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How strong is the evidence for the existence of poverty traps? A multi country assessment[1]

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Abstract: In this paper, we focus on the role of assets in relation to chronic poverty. In particular, we consider the issue of whether it is not just low levels of assets which identify and explain chronic poverty, but also whether the asset accumulation process displays non-linearities and non-convexities that could explain why some households experience persistent poverty. We use parametric and nonparametric methods to test for evidence of the existence of an asset-based poverty trap mechanism across seven panel data sets, in five countries from Africa, Asia and Latin America, and in so doing add substantially to the existing evidence base on this issue.

JEL Classification: I32, O12

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Introduction

Poverty is commonly identified in terms of a household's per capita (or per adult) consumption or income falling below a poverty line; thus the chronic or persistent poor are those whose consumption/income falls below the poverty line in all or most periods within a panel data set. Evidence from a number of countries suggests that the chronic poor identified in this manner typically have a number of distinct characteristics which might be considered possible explanations of chronic poverty (McKay and Lawson, 2003). For instance, minority groups, who may suffer from discrimination, are often disproportionately represented (e.g., indigenous populations in Latin America, Scheduled Castes or Tribes in India); there are often distinct spatial characteristics with concentrations in "lagging regions" which are often more remote or less well resourced; the chronic poor are typically working in low return activities such as being agricultural labourers or cultivating marginal areas of land.

But one key characteristic that most chronic poor share is the low level of assets they own or access. These assets may take a range of different forms, for example corresponding to the five categories identified in the livelihood literature: physical, human, natural, financial and social (Ellis, 2001). A low level of assets can be both an important explanation for poverty and perhaps a good measure of chronic poverty in its own right.

But in addition low asset levels, combined with an inability to accumulate sufficiently, result in some households being caught in a poverty trap. The existence of poverty traps is widely discussed in the literature but sometimes in the policy context, but the currently available empirical evidence in relation to poverty traps is not that strong. This is the motivation behind this special issue on poverty traps and asset dynamics, to assess the strength of available empirical evidence drawing on recent studies. In this introductory article besides setting out the issue, we also present evidence for asset-based poverty traps by applying a common methodology across seven panel data sets from five countries (Bolivia, South-Africa, Tanzania, Uganda and Vietnam). Other articles in this special issue represent more detailed studies in a single country. In our analysis in this paper we focus on the asset accumulation process and test whether this displays non-linearities and non-convexities that could explain why some households experience persistent poverty. We apply the Carter and Barrett (2006) specification of an asset-based poverty trap to test for evidence of the existence of this mechanism across the panel data sets. This adds substantially to the existing evidence base on this issue. In this case we do not find evidence of the existence of a poverty trap as defined by Carter and Barrett. While in some cases there is evidence of non-linearities in the accumulation process, there is no evidence of non-convexities. In other cases there is no evidence of either non-linearities or non-convexities.

The remainder of the paper is organised as follows. In the second section, we present the origin of an asset-based poverty trap mechanism and summarise the evidence from previous studies. In a third section, we describe the data and present the methodology used to create an asset index which is then used to look at asset accumulation. In a fourth section, the different tests in each case and their results are analysed. A fifth section gives the limits of this asset-based mechanism and concludes.

1 Macro and micro poverty trap mechanisms

1.1 Model of growth and poverty traps

As well as potentially helping in identifying poverty, assets play a key role in explaining income levels, both at a macro and at a micro level. At the macro level, according to conventional models of economic growth such as the Solow model, growth reflects investment in physical or human capital, and the marginal return to these capitals decreases monotonically as their levels increase. Thus there will be high rates of investment when levels are low, and a country will always converge to a steady state situation, the position of which reflects model parameters, such as savings rates, population growth rates and the rate of technical change. When a country is below its steady state it will converge towards it over time. Countries may display unconditional or conditional convergence in relation to each other depending on whether key parameter values (other than technical change) are the same or differ across countries. These models though rely on a number of assumptions, including convexity of technology, completeness of markets with free entry and exit and relatively low transactions costs (Azariadis and Drazen, 1990; Azariadis and Stachurski, 2004). Empirical evidence though often does not find evidence for convergence across countries, certainly globally (e.g. Mankiw, Romer and Weil, 1992). There are reasons to question the models' assumptions for poorer countries: increasing returns to scale may be important (at least over a range of production values) when industrialisation relies on adoption of new technologies which often have a fixed cost in operation and require significant levels of skilled labour. With increasing returns to scale the returns to investment may be increasing over part of the range. In addition there is lots of evidence for the incompleteness of markets for credit and insurance, which can result in agents adopting risk-reducing but inefficient production processes which may keep them in poverty.

