Session 7D: Well-Being Over Time I
Time: Friday, August 10, 2012 AM

Paper Prepared for the 32nd General Conference of
The International Association for Research in Income and Wealth

Boston, USA, August 5-11, 2012

Chronic Poverty and Poverty Dynamics: Combining Normative and Positive Approaches to Reconcile Persistence and Depth Sensitivity

Natalie N. Quinn

For additional information please contact:

Name: Natalie N. Quinn
Affiliation: University of Oxford, UK

Email Address: natalie.quinn@lmh.ox.ac.uk

Chronic Poverty and Poverty Dynamics: Combining Normative and Positive Approaches to Reconcile Persistence and Depth Sensitivity.

Work in progress: please do not cite.

Natalie Naïri Quinn*

July 2012

Abstract

This paper combines positive models of wellbeing dynamics with normative evaluation of poverty to resolve the conflict between normatively justified but incompatible properties of intertemporal poverty measures. The theoretical tension between sensitivity to persistence of poverty and appropriate treatment of intertemporal compensation in an intertemporal poverty measure is reviewed. It is proposed to separate the normative evaluation of poverty from the implicit assumptions about dynamics inherent in some chronic poverty measures. A variety of approaches is used to model wellbeing dynamics, illustrated by application to data from rural Ethiopia. The results of naive application of several intertemporal poverty measures suggested in the recent literature to data from observed periods only are compared with application of the measures to the modelled wellbeing trajectories. It is found that the normatively preferred intertemporal poverty measures tend to overestimate the degree of poverty when applied only to periods in which observations are available. Explicit modelling of wellbeing in unobserved periods gives bounds for 'true' intertemporal poverty, which interestingly are found to be consistent with the naive application of two 'chronic' poverty measures. This suggests that the 'chronic' poverty measures may serve as a good proxy for intertemporal poverty in a way that reflects different normative judgements from those apparently inherent in the measures.

*Lady Margaret Hall and CSAE/Department of Economics, University of Oxford. Email natalie.quinn@economics.ox.ac.uk.

1 Introduction and Motivation

Traditional measures of poverty, ranging from the dollar-a-day headcount used for international comparisons Chen and Ravallion (2008) and government monitoring based on locally-established poverty lines to inequality-sensitive measures such as the poverty-gap squared measure (Foster, Greer, and Thorbecke, 1984), are calculated from data about a cross-section sample of individuals or households and thus provide a snapshot of the incidence or burden of poverty at a particular moment in time. Repeated cross-sections allow a poverty analyst to determine how the total burden of poverty in the population being studied evolves over time, but cannot distinguish between situations in which the same individuals are remaining poor on a persistent basis and situations in which individuals experience fluctuating levels of wellbeing, so that the identity of the poor changes more rapidly than the proportion of the population that is poor.

The primary reasons for conducting quantitative poverty measurement are to identify targets for and to evaluate poverty alleviation policies. It is widely accepted that different forms and causes of poverty require different policy interventions. For example, if poverty is transient, perhaps arising from an inability to smooth consumption in the face of income fluctuations, appropriate intervention could involve supportive intervention in insurance markets, provision of social insurance or support for informal insurance institutions. When poverty is persistent, perhaps arising from an inability to accumulate human or physical capital (as a result of social, physical or economic constraints) then an insurance-focused policy would be less effective or appropriate.

If different forms of poverty require different policy interventions then methods of measurement and evaluation of poverty should be able to distinguish between these different forms. A particular concern is that with the contemporary policy focus on the Millennium Development Goals, in particular the goal of halving the $1 per day headcount poverty rate by 2015, those experiencing deep and persistent poverty are being neglected. These issues are discussed in detail by Hulme and Shepherd (2003).

The recent increasing availability of microeconomic panel or longitudinal data collected in both developing[1] and developed countries provides information which permits explicit evaluation of the dynamics of wellbeing and poverty at household level. Understanding these issues is essential for the design of policies whose objectives are to tackle the problem of poverty. Questions which have been addressed in this field include the identification of factors which influence the probability of moving into and out of poverty, the existence and nature of poverty traps and the determinants of escape from poverty. The literature consistently finds that across many times and places, some households remain poor persistently whilst others move into and out of poverty. These two groups are commonly described as *chronically* and *transiently* poor, respectively.

Baulch and Hoddinott (2000) reviewed thirteen panel studies in developing countries, which demonstrated consistently that a significant proportion of households experience transient poverty, in most cases larger than the proportion of households that experience poverty in all of the study periods. In particular, Gaiha and Deolalikar (1993) find that

[1]Notable examples at household level in developing countries include ICRISAT's Village Level Studies (http://www.icrisat.org/gt-mpi/KnowledgeBase/Databases/vls.asp), whose subjects were surveyed annually from 1975–1976 to 1983–1984, and the Ethiopia Rural Household Survey (ERHS) (http://www.ifpri.org/data/ethiopia02.htm) whose subjects were surveyed in 1994, 1994, 1995, 1997, 1999 and 2004. Both of these surveys include information about the welfare of individuals and households in a rural developing country context.

87.8% of the ICRISAT households have incomes below the poverty line in at least one period of the survey, 61.3% in at least five of the nine periods while just 21.8% do in all nine periods. Porter (2008), analysing all rounds of the ERHS except the second, finds that 63.7% of the households have per-adult-equivalent consumption below the poverty line in at least one round, 21.0% in at least three while only 2.6% do in all five rounds. While some observed fluctuations in wellbeing may be ascribed to measurement error, several of the studies surveyed by Baulch and Hoddinott demonstrate that income shocks have explanatory power for consumption, suggesting that measurement error cannot be the only source of the observed fluctuations.[2]

Many of the studies surveyed by Baulch and Hoddinott (2000) model poverty dynamics and economic mobility, while Dercon and Shapiro (2007) review the findings of the more recent literature. Many of the studies reviewed by Dercon and Shapiro find that education and household assets are associated with positive economic mobility while income and health shocks have persistent negative effects, although not all of these results have a clear causal interpretation. Fluctuations in wellbeing are associated with an absence of insurance markets; Dercon (2004b) contains both theoretical and empirical analyses of this relationship and evidence for a causal impact on persistence of poverty.

As well as descriptive and positive empirical analysis of the dynamics of poverty and wellbeing at household level, the availability of household panel data makes possible normative evaluation that takes explicit account of fluctuations in wellbeing over time.[3] When households experience fluctuations in wellbeing, repeated application of a cross-sectional or static measure such as those mentioned above both embodies a particular set of normative judgements and discards relevant information. To take a very simple example, suppose that the headcount measure of poverty in a population is stable at 30% when measured on an annual basis. It could be that the same individuals are poor every year, or that different individuals move in and out of poverty, often described as 'churning'. Whether or not to regard these two situations as equivalent is a normative choice which should be made explicitly by the poverty analyst.

There is a rapidly developing literature in this field; several authors have recently developed indices which aggregate individual-level indicators of wellbeing over an extended period of time to measure 'chronic' or 'intertemporal' poverty. (Some authors aggregate to give a social measure which is responsive to individuals' profiles, but the main innovation is in the individual-level measurement.) The various measures differ in the way that they rank alternative trajectories of wellbeing and thus represent different normative judgements of the relative undesirability of the trajectories. For example, the measures suggested by Foster (2009), Gradin, Del Rio, and Canto (2011) and Bossert, Chakravarty, and D'Ambrosio (2012) are particularly sensitive to persistence or duration of poverty or deprivation, and are thus well described as chronic poverty measures. The measures suggested by Foster and Santos (forthcoming) and Porter and Quinn (forthcoming) are sensitive to transient depth of poverty and thus fluctuation, with that suggested by Porter

[2] Townsend (1994) and Dercon and Krishnan (2000) show that households in the ICRISAT and ERHS villages, respectively, achieve partial but not complete consumption smoothing in the face of income shocks.

[3] Some studies, notably Carter and Barrett (2006), combine elements of both positive and normative analysis. Given the impossibility of perfect measurement or knowledge of the future, incorporating elements of positive modelling is necessary to conduct normative evaluation when the poverty analyst cares about future wellbeing as well as, or rather than, past wellbeing. Such studies have not always made precise the distinction between the normative judgements and positive models or assumptions that they embody.

and Quinn (forthcoming) being particularly sensitive to extremely severe deprivation, allowing for less substitutability of wellbeing across time, the deeper the degree of poverty. While these properties are intuitively normatively desirable, Porter and Quinn (2012) have shown that they are incompatible with sensitivity to persistence of poverty.

