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# Censored Quantile Regressions of Chronic and Transient Seasonal Poverty in Rwanda

Christophe Muller[1]
University of Nottingham

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*It is crucial for social policy in Less Developed Countries to identify correlates of poverty at the household level. This has been done in the literature by estimating household poverty equations typically with Tobit and Probit models. However, when the errors in these equations are non-normal and heteroscedastic, which is usually expected, these models deliver biased estimates. Using quarterly data from Rwanda in 1983, we reject the normality and homoscedasticity assumptions for household chronic and transient latent poverty equations. We treat this problem by estimating censored quantile regressions. Our results of censored quantile regressions and of inconsistent Tobit regressions are substantially different. However, in the case of chronic poverty the signs of the apparently significant coefficients are generally in agreement, while for seasonal transient poverty different variables have significant effects for the two estimation methods. Our second contribution is to study, for the first time, correlates of poverty indicators based on quarterly consumptions. Our results show that in Rwanda different correlates are significant for chronic poverty and for transient seasonal poverty. The effects of the main inputs (land and labour) are more important for the chronic component of poverty than for the transient one. Household location and socio-demographic characteristics play important roles that are consistent with usual explanations of poverty in the literature.*

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## 1. Introduction

Most estimations of poverty equations in the literature are based on the normality of the corresponding latent poverty variable at the household level. However, if this normality is invalid, such estimates are plainly biased and inconsistent when Probit and Tobit methods have been used. OLS estimates of household poverty indices are also likely to be biased and inconsistent because the censorship involved in the defintion of these poverty indices is neglected.

In this paper we test and reject this normality assumption for chronic and transient poverty indicators based on data of several quarters for Rwanda. Then, we indicate how to correct this problem and what difference it makes for the estimation results and their policy consequences. Moreover, we particularly pay attention to the correlates accompanying the variation of poverty across seasons by using poverty indicators based on quarterly consumption observations.

The bulk of the world's poverty is concentrated in rural areas of developing countries (The World Bank, 1990, 2000). The income of households living in these regions mostly comes from local agricultural output, either directly from their own crops when they cultivate land, from the wages they can obtain by working on other exploitations, or else from resources that depend closely on the purchasing power of peasant households, such as for shopkeepers' income. In that context, climatic fluctuations are crucial for understanding the causes of poverty (Nugent and Walther, 1981; Reardon and Taylor, 1996). Because of the high seasonal dispersion of production and the presence of liquidity constraints, the living standards of peasant households may considerably vary across seasons and may even cross the poverty line at some seasons. This explains why the study of seasonal rural poverty in LDCs has attracted considerable interest in the literature (Chambers, 1981; Chambers *et al.*, 1981; Fortmann, 1984; FAO, 1986; Sahn, 1989; Gill, 1991; Lipton and Ravallion, 1993; Muller, 2000). In this paper, we study seasonal poverty fluctuations in Rwanda by estimating household poverty equations. In order to do this, we need to define poverty indicators, to specify poverty equations incorporating correlates of poverty at household level and to choose an estimation method.

Their interest in seasonal poverty invites researchers to use dynamic poverty indicators. Chaudhuri and Ravallion (1992), using Indian annual data for several years, have shown that the averaged dynamic poverty cannot be approximated by any static indicator. Because living standards of peasants change more across seasons than across years, using static indicators, as is almost always done in the literature (based on observations of household annual consumption or household annual income), is likely to be seriously misleading. This suggests the separation of chronic and seasonal components of poverty.

In these conditions, the design of policies to alleviate poverty is delicate. Not only are poor households generally difficult to separate from the rest of the population, but some households, appearing poor in some seasons, may not be poor during the rest of the year, and vice versa. A basic requirement of anti-poverty targeting schemes is the knowledge of correlates of poverty status at the household level. Demographic variables, land owned and household location could be used as efficient screening variables in that they are easy to observe and they cannot be easily modified by the households to hide their true type. If different correlates can be identified for transient and chronic poverty, then separate policies anchored on these correlates will be possible, for example, to distinguish targeting against transient poverty (*TP*) from targeting against chronic poverty (*CP*). One can also take advantage of the knowledge of these correlates to directly use them as policy instruments. For example, since the education level of the household head often appear to be negatively correlated with chronic poverty, it is natural to investigate policies promoting better education for the heads of poor households. Policies against chronic poverty are often based on permanent household assets or characteristics. Some examples are land reform, other human capital policies and agricultural technology improvements. Policies against transient poverty are rather price policies helping to smooth the price evolution, or food aid and other transfer policies designed as a response to urgent situations.

The correlation between poverty, household socio-demographic and environment characteristics has already been studied, although the relationship of these variables broadly varies across periods and countries. In many poverty studies, household composition is controlled for by using equivalence scales (see Jorgenson, 1998; Triest, 1998). Empirically, the choice of the equivalence scale has been found to systematically affect estimates of poverty (van der Gaag and Smolensky, 1982; Buhmann *et al.*, 1988). However, beyond the debate on the choice of the equivalence scale, and the well-known identification problem that it involves (Muellbauer, 1980; Blundell and

Lewbell, 1991), Conniffe (1992) shows by using theoretical models that the assumption of constancy of equivalence scales irrespective of income is not plausible. Then, an alternative approach to using equivalence scales is to directly examine the correlation of income and socio-demographic variables. In many studies, household size and per capita consumption or per capita income have been found inversely related, while household size and income are positively correlated (e.g., for developing countries, Kuznets, 1989; Lanjouw and Ravallion, 1995; for industrialised countries, Lazear and Michael, 1980). Moreover, fertility is higher in poor households. Poor households are often younger and their members live for a shorter time, although this may not be the case if poverty is measured with equivalence scales allowing for large-scale economies (Lanjouw and Ravallion, 1995). The difficulty of defining appropriate equivalence scales, as illustrated by Coulter *et al*. (1992), will lead us to estimate household poverty equations where socio-demographic characteristics appear as regressors, in order to control for imperfect equivalence scales. Such an approach is akin to the common practice of introducing household composition as regressor in food share Engel curves, used as a household welfare indicator (e.g., in Lanjouw and Ravallion, 1995).

One common way of studying the correlates of poverty is to estimate statistical tables or household poverty equations. Tables composed of poverty measures for different populations (poverty profiles) are based on decomposable poverty measures (Foster and Shorrocks, 1988, 1991). For example, Shari (1979), Glewwe (1987) and Slesnick (1993) present tables of poverty incidence by household groups. Rodgers and Rodgers (1993) and Alwang *et al*. (1996) also estimate tables of various poverty measures by groups of households. Alternatively, log-income equations have been estimated.[2] However, when the focus is poverty analysis, econometric estimation of household poverty equations may be more appropriate. It is possible to account for the fact that some households are not poor by incorporating a censorship of the dependent variable in these equations. For example, Lanjouw and Stern (1991), Dercon and Krishnan (1994), Rodriguez and Smith (1994) and Mason (1996) estimate logit and probit models for the incidence of poverty. Coulombe and McKay (1994) conduct a Probit estimation of the incidence of poverty, and show OLS estimates for the depth of

[2] For example, Scott (2000), using data from Chile, and McCulloch and Baulch (2000), using data from Pakistan, all using least-squares estimators.

poverty ($P_1/P_0$). Appleton (1994) accounts for both the quantitative dimension of poverty and for censorship by estimating Tobit models. See Baulch and Hoddinot (2000) for a discussion of other studies. Finally, using six-year panel data from rural China, Jalan and Ravallion (2000) estimate censored quantile regressions of chronic and annual transient poverty measures and find that the correlates of the two components of poverty can be qualitatively different. Thus, successful policy response to *CP* may still leave considerable annual *TP*. It is not known if similar results occur for seasonal fluctuations of living standards. We provide an answer to these questions in this paper.

A common problem in all these studies, apart from the one by Jalan and Ravallion, is that they are generally based on an implicit assumption that the distribution of the errors in the poverty equations follows a normal (or a logistic) distribution. Unfortunately, Probit and Tobit models are subject to drawbacks. First, if the normal distribution assumption is not satisfied, maximum likelihood estimators based on normality assumptions deliver inconsistent estimates.[3] Secondly, because households are very heterogeneous, in particular with respect to their size and their income, the error term in household poverty equations is likely to be heteroskedastic, which is not the case in Probit or Tobit models.[4]

Because of the misspecifications of the usual estimation methods when error terms of poverty equations are non-normal or heteroscedastic, many analyses of poverty may be wrong. We deal with this question empirically in this article by investigating the correlates of chronic and seasonal transient poverty of rural households in Rwanda.