Sachs and others have argued that for many low income countries their production function may have a range over which marginal returns to capital are increasing; this implies that they may be caught in a poverty trap, from which they may be unable to escape without external assistance. Poverty traps can be defined as "self-reinforcing mechanisms that act as barriers to the adoption of more productive techniques and so cause poverty to persist" (Azariadis and Drazen, 1990). Sachs et al. (2004) attribute this poverty trap to many factors including savings, demography, geography, and geopolitics.

1.2 Poverty trap analysis in a microeconomic setting

If countries are caught in a poverty trap this can explain persistent poverty at the macroeconomic level but building on the above analysis, it is also possible to develop analogous concepts at the micro level. The equivalent concept to capital here is the assets the household possesses. Carter and Barrett (2006) develop a model for an agrarian society where households choose between two distinct production strategies, which are represented in terms of the relationship between utility and the household's assets (Figure 1). Households with a low level of assets choose the livelihood strategy L_1, generating a relatively low level of utility; but those with a higher level of assets can access the more productive livelihood strategy L_2, generating higher utility levels. The equilibria at points A_L^* and A_H^* are both stable. These same curves can be used to define a (static) asset poverty line, corresponding to the income poverty line.[2]

The curves for the two livelihood strategies will cross at some point, above which livelihood strategy L_2 is clearly preferred. But even for some values below that crossing point it is worthwhile for the household to save in order to enable it to access the higher livelihood

2 This asset poverty line has been used to distinguish what Carter and May call structural and stochastic poverty (Carter and May, 2001). According to this line, the structural chronic poor are those households that are income poor in all (or most) periods and that have levels of the summary measure of assets which fall below the asset poverty line. Both their assets and income confirm that these households are persistently poor. By contrast the stochastic chronic poor are those whose income is frequently below the poverty line, but whose asset holdings are above the asset poverty line.

strategy. The level of assets above which this applies is referred to as the Micawber threshold; it can also be thought of as a dynamic poverty line defined in asset terms. In this example this line is lower than the static asset poverty line, though that need not necessarily be the case.

The relationship between this period's assets and next period's assets is graphed in the lower chart of Figure 1. Below A_L^* asset values increase over time and the household converges to the equilibrium A_L^*; above A_L^* but below the Micawber threshold value of A^* assets fall over time, again generating convergence to A_L^*. But once the household has asset levels above the Micawber threshold their assets increase over time and converge to the higher equilibrium A_H^*. The Micawber threshold is clearly a critical threshold; above this households can escape from poverty, below this level of assets households are caught in a poverty trap.

