households with income per capita below the third decile cut-off point have not received any form of schooling; whereas non-poor households with per capita income in the uppermost deciles are by and large literate and have completed primary or higher levels of schooling.

The burden of age dependency is inversely proportional with welfare. The average burden of age dependency across expenditure decile decreases with rising income level. The direction of association is negative and the magnitude is relatively high, suggesting a strong association between welfare and household structure on one hand, and between welfare and labor force composition on the other hand. About 95 percent of proportional variance across income group is explained by distribution of household labor force participation. Households with a relatively large proportion in the active labor force are likely to be less poor. The number of dependents is about three times higher in the poorest income groups. In the lowest income decile, the average dependency ratio was about 1.8 in 1994 —the proportion of inactive population was nearly two times larger than active population in poorer households. At the highest income bracket, the average dependency ratio was the lowest, an average value of .62. The results are consistent over time and across geographical regions (Tables 1-3 in Annex).

While the direction of association remains the same between urban and rural areas, important

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[6] For further details on estimation of regional price deflators and adjustment for household structure, see INSD (1999).

[7] For further details on the construction of the poverty lines, see (INSD, 1999; Fofack et al., 2001).

[8] Twelve key assets including productive and non-productive assets are used to construct the household asset variable. These are sewing machine, cart, plough, television, refrigerator, gas stove, radio, improved stove, iron, bicycle, motorcycle, and car.

differences exist and are largely reflected in the magnitude and welfare gap between these two geographical regions. Figure 1 shows the average dependency ratio across expenditure deciles for both rural and urban households in 1998. The direction of association between age dependency ratio and income groups is negative. Over 95 percent of proportional variance in income group is explained by the dispersion in age dependency ratio. Beyond the first decile (the poorest income group), the age dependency ratio is consistently much lower in urban areas, and the trends are uniformly negative.

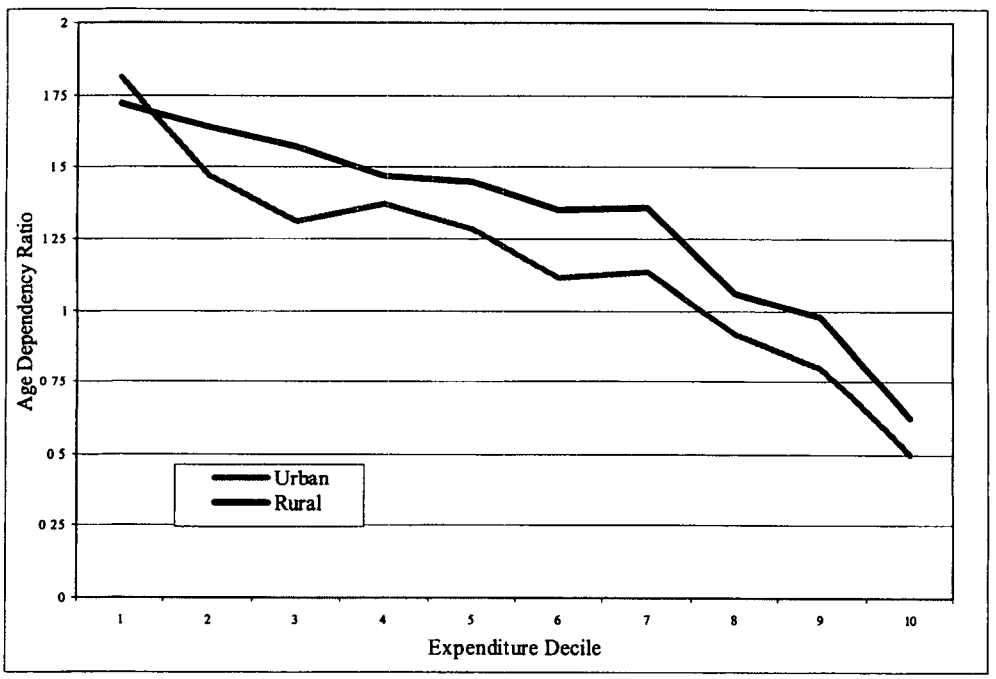

Figure 1: Average age dependency ratio across expenditure decile (EPII)

III. Model and Estimation

The study uses a probit model with binary outcomes to investigate the determinants of poverty over the two reference periods. This model falls within the family of generalized linear model, with the exception that the response variable is not continuous, but discrete. This discrete response is related to exogenous variables through a non-linear probit link function expressed as follows:

$$\eta = \Phi^{-1}(\mu) \qquad (1)$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function (CDF). The transformation to the CDF is important for welfare inference because of its non-decreasing shape. For instance, to the extent that the CDF is a non-decreasing function, under this transformation, the property that an increase in the exogenous variables is associated with increase (or decrease) in the response variable is maintained. In the general linear model, the

response η above is expressed as a function of linear predictors variables $x_1, x_2, \cdots, x_k$, that is:

$$\eta = \mu = \sum_{k=1}^{K} \beta_k x_k \qquad (2)$$

unlike the probit model, where the response and exogenous variables have a non-linear relation.[9]

This model specification is very useful for studying events with binary outcomes, and can be quite appealing for investigating the determinants of poverty when the response is specified as a binomial process, taking values 1 for non poor and 0 for poor households or individuals. However, this model can also be extended to model events with polychotomous outcomes, depending on the nature of the transformation imposed to the initial distribution of income which is continuous and has the positive real line ($y_h^* \in \Re^+$) as support. For instance, the distribution of income in Burkina Faso could be transformed from $y_h^* \rightarrow \tilde{y}_h$, with the transformed response taking three values ($\tilde{y}_h \in \{0,1,2\}$) representing, in increasing order of welfare, extreme poor (0), poor (1) and non poor (2).

This paper assumes that the observations are a random sample of unreplicated data with dichotomous response, accounting for the widespread nature of poverty in Burkina Faso, illustrated notably by the relatively large poverty incidence (45 percent) and poverty gap (14 percent). Hence, the untransformed continuous response derived directly from the constructed aggregated household per capita expenditures y_h^* is transformed into a dichotomous response variable $\tilde{y}_h$ with binary outcomes taking two values ($\tilde{y}_h \in \{0,1\}$), with

$$\tilde{y}_h = 1, \text{ if } y_h^* > l, \ 0 \text{ otherwise}$$

where l is the poverty line and $y_h^* > l$ represents all households or individuals classified as non-poor.[10] In this case, the indicator response variable takes value 1, and 0 when households or individuals are classified as poor. Depending on the outcome, it is common to express these models in probability form. The probability of being non-poor which corresponds to $\tilde{y}_h = 1$, is derived using the following equation:

$$P_r(\tilde{y}_h = 1) = \Phi\left[\sum_{k=1}^{K} \beta_k x_k\right] \qquad (3)$$

Because the response is a binary outcome, the two events derived from disjoint sets are complementary and the probability associated with the alternative event (being poor) is represented by:

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[9] For further details on probit models, see Aldrich and Nelson (1984), Agresti (1990), and Greene (1997).

$$P_r(\tilde{y}_h = 0) = 1 - \Phi\left[\sum_{k=1}^{K} \beta_k x_k\right] \qquad (4)$$