[3] Arabmazar and Schmidt (1982) have shown that the asymptotic bias can be substantial. A possible solution to this problem is to use Klein and Spady (1993) estimator for discrete choice models, which does not impose any assumption of the functional form of the choice probability function. Also, Pudney (1999) proposes a similar new statistical method for modelling the incidence of poverty. Using data from Hungary, he carries out in a first step a nonparametric estimation of the income distribution, then he calculates the poverty measure from that estimated model. Thus, his estimation results for the head-count index are valid under non-normality. Another method is the maximum score estimator introduced by Manski (1975).

[4] When the heteroscedasticity is independent of regressors, a rather special case, it is sufficient to rescale the estimates of these models to account for heteroscedasticity, which preserves their interpretative value. However, in the general case of heteroscedasticity the properties of the Probit method are destroyed and more complex econometric models must be considered, such as the ARCH models used in the finance literature. The critical problem is that for the data of interest the heteroscedasticity is generally statistically related to several regressors, for example the household size.

We present the data and density estimates in Section 2. In Section 3, we test the normality and homoscedasticity hypotheses in equations of transient seasonal and chronic poverty. After the rejection of these hypotheses, we estimate the equations by using censored quantile regressions. To our knowledge, this is the first time these methods are applied to quarterly consumption data. Finally, Section 4 concludes.

## 2. The Data

Rwanda is a small African country with a population of 5.7 million in 1983. The political situation at this period was stable and much more peaceful than that of the recent war. In 1983, per capita GDP was equal to 1983 US$ 270, making Rwanda a very poor country. More than 95% of the population lived in rural areas (Bureau National du Recensement, 1984), and agriculture accounted for 38% of GDP. The growth rate of the population was 3.5% a year, corresponding to an average of 8.3 children per fertile woman. This high demographic growth resulted in an intense pressure on land, which partly explains why food production per capita dropped between 1980 and 1991 at a rate of 1.8% a year. Climatic seasonal fluctuations are notable in Rwanda (*Bulletin Climatique du Rwanda*, 1982, 1983, 1984).

The data for the estimation are taken from the 1983 Rwandan national budget–consumption survey of 270 households that was conducted by the government of Rwanda and the French Cooperation and Development Ministry[5] in the rural part of the country (Ministère du Plan, 1986). The sampling scheme (Roy, 1984) that we completed during our stay at the Direction Générale de la Statistique du Rwanda has four sampling levels (communes, sectors, districts and households). The survey was conducted from November 1982 to December 1983. Households were surveyed quarterly[6] on their demographic characteristics, their budget and their consumption. It is fair to say that the agricultural year 1982–83 is a normal climatic year (*Bulletin Climatique du Rwanda*, 1982, 1983, 1984), which is also devoid of extreme economic or political shocks. The agricultural year is organ-

[5] The main part of the collection was designed by INSEE (French National Statistical Institute). The author was involved in this project until the last stage of the analysis as technical adviser for the French Ministry of Cooperation and Development.

[6] The dates of the quarterly rounds are the following: round A from 01/11/1982 until 16/01/1983; round B from 29/01/1983 until 01/05/1983; round C from 08/05/1983 until 07/08/1983; round D from 14/08/1983 until 13/11/1983.

ised around two growing seasons. The first growing season extends from October (seeding) to January (harvest), when beans and other pulses are mostly cultivated. Corn is also mostly cultivated at this season. The second growing season is often a period of cereal cultivation, mostly sorghum, and lasts from March (seeding) to July (harvest). The harvests begin at the end of December to finish in April, then from June to July. Then, the fourth round is a period with limited harvest. Nonetheless, the cropping of cassava and banana is spread all around the year, making it hard to link with a specific season. As a matter of fact, the mountainous character of Rwanda locally modifies these general seasonal features to produce an extreme variety of cultural contexts in Rwanda.

We have calculated quarterly consumption indicators that are of very high quality. This quality is supported by the proximity of income and consumption indicators for most households. Indeed, it is frequent to observe in other surveys that income is largely underestimated relatively to consumption, whereas the very poor African households that we consider have not the opportunity of much saving. Therefore, this discrepancy is generally attributed to large measurement errors for income and consumption. The ratios (income-consumption)/consumption are on average 0.16 over the sample of surveyed households, with a median of 0.078, a first quartile of –0.13 and a third quartile of 0.36. Very intensive collection and treatment explain the quality of consumption indicators. For example, the volume of all containers and the traditional measurement units employed by the households were measured for each household. Then, we could obtain accurate measures of quantities of goods. Every household was visited at least daily during two weeks at each quarter. The enumerators conducted daily interviews covering these two weeks and retrospective interviews covering the quarter. They weighed the food at every meal. Moreover, every household was left with a diary where the transaction information was recorded between the survey rounds. The surveyed topics were extensive, and much information was repeatedly collected. This situation permitted multiple controls, which enhanced the quality of the collection and of the data cleaning. Finally, we designed algorithms for the calculus of consumption indicators so as to reduce measurement errors by combining several information sources and exploiting the redundancies present in the data.

Table 1 shows the descriptive statistics of the main variables for the

Table 1: *Descriptive Statistics*

| Variable | Mean | Standard deviation |
|---|---|---|
| Total consumption | 51,847 | 25,409 |
| Total production | 57,027 | 36,682 |
| Per capita total consumption | 18,856 | 5,344 |
| Total surplus | 5,180 | 26,521 |
| Female head | 0.20 | 0.40 |
| Age of the head | 47.4 | 16.3 |
| Household size | 5.2 | 2.3 |
| Average age of members | 24.3 | 13.4 |
| Tutsi head | 0.10 | 0.31 |
| Land area ($m^2$) | 12,398 | 13,156 |
| No. of children aged 0–3 years | 0.85 | 0.87 |
| No. of children aged 4–10 years | 1.07 | 1.05 |
| No. of adolescents aged 11–15 years | 0.74 | 0.92 |
| No. of young adults aged 16–20 years | 0.50 | 0.77 |
| Number of adults | 2.04 | 0.75 |
| Northwest | 0.14 | 0.35 |
| Southwest | 0.15 | 0.36 |
| Centre-North | 0.20 | 0.40 |
| Centre-South | 0.24 | 0.43 |
| East | 0.24 | 0.43 |
| Education of the head | 1.80 | 2.49 |

256 observations.

household sample. The average household has 5.2 members, with 2.6 children.[7] The average age of members is 24.3 years. The household head is generally not educated. Only a few of these heads are women (mainly widows) or belong to the Tutsi ethnic group. The land farmed by the average household is very small (1.24 ha). Most of the average production of 57,028 Frw (Rwandan Francs[8]) is used for an average household consumption of 51,848 Frw. The equivalence scales are defined by $es = \Sigma_k\, a_k nm_k$, where $nm_k$ is the number of members in class

[7] Although the fertility is over 8 in Rwandan households, the older children generally leave the household housing relatively early to built their own house. This explains the moderate average size of Rwandan households.
[8] In 1983, the average exchange rate was 100.17 Frw for one 1983 US$, i.e., 60.16 Frw for one 1999 US$ (sources: IMF, Penn Tables).

$k$ and $a_k$ is the adult-equivalent coefficient for a member of class $k$. Four classes have been defined: male adults ($k$ = 1), female adults ($k$ = 2), children over 10 years old ($k$ = 3), and children between 0 and 10 years old ($k$ = 4). es0 corresponds to the per capita consumption ($a_k$ = 1 for all members); *es*1 is defined by: $a_1 = a_2 = 1$, $a_3 = 1/3$, $a_4 = 1/4$; *es*2 is defined by: $a_1 = 1$, $a_2 = 0.7$, $a_3 = 0.2$, $a_4 = 0.15$. We do not consider the change of household composition across the seasons because of the lack of reliable data. To shorten the exposition, we focus on per capita consumption that is the most commonly used living standard indicator and enables the comparison with other studies.

Let us first choose a general perspective by looking directly at the distribution of household per capita consumption for different quarters and for the year. Figures 1 and 2 show kernel density estimates of quarterly and annual real per capita consumption distributions in levels, based on the Epanechnikov method,[9] with the three vertical lines representing the poverty lines used in this paper (see below).

The shape of the estimated living standard distribution varies a lot across quarters. At quarter D (after the dry season), the mode is higher and centred at a lower value, which corresponds to a higher incidence of poverty. The other quarters cannot be ordered in terms of poverty from their per capita consumption density estimates. Let us now define the used poverty measures.