This fundamental conflict between two apparently reasonable and normatively justified properties of intertemporal poverty measures deserves further attention and exploration. I suggest that the poverty analyst (who is making the normative judgement) may really be interested in the individual's trajectory of wellbeing or experience of poverty over an extended period of time or their whole lifetime, not just the particular time periods in which they are observed. As deprivation and poverty are well understood to persist over time and even over generations, it is possible that a poverty analyst applying a duration-sensitive measure is implicitly using persistence of poverty within an extended period of observation to proxy for future or lifetime experience. This leads to the natural conclusion that, where suitable data is available, a better approach would be to draw on the literature modelling welfare and poverty dynamics to build an explicit model of future or lifetime wellbeing for the individual. A normative measure of intertemporal poverty may then be combined with the prediction of the positive model to measure poverty over time in a way that reconciles the two desirable but conflicting properties.

The paper proceeds as follows. In section 2 I describe the characteristics of the consumption data from the Ethiopian Rural Household Survey which will be used to illustrate the analysis. In section 3 I review some of the recently-suggested intertemporal and chronic poverty measures, focussing on the way in which the properties of the measures embody both normative judgements and positive assumptions. In section 4 I apply several alternative approaches to model explicitly the evolution of household wellbeing over the duration of the ERHS study. In section 5 I apply the intertemporal poverty measures to the modelled data and discuss the results. Section 6 concludes.

2 The Data

Although the focus of this paper is primarily methodological, the analysis will be illustrated throughout by application to data from the Ethiopian Rural Household Survey (ERHS).

The ERHS is a panel or longitudinal study that was conducted by the Economics Department of Addis Ababa University, the Centre for the Study of African Economies at the University of Oxford and the International Food Policy Research Institute (IFPRI), based in Washington D.C.[4] Households in eighteen Peasant Associations[5] (PAs) in rural Ethiopia were surveyed twice in 1994, then in 1995, 1997, 1999 and 2004.[6] The eighteen Peasant Associations surveyed belong to fifteen different districts (Woredas). Within each Peasant Association surveyed, the households were randomly sampled subject to stratification into female-headed/non-female-headed and landless/non-landless categories. (Six of the PAs had been included in a 1989 IFPRI study; in these PAs the sample was rerandomised.) The sample sizes in the eighteen PAs were chosen so that proportions in

[4]Funding was received from the UK Economic and Social Research Council (ESRC), the Swedish International Development Agency (SIDA) and the US Agency for International Development (USAID).

[5]Created after the 1974 revolution, Peasant Associations are the lowest level administrative division in rural Ethiopia. Each comprises one or a few villages.

[6]A seventh round has been collected more recently but the data is not available.

the pooled sample were representative of the agro-climatic zones of Ethiopia.[7]

The original analysis of poverty and poverty changes in the ERHS sample was made by Dercon and Krishnan (1998) who analysed data from the first three rounds, comparing with data from the 1989 IFPRI survey for those households included in both surveys. Dercon and Krishnan constructed a household aggregate consumption measure comprising the nominal value of purchased and non-purchased food items consumed as well as non-investment non-food items, but excluding expenditure on durables, house expenses, health and education. This was scaled according to the household composition to give a per-adult-equivalent monthly value, following World Health Organisation guidelines for weighting male and female adults and children.

Dercon and Krishnan conducted their poverty analysis of the consumption aggregate relative to a poverty line determined by the cost-of-basic-needs approach; a food consumption basket typical of the diet of the nominally poorest half of the sample was constructed and scaled so as to provide 2300 Calories (kilocalories) per day. The non-food share of consumption for a household at the poverty line was estimated and the nominal value of the poverty line was computed for each PA in each period, using local prices. More details and a comprehensive discussion of the issues arising may be found in Dercon and Krishnan (1998). Porter (2008) extended the analysis to include the later rounds of the ERHS, omitting round 2 (the second 1994 round) to avoid seasonality issues (the first three rounds had been conducted in a very short time frame in comparison to the rest of the survey).

2.1 Wellbeing Indicator

The EHRS data includes comprehensive information on household income and consumption as well as household and individual characteristics. Porter (2008) and Porter and Quinn (forthcoming) use the monthly consumption aggregate as constructed by Dercon and Krishnan (1998) and extended by Porter (2008) as an indicator of wellbeing for the analysis of poverty. This is partly because it is well-established that consumption data is more reliable than income data in the ERHS and similar household surveys, but primarily because value of consumption already takes into account the household's intertemporal smoothing strategies and thus serves as a much better proxy for experienced wellbeing. The same consumption aggregate is used for the analysis in this paper.

In order to establish comparability between households (within PA) and over time, the consumption aggregate has been deflated to 1994 prices for each locality, and by the number of adult equivalents present in the household in each period. The real, per-adult-equivalent consumption aggregate for household i in PA j in time period t is x_{ijt}. Consumption enters into all of the poverty measures that we shall consider only as a proportion of the poverty line (that is, as $\frac{x}{z}$) so we may establish comparability between PAs by additionally deflating by the 1994 poverty line in local prices z_{jt} calculated by Dercon and Krishnan (1998). The resulting *consumption ratio* $r_{ijt} = \frac{x_{ijt}}{z_{jt}}$ is comparable between households (within PA), between PAs and over time. r_{ijt} is greater than one for a household above the poverty line and below one for a household below the poverty line.

[7]Detailed sampling documentation may be found at www.csae.ox.ac.uk/datasets/Ethiopia-ERHS/erhs/docoutline-erhs.html.

2.2 Unit of Analysis

The consumption data in the EHRS is measured at household rather than individual level. In order to estimate the population incidence of poverty (although not allowing for intrahousehold distribution issues) it would be necessary to weight by household size when aggregating over the sample. As this paper is primarily methodological and a test of concept, we take the household as the unit of analysis and so do not perform this weighting. Care must therefore be taken to interpret the results as estimates for the population of households and not for the population of individuals.

2.3 Subsample

A total of 1477 households were sampled in the first round of the ERHS; attrition was relatively low. Following Porter (2008) we use data from rounds 1, 3, 4, 5 and 6 only, restricting analysis to the 1218 households for which the consumption aggregate is available in at least three of these five rounds. The temporal patterns of consumption aggregate availability in this subsample are as shown:

Pattern	**Frequency**	**Percent**	**Cum**
11111	1089	89.41	89.41
11110	93	7.64	97.04
10111	25	2.05	99.10
10110	5	0.41	99.51
01111	2	0.16	99.67
01110	1	0.08	99.75
10011	1	0.08	99.84
11011	1	0.08	99.92
11101	1	0.08	100.00
	1218	100.00	

As non-availability of the data is likely to be correlated with household characteristics and wellbeing, it should be noted that there is the potential for selection bias if the results are interpreted as estimates of poverty incidence in the sampled villages or in rural Ethiopia as a whole.

2.4 Descriptive statistics by round

The consumption ratio is summarized below across the subsample, by PA.

It may be seen that in most PAs there is a general trend of increasing wellbeing over the period covered by the study (1994–2004); several PAs have a significant upward trend while Adele is the only to have a significant downward trend. This pattern is reflected in the PA poverty headcounts, which increase over the period, most PAs having a significant downward trend with Adele being the only PA to have a significant upward trend.

Pooling across the whole subsample (1218 households, five rounds), the consumption ratio and its logarithm have the following characteristics.

Variable	**Obs**	**Mean**	**Std. Dev**	**Min**	**Max**
Consumption ratio	5954	2.261391	2.324249	.0296143	59.99699
Log ratio	5954	.4786473	.8292168	-3.519497	4.094295

Table 1: **Mean consumption ratio, by Peasant Association**

PA	# HH	Pov line	ratio94	ratio95	ratio97	ratio99	ratio04
Haresaw	74	44.00	1.77	1.87	2.64	2.39	1.92
Geblen	58	55.00	0.69	0.75	1.90	1.37	2.23
Dinki	76	44.00	1.46	1.20	1.49	2.01	2.04
Yetemen	53	40.00	3.36	1.86	2.85	2.16	3.17
Shumsheha	109	42.00	3.07	3.09	2.89	3.59	3.44
Sirbana Godeti	72	38.00	3.11	2.88	2.97	4.93	5.53
Adele	86	53.00	2.12	2.68	2.84	1.72	1.58
Korodegaga	88	44.00	0.92	1.18	1.65	2.40	1.74
Trurufe Ketchema	88	36.00	2.95	2.04	2.39	3.81	3.62
Imdibir	62	38.00	1.31	0.93	1.85	1.51	1.47
Aze Deboa	56	36.00	2.75	1.85	2.50	1.04	3.15
Adado	82	41.00	2.04	1.46	2.60	1.92	1.36
Gara Godo	91	49.00	0.61	0.59	1.15	1.14	1.91
Domaa	56	58.00	0.85	1.82	1.14	1.83	1.82
db-Milki	57	49.00	2.35	1.96	4.59	3.06	4.06
db-Kormargefia	53	49.00	2.09	1.84	3.60	3.12	3.53
db-Karafino	33	49.00	2.48	1.43	2.74	2.84	2.68
db-Faji Bokafia	24	49.00	2.51	1.87	3.63	3.44	5.22
Total/Mean	1215	44.70	2.00	1.78	2.43	2.46	2.66