Equations (2) and (3) above are used to estimate the predicted probabilities given the set of values taken by explanatory variables. For instance, it may be useful in the context of this study to estimate the predicted probability of being poor given the household asset structure and education level of household head. When combined with the estimated probit coefficients $\hat{\beta}_k$, the predicted probability can prove even more useful in deriving the marginal effect on the probability of an event. This marginal effect is derived by taking the partial derivative of equation (3) above with respect to an independent variable x_k, that is

$$\frac{\partial \Pr ob(Y=1)}{\partial x_k} = \Phi\left[\sum_{k=1}^{K} \beta_k x_k\right] * \beta_k \qquad (5)$$

The set of regressors x_k in equation (2)-(4) includes mapping of geographical regions conditioned upon headcount and poverty gap index to account for spatial effects, socioeconomic groupings conditioned upon headcount and poverty gap, household ownership of assets, education and literacy level of household heads, age dependency ratio and household amenities. These regressors also include interaction terms to account for joint effects and capture the non linear curvature shape of the probit link function. These interaction terms include combined poverty map and household assets ownership, poverty map and education level of household head and combined socioeconomic and household asset ownership. Spatial effects and to a large extent socioeconomic grouping are used as control variables, assumption on the latter variable being largely motivated by the highly segmented nature of labor markets in most countries in Sub-Saharan Africa (Horton, Kanbur and Mazumdar, 1994; Agenor, 2000; Agenor, Izquierdo and Fofack , 2001).

The interaction variable is constructed by first assigning the highest rank order score to the region or socioeconomic group which has the lowest headcount and/or poverty gap index. Hence, if R_j represents Region j for $j = 1,2,\cdots,8$, and $\zeta_{(k,\hat{P}_0)}$ is the rank order of regions on the basis of the headcount index, then $\zeta_{(k,\hat{P}_0)} > \zeta_{(l,\hat{P}_0)}$ if $(\hat{P}_0 \mid R_k) < (\hat{P}_0 \mid R_l)$, $\forall\ l \neq k$. The same principle is applied for rank ordering socioeconomic groups on the basis of the poverty gap. The product of these rank order variables and uncontrolled analogues produces interaction terms.[11]

The parameters $\hat{\beta}_k$ in the probit model are estimated using maximum likelihood estimation (MLE) method. The estimated parameters are the ones which maximize the log of the probit likelihood function. The model assumption hypothesizes that the response variable has a sample of N observations which are independent and the likelihood function is represented by the following equation:

[11] The set of uncontrolled variables include education level of household head and household assets ownership.

$$L(\tilde{y} \mid x, \beta) = \prod_{i=1}^{N} \left[\Phi\left(\sum_{k=1}^{K} \beta_k x_k \right) \right]^{\tilde{y}_i} \left[1 - \Phi\left(\sum_{k=1}^{K} \beta_k x_k \right) \right]^{1-\tilde{y}_i} \quad (6)$$

This probit model is used sequentially to investigate the dynamics of poverty determinants over time. The same model is used over the two reference periods t_0 for the first survey carried out in 1994 and t_1 for the second one carried out in 1998. For each reference period, the poverty determinants are represented as a function of host of variables, conditioning variables, interaction terms, and the parameters estimated from the model in each period. Hence, if $D_t(\bullet)$ is a function representing the determinants of poverty at time t, then it can be represented by the following equation:

$$D_t = f(x_0, x_1, \cdots, x_j, x_{j+1}, \cdots, x_n, x_j \mid \hat{P}_{(\alpha,t)}, x_j * x_l \mid \hat{P}_{(\alpha,t)}; \hat{\beta}_t) \quad (7)$$

where $\hat{P}_{(\alpha,t)}$ is either the headcount index for $(\alpha = 0)$ or the poverty gap index for $(\alpha = 1)$. A reduced form of this equation can take on the following specifications:

$$D_t = f(\bullet \mid \hat{P}_{(\alpha,t)}, \hat{\beta}_t) \quad (8)$$

where the conditioning variable $\hat{P}_{(\alpha,t)}$ is known and the objective is to estimate the regression parameters $\hat{\beta}_t$, so as to maximize the log of the probit likelihood function. A relatively large number of regressors are considered in the initial model and then gradually reduced through a calibrated stepwise procedure. The regressors retained in the model are such that the set of pairs $(x_k, \hat{\beta}_k)$ selected are the ones which maximize the likelihood function. The sample size, though slightly different, is substantially large over the two sample periods. Hence the asymptotic properties of the maximum likelihood estimates are preserved. By the large sample properties, these parameters are unbiased, efficient and asymptotically normal.[12]

IV. Empirical Results

Key socioeconomic determinants of poverty in Burkina Faso include asset ownership, spatial location of households, education and literacy, household amenities and the burden of age dependency. These determinants are derived using a sequential probit model which identifies the most significant determinants through a stepwise procedure. The dynamics of these determinants over time are assessed by applying the model over the two reference periods. The regression results are then used to estimate the predicted probability of being poor and the marginal effects on the event probability given the response level. Because of the ease in understanding the probability of an event occurring, inference on the nature and dynamics of these determinants is drawn mainly from the predicted and marginal probabilities.

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[12] For further details on the properties of MLE estimates of probit models, see Amemina (1981) and Greene (1997).

Determinants of Poverty at the National Level

Table 1 provides the results of probit regressions in the first period. The likelihood ratio statistics show that the model is significantly different from the null or intercept only model. All predictors have estimates significantly different from 0, as judged by the size of $\hat{\beta}$ relative to the asymptotic standard error, and further by the size of $p-values$ which gives the upper bound of Type I error probability.[13] The analysis focuses on the predictors which have the largest marginal effects on the event probability (in absolute terms). These predictors include both physical and human assets proxy by household asset ownership structure, education and literacy of household members.

At the national level, age dependency ratio, which captures the preponderance of non-wage earners at the household level, has the largest probit coefficient over the two reference periods $(\hat{\beta} \geq .270)$. This predictor also has a relatively low asymptotic standard error, with correspondingly large Chi-Square statistics, and a $p-value$ which is smaller than the critical threshold (Table 1).[14] The sign of this coefficient is positive and consistent over the two reference periods. This non negative sign suggests a positive association between the burden of age dependency and declining welfare. Indeed, when plotted against the burden of age dependency, the cumulative predicted probability of being poor is non-decreasing. The predicted probability is estimated by assigning integer values ranging between 0 and 12 to age dependency ratio and setting the values of other independent variables to their sample means.

The probability of being poor takes its lowest value $(P_r(p) = .21)$ when the burden of age dependency is assigned the smallest value (0), corresponding either to single-member household where the head is working or household where all members are part of the active labor force contributing to the formation of household income.[15] However, the probability rises, for increasing burden of age dependency. The predicted probability becomes $\hat{P}_r(p \mid x = \bar{x}) = .3328$, when the burden of age dependency is at its mean value. In other words, if age dependency ratio were set at its mean values, the incidence of poverty would be over 30 percent, much lower than the current estimate. However, as age dependency ratio increases, the predicted probability of being poor increases rapidly, converging to unity.