## 3. Poverty Equations

### *3.1 Poverty Measures and Their Estimators*

In this sub-section, we present the poverty lines and the poverty indicators that we use, then we discuss the notions of chronic and

[9] A kernel density estimator $f_K(x)$ is defined by summing the values of the variable of interest weighted with the kernel function $K$ as follows:

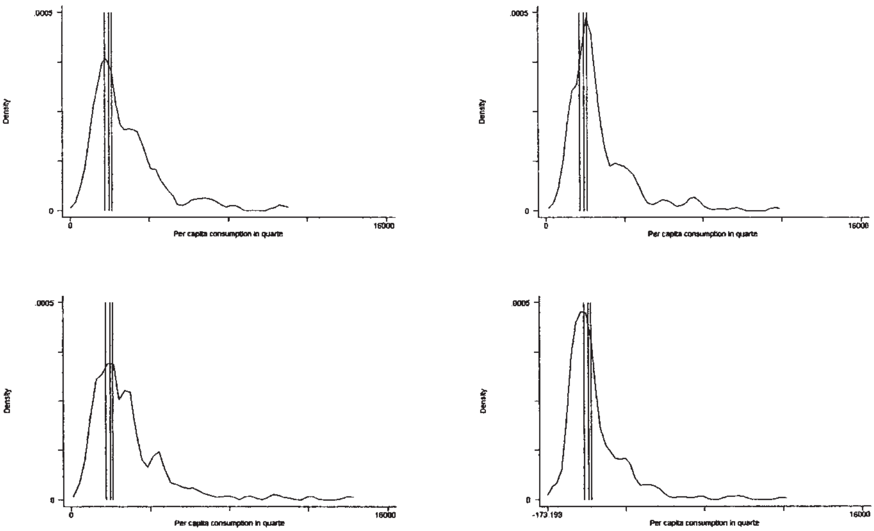
$$f_K(u) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{u - U_i}{h}\right)$$

where $u$ is the variable for which the density is calculated, $n$ is the sample size, $U_I$ are the observations of the variable of interest, $h$ is a 'window width' parameter chosen by the researcher. The Epanechnikov kernel is defined as

$$K(u) = 3\ (1 - u^2/5)/(4 \times 5^{1/2})$$

if $|u|$ is inferior to $5^{1/2}$, and 0 otherwise.

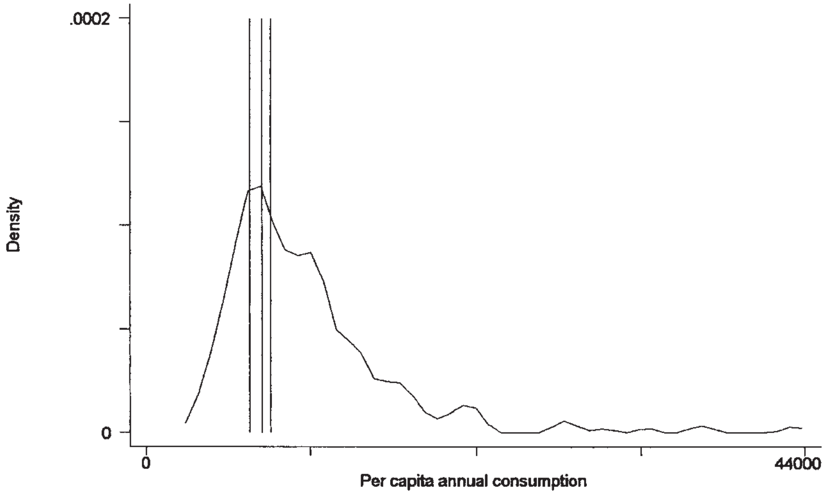
Figure 1: *Quarterly Per Capita Consumption*




transient poverty, and finally we discuss the estimators of *CP* and *TP* and the estimation results. Our unit of analysis is the household because we do not have information on individual consumptions or individual incomes. A point of interest is whether poverty correlates vary with the chosen poverty line. Indeed, the definition of the poverty line is a very contentious topic (Ravallion, 1998), and one may want to design a poverty policy by using correlates that are robust to the choice of the poverty line. Alternatively, since different poverty lines may define different populations of poor households that may each be of interest (for example, so as to separate the extremely poor from the rest of the poor), one may wish to take advantage of different correlates for different poverty lines in order to obtain some flexibility for the policy design.

We use three different poverty lines expressed in terms of Rwandan francs. Various types of poverty lines have been proposed (van Pragg *et al.*, 1982; Ravallion, 1998). In the absence of a definitive doctrine in this matter, our definitions are based on second quintiles of the per capita consumption distributions for all periods. We choose these poverty lines because we believe that they are located in reasonable parts of the distribution for Rwanda and make sense for policy against poverty in this country. Focusing on too large a share of the population

Figure 2: *Annual Per Capita Consumption*




would exceed the possibility of government action, while using a very small population of the poor would amount to neglecting some very dramatic household situations. In Rwanda, using poverty lines calculated from nutritional minima leads one to consider the quasi-totality of the rural population as poor (The World Bank, 2000). Such poverty lines are useful for comparisons across countries, but they do not seem useful for guiding anti-poverty targeting in Rwanda. In such situations, using poverty lines based on bottom quintiles ensures that most of the population cannot be considered poor. Note that we shall be able to obtain meaningful results with these low poverty lines, i.e., under limited measurement information, without having to artificially inflate the poverty lines (like in Jalan and Ravallion, 2000). We define the poverty lines as follows: $z_A$ is the second quintile of the annual per capita consumption; $z_B$ is the sum of the second quintiles of the quarterly per capita consumption; $z_C$ is four times the minimum (across quarters) of the second quintiles of the quarterly per capita consumption.

In this paper we restrict ourselves to identical poverty lines across quarters. Indeed, to allow variations of poverty lines across quarters without much information on which to base this variation would overly determine the results of the analysis. Because our poverty lines are deduced from reasonable choice rather than estimated from a model, we consider that they are known a priori and that the poverty estimations for different poverty lines are separately implemented.

For each poverty line, we estimate Foster–Greer–Thorbecke squared poverty gaps (Foster *et al.*, 1984), for every quarter $t$ in 1983. The aggregate squared poverty gap is defined as

$$P_2 = \int_0^z (1 - y / z)^2 \, \mathrm{d}F(y)$$

where $F$ is the cumulative distribution factor (c.d.f.) of the distribution of the real per capita consumption, $y$, and $z$ is the poverty line. $P_2$ satisfies the monotonocity axiom, the transfer axiom and the sub-group monotonicity axiom.[10]

We use the following notions of living standards. The *annual per capita consumption* is the sum of the four quarterly per capita consumptions. The mean per capita consumption of a household over the studied agricultural year is denoted *chronic per capita consumption.* Note that it is not the permanent income for the entire lifetime of the household. Because of the short length of the observation period, discount factors between the quarters are omitted.

The notions for poverty measures share similar names with per capita consumption indicators, although they are of a different nature since these names are directly taken from the literature on poverty studies (Ravallion, 1988; Rodgers and Rodgers, 1993; Jalan and Ravallion, 2000). Chaudhuri and Ravallion (1994) and McCulloch and Baulch (1999) use the definition of the aggregate poverty measure for several years as an arithmetic average of the period-specific indices:

[10] Other poverty measures would be possible, for example, the poverty gap $P_1$. In Muller (2000) we present results based on this measure, as well as on $P_3$ and on the Watts poverty measure. To save space, we refrain here from providing estimates for too many measures. Then, we focus on the most frequently used axiomatically valid poverty measure. The poverty gap has the drawback of not satisfying the transfer axiom and we prefer to base the poverty equations on $P_2$ that satisfies this axiom. However, using axiomatically valid indicators also implies that they are sensitive to outliers caused by measurement errors (Cowell and Victoria-Feser, 1996). In a sense, this situation must be accepted as an inevitable shortcoming of poverty indicators of quality. We discuss the measurement error problem further on and partly deal with it by using estimation methods that are robust to the presence of outliers.

$$AP = \frac{1}{T}\sum_{t=1}^{T} P_t$$

where $P_t$ is the poverty measure of period $t$ (in this literature the period is the year) and $T$ is the number of periods. In our case, the periods are the four quarters, and $AP$ is the *annual poverty*.