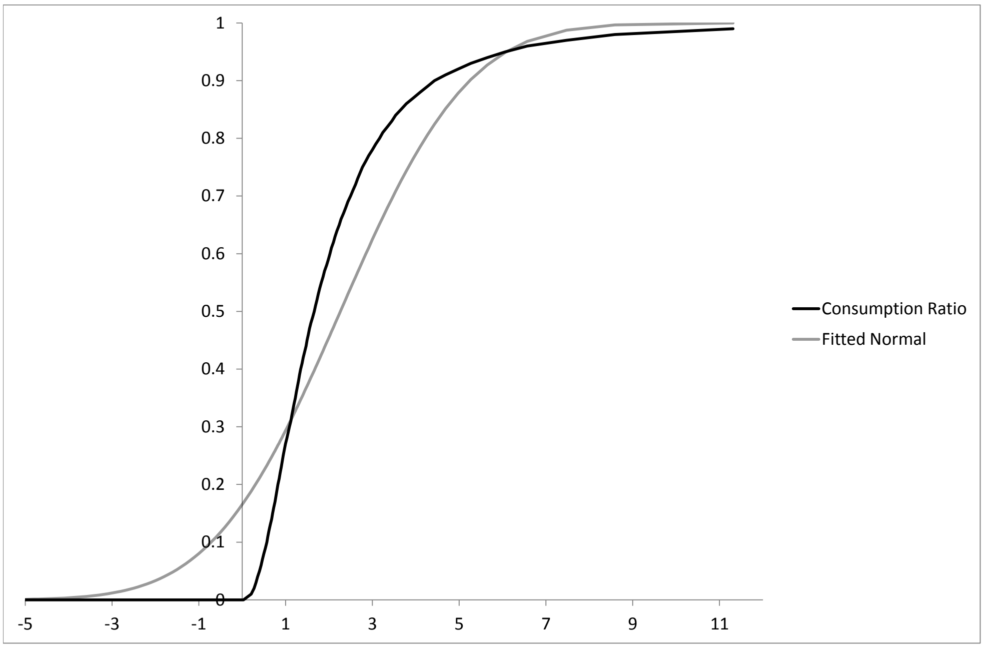
Number of households, poverty line in Ethiopian birr per month per adult equivalent (1994 prices) and consumption ratio for each round. *Source:* ERHS, rounds 1, 3, 4, 5 and 6

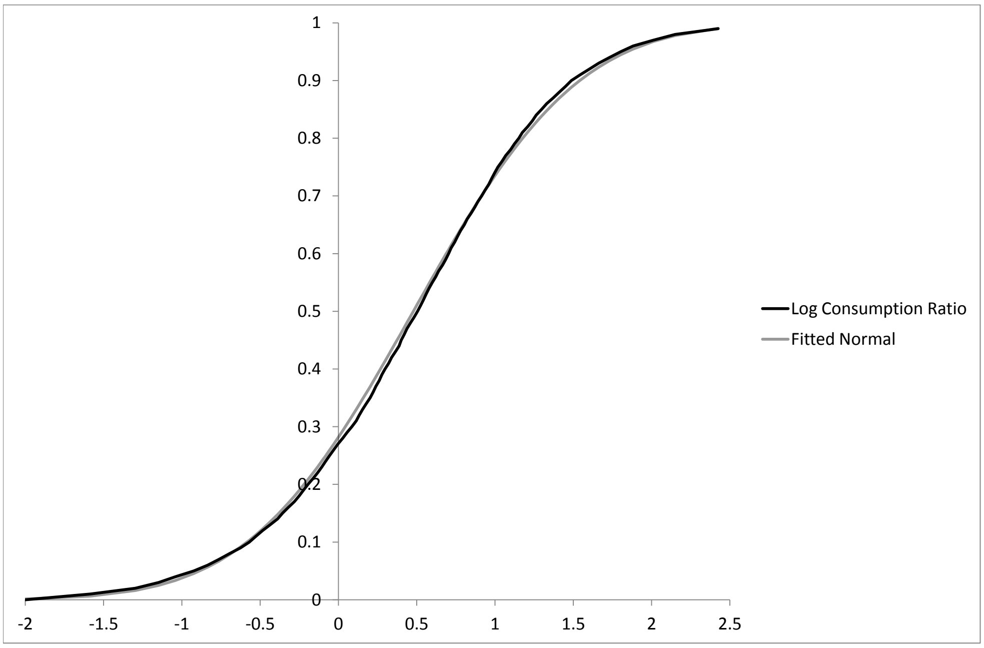
Table 2: **Poverty headcount by PA**

PA	1994	1995	1997	1999	2004
Haresaw	0.27	0.41	0.19	0.14	0.25
Geblen	0.84	0.81	0.31	0.52	0.27
Dinki	0.49	0.49	0.41	0.29	0.19
Yetemen	0.04	0.17	0.06	0.19	0.04
Shumsheha	0.08	0.05	0.08	0.01	0.01
Sirbana Godeti	0.10	0.01	0.04	0.00	0.00
Adele	0.15	0.07	0.05	0.35	0.33
Korodegaga	0.65	0.53	0.26	0.14	0.28
Trurufe Ketchema	0.13	0.17	0.15	0.09	0.10
Imdibir	0.34	0.76	0.24	0.37	0.43
Aze Deboa	0.14	0.52	0.23	0.59	0.14
Adado	0.22	0.41	0.17	0.24	0.40
Gara Godo	0.87	0.84	0.63	0.57	0.37
Domaa	0.77	0.36	0.55	0.29	0.30
db-Milki	0.26	0.33	0.05	0.04	0.02
db-Kormargefia	0.25	0.23	0.04	0.11	0.02
db-Karafino	0.24	0.24	0.06	0.09	0.09
db-Faji Bokafia	0.21	0.25	0.00	0.13	0.00
Mean	0.34	0.37	0.21	0.23	0.20

Source: ERHS, rounds 1, 3, 4, 5 and 6

While the Shapiro-Francia test rejects normality of both variables (with p-values of 0.00034 and 0.04303 respectively) it does so less strongly for the logarithm of the consumption ratio; furthermore, quantile plots show that the distribution of the logarithm is reasonably closely approximated by a normal distribution.





3 Chronic and Intertemporal Poverty Measures

As discussed in the introduction, when households experience fluctuations in wellbeing, repeated application of a cross-sectional or static measure embodies a particular set of normative judgements and discards relevant information. Several chronic and intertemporal poverty measures which may be applied to evaluate poverty over an extended period of time have been suggested in a rapidly developing literature. The various measures differ in the way that they rank alternative trajectories of wellbeing and thus represent different normative judgements of the relative undesirability of the trajectories.

These measures and the normative judgements that they embody have been reviewed in some detail by **?**, so we shall not explore them comprehensively here, but rather focus on the issues that are pertinent to the present analysis. In each case the measure comprises a trajectory-ordering measure p which is applied to individual or household trajectories of wellbeings and then aggregated over the sample. We shall quote and focus on the trajectory-ordering measures suggested by the various authors; in the illustrative analysis we shall aggregate over the sample according to the FGT poverty-gap-squared transformation of the constant-wellbeing equivalents $c(p)$, which does not necessarily reflect the aggregation applied by the authors. We do this because this aggregation has attractive properties and further to ensure comparability across measures, so that any differences in results may be clearly ascribed to the different trajectory orderings induced by the measures with no ambiguity; if different forms of social aggregation were used then differences in results might also arise from differences in the way the measures evaluate depth of poverty. The form of the intertemporal poverty measure P is then

$$P = \frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{c(p_i)}{z}\right)^2 . \tag{1}$$

where n is the number of individuals, z is the period poverty line, p_i is the value of the trajectory measure for individual i and $c(p_i)$ is its constant-wellbeing equivalent. We may now focus on the properties of the trajectory ordering represented by the trajectory measure p.

Two properties discussed by Porter and Quinn (forthcoming) which reflect sensitivity to chronicity of poverty are as follows.