We also estimate the marginal effect of this regressor on the event probability. Its marginal effect is relatively high. A unit change in age dependency ratio would result in increased event probability of being poor by approximately 9 percent (in absolute terms), holding other predictors constant at their mean value. The marginal increase associated with this determinant is also the most significant. The significance of age dependency ratio is consistent with earlier

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[13] Type I error probability here refers to non-poor individuals and households that are classified as poor.

[14] The Chi-Square test for individual parameter values are Wald test based on the observed information matrix and the parameter estimates.

[15] Where the little case p stands for poor, and of course $P_r(\bar{p})$ represents the probability of being non-poor.

findings (Visaria, 1980; Lipton, 1983). Indeed a study based on a sub-sample of Asian countries confirms the existence of a strong and negative correlation between welfare proxied by mean per capita expenditure across decile and burden of age dependency (Visaria, 1980).

The burden of age dependency remains significant and consistent in the post-devaluation growth period. The standard error of this estimate also remains fairly low while its sign is unchanged (Table 2). However, the predicted probability of being poor associated with this predictor is consistently much higher in the second period (Figure 2). When this predictor takes values at the lower end of its range when $(x = x_{(1)} = 0)$, the predicted probability of being poor, initially at 0.21, increased to 0.30 in 1998.[16] This noticeable increase is not the fact of change in the magnitude of the estimated coefficient between the two periods, however. The size and sign of the coefficient of this predictor did not change. The difference may be the result of change in the structure of the probit link function, which is based on a different set of regressors in the second period to account for changes in the determinants of poverty over time. Some of the regressors which were significant in the first round and felt to be so in the second were removed from the model and replaced by new significant predictors.[17]

The relatively large difference observed at the lower end of the range of the predicted probability decreases uniformly for increasing burden of age dependency, approaching 0 toward the end of the range of the predictor, where the two predicted probabilities converge to unity, and the cumulative predicted probabilities are tangent to the horizontal line (Figure 2). In other words, when the burden of age dependency exceeds 10, the likelihood of being poor is high and most individuals in households with such a structure are likely to have per capita expenditure below the poverty line.

The marginal effect, which was already high in the first period, increases even further in the second, reaching 12 percent (Table 2). This implies that a unit change in the burden of age dependency, other things being equal, would translate into significant change in the event probability. The fact that the predicted probability converges to unity relatively quickly, and that the marginal effect is consistently high over the two reference periods is also a reflection of the stability of the predictor over time. However, while one would expect the burden of age dependency to be a good predictor of poverty (Gaiha, 1982; Lipton, 1983), rarely would one expect its predictive power to be this stable over time. To the extent that this predictor is a reflection of Burkina Faso's demographic structure, growth prospects and employment opportunities, and poverty alleviation strategies which consider raising the income level of the poor and reducing the poverty gap in the short-run may focus primarily on the promotion of labor-intensive programs because demographic pattern is less subject to short-term changes.

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[16] Where $x_{(1)}$ is the smallest order statistics in the rank order set of values taken by the predictor variable age dependency ratio.

[17] These new predictors are mainly interaction terms and include geographical mapping of poverty on the income gap scale to account for vulnerability, the socioeconomic mapping on the headcount scale, combined socioeconomic mapping and household asset ownership structure.

Table 1: Probit Regression Results based on the 1994 Priority Survey (national level)

Variables	Estimate	Standard error	Chi-Square	P-value	Marginal effects
INTERCEPT	-.0649	.13092	.2458	.6201	-.0216
DEPRATIO	.27712	.01809	234.58	<.0001	.09223
HEDUC	-.19653	.05702	11.8803	.0006	-.06541
FEMALIT	-.17648	.04214	17.5429	<.0001	-.05873
TASSET	-.13606	.06753	4.0593	.0439	-.04528
POVMAPH	-.07421	.01660	19.9828	<.0001	-.02469
GSEMAPG	-.13938	.02391	33.9964	<.0001	-.04638
MAPEDUCH	-.04393	.01822	5.816	.0159	-.01462
MAPEDUCG	.06469	.01678	14.8561	.0001	.021531
GSEEDUCH	-.15445	.03123	24.4603	<.0001	-.05140
GSEEDUCG	.14253	.03319	18.4436	<.0001	.047437
MAPASETH	-.1434	.03575	16.0879	<.0001	-.04772
MAPASETG	.12864	.03697	12.1101	.0005	.042814
GSEASETG	-.05066	.02035	6.1966	.0128	-.01686
WATER	.19159	.04179	21.0213	<.0001	.063765

Table 2: Probit Regression Results based on the 1998 Priority Survey (national level)

Variables	Estimate	Standard error	Chi-Square	P-value	Marginal effects
INTERCEPT	-.04575	.1114	.1686	.6813	-.01981
DEPRATIO	.27839	.01722	261.42	<.0001	.12052
HEDUC	-.13532	.02295	34.7789	<.0001	-.05860
FEMALIT	-.04100	.02957	1.9221	.1656	-.01775
TASSET	-.18249	.06363	8.2266	.0041	-.07903
POVMAPH	.10597	.02697	15.436	<.0001	.04589
POVMAPG	-.13800	.02721	25.719	<.0001	-.05976
GSEMAPH	-.13676	.01583	74.673	<.0001	-.05922
MAPASETH	-.12657	.03637	12.108	.0005	-.05481
MAPASETG	.13140	.03563	13.601	.0002	.05690
GSEASETH	-.03760	.01219	9.516	.0020	-.01628
FUEL	.02863	.01348	4.508	.0337	.01239
WATER	.19864	.03501	32.187	<.0001	.08603

Household asset ownership structure is also consistent over the two reference periods as judged by the size of $\hat{\beta}$ relative to its asymptotic standard error, and further by the size of the *p-values,* which are consistently below the .05 level of significance (Table 1 and Table 2). This predictor has a negative sign over the two reference periods, suggesting that asset ownership has a positive welfare effect. Figure 3, which plots the predicted probability curves as a function of asset ownership structure over the two reference periods, provides a good illustration of the positive association. These graphs have negative slopes and attain their maximum when households possess none of the key assets listed. At this inflexion point, the probability of being poor is much larger in 1998, where about 50 percent of the population are likely to be poor, compared to approximately 37 percent in the first period. However, this gap narrows gradually as household asset ownership increases.

The significance of asset ownership is further illustrated by the magnitude of the marginal effect on the event probability of being poor. The marginal effects of this predictor on the event probabilities are about 5 percent and 8 percent in 1994 and 1998, respectively. This suggests that a unit change in household assets would induce a decrease in the probability of being poor by 5 percent and 8 percent in 1994 and 1998, respectively. The difference in the marginal effects reflects the gap in the predicted probability curves over the two periods.