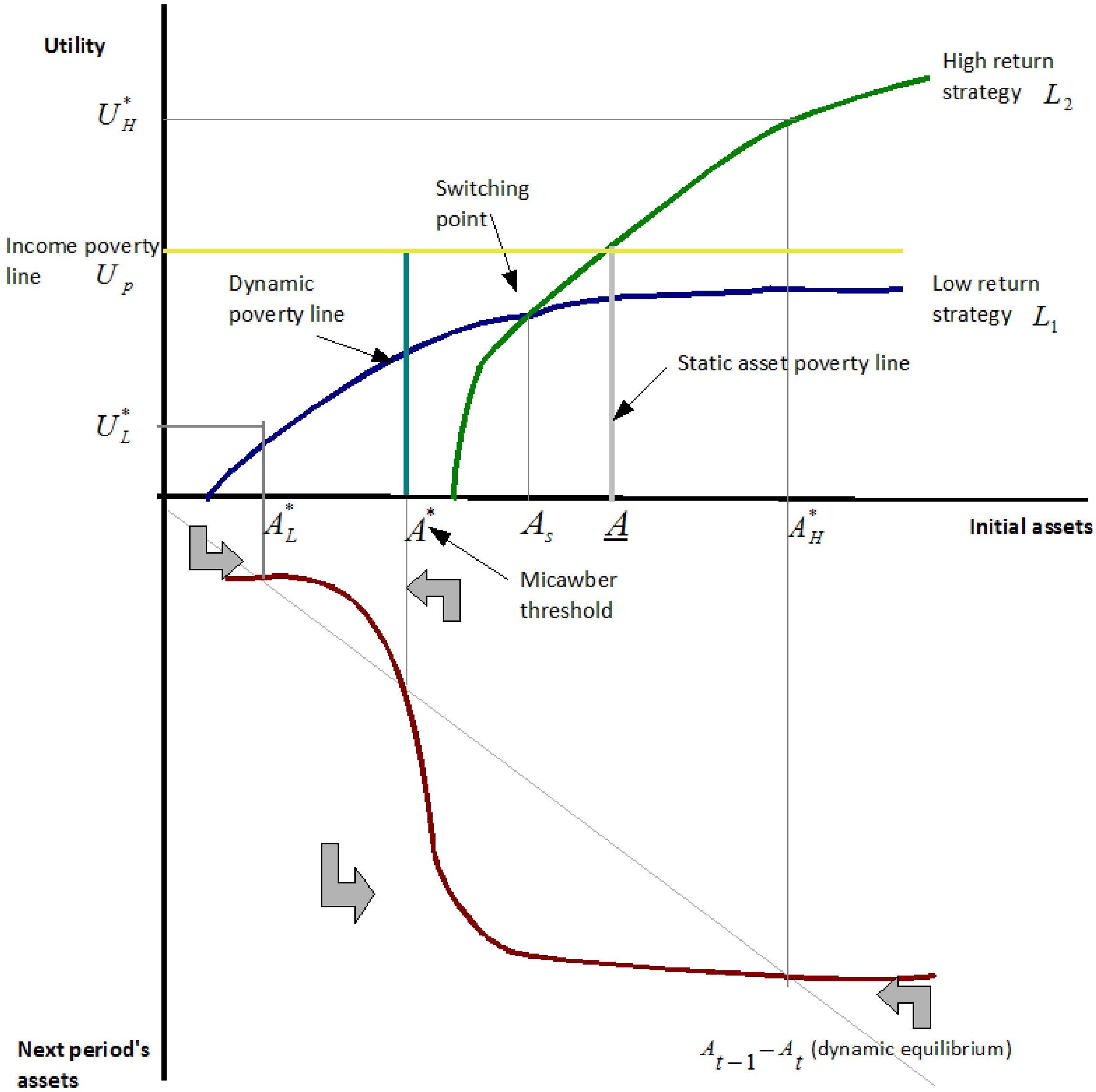


Figure 1: Poverty trap mechanism from Carter and Barrett (2006)

Analogous to the macroeconomic example above, this model, based on two alternative livelihood strategies, generates a range of increasing returns to scale and so an S shaped relationship between this period's assets and next period's assets. This model shows how households with low levels of assets may be caught in a poverty trap while those with sufficient assets are able to escape. If this is the case this has clear policy implications for tackling persistent poverty, in particular the need to seek to raise living conditions not to the poverty line but rather to the Micawber threshold (which may be higher or lower). But the existence of this S shaped relationship is critical to generating the poverty trap.

1.3 Earlier evidence for asset-based poverty trap

How strong is the empirical evidence for this phenomenon? This has been investigated quantitatively by means of a number of parametric and non-parametric methods based on panel data. At the outset it is important to recognise the difficulty of what is being tested; it is necessary to identify an S shaped part of a curve when relatively few households might be located in the critical area of inflection. Further, the aim is to identify a pattern which applies to individual households over time based on differences between households over a short period of time, and therefore implicitly assuming that different households may be in similar accumulation regimes. And there may be issues about the reliability with which assets are measured. Despite these difficulties a number of attempts have been made to test for asset-based poverty traps.

An early study by Lybbert et al. (2004) did find evidence of poverty traps among pastoralist communities in Southern Ethiopia, though in this case taking household livestock as the only asset considered. Here the lower equilibrium is associated with a herd size of one and the higher threshold with a herd size 40-75; the Micawber threshold is identified as around 15. Households with fewer than 15 animals are likely to return to the low level equilibrium; above 15 they will converge in time to the higher equilibrium. Barrett et al. (2006), looking at communities in Kenya and Madagascar, did find similar evidence in pastoralist communities in Northern Kenya (here with bifurcation at around 5-6 Tropical Livestock Units per capita), but there is much less evidence for S-shaped asset trajectories in Madagascar. Their qualitative investigations supports the idea of persistent poverty and hence poverty traps in both cases, but this does not necessarily confirm that an asset-based poverty trap logic is in operation. Adato et al. (2006), using an asset index integrating four assets for KwaZulu Natal, South Africa, did find evidence of the existence of a poverty trap and an S-shape curve in the asset accumulation process. They identified a Micawber threshold equal to twice the poverty line, and households at a low equilibrium have a level of well-being about 90 percent of the poverty line.

On the contrary, other studies did not manage to find evidence for the existence of a poverty trap. As already noted, Barrett et al. (2006) did not find evidence based on the quantitative study of a poverty trap for households living in Madagascar. Defining an asset index using factor analysis following Sahn and Stifel (2000)'s methodology, they look at asset accumulation over time and do not find evidence of the existence of non-linearities that could explain the existence of a poverty trap. Naschold (2005) constructs asset indices including a wide range of assets for Ethiopia and Pakistan, and despite using parametric, nonparametric and semiparametric specifications is not able find evidence of a poverty trap in either case. Likewise Quisimbing and Baulch (2009) do not find evidence for poverty traps in Bangladesh in relation to land or a range of other household assets.

In a different approach, Jalan and Ravallion (2001) looked at non-linearities in income and expenditures in China. While they found evidence of non-linearities, they did not find evidence of non-convexities that could show the existence of an unstable equilibrium trapping poor households into poverty.