(1) Duration Sensitivity: *For any poor trajectory, a transfer of wellbeing between periods such that the number of periods below z increases must increase the trajectory measure.*

(2) Contiguity: *When applied to two trajectories comprising the same set of wellbeings in a different sequence, the trajectory measure evaluates as more poor that sequence in which more of the wellbeings below z are contiguous.*

Many of the measures which have been described as 'chronic' poverty measures, for example those suggested by Jalan and Ravallion (2000), Calvo and Dercon (2009) and Foster and Santos (forthcoming), are not in fact sensitive to persistence or chronicity of poverty as such, not satisfying the duration sensitivity or contiguity properties. Other measures, suggested by Foster (2009), Bossert, Chakravarty, and D'Ambrosio (2012) and Gradin, Del Rio, and Canto (2011) *are* sensitive to chronicity. For illustration we shall apply Foster's measure with a duration-cutoff $\tau = 0.6$

$$p_{\mathrm{F}}(\boldsymbol{x}_i) = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{x_{it}}{z}\right)^{\alpha}\mathbb{I}(x_{it} \leq z)\mathbb{I}\left(\sum_{t=1}^{T}\mathbb{I}(x_{it} \leq z) \geq \tau T\right) \tag{2}$$

and Gradin et. al's measure (closely related to Bossert et. al's measure) with $\alpha = 2$ and $\beta = 1$,

$$p_{\mathrm{G}}(\boldsymbol{x}_i) = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{x_{it}}{z}\right)^{\alpha} w_{it} \tag{3}$$

where

$$w_{it} = \left(\frac{s_{it}}{T}\right)^{\beta}. \tag{4}$$

However, these chronicity-sensitive measures have some unsatisfactory properties. They induce discontinuities in the space of trajectories, leading to perverse ordering of some trajectories. Furthermore, they have the counterintuitive property of allowing a *greater* degree of compensation between periods of very low wellbeing than between periods of higher wellbeing. This conflicts with a reasonable normative judgement, that it should be more difficult to compensate for periods of profound poverty. This property is defined by Porter and Quinn (forthcoming):

(3) NON-DECREASING COMPENSATION: *Given a poor trajectory, the marginal rate of compensation between the wellbeings in any two periods should not decrease, as the period wellbeings increase in proportion.*

While there is no fundamental conflict between continuity and sensitivity to chronicity of poverty (Quinn (2009) has suggested a chronic poverty measure which *is* continuous in the space of trajectories), there *is* a conflict between sensitivity to persistence or chronicity of poverty, and the attractive normative property of allowing no greater degree of compensation between periods of very low wellbeing than between periods of higher wellbeing. (This is closely related to the property of particular sensitivity to *depth* of poverty.) This relationship is proved and discussed by Porter and Quinn (2012).

(It is important to note that all of the poverty measures tend to evaluate as worse trajectories in which wellbeing is less in *every* period; the interesting inconsistencies arise in the way the measures evaluate trajectories which are worse in some periods but better in others.)

The conflict between the apparently normatively desirable properties of sensitivity to chronicity and sensitivity to depth of poverty is unsatisfactory. It may be that the desire for a poverty measure to reflect sensitivity to chronicity is not because a trajectory which is chronically poor should be judged to be intrinsically worse than a fluctuating trajectory which reaches deeper poverty transiently, but because the poverty analyst implicitly considers persistence of poverty over observations to predict poverty in unobserved periods, either between observations or into the future. In fact, some of the authors who introduced the chronicity-sensitive measures mentioned above explicitly invoke such an argument to motivate these properties.

This leads to the possibility that the normative judgement be separated from the positive prediction of unobserved wellbeings. For the latter, a dynamic model should be applied to model explicitly the evolution of individual or household wellbeings in unobserved periods. For the former, an intertemporal poverty measure which satisfies

NON-DECREASING COMPENSATION and is sensitive to depth of poverty should be applied to both the observed and modelled data, for example the measures suggested by Foster and Santos (forthcoming), a representative example being

$$p_{\text{FS}}(\boldsymbol{x}_i) = \max\left[0, \frac{1}{T}\sum_{t=1}^{T}\left(\left(\frac{x_{it}}{z}\right)^{-1} - 1\right)\right] \tag{5}$$

or Porter and Quinn (forthcoming), an example being

$$p_{\text{PQ}}(\boldsymbol{x}_i) = \max\left[0, \frac{1}{(k+1)T}\sum_{t=1}^{T}\left(\left(\frac{z}{x_{it}}\right)^{2} + \ln\left(\frac{z}{x_{it}}\right) - 1\right)\right]. \tag{6}$$

In the next section I develop appropriate dynamic models, while in the following section I apply intertemporal poverty measures to the observed and modelled wellbeing data to evaluate poverty in rural Ethiopia, comparing the results to those obtained by the 'chronic' poverty measures which implicitly combine the normative and positive procedures.

4 Dynamic Models

In this section I describe four approaches that may be used to model explicitly the evolution of the household wellbeing indicator over time.

As discussed above, chronic poverty measures may be thought of as implicitly taking account of wellbeing in the future (beyond the period for which data is available) and wellbeing in time-periods between observations. If the poverty analyst is interested in lifetime wellbeing then it is necessary to model both. However, *future* wellbeing has significant challenges associated with lifetime duration; how to model, and how to evaluate length of life normatively in the poverty measure. While these difficulties will not be insurmountable, for now we focus on wellbeing in time-periods between observations.

The irregular time-structure of the ERHS provides an ideal environment in which to develop methods. As we wish to use the consumption ratio discussed above as an indicator of wellbeing for poverty measurement, it is that which we require to model between observations. While the consumption ratio refers to consumption per month (constructed from recall questions covering a variety of periods) we shall treat it as an indicator of wellbeing in the year of observation; we therefore require to predict the consumption ratio in the intervening years between rounds of the survey, that is, 1996, 1998, 2000, 2001, 2002 and 2003. Its logarithm approximates a normal distribution more closely than the consumption ratio itself and so is used as the dependent variable throughout this section; this is beneficial in order to minimise specification errors and for the sample properties of the estimators.

The application of statistical and econometric methods to model evolution of wellbeing over time at individual or household level is not new; beyond the descriptive analyses of poverty dynamics that have been carried out in many contexts, work led by Dercon (2004a, 2006) and continued by Dercon, Gilligan, Hoddinott, and Woldehanna (2009) and Porter (2010) among others has elucidated the causal impact of factors (policy, shocks and characteristics) on household or individual wellbeing.

The empirical methods suggested here differ significantly from the methods applied in the studies mentioned above. Those studies were focussed on elucidating *causal* impacts and their authors therefore paid close attention to identification and avoidance of bias in the parameter estimates. In the present analysis we are not concerned with causal interpretation but with effective prediction and may therefore make use of simpler modelling strategies.

We are limited in the extent to which we may make use of household characteristics to predict wellbeing. Time-invariant household characteristics are taken into account through household-specific intercepts and slopes (depending on the model) and so need not explicitly enter the models. It is more difficult to deal with time-varying characteristics. While any such characteristic that has explanatory power for wellbeing would improve the accuracy of the model, the reason for constructing the model is to predict wellbeing in periods in which data is not available and so the inclusion of the instantaneous effect of such characteristics cannot add anything and in fact would render the model ineffective for prediction. It *may* be possible to account for dynamic effects; construction of such a model would not be straightforward when the time-structure of the data is not regular, as in the ERHS.

4.1 Model A: Linear Interpolation

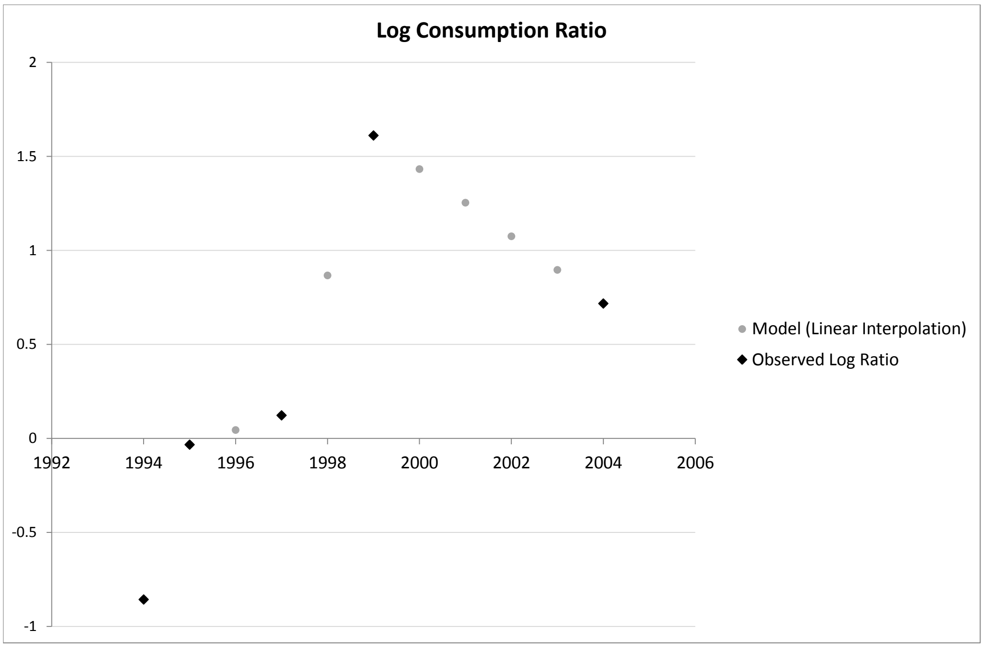
The most straightforward approach is to interpolate wellbeings between observations. As we are modelling the logarithm of the consumption ratio, linear interpolation amounts to an assumption of constant growth rate of consumption between observations. This is not unreasonable but might tend to underestimate variability in wellbeing over time, which will lead to a downward bias in any poverty measure which is sensitive to variability over time. An attractive characteristic of this method is that it is not necessary to impose any homogeneity assumptions across households; the interpolation may be carried out separately for each household.