The determinant education level of household head is also significant and consistent over the two periods. The relative stability of this predictor is reflected in the scope of the standard error which is consistently low $(\hat{\sigma}_{\beta h} < .06)$, and the magnitude of the probit coefficient. This predictor has a negative sign, suggesting that increased number of years of schooling positively impacts on welfare. However, the welfare effect of education attainment varies between 1994 and 1998. The predicted probability of being poor is consistently much higher in the late nineties. When the household head has no education, the probability of being poor takes the largest value, (.37) and (.45) in 1994 and 1998, respectively (see Figure 1 in Annex). It decreases rapidly, reaching (.096) and (.24), respectively, at the highest end of the range.[18]

The consistent gap observed in the predicted probability over the range of this determinant suggests that changes in human development may explain the relatively more important proportional variance of welfare in the second half of the nineties. Surprisingly, the marginal effects of this predictor on the event probability are not significantly different over the two periods. These effects are about 6.5 percent and 6 percent (in absolute terms) in 1994 and 1998, respectively. This suggests that a unit change in education level of the household head, let us say from primary to secondary education, would decrease the probability of being poor by about 6 percent. This result is not surprising because the variable is measuring the cycle completed and not the number of years of schooling, which will be more subject to change in the short run.

[18] The inverse association between welfare measured by poverty and education is further illustrated by cross-correlation results in Table I in Annex.

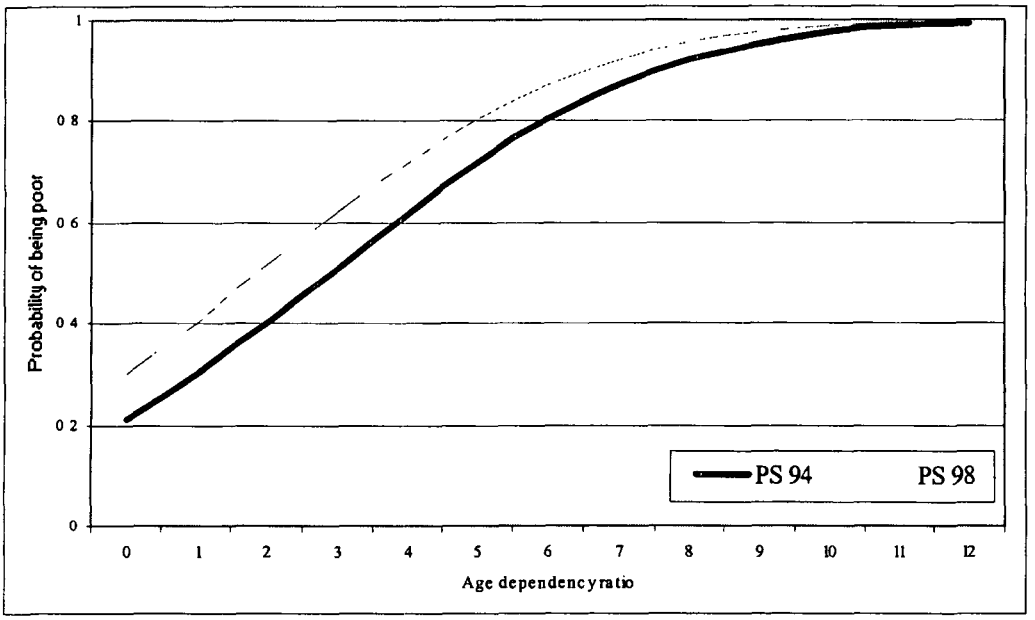

Figure 2: Probability of being poor by age dependency ratio over time

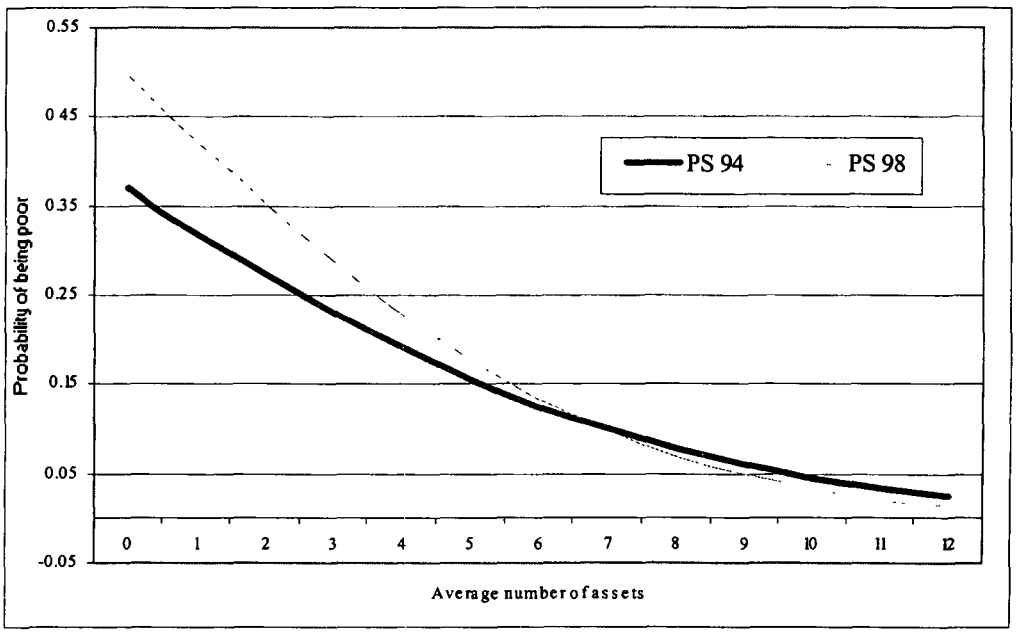

Figure 3: Probability of being poor across asset ownership structure

While education and human development indicators are largely strong determinants of poverty, the growth process did not translate into significant change in the distributional patterns of education to have tangible welfare effects. The distribution of population across education level remains largely skewed between the two periods, with over 82 percent of the population listed as having no education.[19] Yet secondary and tertiary sector growth, which are known to account for most of the poverty reduction (see Ravallion and Datt, 1991), require increased skills acquisition and human capital endowment. The relatively short time between the two reference periods may partly explain the growth-poverty contrast.

Similarly, the growth process did not significantly affect the distribution of assets, though asset acquisition is likely to be more responsive to short-terms changes. Over 85 percent of households possess no more than one of the twelve key assets listed. The slight change in the distribution of assets in the post-devaluation growth period is the result of a 10 percent increase in the share of households with a single asset, compensating an equal reduction in the share of households with none. Change in asset structure is more important in rural areas, especially in the lowest deciles. However, while increased assets acquisition, particularly in the bottom decile, may be an indication of wealth accumulation likely to contribute to a reduction of asset disparities, the gap remains far more important between the uppermost and the lowermost deciles, (the non-poor and the poor).

Determinants of Poverty Across Economic Regions

This section focuses on the determinants of poverty in urban and rural areas. Household asset ownership structure, age dependency ratio and household amenities are significant determinants of poverty in urban and rural areas. (Table 6 and 7 in Annex provide results of probit regression coefficients in urban and rural areas over the two reference periods). All predictors have estimates significantly different from 0, as judged by the size of $\hat{\beta}$ relative to their asymptotic standard error, and the size of the $p-values$. However, though most predictors in the model are significant, their relative contribution to the overall probability of being poor differs markedly. The marginal effects of poverty determinants are relatively low in urban areas, implying that a unit change would have a proportionate marginal effect on the overall event probability. The most significant determinants in 1994 include human development, in particular male literacy rates, which exhibit the largest marginal change in event probability (1.3 percent). This, however, remains relatively low, especially given the relative contribution of this predictor to the overall event probability in rural areas during the same period.