Using the framework of welfare optimality developed in Harris (1978) and Hammond (1981), it can be seen that the sum of the aggregate poverty measures over the whole set of periods can be interpreted as the opposite of an ex-post social welfare function. 'Ex post' means here that the welfare criterion is based on realisations of consumption rather than expectations of present and future consumptions, as is the case in the standard Arrow–Debreu framework of decisions under uncertainty. Moreover, poverty at a given period can be seen as the opposite of a social welfare function specific to this period. All this is correct under the assumption that price indices and equivalence scales validly convert income or consumption information in living standards. Here, since only four quarters are observed, we can consider that $AP$ is akin to the opposite of an ex-post social welfare function over the year.

The *chronic poverty* ($CP$) is defined by using the poverty measure formula applied to the chronic per capita consumption (average of the per capita consumption of the four quarters). It is the poverty indicator that one may like to measure if people could have smoothed consumption if desired. It corresponds to the usual poverty indicators of the literature. The term 'chronic' refers here to the use of the chronic per capita consumption in the calculus. The definition of chronic poverty is therefore reminiscent of the consumer theory of life-cycle consumption, where the permanent income is enough to explain consumption at each period. Although there is no precise theoretical framework here, this indicator acts as a convenient landmark for analysing poverty fluctuations. The same poverty line is used in calculating each one of the quarterly poverty measures, $P_t$ ($t$ = 1, 2, 3, 4), and the chronic poverty measure, $CP$.

The *transient poverty* over the year is defined as the residual of the annual poverty once the chronic poverty has been taken into account: $TP = AP - CP$. Thus, $TP$ is the poverty increase that can be attributed to the variability of consumption about its intertemporal mean during the year. The definitions of $AP$, $CP$ and $TP$ are based on Ravallion

(1988), who defines *AP* as the mean level of poverty on the considered period (as an analogous of expected poverty) and *CP* as the level of poverty which will be found at stabilised incomes. These definitions are now standard. Variants accounting for survey design appear in Gibson (2001). To stress the fact that this component of the measured annual poverty comes from the seasonal fluctuations of consumption, we denote it *transient-seasonal poverty*. Naturally, *TP* could be negative for some poverty indices and data sets, although this does not normally occur in practice. The share of annual poverty caused by seasonal fluctuations is the ratio $F = (AP - CP)/AP$.

We do not use the head-count index $P_0$ in the equations, mostly because it is invariant to changes in the distribution of welfare amongst the poor, which makes its analysis less attractive from a normative point of view. Using the poverty gap $P_1$ would imply that $TP = 0$ if there is no household crossing the poverty line across periods. This is due to the neutrality of this indicator with respect to poverty risk. This feature points out problems arising when using non-axiomatically valid poverty measures. When households cross the poverty line across periods, *TP* is generally non-null even when based on $P_1$. Another approach, not followed in this paper, is to define chronic and transient poverty indicators in terms of the length of consecutive poverty spells, *CP* being assimilated to long spells and *TP* to short spells (Rodgers and Rodgers, 1993; Baulch and McCulloch, 1998). A drawback of this approach is that poverty severity is not accounted for.

If we possessed seasonal data for several years, we could define seasonal poverty from residuals of moving averages of per capita consumption calculated over a larger time interval, rather than from observations of poverty at four quarters. This would also allow the separation of the trend and random shocks from the seasonal component, which is impossible here.

For any household *i*, one can define its chronic poverty index, $CP_i$, and its transient poverty index, $TP_i$, by considering the population composed of the household only. National poverty measures generally result from aggregating individual poverty measures (Atkinson, 1987). $TP_i$ and $CP_i$ are null for a large set of observed households and strictly positive for others.

Let us turn to how the aggregate poverty measures are estimated. We estimate the aggregate poverty measure $P_2$ at quarter *t* by using sampling weights with the usual formula. Kish (1965) discusses this commonly used estimator. *TP*, *AP* and *CP* are estimated by using similar estimators. The estimators of the sampling standard errors are discussed in Appendix 1.

One permanent concern in empirical studies of transient poverty is how much of transient poverty is caused by measurement errors. The problem of distinguishing between transitory changes in consumption or income, and measurement errors is fundamental. Various techniques have been developed in the literature to attempt to deal with this problem, for example, by using income dynamic components as instruments for consumption (as in Alderman, 1996), or by simulating the effect of regular measurement errors with convolution product methods (Chesher and Schluter, 2000). Although such approaches are useful, they may also eliminate crucial observations for poverty analysis. Indeed, as Cowell and Victoria-Feser (1996) have shown, even if poverty indicators are sensitive to measurement errors causing outliers, it is this sensitivity to outliers that makes them interesting as axiomatically valid welfare indicators. Moreover, the lowest consumption observations are the ones that incorporate much of the relevant information for poverty analysis. Therefore, there is a trade-off between measurement error treatment and extraction of optimal consumption information for poverty indicators.

We partially deal with these problems in the following way. First, we use consumption indicators of exceptional quality, based on a very intensive collection process. This is likely to remove much of the consumption measurement problems met in many studies. Secondly, we have estimated in Muller (2000) the robustness of poverty estimates to the presence of measurement error by using the Chesher and Schluter (2002) method. The results show that only a very large amount of measurement error could modify the overall picture of chronic and transient poverty in Rwanda.[11] We also tried to instrument

[11] Let $Z$ be the contaminated distribution of living standard, and let $X$ be the error-free distribution. They are assumed related by the relation $Z = XV$ where

$$V = \exp(-\sigma^2/2)U^\sigma$$

is a multiplicative measurement error component such that $\ln U$ has mean zero and variance one, and $\sigma^2$ is a parameter describing the extent of the measurement error. Parameter $\sigma^2$ is such that

$$\mathrm{Var}(\ln Z)/\mathrm{Var}(\ln X) = 1 + \sigma^2/\mathrm{Var}(\ln X).$$

The chosen values of $\sigma^2$ correspond to values of $\mathrm{Var}(\ln Z)/\mathrm{Var}(\ln X)$ ranging from consumption with income and other variables, but this yields unusable results because of the poor goodness-of-fit of predictive equations. Indeed, it is doubtful that such a method is appropriate for Rwanda, where, because of very high levels of own-consumption, income and consumption indicators are largely endogenous, and only residual income information can be used, producing poor predictions of consumption. Finally, because our main concern is the estimation of household poverty equations, the measurement error problem must be dealt with in this context. This is done by using an estimation method, the censored quantile regression, which is robust to various measurement error problems, including the presence of outliers. Naturally, there are always measurement error problems that would escape the robustness properties of the quantile regressions, such as if all observations are subject to systematic random errors. What the quantile regressions do is to remove the excessive influence of a few extreme types of measurement errors. However, this method should alleviate some of the influence of general data contamination in the estimated equations. Of course, not all the impact of errors can be removed, and we may only be able to obtain proxy variables of *TP* and *CP*.

Table 2 shows the estimates of $P_2$ for the three poverty lines, by quarter and for the whole year. Corresponding estimates of *AP, CP, TP* and *F* are also shown. The sampling standard errors in parentheses indicate that all these poverty estimates are significant at common levels. The worst quarter for the poor is quarter D, occurring just after the dry season. At this period, the stocks have not yet been reconstituted before the next important harvests, in particular the beans harvest at the end of December and the beginning of January. The best period for the poor is quarter B. The second worst quarter for the poor is quarter A, although the level of poverty in this period is close to that of quarter C. For all poverty lines, the poverty rise between the first and the last quarter is dramatic.

Using chronic poverty measures only based on annual consumption delivers lower levels of poverty indicators than using annual poverty measures for all tried poverty measures. In particular, when using indicators based on $P_2$, the share of annual poverty caused by seasonal

100.1 to 155%, which includes very high level of data contamination, probably not reached in the used data set. For these values of $\sigma$ in [0, 0.32], the share of transient poverty in annual poverty changes by less than 10% owing to measurment errors in this model.

Table 2: *Estimates of the Squared Poverty Gap*

| | $z_A$ | $z_B$ | $z_C$ |
|---|---|---|---|
| Quarter A | 0.057 (0.0076) | 0.0468 (0.0067) | 0.0345 (0.005) |
| Quarter B | 0.0442 (0.0075) | 0.0355 (0.0064) | 0.0247 (0.0051) |
| Quarter C | 0.0566 (0.0062) | 0.0467 (0.0055) | 0.0343 (0.0047) |
| Quarter D | 0.0873 (0.015) | 0.0731 (0.014) | 0.0555 (0.012) |
| Annual poverty: *AP* | 0.0613 (0.0053) | 0.0505 (0.0045) | 0.0373 (0.0037) |
| Chronic poverty: *CP* | 0.0302 (0.0027) | 0.0221 (0.0023) | 0.0133 (0.0019) |
| Transient poverty: *TP* | 0.0310 (0.0043) | 0.0284 (0.0039) | 0.0239 (0.0034) |
| Share of *TP*: *F* | 0.507 | 0.561 | 0.643 |

The estimates of the squared poverty gap are shown in the cells. Standard errors are in parentheses. All poverty estimates are significant at 5 % level. 256 observations. The poverty lines are $z_A$= Frw 8352.49, $z_B$ = Frw 7762.88 , $z_C$ = Frw 6944.97.

consumption fluctuations ranges between 50 and 65% for the squared poverty gap with the tried poverty lines. This feature has been confirmed for many poverty measures and poverty lines with the same data in Muller (2000).