Consider time periods s and f in which wellbeing is observed, with no observations in between. If household i's log consumption ratio is r_{is} in the earlier observation period and r_{if} in the later, then the interpolated value in period t between s and f is

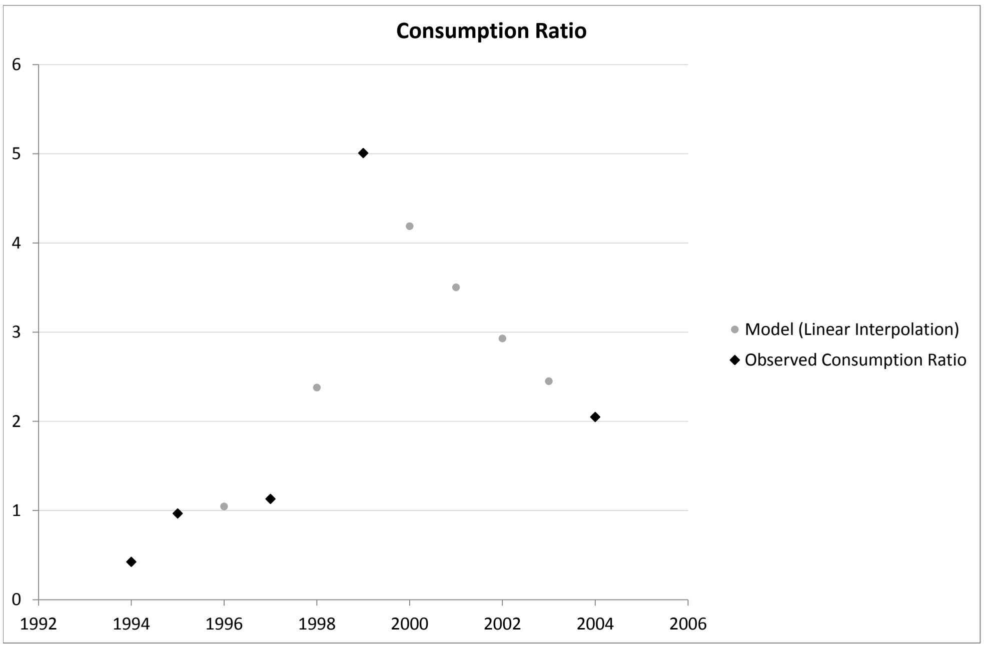
$$r_{it} = \frac{r_{if} - r_{is}}{f - s}(t - s) + r_{is} \tag{7}$$

The irregular time structure of the dataset does not pose any particular challenges for this method.

The interpolation was carried out separately for each household; the graph below illustrates for one particular household. (It was chosen semi-arbitrarily; its trajectory of observed consumption ratios demonstrates the general trend of increase over time with significant variability around the trend.)



As the poverty measures are functions of the consumption ratio, the modelled values must be de-logged before the poverty measures are calculated.



4.2 Model B: Household-Specific Time Trends

The next approach is to model the log consumption ratio in unobserved periods according to its linear trend over the observed periods. (Note that this amounts to an assumption of constant growth rate of the consumption ratio over time.) There is considerable variation in the experiences of households in the sample, many exhibiting a trend of increasing wellbeing over time while others suffer a decline. With five observations per household, there is sufficient data to determine the trend experienced by each household individually. Again, it is not necessary to make any assumption of homogeneity across households.

The model for log consumption ratio experienced by household i in period t

$$r_{it} = \alpha_i + \beta_i t + u_{it} \tag{8}$$

may then be estimated for each household (OLS was used) and the estimates used to predict the log consumption ratio in unobserved periods,

$$\hat{r}_{it} = \hat{\alpha}_i + \hat{\beta}_i t. \tag{9}$$

$\hat{\alpha}_i$ is the household-specific intercept and $\hat{\beta}_i$ the household-specific slope coefficient. In practice for computational efficiency these household-specific equations were estimated by Woreda, using the household IDs and their interations with time as the regressors.

Space precludes reporting of the household-specific slope coefficients, but they are distributed with mean .0439 (corresponding to an annual growth rate of consumption ratio of 4.49% on average across households) and standard deviation of 0.0853.

It is clear that this approach will underestimate the variability of wellbeing over time, leading to a downward bias in any poverty measure which is sensitive to variability over time. This was addressed by adding a random term, so that

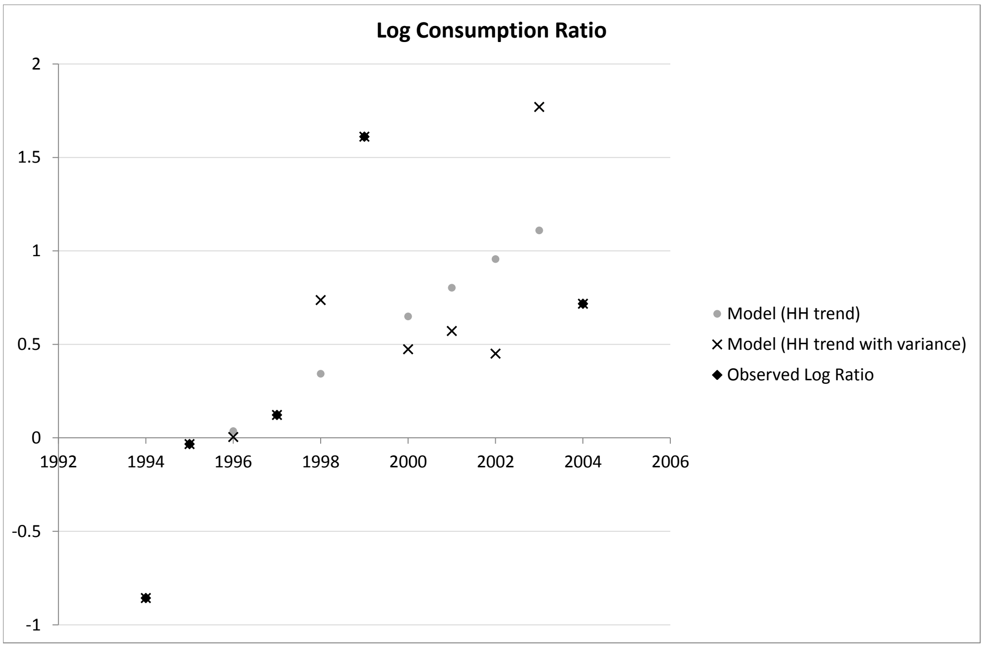
$$\hat{r}_{it} = \hat{\alpha}_i + \hat{\beta}_i t + z_{it}\hat{\sigma}_i \tag{10}$$

where z_{it} is a standard normal random variable and $\hat{\sigma}_i$ is the estimated standard deviation of the household's residuals, that is, the deviations of observed values from the regression line.