In contrast, the marginal effects are much higher in rural areas. The most significant determinants of rural poverty in the first period include age dependency ratio, education level of household head, household assets and female literacy, some of which have marginal effects

[19] For further details, see distribution of population across education level in Table 4 and 5 in Annexes; the latter also provides the distribution of population with no formal education across expenditure deciles over the two periods, at the national and regional levels. Note that the distribution across decile remains largely bias, with a relatively proportion of uneducated population falling at the lower end of the distribution.

above 10 percent. For instance, the burden of age dependency, which had a relatively low marginal effect in urban areas, has the largest effects in rural areas (15 percent). A marginal effect this large implies that a unit change in age dependency ratio would increase the probability of being poor by about 15 percent, other things being equal. This urban-rural difference is reflected in the predicted probability of being poor across the range of the predictor (Figure 4).

Let $\hat{P}^{t}_{r(x,S)}(p)$ be the predicted probability of being poor at time t (94 and 98) over the range of the predictor variable x and the space S; where S represents either the nation space, urban or rural areas. The size of the predicted probability varies between $(0 < \hat{P}^{94}_{r(x,U)}(p) < .6)$ in urban areas, and $(0 < \hat{P}^{94}_{r(x,R)}(p) < 1)$ in rural areas. Moreover, the graph is convex over the range of the predictor in urban areas, reflecting the relatively small size of the slope of the curve at the lower range of the predictor variable. Indeed, up to $(x \leq 7)$ the probability of being poor is confined between $(0 < \hat{P}^{94}_{r(x,U)}(p) < .2)$. However, as $(x \rightarrow 12)$, the urban predicted probability increases rapidly, reaching the maximum $(\hat{P}^{94}_{r(x,U)}(p) = .56)$ when $(x = 12)$.

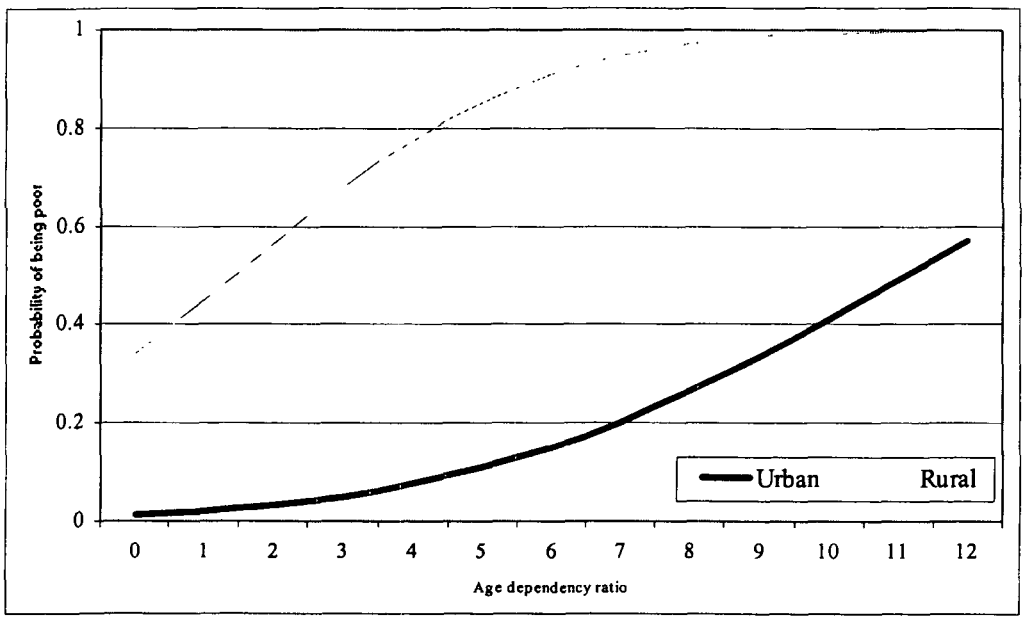

Figure 4: Probability of being poor by age dependency ratio across urban and rural areas (PS 1994)

On the other hand, the rural predicted probability curve is consistently much larger over the range of the predictor and converges rapidly to 1 as $(x \rightarrow 12)$. The rapid increase is reflected by the concave shape of the rural predicted probability curve and the consistent rural-urban gap in the predicted probability over the range of the predictor. This gap reflects both the difference in

rural and urban household labor force structure— the burden of age dependency is much higher in rural areas— and the fact that the welfare implications of age dependency ratio are much stronger in rural areas. The coefficient of correlation between age dependency ratio and welfare is negative in both regions and consistently much higher in rural areas (over 93 percent in absolute terms), implying that over 93 percent of proportional variance in household welfare is explained by changes in the burden of age dependency, other things being equal; this estimate is about 78.5 percent in urban areas.

Other significant regional determinants of poverty in the first period include male and female literacy, asset ownership and housing amenities. Note, however, that the variable education level of household head, which is significant at the national level and in rural areas, with large marginal effects on the overall event probability, is not a significant determinant of urban poverty in 1994. This probably reflects the relatively large urban bias in human development, characterized by a consistently low level of education and literacy in rural areas.

The probit estimates based on the 1998 priority survey are consistent with the regional poverty determinants in the first period, a further indication of the relative stability of the determinants of poverty. In urban areas, age dependency ratio, male literacy, and household amenity variables— in particular, access to safe water and type of fuel for cooking— are the most significant determinants of urban poverty in 1998 (Tables 6 and 7 in Annex).

These also provide estimates of other regional determinants of poverty in Burkina Faso. Note that most determinants have estimates significantly different from 0. The signs of these determinants are consistent over time. The marginal effects of urban poverty determinants are also relatively low in 1998 (less than 3 percent for most predictors), implying that a unit change in any of these predictors will have a proportionately small marginal effect on the overall event probability. The burden of age dependency is the most significant determinant of urban poverty in the late nineties. It has the largest marginal effects. Other significant determinants of poverty include spatial effects captured by the mapping of poverty, and human development. However, though significant, human development variables, especially male literacy rates and household amenity variables, have much lower marginal effects (less than 2 percent).

The burden of age dependency, education level of household head, and household ownership of assets remained the most significant determinants of poverty in the late nineties. The burden of age dependency continued to exhibit the largest marginal effects (14 percent). This implies that a unit change in age dependency ratio is likely to translate into an increase in the event probability of being poor of nearly similar magnitude, other things being equal. The urban-rural difference in the degree of significance of this determinant is important. This difference is reflected in the predicted probability of being poor across the range of the poverty predictor (Figure 5).

Figure 5 shows the predicted probability of being poor over the range of the predictor in urban and rural areas in 1998. Note that the size of the predicted probability remains consistently much larger in rural areas, varying between $(0 < \hat{P}^{98}_{r(x,R)}(p) < 1)$. Also, the urban predicted probability curve shows that the scope of the probability is relatively more important in 1998 compared to the 1994 estimate. Despite the persistent large gap between rural and urban areas, especially at the lower end of the range of the predictor, the predicted probability of being poor converges rapidly to 1 as $(x \to 12)$. Also, the rural predicted probability curve is consistently much larger

than the urban probability curve over the range of this determinant. However, to the extent that the burden of age dependency is consistently much higher in rural areas, the narrowing gap between the two predicted probabilities in 1998 may reflect increased association between age dependency ratio and household welfare over time, illustrated by the rise in the urban correlation coefficient. Between 1994 and 1998, the Spearman coefficient of correlation increased from 78 to over 90 percent in absolute terms.