The importance of the seasonal-transient poverty cannot be attributed to a 'bad year' since 1982–3 is a normal agricultural year. The observed low levels of living standards in quarter D of 1983 are usual at this season. The non-negligible sizes of both *CP* and *TP* justify a separate investigation of the correlates of *CP* (the usual poverty indicator in the literature), and those of *TP*. This is undertaken in Sections 3.4 and 3.5. However, we first need to present the model and to test the normality of errors in poverty equations in the following section.

### *3.2 The Model and the Tests of Normality*

In this section we model the correlates of the two components of annual poverty with the household as the basic statistical unit. Another approach to the study of poverty correlates could be to refer to the huge literature on consumption smoothing (e.g., Deaton, 1990, 1992, 1997; Townsend, 1994; Ravallion and Chaudhuri, 1997; Attanasio, 1999). Indeed, people would be better off if their consumption was smoothed, and the poverty indicator used much as a welfare function. If consumption smoothing were perfect, the difference between average poverty and chronic poverty would disappear. For Rwanda, the poverty statistics in Section 3.1 have shown that the degree of consumption smoothing for the poor is weak, too weak to protect them against large seasonal welfare variation. This is less true for richer categories of households, although much consumption seasonal variability remains for all quantiles of the per capita consumption distribution. Muller (2001) presents quarterly means of per capita consumption for each quintile, which vary a lot across quarters. This is confirmed by low correlation coefficients of the household per capita consumption across quarters for all quintiles.

A large variety of models has been proposed for explaining the fluctuations of household consumption over time, and as Deaton advocates, although suggestive explanations have been proposed, much work is still to be done before a satisfactory model can be estimated. One difficulty is the probable presence of liquidity constraints that prevent anchoring of the model on smooth Euler equations for consumption evaluation. In this situation numerical simulation methods are available, but only very simple specifications are presently tractable. One problem is that the household income processes are serially correlated and that this largely increases the computation burden of such consumption models.

Although this does not seem to be appropriate in poor LDCs with an imperfect credit market, like Rwanda, one approach is to neglect the liquidity constraints. For example, one could estimate a model of expenditure dynamics across quarters, similar to Paxson (1992, 1993) or Alderman (1996). This type of model could be used to derive implications concerning the effects of exogenous variables on poverty. For the estimation of such a model, we would need to observe quarterly income data, local weather information and several years of consumption. In particular, one may want to observe the household responses to successive annual shocks that may be important (Alderman, 1996). Unfortunately, our data are not well suited to this task since this information is not available, and because there are only four observations per household. Moreover, because our major concern is the study of poverty, our strategy is to focus on the population of the poor and we directly investigate the correlates of household transient and chronic poverty measures based on indicator

$P_2$. Thus, we also avoid the difficulty caused by the unobserved liquidity constraints.

The estimated model is the following. Two dependent variables are considered for household $i$:

$$CP_i = (1 - (y_{i1} + y_{i2} + y_{i3} + y_{i4})/4z)^2 I_{[yi1 + yi2 + yi3 + yi4 < 4z]}$$

is the chronic poverty measure of household $I$, where $I[.]$ is the indicator function;

$$TP_i = \{[(1 - y_{i1}/z)^2 I_{[yi1 < z]} + [(1 - y_{i2}/z)^2 I_{[yi2 < z]} + [(1 - y_{i3}/z)^2 I_{[yi3 < z]} + [(1 - y_{i4}/z)^2 I_{[yi4 < z]} \}/4 - CP_i$$

is the transient poverty measure of household $i$. Household $TP_i$ and $CP_i$ indicators are calculated using the deflated per capita consumption and the three poverty lines.

It is important to model the censorship. The distributions of $CP_2$ and $TP_2$ are characterised by a large spike at zero corresponding to households that are not poor in these senses. It is analytically convenient and typical to model such a spike as a result of censorship of a latent variable. Thus, one can define an extension of the observed poverty measure that would take negative values for non-poor people. This usual econometric approach is justified by the continuity of the subjacent living standard distribution across the poverty line.

We define two latent variables, 'the latent transient poverty', $TP^*{}_i$, and 'the latent chronic poverty', $CP_i^*$, in order to interpret the null values of $TP_i$ and $CP_i$ as resulting from censorship. The link between latent and observed variables is the following:

(1) $$TP_i = TP_i^* \text{ if } TP_i^* > 0,\ TP_i = 0 \text{ otherwise;}$$
$$CP_i = CP_i^* \text{ if } CP_i^* > 0,\ CP_i = 0 \text{ otherwise.}$$

Then, we specify equations for the two latent poverty variables:

(2) $$TP_i^* = X_i' \beta + u_i \text{ and } CP_i^* = X_i' \gamma + v_i$$

where $X_i$ is a vector of poverty correlates for household $i$, $\beta$ and $\gamma$ are parameters, and $u_i$ and $v_i$ are error terms. The basis of the separate estimations of the censored regressions is eqs. (1) and (2). The usual method employed for these estimations is the Tobit regression. However, this method relies on the hypothesis that the errors in (2) are normally distributed and homoscedastic. Therefore, we need to test these hypotheses before employing this estimation method.

We test normality and homoscedasticity for Tobit estimates (for all

*TP* and *CP* indicators), using tests proposed by Gouriéroux *et al.* (1987) and Pagan and Vella (1989). The tests are based on the following restrictions:

$$\text{(M1)} \qquad N^{-1}\sum_{i=1}^{N} E\left[E\left(u_i^{3}\middle|y_i\right)\right]=0$$

where $u_i$ is the residual, $y_i$ is the dependent variable and σ is the fixed variance;

$$\text{(M2)} \qquad N^{-1}\sum_{i=1}^{N} E\left[E\left(u_i^{4}\middle|y_i\right)-3\sigma^4\right]=0$$

for the normality test; and

$$\text{(M3)} \qquad N^{-1}\sum_{i=1}^{N} E\left[E\left(u_i^{2}\middle|y_i\right)-\sigma^2\right]=0$$

for the homoscedasticity test, and where $u_i$ is the error term for household $i$ and $y_i$ the dependent variable, i.e., the household poverty indicator of interest in our application.

For the Tobit model, the $E(u_i^k \mid y_i = 0)$ ($k$ = 2, 3, 4) are calculated by using:

$$E(u_i \mid y_i = 0) = -\sigma\lambda_i$$

where

$$\lambda_i = \varphi\,(x_i'\beta/\sigma)/\Phi(x_i'\beta/\sigma)$$

with φ and Φ respectively the p.d.f. and the c.d.f. of the standard normal law, and

$$E(u_i^{k+1} \mid y_i = 0) = \sigma^2 k E(u_i^{k-1} \mid y_i = 0) - \sigma(-x_i'\beta)^k\lambda_i$$

for $k$ = 1, 2, 3.

Pagan and Vella (1989) show that the test statistics can be calculated by regressing the moments M1, M2, M3 against 1 and the score of the log-likelihood, and test if the coefficients on the intercepts are zero by reading the value of the t-statistics. We follow this approach for Table 3.

Table 3: *Normality and Heteroscedasticity Tests*

| | TP $z_A$ | TP $z_B$ | TP $z_C$ | CP $z_A$ | CP $z_B$ | CP $z_C$ |
|---|---|---|---|---|---|---|
| Normality (M1) | 5.58 | 6.15 | 6.60 | 6.01 | 7.64 | 8.80 |
| Normality (M2) | 4.18 | 4.68 | 5.08 | 5.60 | 7.12 | 8.15 |
| Heteroskedasticity (M3) | 5.54 | 6.04 | 6.44 | 5.83 | 7.39 | 8.57 |

The table shows the values of the absolute t statistics used for the test. The null hypothesis of normality or heteroscedasticity is rejected at 5% level if the absolute value of the Student's t is above 1.96, and at 1% level if it is above 2.58. These statistics correspond to the Tobit results with the whole set of correlates. The column headers show the dependent variable (*TP* or *CP*) and the used poverty line. The line headers show the stochastic moment used for the test. Restricted sets of correlates yield the same qualitative results. The rejection of the heteroskedasticity is very general and occurs with many socio-demographic and economic variables used as instruments. Here, for example, the statistics shown correspond to the use of the local price of palm oil as instrument. The poverty lines are $z_A$ = Frw 8352.49, $z_B$ = Frw 7762.88, $z_C$ = Frw 6944.97.