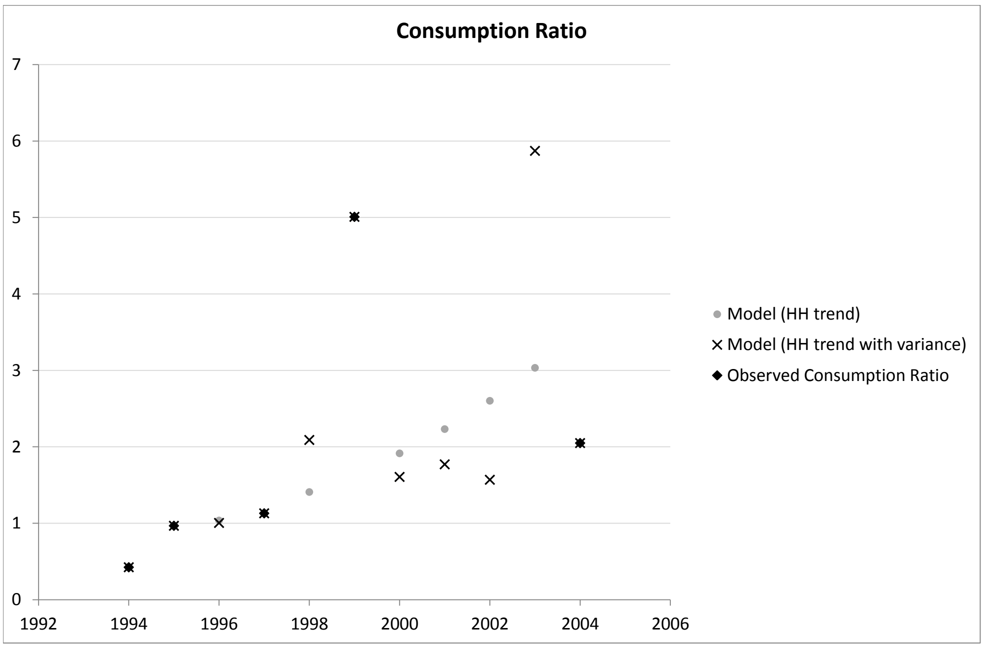
Introducing variability in this way assumes that there is no autocorrelation of shocks. If there were some degree of autocorrelation then the temporal variability of the modelled wellbeings will have been overestimated which will lead to an upward bias in any poverty measure that is sensitive to variation over time.

I believe that the degree of upward bias will be less than the degree of downward bias that would arise when the extra variation is not modelled. Although this cannot be directly ascertained, we shall assess the robustness of the results by computing the poverty measures with and without the modelled variation to determine an upper and lower bound.

The graph below illustrates the modelled log consumption ratio with and without the added variation, for the same household illustrated above; observed values are used in periods in which they are available.



As the poverty measures are functions of the consumption ratio, the modelled values must be de-logged before the poverty measures are calculated.



4.3 Model C: Autoregression with Household Fixed Effect

It may be that the evolution of household wellbeing over time is better modelled with a more sophisticated dynamic model than simple constant growth of the consumption ratio as above. In particular, it is reasonable to expect some degree of autocorrelation of wellbeing due both to autocorrelation of shocks and persistence of their effect. A first-order autoregressive model is perhaps the most straightforward way to incorporate autocorrelation in the model.

Unfortunately, the irregular time structure of the dataset means that it is not possible to use all rounds to estimate the model; we have evenly-spaced observations from 1995, 1997 and 1999 which may be used. There is not enough data to estimate household-specific autocorrelation but it is possible to include household fixed effects to account for the variation in level of wellbeing between households. The model to be estimated is thus

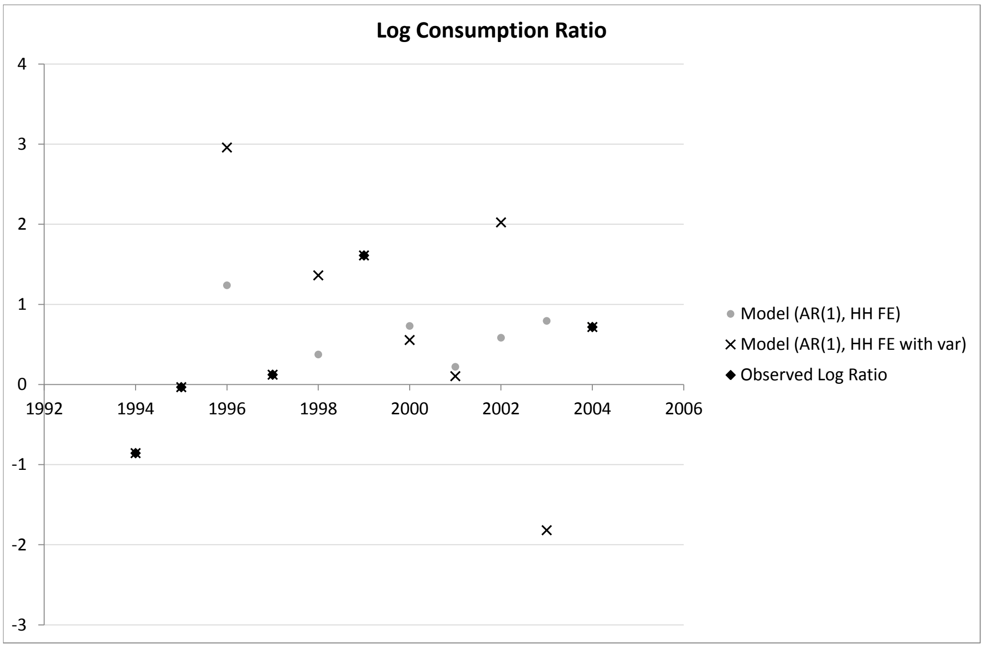
$$r_{it} = \alpha_i + \beta r_{i(t-2)} + u_{it}. \tag{11}$$

1216 households were included in the estimation sample (all those for which observations were available in 1995 and 1997 and/or 1997 and 1999) and the value of the estimated autoregressive coefficient was $\hat{\beta} = 0 - .412$ (standard error 0.025). The household-specific constants are too numerous to report. The magnitude of the autoregressive coefficient is significantly different from zero and from one so we can be confident that there is significant autocorrelation and that the process is stable rather than explosive. The negative coefficient demonstrates a tendency for fluctuation in the process. However, these results should be treated with caution due to the very small number of time periods. In a refined version of the model it may be possible to make use of the discarded observations from round 1 and round 6 as well as other information which has been discarded.

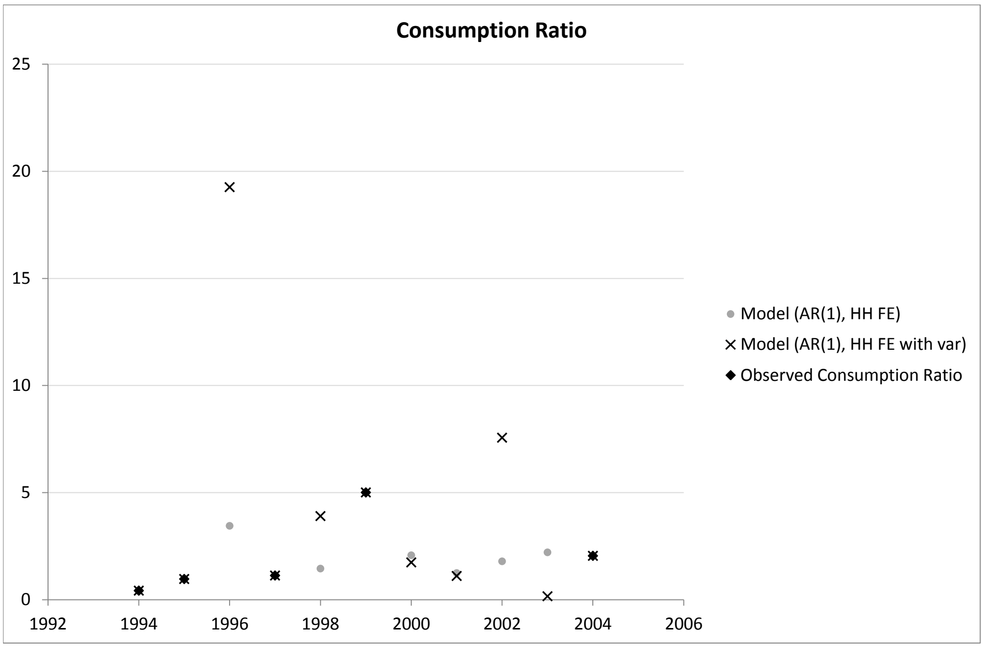
The estimated model was used to predict the value of the log consumption ratio in the unobserved periods; several iterations were necessary to obtain predictions for all unobserved periods. Those utilised for the poverty measure are as follows.

Year	Observed	Iteration 1	Iteration 2	Iteration 3	Iteration 4
1994	✓				
1995	✓				
1996		✓			
1997	✓				
1998			✓		
1999	✓				
2000				✓	
2001		✓			
2002					✓
2003			✓		
2004	✓				

As is visible from the illustrations below, because the estimated autoregressive process is stable, this model will tend to underestimate variation in the later time periods. To address this we may add a random term $z_{it}\hat{\sigma}_i$ to the predicted value where z_{it} is a standard normal random variable and $\hat{\sigma}_i$ is the estimated standard deviation of the residuals for household i. The graph below illustrates the modelled values of the log consumption ratio for one household.