Ownership of assets is another key determinant of rural poverty in the late nineties. The sign of the probit estimate of this determinant remains negative, with a relatively small standard error. This determinant has the largest marginal effect (9 percent in 1994 and over 15 percent in 1998 in rural areas), implying that the probability of being poor decreases as household asset ownership structure increases, and the decrease is proportional to the size of the marginal effect.

The dynamics of poverty determinants across regions are further assessed graphically by plotting the predicted probability curves of being poor over the range of household asset ownership structure in rural areas over the two reference periods (Figure 6). Note that the two curves have negative slopes with exponential decay shape, reflecting the positive welfare effect of assets. The probability of being poor decreases as household asset ownership structure increases. The slope of the curve is much higher (in absolute terms) in 1998, a reflection of a much larger marginal effect in the late nineties. Also, note that the two predicted probability curves intersect around $(x = 3)$, the point at which the gap in average asset ownership structure is the lowest over the two periods. However, for $(x > 3)$, the predicted probability curve is consistently much smaller in 1998 $(\hat{P}^{98}_{r(x,R)}(p) < \hat{P}^{94}_{r(x,R)}(p))$ for $(x > 3)$ and converges to the horizontal axis $(y = 0)$ as $(x \to 12)$.

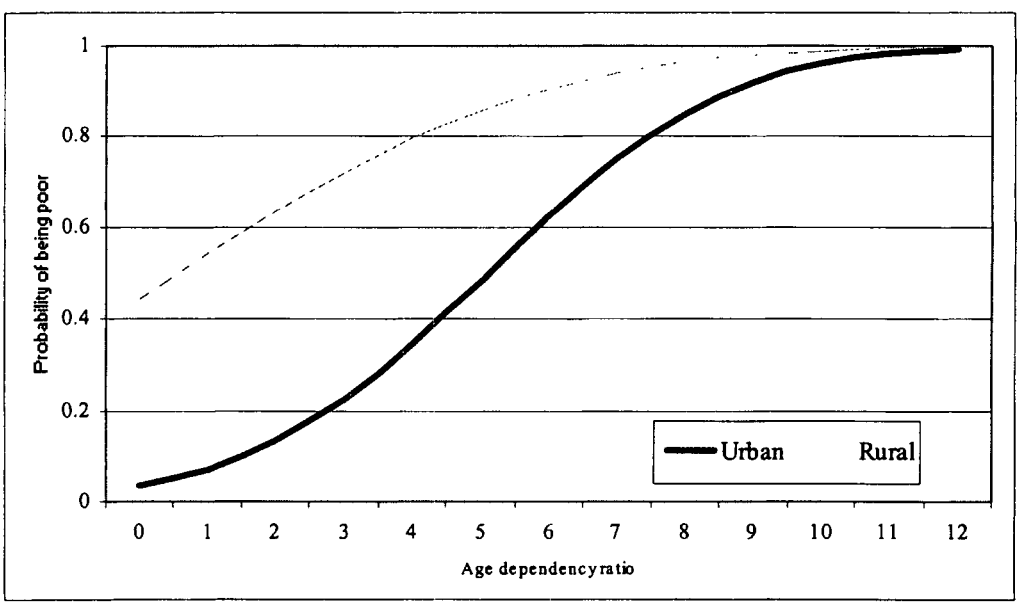

Figure 5: Probability of being poor by age dependency ratio across urban and rural areas (PS 1998)

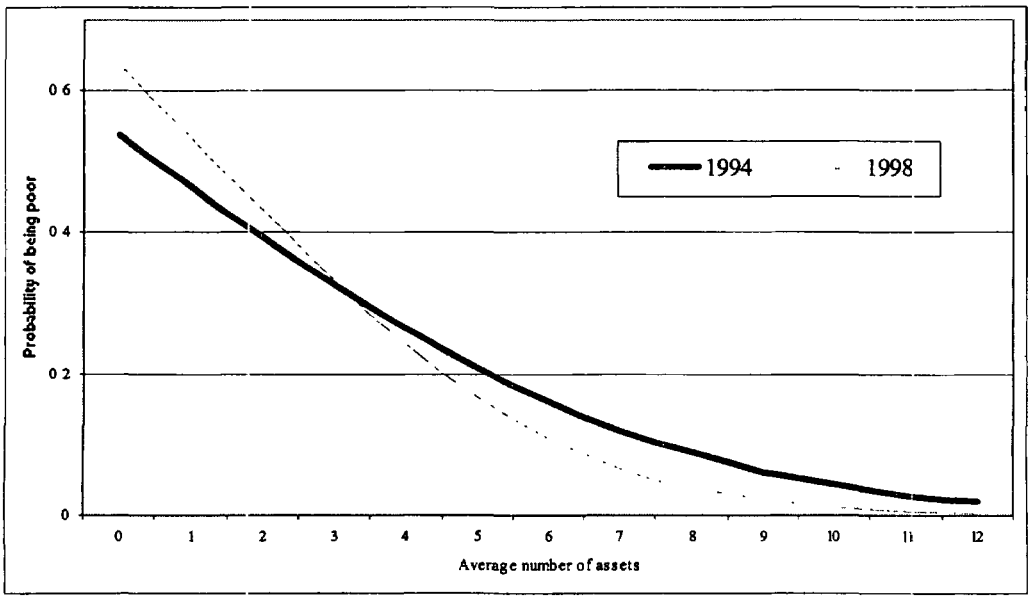

Figure 6: Probability of being poor by asset ownership structure in rural areas over the two reference periods

V. Concluding Remarks and Policy Implications:

This paper attempts to identify the determinants of poverty in Burkina Faso during the post-devaluation growth period in the 1990s, using a probit model with binary outcomes over two reference periods. The study identifies the burden of age dependency, asset ownership structure, household amenities and spatial location of households as key determinants of poverty in Burkina Faso. These determinants are significant and relatively stable over time with low asymptotic standard errors. The direction of association between these determinants and household welfare is stable across geographical regions and over the reference period. While the age dependency ratio is negatively associated with welfare, asset ownership structure is positively associated. The probability of being poor increases proportionally with a rising ratio of age dependency. This probability is inversely proportional to asset ownership structure, and decreases with increasing value of number of assets owned by households.

These determinants are also stable over time; invariably, the burden of age dependency exhibits the largest marginal effects on the probability of being poor. The preponderance of age dependency ratio as the most significant determinant of poverty over time points to a continuously large burden of demographic factors, especially in an environment where poorer households have structurally low income and the distribution of growth is skewed. Indeed, the growth rate of income per capita was much lower at the lowest end of the distribution. While the household per capita income grew by about 45 percent in the first decile, it grew by over 50 percent in the highest decile, even though the initial income level was already significantly much lower in the first decile (see Table 1 in Annex). The distributional effects of income growth on

poverty are exacerbated by the stability in the pattern of household demographics, which after all are less likely to change significantly in the short run.