The test results shown in Table 3 indicate that normality is very strongly rejected at the 1% level for all poverty lines. Moreover, homoscedasticity is rejected at the 5% level for different types of heteroscedasticity. This is also the case for a very large number of alternative sets of regressors. The results of these tests imply that the estimations of poverty equations produced by using Probit and Tobit models are inconsistent. We shall therefore use an alternative estimation method, which is robust to non-normality and heteroscedasticity. We present this method in the next sub-section.

### *3.3 The Estimation Method*

Censored quantile-regressions are robust to heteroscedasticity and non-normality assumptions and constitute a convenient response to the test results of the previous section. Consequently, we base our estimation on this method. The censored quantile regression estimators (Csqr) from $CP_i$ and $TP_i$ are discussed in the Appendix 2.

We now discuss the correlates of the model. Information about cultivated land by the household, which is the main agricultural input, and about the household labour force can be incorporated as fundamental income sources whether it is via agricultural production or via the labour market. We dispose of an indicator of the land area cultivated by the household, and we know the household composition for five age classes. These variables are included in the set of correlates. In human capital theories (Willis, 1986), household earnings are largely explained by the age and the education levels of the members. Only the age and the education levels (in years) of the household heads can be incorporated in the equations. The access to markets is also important in that it determines the economic return of household production and the opportunity costs of the goods it consumes. This is described in the equations by the distance to the nearest market. Finally, some regressors are there to control for economic or econometric misspecifications. They are various socio-demographic variables (household composition, characteristics of the head such as age, gender, and education). In particular, they help to control for imperfect adult-equivalent scales, for the unobserved heterogeneity of households, and for omitted demographic changes correlated with poverty status (e.g., caused by household fertility). They may also be correlated with segregation restricting household access to certain resources. Regional dummy variables can play similar roles, while also accounting for the geographical heterogeneity of the environment. We now turn to the regression results.

### *3.4 The Estimation Results*

Table 4 shows the estimates of censored quantile regressions (Csqr) of the chronic and transient poverty measures and Table 5 shows the corresponding estimates with Tobit regressions. To save on degrees of freedom, variables whose coefficient had a P-value over 0.5 in preliminary estimators have been eliminated from the equations. This explains why estimations corresponding to different poverty lines have different sets of independent variables. It is important to eliminate such useless regressors because we lack degrees of freedom due to a small sample. These yields better results than badly determined estimates obtained with too many regressors. Such approach is appropriate because we do not base the estimation on a fully specified theoretical model.

The comparison of Tobit and censored quantile regressions results based on the same restricted set of regressors shows that while the

Table 4: *Censored Quantile Regressions of Household Transient and Chronic Poverty*

| Independent variables | $z_A$ | $z_B$ | $z_C$ |
|---|---|---|---|
| | | Latent chronic poverty | |
| Constant | 0.179 (0.000) | 0.100 (0.023) | –0.126 (0.154) |
| No. of babies | 0.0496 (0.001) | | 0.0790 (0.003) |
| No. of children | 0.0674 (0.000) | 0.0599 (0.005) | 0.0347 (0.078) |
| No. of adolescents | | | 0.0264 (0.207) |
| No. of young adults | | | –0.0342 (0.226) |
| No. of adults | –0.0749 (0.001) | | |
| Tutsi head | 0.243 (0.017) | 0.226 (0.008) | 0.139 (0.096) |
| Female head | | | 0.0769 (0.113) |
| Age of the head | 0.00252 (0.025) | | 0.00273 (0.075) |
| Head's education | –0.0123 (0.130) | –0.0126 (0.089) | |
| Distance to market | 0.00106 (0.070) | 0.00124 (0.040) | 0.000716 (0.365) |
| Land | –0.00442 (0.000) | –0.00449 (0.000) | –0.00656 (0.002) |
| Northwest | 0.0672 (0.393) | | |
| Southwest | 0.0617 (0.095) | | 0.0780 (0.181) |
| Centre-South | 0.146 (0.000) | 0.0729 (0.049) | 0.0553 (0.181) |
| | | Latent transient poverty | |
| Constant | 0.149 (0.008) | 0.196 (0.000) | 0.179 (0.000) |
| nb children | 0.0120 (0.214) | 0.0149 (0.211) | 0.0151 (0.243) |
| nb young adults | –0.0101 (0.284) | –0.0117 (0.223) | –0.0118 (0.191) |
| nb adults | 0.0137 (0.476) | | |
| Female head | –0.0594 (0.056) | –0.0698 (0.003) | –0.0562 (0.0008) |
| Age of the head | | –0.000619 (0.300) | –0.000583 (0.337) |
| Distance to market | –0.000317 (0.488) | | |
| Land | –0.00154 (0.051) | –0.00140 (0.067) | –0.000634 (0.360) |
| Southwest | –0.0340 (0.456) | | |
| Centre-South | –0.0532 (0.093) | –0.0458 (0.044) | –0.0472 (0.032) |
| East | –0.0410 (0.236) | –0.0405 (0.129) | –0.0457 (0.049) |

P-value in parentheses. 256 observations. The poverty lines are $z_A$ = Frw 8352.49, $z_B$ = Frw 7762.88, $z_C$ = Frw 6944.97.

estimated coefficients can be substantially different, on the whole the significant correlates (at 5% level) of *CP* revealed by censored quantile regressions and Tobits are often qualitatively similar. By contrast, the

Table 5: *Tobit Regressions of Household Transient and Chronic Poverty*

| Independent variables | $z_A$ | $z_B$ | $z_C$ |
|---|---|---|---|
| | | Latent chronic poverty | |
| Constant | –0.204 (0.001) | –0.0978 (0.000) | –0.254 (0.000) |
| No. of babies | 0.0434 (0.001) | | 0.0523 (0.000) |
| No. of children | 0.0315 (0.001) | 0.0363 (0.000) | 0.0267 (0.001) |
| No. of adolescents | | | 0.0143 (0.147) |
| No. of young adults | | | 0.00448 (0.686) |
| No. of adults | –0.0216 (0.098) | | |
| Tutsi head | 0.0328 (0.230) | 0.0285 (0.293) | 0.0325 (0.206) |
| Female head | | | 0.0448 (0.042) |
| Age of the head | 0.00138 (0.075) | | 0.00171 (0.009) |
| Head's education | –0.00586 (0.193) | –0.00712 (0.068) | |
| Distance to market | 0.000902 (0.027) | 0.000693 (0.088) | 0.000985 (0.012) |
| Land | –0.00153 (0.066) | –0.00172 (0.036) | –0.00181 (0.025) |
| Northwest | 0.0356 (0.219) | | |
| Southwest | 0.0603 (0.018) | | 0.0537 (0.019) |
| Centre-South | 0.0662 (0.006) | 0.0440 (0.031) | 0.0563 (0.005) |
| | | Latent transient poverty | |
| constant | –0.00856 (0.436) | 0.00346 (0.729) | 0.00870 (0.367) |
| nb children | –0.0116 (0.000) | 0.0114 (0.000) | 0.0102 (0.000) |
| nb young adults | –0.00277 (0.462) | 0.00209 (0.559) | 0.00166 (0.631) |
| nb adults | 0.000856 (0.837) | | |
| Female head | 0.00900 (0.260) | –0.0109 (0.141) | –0.0111 (0.119) |
| Age of the head | | 0.000158 (0.388) | 0.000135 (0.442) |
| Distance to market | –5.9E–6 (0.967) | | |
| Land | 0.000389 (0.133) | –0.000366 (0.143) | –0.000351 (0.145) |
| Southwest | –0.00520 (0.519) | | |
| Centre-South | | 0.00512 (0.442) | 0.00566 (0.380) |
| East | 0.0246 (0.001) | –0.0216 (0.003) | –0.0195 (0.006) |

P-value in parentheses. 256 observations. The poverty lines are $z_A$ = Frw 8352.49, $z_B$ = Frw 7762.88, $z_C$ = Frw 6944.97.

significant correlates (at 5% level) of *TP* are radically different across the two estimation methods.