The following graph illustrates the modelled values of the consumption ratio itself.



4.4 Model D: Autoregression with PA Trend and Household Fixed Effect

There are several limitations to the model above. One important limitation is that the stable autoregressive process tends toward a constant for each household, which cannot reflect the general upward trend in the data. As the autoregressive process can only be estimated from three rounds due to the irregular time structure, it is impossible to incorporate household-specific trend terms as well as constants. Different PAs experience different general trends over the survey period as illustrated in section 2 so a trend term was added at this level. The model is thus, for household i in PA j in time period t,

$$r_{ijt} = \alpha_i + r_{ij(t-2)} + \gamma_{ij} t + u_{ijt}. \tag{12}$$

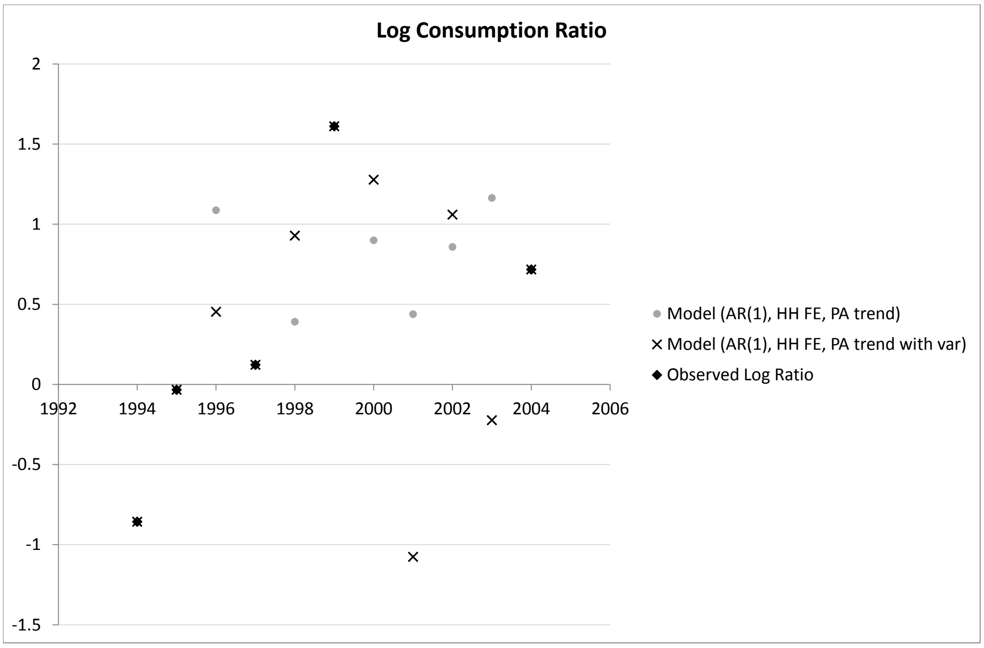
The estimated autoregressive and slope coefficients are given in table 3.

Table 3: **Estimated Coefficients (AR(1) with PA trends and HH FE)**

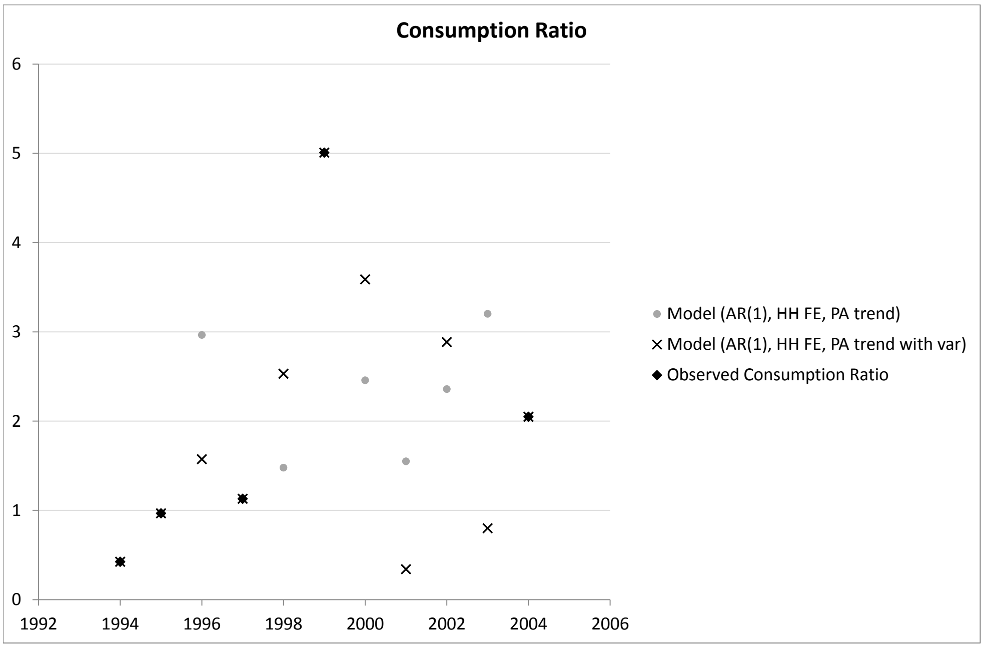
Coefficient	**Value**	**t-stat**
β	-0.4561108	-16.86
γ-Haresaw	0.0953734	2.14
γ-Geblen	0.0260654	0.52
γ-Dinki	0.1209254	2.80
γ-Yetemen	-0.0682304	-1.32
γ-Shumsheha	0.1003553	2.77
γ-Sirbana Godeti	0.2723750	6.19
γ-Adele	-0.2466011	-6.01
γ-Korodegaga	0.2115403	5.28
γ-Trurufe Ketchema	0.2397709	5.78
γ-Imdibir	0.1106095	2.29
γ-Aze Deboa	-0.2726735	-5.40
γ-Adado	-0.0100366	-0.24
γ-Gara Godo	0.1768173	4.36
γ-Domaa	0.1259496	2.48
γ-db-Milki	0.0786189	1.57
γ-db-Kormargefia	0.0857802	1.65
γ-db-Karafino	0.1292568	1.96
γ-db-Faji Bokafia	0.0955113	1.25

Source: ERHS, rounds 3, 4 and 5

There is a significant upward trend for many of the PAs but a significant downward trend for Adele and Aze Deboa. The highly significant negative autoregressive coefficient again indicates a stable fluctuating process. As above we may add a random term to introduce variability to the modelled values. The graph below illustrates the modelled values of the log consumption ratio for one household.



The following graph illustrates the modelled values of the consumption ratio itself.



4.5 Comparison and Evaluation

The assumptions and limitations of the various methods are discussed above; none is without limitations. We may compare their efficacy by using the models to predict a value of the log consumption ratio for the year 2004 and comparing that prediction with the actual value for that year. (It does not make sense to do this for the interpolation model.)

Model	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Observed	1119	0.64896	0.79720	-2.6171	3.7737
B: HH-specific trends	1119	0.70964	0.73813	-2.1196	3.4622
B: HH-specific trend + var	1119	0.72200	0.88451	-2.0418	4.2242
C: AR(1) + HH FE	1115	0.54294	0.60530	-1.7055	2.2518
C: AR(1) + HH FE + var	1115	0.55272	0.82762	-3.1667	3.5962
D: AR(1) + PA tt + HH FE	1115	0.87844	0.90240	-2.1475	3.4216
D: AR(1) + PA tt + HH FE + var	1115	0.86587	1.02607	-2.8153	4.1459

The HH-specific trend models tend to overestimate the log consumption ratio in 2004 while the autoregressive plus fixed effects models tend to underestimate it; the autoregressive models with PA-specific trend tend overestimate. The HH-specific trend models most closely model the observed values. The values predicted by the models with added variance are more widely distributed than the observed values while the values predicted by the models without added variance are more narrowly distributed, except in the case of the autoregressive model with trend.

The correlations between the observed and modelled values are as follows, for those observations (1115) with predictions available for all models.

	Observed	B	Bvar	C	Cvar	D	Dvar
Observed	1.0000						
Model B	0.9364	1.0000					
Model Bvar	0.7504	0.8064	1.0000				
Model C	0.3637	0.5146	0.4022	1.0000			
Model Cvar	0.2457	0.3731	0.2972	0.7371	1.0000		
Model D	0.3254	0.4949	0.4096	0.6825	0.5343	1.0000	
Model Dvar	0.2744	0.4184	0.3342	0.6011	0.4733	0.8782	1.0000

It is clear from these results that model B (household-specific trends) performs best as a predictor of the 2004 wellbeings. The relatively poor performance of models C and D is likely to be due to the fact that these models assumed a much greater degree of homogeneity across households and also discarded the information from rounds 1 and 6.