The significance of age dependency ratio is more important in rural areas, where employment opportunities and income levels are much lower and the incidence of poverty is significantly higher. The preeminence of age dependency ratio as the most significant determinant of rural poverty is consistent over the two periods. This determinant remains the strongest predictor of rural poverty, with the largest marginal effect on the probability of being poor. However, the preeminence of age dependency ratio as one of the most significant determinants of rural poverty need not overshadow the relevance of economic growth in attaining the poverty reduction objectives in Burkina Faso. Broad-based sustained economic growth is likely to lead to increased public investment in economic and social infrastructure, increased education and literacy, and increased employment opportunities and income, which in turn will contribute to reducing the age dependency ratio if the relatively high rate of age dependency ratio is motivated by wealth effects and indigence. By contrast, if the relatively high ratio of age dependency is the result of high fertility rate, motivated by risk insurance considerations, especially among the rural poor, then in addition to economic policies that foster robust and sustained economic growth, it becomes important to have in place social safety net mechanisms to help poor and vulnerable groups cope with uncertainty.

Other significant determinants of rural poverty include asset endowment (both physical and human development assets). The structure of urban determinants of poverty is slightly different. The significance of age dependency ratio is much lower in urban areas, and the marginal effect of this predictor on the probability of being poor is consistently lower. On the other hand, gender-type variables, male and female literacy rates, and household amenities appear to be the most significant determinants of urban poverty. Nonetheless, even though these variables appear to be the most significant, their marginal effects on the probability of being poor remained fairly small over the two periods. The difference between urban and rural determinants of poverty is reflected in the persistent gap in the predicted probability curves over the support of the poverty predictor between 1994 and 1998.

The determinant household asset ownership is also significant over time, at the national and regional level. The significance of this determinant is reflected in the magnitude of the Chi-Square statistics and the graph of the predicted probability curve over the growth period. The area between the two probability curves remains relatively small over the time space, and at some points they even intersect. This is in contrast with the comparisons over the space dimension, where the area between the rural and urban predicted probability curves is consistently larger with no intersecting point. This may suggest that spatial effects are more important than the time dimension effect in explaining the nature and dynamics of poverty. Another critical factor which may explain the dynamics of poverty determinants is labor market structure. Future research will investigate the dependency structure between labor market structure and household composition and assets, in particular, the burden of age dependency, household asset ownership structure and education level of household head.

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Table 1: Average Household Welfare Indicators by Expenditure Decile at the National Level

	Assets Ownership		Education level of head		Ratio of Age dependency		PCE in (000) CFA	
Exp. Decile	94	98	94	98	94	98	94	98
1	.29	.38	1.16	1.08	1.79	1.72	16.83	25.09
2	.35	.43	1.11	1.11	1.67	1.62	24.78	38.2
3	.36	.51	1.16	1.13	1.54	1.54	30.59	48.13
4	.41	.55	1.22	1.18	1.58	1.46	36.65	57.4
5	.45	.55	1.24	1.16	1.43	1.43	43.99	68.43
6	.49	.61	1.23	1.21	1.23	1.31	53.99	82.4
7	.61	.69	1.33	1.29	1.22	1.31	68.69	102.13
8	.79	.86	1.63	1.49	1.25	1.02	92.52	134.77
9	1.27	1.41	2.07	1.82	1.03	.88	141.8	204.45
10	2.22	2.44	3.51	2.77	.62	.53	437.8	656.6
Cor.	.813	.799	.754	.783	-.945	-.948	-	-

Source: Author's calculation.

Table 2: Average Household Welfare Indicators by Expenditure Decile in Urban Areas

	Assets Ownership		Education level of head		Ratio of Age dependency		PCE in (000) CFA	
Exp. Decile	94	98	94	98	94	98	94	98
1	.438	.643	1.18	1.43	1.48	1.81	18.18	25.66
2	.535	.551	1.21	1.34	1.49	1.47	25.04	38.77
3	.564	.764	1.45	1.18	1.36	1.31	30.82	47.92
4	.758	.964	1.38	1.56	1.46	1.37	37.01	57.85
5	.745	.871	1.38	1.40	1.61	1.28	44.42	67.93
6	.841	.879	1.51	1.61	1.42	1.11	54.30	82.85
7	.901	1.08	1.81	1.61	1.34	1.13	69.84	103.8
8	1.23	1.41	2.03	1.97	1.19	.915	94.82	135.3
9	1.67	2.04	2.40	2.19	1.05	.799	144.1	209.3
10	2.63	2.90	3.72	3.03	.66	.496	452.8	711.9
Cor.	.864	.858	.842	.831	-.784	-.960	-	-

Table 3: Average Household Welfare Indicators by Expenditure Decile in Rural Areas

	Assets Ownership		Education level of head		Ratio of Age dependency		PCE in (000) CFA	
Exp. Decile	94	98	94	98	94	98	94	98
1	.290	.373	1.16	1.07	1.80	1.72	16.80	25.07
2	.350	.427	1.11	1.10	1.68	1.64	24.77	38.15
3	.350	.489	1.14	1.12	1.55	1.57	30.60	48.15
4	.380	.501	1.21	1.13	1.59	1.47	36.62	57.35
5	.430	.514	1.23	1.14	1.42	1.45	43.96	68.50
6	.451	.561	1.19	1.14	1.20	1.35	53.96	82.33
7	.540	.586	1.23	1.19	1.19	1.36	68.46	101.65
8	.611	.609	1.48	1.27	1.27	1.06	91.60	134.53
9	.890	.751	1.77	1.43	1.03	.976	139.8	199.44
10	1.34	1.46	3.06	2.24	.560	.621	406.6	541.29
Cor.	.852	.765	.719	.716	-.935	-.945	-	-

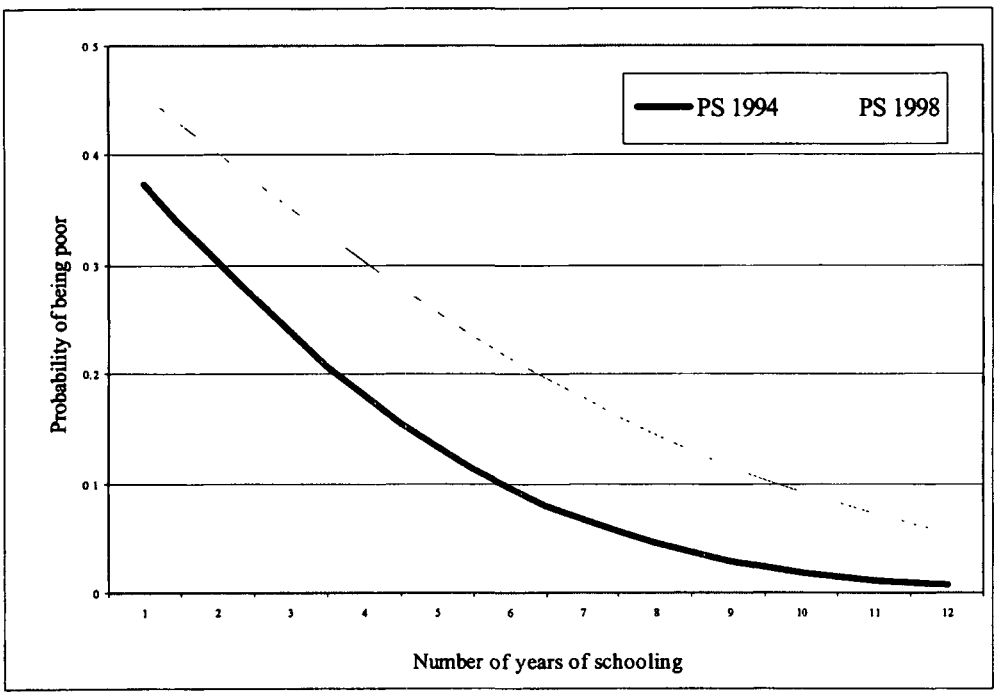

Figure 1: Probability of being poor across education level of household head over time