The number of coefficients significant at 5% level in equations for *TP* and *CP* is roughly the same whether Tobit or Csqr methods are used.

The sensitivity of the results to the choice of the poverty line also looks similar across the two estimation methods. Not only are significant coefficients different for the two methods, but also the levels of the estimated coefficients differ markedly. Very often higher levels of the effects of regressors are found with Csqr. Let us examine more closely the differences in significant effects for the two methods, focusing on 1, 5, 10 and 15% significance levels. On the one hand, for chronic poverty Csqr results show more effectively the influence of the number of adults, the education level and the ethnic group of the household head, and of land. In contrast, Tobit results exhibit more significant responses for the numbers of children and adolescent, female heads and market distance, although these responses, or at least their significant levels, are likely to be illusions caused by the rejected normality hypothesis. Some differences of significance for region dummies also occur across methods.

On the other hand, for transient poverty the Csqr elicits more significant effects of the head's gender and of the location in region Centre-South. Tobit estimates show, probably wrongly, more significant influences for the number of children, the number of young adults and the location in the East region. Note also that the non-significance of the intercept term for the Tobit model may be interpreted as a hint at its misspecification. On the whole for TP and CP together, Tobit estimates exhibit exaggerated effects of household composition and insufficient effects of the characteristics of the household head.

The Tobits fail to reveal important influences that are better captured by Csqr. Not only does Csqr better show significant influences, but also the size of the effects elicited with this method is larger. Moreover, Tobit estimates are not only inconsistent but also the corresponding P-values are also inconsistent and therefore invite the deduction of erroneous inferences. The differences between Tobit and Csqr are large enough to suspect many of the conclusions that would be obtained by using Tobit models.

The marked difference between estimates obtained with Tobits against censored quantile regressions raises doubts about the validity of many estimated poverty equations in the literature based on Tobit or Probit models, i.e., on implausible normality assumptions. This implies that policies to alleviate poverty and notably anti-poverty targeting may be misguided by traditional estimation method. We now proceed with the comment of the consistent quantile regression estimates.

Slightly different correlation structures correspond to different poverty lines. However, the signs of the estimated coefficients are stable across poverty lines when they are significant. There are clear differences in the effects of correlates for *TP* and *CP*, although the only significant effects with opposite signs for *TP* and *CP* are that of the Centre-South region and female head if one considers a 15% significance level. The number of adolescents, the number of young people and the dummy for the North-West region are never significant at the 5% level and we neglect them in our comment.

The estimates are consistent with the beneficial influence of the volume and the quality of the main inputs (land and labour) on living standards. A few variables are always significant whatever the poverty line used. Thus, the number of children and the dummy for Tutsi heads are associated with higher *CP* and the land area with lower *CP*. The dummy for female heads and the dummy for the Centre-South region are related to lower *TP*. The coefficients of the other variables are only significant for some poverty lines. In that case, the number of babies, the age of the head, the distance to the market and the location in the South-West region are linked with higher *CP*, while the number of adults and the education of the head are associated with lower *CP*. Finally, a large land area and a location in the eastern region correspond to lower *TP*.

Let us analyse these effects in more detail. The positive impact of land, of the head's education, and of the number of adults on the reduction of chronic poverty can be explained by the direct contributions of land and labour input to household production and income. By contrast, the numbers of babies and young children have negative effects on chronic poverty. This may reflect the fact that these categories of members are a burden for households. This suggests developing programmes of fertility control to alleviate this problem. The household composition and the area of cultivated land could be used as screening variables for policy against chronic poverty. Also, policies favouring the access of poor households to land and the improvement of their labour force are likely to alleviate chronic poverty. Improvements of agricultural technology should also enhance the productivity of these factors.

Other socio-demographic characteristics matter for the chronic poverty status. Female heads and old heads are weakly associated with higher *CP*. This may be caused by lower productivity, but also by limited access to economic opportunities for these households.

Households led by a Tutsi head are associated with higher *CP*. This is consistent with past negative shocks on their living standards due to political events. Notably, civil troubles in 1959 and 1973 severely hit the Tutsi community. These head characteristics could be used for targeting policies against *CP*, although the ethnic group is to be avoided because of the delicate political context. Specific help could be directed towards households led by female heads or old heads, for example in the form of local solidarity schemes.

The household location is also important. The dummy variables for the South-West, Centre-South and East regions sometimes have significant effects, although they are difficult to interpret because of the large size of these regions. These effects may correspond to regional crop specialisation. Moreover, a large distance to the market is related to high levels of *CP*. This is consistent with costly access to the market that reduces opportunities for transactions and jobs, and results in lower permanent exchange gains. Policies against *CP* should be directed more intensively towards households in disadvantaged regions or household living far from the main roads or from trade centres. Investments in transport, communication and road infrastructure are also likely to improve the situation of the chronic poor.

The land area, the gender of the head, and regional dummies for Centre-South and East are the correlates of *TP* that policy fighting *TP* could use. Owning a large area of land is associated with a higher level of *TP*, probably due to the fact that these households specialise in agricultural activities dependent on seasonal climatic fluctuations. Consequently, policies against *TP* could be more than proportionally directed towards peasants who do not diversify their activities in other sectors. In Rwanda, land is the signal of relative wealth in terms of chronic poverty, but also of a larger vulnerability to transient seasonal poverty. The significant effects of regional dummies on *TP* may come from different regional crop specialisations. If that is the case, policies against *TP* should account for local agronomic characteristics. They may be more efficient when adapted to each local mix of crops rather than when planned uniformly at a national level. Finally, the fact that female led households have lower *TP* is consistent with widows often relying on regular food and income transfers from family members. Such transfer schemes, which constitute a traditional obligation, could be encouraged in the direction of other household types by offering, for example, public subsidies.

## 4. Conclusion

The non-normality and heteroscedasticity of error terms in household poverty equations is likely to invalidate many estimates in the literature obtained by using Tobit and Probit models. Moreover, because of the frequent occurrence of seasonal poverty in LDCs, social policy could be guided by separate correlates for transient seasonal poverty and chronic poverty at the household level. We deal with these questions by using data from Rwanda in 1983, for which we test and reject the normality of error terms in household poverty equations. Then, we treat non-normality and heteroscedasticity by estimating censored quantile regressions of household poverty measures. Also, in contrast with most of the literature, we consider quarterly household consumption variations rather than annual variations.

Our estimated coefficients of the correlates of chronic and transient household poverty indicators are sufficiently different with Tobit and censored quantile regressions to raise doubts about the validity of inferences obtained from Tobit models of household transient and chronic poverty. This may have serious consequences on the way policies to alleviate poverty are guided by Tobit estimates of poverty equations or by other methods relying on implausible error assumptions.

The censored quantile regression estimates show that different correlates are significant for chronic poverty and for transient poverty in Rwanda. The effects of the main inputs (land and labour) are more important for the chronic component of poverty than for the transient one. Moreover, household location and its socio-demographic characteristics matter for describing its poverty status. The significant correlates are well suited to differentiated strategies against chronic poverty and transient poverty based on different instrument or target groups.

What kind of policies can be improved by the information obtained from the estimates? Clearly, to base anti-poverty policies only on estimates of household poverty equations is a risky exercise and it is not what is typically proposed in the best articles in this domain. Moreover, Atkinson and Bourguignon (2000) convincingly argue that a consistent model explaining income distribution and poverty should involve a dynamic general equilibrium approach, which is far from what can be obtained from household poverty equations. Then, the design of sound anti-poverty policies remains a challenge under limited knowledge about the relevant economic mechanisms.

However, it is possible to use the estimates of household poverty equations as a first stage of the analysis to suggest directions in which policies to alleviate poverty could be developed. Three general avenues could be explored. First, anti-poverty targeting schemes can be guided by these estimates by enabling a better screening of households benefiting from these schemes. What is interesting here is that it is possible to differentiate targeting schemes for chronic poverty, which could be based on the observation of household composition, land, age and sex of the household head and distance from trading centres. Regional targeting is also likely to be efficient against chronic poverty over the year. For targeting against transient seasonal poverty, the observations of non-agricultural activities are key variables since households more specialised in agriculture are more vulnerable to agricultural production shocks that have a strong seasonal component and more effort to observe these activities would help policies against seasonal transient poverty. Seasonal public works could be used to alleviate poverty by providing low wage jobs at crucial periods to poor households that would self-select themselves for these jobs. Thus, 'leakages' of these schemes towards over-wealthy populations can be avoided.