None of the approaches implemented above is fully satisfactory. It is frustrating to have to throw away information on time-varying household characteristics, while in the autoregressive models the irregular time structure meant that wellbeing information from rounds 1 and 6 was not incorporated. It may be possible in further work to estimate a more sophisticated model that makes use of all the wellbeing information. Furthermore, it may be possible to make use of time-varying household characteristics such as shocks and asset stocks, having carefully modelled their impact on the *evolution* of wellbeing[8] and therefore being able to make predictions for periods in which data on the characteristics is not available.

[8] The work of Carter and Barrett (2006) may be relevant here.

5 Application and Comparison

In this section I shall combine the positive predictions of the dynamic models above with the normative judgements inherent in the intertemporal poverty measures discussed in section 3 above. For clarity I shall restrict analysis to the subsample of 1089 households for which consumption data is available in all five observed years (and for which the dynamic models generate predictions for all six unobserved years).

For comparison, I start with a naive application of the chronic and intertemporal poverty measures P_{F}, P_{G}, P_{FS} and P_{PQ} to the ERHS data, taking as time periods $t = 1, 2, 3, 4$ and 5 rounds $1, 3, 4, 5$ and 6 of the survey without considering the irregular time structure. Applying these measures to the sample of 1089 households, the aggregate poverty measures are as follows.

Measure	**Value**
P_{F}	0.03310
P_{G}	0.02556
P_{FS}	0.03937
P_{PQ}	0.05322

The chronicity-sensitive measures evaluate the degree of poverty as less. This makes sense intuitively, as the normalisation means that all of the measures will evaluate in a similar way trajectories of broadly similar wellbeing levels, but the depth-sensitive measures will evaluate as relatively worse trajectories of fluctuating wellbeing levels.

The depth-sensitive measures P_{FS} and P_{PQ} are now applied to the trajectories of modelled wellbeings discussed in section 4 above. The time periods are now the eleven years spanned by the survey, 1994–2004.

Measure	P_{FS}	P_{PQ}
Model A (linear interpolation)	.02577	.03594
Model B (hh-specific trend)	.02500	.03459
Model Bvar	.03245	.04532
Model C (AR(1) with HH FE)	.02807	.03673
Model Cvar	.03920	.05622
Model D (AR(1) with PA trend and HH FE)	.02573	.03660
Model Dvar	.03385	.04970

In general we may observe that evaluating intertemporal poverty having explicitly modelled wellbeing in the years in which it was not observed gives results which are lower than if poverty were evaluated using just the years in which wellbeing was observed. In fact, the results are remarkably close to the results obtained by the 'chronic' poverty measures P_{F}, P_{G}. This demonstrates that despite their theoretical limitations, they may serve as a good proxy for a two-stage analysis such as that carried out here, in which the evolution of wellbeing over time is explicitly modelled before intertemporal poverty is evaluated.

We established above that model B (household-specific time trends) had the best predictive power. We expected that the verison without added variation would tend to underestimate poverty but the version with added variation would tend to overestimate poverty. Focussing on the results obtained for this model, we may be confident that the 'true' degree of intertemporal poverty according to P_{FS} is between 0.0250 and 0.0324, while the 'true' degree of intertemporal poverty according to P_{PQ} is between 0.0346 and 0.0453. In each case it is clear that the naive application of the measures overestimated poverty in the sample.

In order to further explore the effect of this procedure it would be interesting to decompose the results by PA and to compare the ranking of PAs obtained by the different methods.

6 Concluding Remarks

This is an exploratory study and a test of concept. The specification of the dynamic model may be improved to make better use of the available information. Further reflection about the normative principles involved may enable modelling of the future trajectory of an individual's wellbeing as well as interpolation. Other issues that remain to resolve include the role of discounting and the degree of uncertainty inherent in the method as well as a full treatment of sampling errors and their impact on the poverty measure estimates.

Acknowledgements

I would like to thank Catherine Porter and Stefan Dercon for conceptual discussion and for use of the ERHS consumption data. All errors are my own.

References

Baulch, B., and J. Hoddinott (2000): "Economic Mobility and Poverty Dynamics in Developing Countries," *Journal of Development Studies*, 36(6), 1.

Bossert, W., S. Chakravarty, and C. D'Ambrosio (2012): "Poverty and time," *Journal of Economic Inequality*, 10(2), 145–162, 10.1007/s10888-011-9175-2.

Calvo, C., and S. Dercon (2009): "Chronic Poverty and All That," in *Poverty Dynamics*, ed. by T. Addison, D. Hulme, and R. Kanbur, pp. 29–58. Oxford University Press, Oxford.

Carter, M. R., and C. B. Barrett (2006): "The economics of poverty traps and persistent poverty: An asset-based approach," *Journal of Development Studies*, 42(2), 178 – 199.

Chen, S., and M. Ravallion (2008): "The Developing World is Poorer Than We Thought, But No Less Successful in the Fight against Poverty," Discussion paper, World Bank.

Dercon, S. (2004a): "Growth and shocks: evidence from rural Ethiopia," *Journal of Development Economics*, 74(2), 309–329.

——— (2004b): *Insurance against poverty*, Studies in development economics. Oxford University Press, Oxford.

——— (2006): "Economic reform, growth and the poor: Evidence from rural Ethiopia," *Journal of Development Economics*, 81, 1–24.

Dercon, S., D. O. Gilligan, J. Hoddinott, and T. Woldehanna (2009): "The impact of roads and agricultural extension on consumption growth and poverty in fifteen Ethiopian villages," *American Journal of Agricultural Economics*, 91(4), 1007–1021.

Dercon, S., and P. Krishnan (1998): "Changes in Poverty in Rural Ethiopia 1989-1995: Measurement, Robustness Tests and Decomposition," Discussion Paper WPS/98-7, Centre for the Study of African Economies.

——— (2000): "In Sickness and in Health: Risk Sharing within Households in Rural Ethiopia," *Journal of Political Economy*, 108(4), 688.

Dercon, S., and J. S. Shapiro (2007): "Moving On, Staying Behind, Getting Lost: Lessons on Poverty Mobility from Longitudinal Data," in *Moving out of Poverty: Cross-disciplinary Perspectives*, ed. by D. Narayan, and P. L. Petesch, vol. 1. World Bank.

Foster, J., J. Greer, and E. Thorbecke (1984): "A Class of Decomposable Poverty Measures," *Econometrica*, 52(3), 761–766.

Foster, J. E. (2009): "A Class of Chronic Poverty Measures," in *Poverty Dynamics: Interdisciplinary Perspectives*, ed. by T. Addison, D. Hulme, and R. Kanbur, pp. 59–76. Oxford University Press, Oxford.

Foster, J. E., and M. E. Santos (forthcoming): "Measuring Chronic Poverty," in *Poverty and Social Exclusion: New Methods of Analysis*, ed. by G. Betti, and A. Lemmi. Routledge.

Gaiha, R., and A. B. Deolalikar (1993): "Persistent, expected and innate poverty: estimates for semi-arid rural South India, 19751984," *Cambridge Journal of Economics*, 17(4), 409–421.

Gradin, C., C. Del Rio, and O. Canto (2011): "Measuring Poverty Accounting for Time," *Review of Income and Wealth*, 58(2), 330–354.

Hulme, D., and A. Shepherd (2003): "Conceptualizing Chronic Poverty," *World Development*, 31(3), 403–423.

Jalan, J., and M. Ravallion (2000): "Is Transient Poverty Different? Evidence for Rural China," *Journal of Development Studies*, 36(6), 82.

Porter, C. (2008): "Analysing Welfare over Time: Three Approaches for Rural Ethiopia, 1984–2004," Ph.D. thesis.

——— (2010): "Safety Nets or Investment in the Future: Does Food Aid have any Long-Term Impact on Childrens' Growth?," *Journal of International Development*, 22, 1134–1145.

Porter, C., and N. N. Quinn (2012): "Normative Choices and Tradeoffs when Measuring Poverty over Time," .

——— (forthcoming): "Measuring Intertemporal Poverty: Policy Options for the Poverty Analyst," in *Poverty and Social Exclusion: New Methods of Analysis*, ed. by G. Betti, and A. Lemmi. Routledge.

Quinn, N. N. (2009): "Measuring Poverty over Time: A Formal Analysis," Ph.D. thesis.

Townsend, R. M. (1994): "Risk and Insurance in Village India," *Econometrica: Journal of the Econometric Society*, 62(3), 539–591.