Table 4: Distribution of Population by Education Level of Household Head

	Priority Survey 1994			Priority Survey 1998		
Education level of Head	**National (%)**	**Urban (%)**	**Rural (%)**	**National (%)**	**Urban (%)**	**Rural (%)**
None	82.22	54.27	88.95	82.18	52.19	90.92
Primary not completed	5.86	10.70	4.70	6.28	18.58	2.69
Primary completed no secondary	4.87	11.55	3.27	4.36	8.44	3.17
Secondary not completed	4.77	15.19	2.26	4.16	10.83	2.22
Secondary completed and higher	2.28	8.29	.83	3.03	9.96	1.00
Total	100	100	100	100	100	100

Table 5: Distribution of Population with no Level of Education Across Expenditure Decile

	National level		Urban areas		Rural areas	
Decile	**1994**	**1998**	**1994**	**1998**	**1994**	**1998**
1	11.38	11.74	1.69	2.05	12.80	13.36
2	11.59	11.48	2.07	4.41	12.98	12.66
3	11.40	11.44	2.63	5.94	12.68	12.36
4	11.01	11.20	5.10	6.80	11.88	11.93
5	11.03	11.21	5.82	6.84	11.80	11.95
6	11.09	10.92	9.13	10.15	11.38	11.05
7	10.70	10.54	12.26	13.77	10.47	9.99
8	9.56	9.55	17.71	14.96	8.37	8.65
9	8.09	7.66	24.94	19.98	5.61	5.60
10	4.16	4.27	18.66	15.11	2.03	2.46
Total	**100**	**100**	**100**	**100**	**100**	**100**

Table 6-A: Probit Regression Results in Urban Areas based on the 1998 Priority Survey

VARIABLE	Estimate	STANDARD ERROR	Chi-Square Pr	Chi-Square Label	MARGINAL EFFECT
INTERCEPT	0.04561	0.24883	0.0336	0.8546	0.002942
DEPRATIO	0.35819	0.03863	85.9660	<0001	0.023104
MALELIT	0.07668	0.03587	4.5691	0.0326	0.004946
POVMAPH	0.38917	0.15987	5.9255	0.0149	0.025102
POVMAPG	-0.41088	0.15577	6.9576	0.0083	-0.026502
GSEMAPH	-0.07312	0.02205	10.9928	0.0009	-0.004716
GSEEDUCH	-0.04027	0.0089411	20.2846	<0001	-0.002597
MAPASETH	-0.26909	0.11800	5.2003	0.0226	-0.017357
MAPASETG	0.23215	0.11843	3.8423	0.0500	0.014974
WATER	0.15216	0.07328	4.3113	0.0379	0.009814
FUEL	-0.26996	0.05086	28.1688	<0001	-0.017413

Table 6-B: Probit Regression Results in Rural areas based on the 1998 Priority Survey

VARIABLE	Estimate	STANDARD ERROR	Chi-Square Pr	Chi-Square Label	MARGINAL EFFECT
INTERCEPT	0.23613	0.08694	7.3763	0.0066	0.136957
DEPRATIO	0.24213	0.01883	165.3265	<0001	0.140437
HEDUC	-0.10036	0.03031	10.9674	0.0009	-0.058209
TASSET	-0.26318	0.07351	12.8192	0.0003	-0.152646
POVMAPH	0.0797	0.02666	8.9360	0.0028	0.046226
POVMAPG	-0.10785	0.02698	15.9838	<0001	-0.062554
GSEMAPH	-0.08985	0.02220	16.3824	<0001	-0.52113
MAPASETH	-0.10197	0.03673	7.7072	0.0055	-0.059143
MAPASETG	0.1417	0.03601	15.4846	<0001	0.082187
GSEASETH	-0.06231	0.01807	11.8875	0.0006	-0.03614
FUEL	0.05737	0.01399	16.8222	<0001	0.033275

Table 7-A: Probit Regression Results in Urban Areas based on the 1994 Priority Survey

VARIABLE	ESTIMATE	STANDARD ERROR	Chi-Square Pr	Chi-Square Label	MARGINAL EFFECT
INTERCEPT	-0.76775	0.19008	16.3140	<0001	-0.015861013
DEPRATIO	0.20200	0.04169	23.4718	<0001	0.004173135
MALELIT	0.65502	0.24389	7.2131	0.0072	0.013532114
FEMALIT	-0.16542	0.05966	7.6881	0.0056	-0.003417426
TASSET	-0.22063	0.10273	4.6123	0.0317	-0.004558014
GSEMAPH	-0.38683	0.14756	6.8729	0.0088	-0.007991554
GSEMAPG	0.20312	0.14546	1.9499	0.1626	0.004196273
GSEASETH	0.13872	0.10776	1.6572	0.1980	0.002865828
GSEASETG	-0.17899	0.10489	2.9121	0.0879	-0.00369777
WATER	0.24725	0.07805	10.0353	0.0015	0.005107959
FUEL	-0.08529	0.04744	3.2326	0.0722	-0.001762013

Table 7-B: Probit Regression Results in Urban Areas based on the 1994 Priority Survey

VARIABLE	Estimate	STANDARD ERROR	Chi-Square Pr	Chi-Square	MARGINAL EFFECT
INTERCEPT	-0.01697	0.10512	0.0261	0.8717	-0.008487164
DEPRATIO	0.29242	0.01858	247.7938	<0001	0.146247287
HEDUC	-0.23429	0.06971	11.2963	0.0008	-0.117174874
FEMALIT	-0.14419	0.05188	7.7257	0.0054	-0.072113386
TASSET	-0.18026	0.07275	6.1397	0.0132	-0.090152985
POVMAPH	-0.08236	0.01953	17.7908	<0001	-0.041190502
POVMAPG	0.06307	0.02442	6.6721	0.0098	0.031543042
GSEMAPH	0.04643	0.05098	0.8294	0.3624	0.02322092
GSEMAPG	-0.10562	0.04662	5.1324	0.0235	-0.052823468
MAPEDUCG	0.04851	0.01533	10.0096	0.0016	0.024261186
GSEEDUCH	-0.04272	0.01440	8.8015	0.0030	-0.021365447
MAPASETH	-0.14573	0.03385	18.5382	<0001	-0.072883582
MAPASETG	0.11661	0.03331	12.2522	0.0005	0.058319869
FUEL	0.06654	0.02069	10.3456	0.0013	0.033278485

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