Secondly, policy measures directed towards improvement of household human and physical capital, household productivity and agricultural technology, and household environment may be efficient against poverty. Again, actions directed against *CP* and against *TP* could be sometimes be separable. Measures improving permanently agricultural technology and land and labour productivity are likely to reduce *CP*, as it is also the case for investments in transports and communication infrastructures. Health and fertility control programmes are likely both to permanently improve the household human capital, and also reduce the domestic burden brought by children and ill person household members.

Thirdly, support to insurance and solidarity institutions seems to be necessary to reduce the riskiness of rural incomes. This should contribute to the alleviation of both *CP* and *TP*, depending on the time scope of the insurance mechanisms. Several types of programmes are possible, including credit schemes, buffer stocks and crop insurance schemes. The estimates suggest that such solidarity programmes against chronic poverty should be more directed toward female and old heads, while widows would need to be helped more against transient seasonal poverty. However, if public action to provide better insurance seems necessary, its implementation is complicated by the fact that traditional insurance and solidarity schemes are already in place, as well as household protection strategies against income risk. This calls for further studies in these domains.

Finally, the policies of interest may have implications for the methodology. In particular, it would be very useful to introduce questions directly related to these policies in household surveys, for example: who is part of a traditional solidarity scheme? Who has been affected by a specific public policy? Who has benefited from a specific development project and how?

However, in the longer run, one may want to go beyond targeting schemes for anti-poverty policies. This is notably the case because agricultural households develop their own protection strategies against chronic and transient poverty and these strategies are likely to be correlated with some observable characteristics used for defining the target group or the policy measures. For example, Fafchamps (1992) shows how food security concerns may lead peasants with different amounts of land to choose different protection strategies based on own-consumption or on crop diversification. Then, informed anti-poverty policies would benefit from a better knowledge of household strategies and should be designed in co-ordination with these strategies. This interesting research line is left for future work.

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**Appendix 1: Sampling Standard-error Estimators**

The complexity of the actual sampling scheme does not enable a robust use of classical sampling variance formula. We use an estimator for sampling standard errors (see Appendix 1) that is a combination of 'linearisation' estimators obtained using balanced repeated replications (Krewski and Rao, 1981; Roy, 1984; Shao and Rao, 1993) and that is simpler and quicker than stratified bootstrap procedures. Howes and Lanjouw (1998) show that the sampling design can substantially modify the estimated standard errors for poverty measures. Consequently, our estimators for the sampling standard errors account for the sample design.

The poverty indicator of a sub-population is estimated by a ratio of the type

$$\bar{y}'_x = \frac{z'}{x'}$$

where $'$ denotes the Horwitz–Thompson estimator for a total (sum of values for the variable of interest weighted by the inverse of inclusion probability), $z$ is the sum of the poverty in the sub-population and $x$ is the size of the sub-population. The variance associated with the sampling error is then approximated by:

$$V(\bar{y}'_x) = \frac{V(z') - 2\bar{y}'_x \mathrm{Cov}(z', x') + (\bar{y}'_x)^2 V(x')}{(x')^2}$$

obtained from a Taylor expansion at the first order from function $Y = \mathrm{f}(Z/X)$ around $(Ey', Ex')$ and because $Ez' \neq 0$ and $x'$ does not cancel, where the appropriate expectancies are estimated by $x'$ and $\bar{y}'_x$.

We divide the sample of communes (first actual stage of the sampling since all the prefectures are drawn) in five superstrata ($\alpha$ = 1–5) so as to group together the communes sharing similar characteristics, and to reduce a priori the variance intra-strata. Several sectors are assumed to have been drawn in each stratum. This allows the estimation of the variance intra-strata, while the calculation of the variance intra-commune was impossible, since in fact only one sector had been drawn in each commune. Then, the Horwitz–Thompson formula for superstratum $\alpha$ is:

$$z'_\alpha = \sum_h \frac{M_h}{m_{h_\alpha}} \sum_{i=1}^{m_{h_\alpha}} \frac{N_{hi}}{n_{hi}} \sum_{j=1}^{n_{h_i}} \frac{Q_{hij}}{q_{hij}} \sum_{k=1}^{q_{hij}} z_{hijk}$$

and

$$x'_\alpha = \sum_h \frac{M_h}{m_{h_\alpha}} \sum_{i=1}^{m_{h_\alpha}} \frac{N_{hi}}{n_{hi}} \sum_{j=1}^{n_{h_i}} \frac{Q_{hij}}{q_{hij}} \sum_{k=1}^{q_{hij}} x_{hijk}$$

where $M_h$ is the number of communes in prefecture $h$; $m_{h\alpha}$ is the number of communes in prefecture $h$ and drawn in superstratum $\alpha$; $N_{hi}$ is the number of sectors in commune $i$ of prefecture $h$ and superstratum $\alpha$; $n_{hi}$ is the number of sectors drawn in commune $i$ of prefecture $h$ and superstratum $\alpha$; $Q_{hij}$ is the number of households in sector $j$ of commune $i$ of prefecture $h$; $q_{hij}$ is the number of households drawn in sector $j$ of commune $i$ of prefecture $h$ and superstratum $\alpha$. A similar formula can also be used to account for the intermediary drawing of several districts in every sector.

Cov($z'$,$x'$) is estimated by:

$$\hat{\mathrm{C}}\mathrm{ov}(z', x') = \frac{1}{20} \sum_{\alpha=1}^{5} (z'_\alpha - z')(x'_\alpha - x').$$

Similar formulae for $V(x)$ and $V(z)$ are obtained by making $x = z$.

## Appendix 2: Censored Quantile Regressions

The censored quantile regression estimator for $CP_i$ and quantile $\theta$ is defined as the solution to the minimisation of

$$\frac{1}{N} \sum_i \rho_\theta \left[ CP_i - \max(0, X'_i \gamma) \right]$$

where

$$\rho_\theta[u] = \{\theta - I[u < 0]\}|u|$$

and $N$ is the sample size. A similar estimator can be defined for $TP_i$.

Powell (1983, 1986) and Buchinsky and Hahn (1998) study the properties of these estimators. As described in Buchinsky (1994, 1995), the estimation is obtained by a combination of a linear programming algorithm and selection of a sub-sample at each iteration of the optimisation. We estimate the confidence intervals of the censored quantile regression estimates by using the bootstrap method with 1000 bootstrap iterations. Hahn (1995) shows that these confidence interval estimators have asymptotically correct probabilities. The bootstrap estimation of the variance–covariance matrix of parameters is applied when convergence has been obtained.

The main reason why we use the quantile regression method is because it provides consistent estimates even under non-normality and heteroscedasticity. It also provides estimates that are robust to the presence of outliers, a permanent concern in poverty analysis because of measurement errors in consumption surveys. It has been argued that this method helps the analysts to focus on the population of interest by choosing quantiles corresponding to the poor. This latter argument is exaggerated since the quantile is that of the conditional distribution, i.e., of the error term, and not directly of the latent poverty index. However, because the usual household poverty equation explains only a small part of the variability of the household poverty distribution, one would expect there to be a strong correlation between quantiles of these conditional and unconditional distributions of the household latent poverty measures. In any case, the focus property of the quantile regression is not the main reason for using the quantile regressions in this paper. Because we deal with *TP* and *CP*, a simultaneous estimation method would have been convenient. Unfortunately, no quantile regression method for simultaneous equations is presently available in the literature. This, the absence of strong structural priors about income generating processes and data limitations, explains why we have separate estimations for household *TP* and household *CP*.

The choice of the quantile in the censored quantile regressions is in part motivated by the interest of focusing on the population of the poor so that the observation of very rich households plays little role in the estimation. As discussed before, caution must be applied for this type of interpretation. This approach corresponds to specifying quantiles close to zero in the regressions of the latent poverty indices. More importantly, as both the censorship and the robustness of estimation methods are associated with a loss of accuracy, a major reason for choosing quantiles close to zero is to dispose of most of the information described by poverty indicators in the maximised objective function. Indeed, the shape of the objective function imply that the influence of observations such that $I_{[u \geq 0]}$ do not intervene in the asymptotic first-order conditions associated with the roots of the optimisation problem. These observations correspond to error terms beyond quantile θ. Then, when very low quantiles are chosen, a very large proportion of observations play no role in the calculation of the estimates for the final interactions of the algorithm. Thereby, we improve the precision of the estimates. After a few trials, quantiles 0.10 are used for the estimation tables for transient poverty, and quantiles 0.025 for chronic poverty. Here, 0.025 could be interpreted as if we focus on the observations that fall in the lower tail of the error term distribution and corresponding to 2.5% of the population.