In short the evidence in relation to poverty traps is mixed. Some of the strongest evidence for poverty traps comes from studies of pastoralist communities where households rely predominantly on one asset. But it is important to seek to assemble a wider body of evidence on the important issue of evidence for poverty traps, and in particular drawing on households with a wider range of assets. This is the motivation behind this entire special issue, and behind this specific paper. Here we week to test for a poverty trap mechanism in several contexts, either at the national level (Uganda, Vietnam), at the regional level (Kagera in Tanzania, KwaZulu Natal in South Africa) or focusing on one specific population (the Tsimane' in Bolivia).

2 Data used and summary information from data

Testing the evidence for an asset-based poverty trap at the household level requires both the availability of panel data sets that also have a large amount of information on different types of assets.

2.1 Data used

Panel data are still not widely enough collected, but here we obtained seven panel data sets for five countries, sometimes nationally representative, sometimes specific to a particular region. The nationally representative surveys used here are the Uganda National Household Survey collected in 1992 and again in 1999, surveying 1,077 households in both years; and the Vietnamese Household Living Standards Survey (VHLSS) 2002-2006. From the latter data sets we constructed and used the 2002-2004 panel and the 2002-2004-2006 panel. In the first panel (02-04), 4,092 households were re-interviewed in both waves while in the second panel (02-04-06), 1,952 households were interviewed all three years.

We also use the KwaZulu Natal Income Dynamics (KIDS) data 1993-1998 in South Africa, and the Kagera Health and Demographic Survey (KHDS) data collected in the Tanzanian region of Kagera over a 13 year-period from 1991-2004. KHDS collected data on a yearly basis between 1991 and 1994, and again in 2004.

The last dataset we used are the TAPS data which are panel data collected on a annual basis between 2002 and 2006 on an indigenous population in Bolivia, the Tsimane'.

2.2 Summarising asset information with asset index

The case for using asset data in analysing poverty is that they might be easier to measure than income or consumption (assuming respondents are willing to reveal the assets they own), and that they are likely to be less volatile over time (Sahn and Stifel, 2003; Moser, 2007). This volatility of measured income or consumption over time is potentially a significant problem for measurement, and will indicate more transitory poverty than there really is. But a challenge in using asset data is that households may have many different assets, which somehow need to be combined into a single measure.

If all assets have monetary values then they can be aggregated in these terms, but this valuation is not necessarily appropriate and some assets, such as human and social capital, may not be readily valued. Another way of aggregating assets could be by using the coefficients of assets in a regression of household income or consumption per capita on a household's holdings; in this way assets are combined with weights which reflect their association with household consumption/income (Adato et al., 2006). But here we opt instead (in line with other researchers) for a third approach which does not depend on valuations or household income; we combine the different assets into an asset index using factor analysis. This approach relies on patterns of correlation between assets in the data to extract the first factor, which can then be considered as an asset index summarising the patterns revealed by the asset data if (i) the patterns of the weights are consistent; and (ii) the index explains a sufficiently high proportion of variation in the data (Sahn and Stifel, 2000, 2003).

2.2.1 Methodology to build an asset index using factor analysis

Assets potentially cover a wider range of welfare than consumption and income. And there are many advantages of constructing an asset index. It is possible to combine different categories of assets (not just for example livestock or physical tools). It avoids the need for monetary conversion factors and comparability problems as only quantities of assets or dummies need to be considered and asset indices can be built on as similar a basis as possible. Because an asset index does not have any unit, comparisons over time and spatial comparisons can be more easily undertaken without needing to worry about deflators (Sahn and Stifel, 2000; Naschold, 2005).

Factor analysis establishes weights for each asset. It is *"a statistical technique that consists in representing a set of variables in terms of lower number of hypothetical variables"* (Lawley and Maxwell, 1973; Friel, 2007). Its aim is to indicate these hypothetical or unobserved variables, also called underlying factors (Lawley and Maxwell, 1971; Lewis, 1994), and to retain a single common factor which accounts for the largest part of the variance of the variables (determined by its corresponding eigenvalue) (Lewis, 1994; Friel, 2007).

This common factor is used to divide the variance of each asset into a unique variance which is *"a combination of the reliable variance specific to the variable and a random-error variance"* (Lewis-Beck, 1994). As a result, the common factor is a weighted average of multiple assets.

Different types of factor analysis methodology are available. The most common ones are principal components analysis and the principal factor analysis, which differ in how the factors explain the variance. The former forces all the components to explain completely the variance of the variables, while the latter allows the factors not to explain totally the variance of the variables (Lewis, 1994; Sahn and Stifel, 2000).

In order to proceed to a factor analysis, the first step is to determine if the assets share enough correlation that could be explained by one factor, which can be judged by the Bartlett test for sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy.[3] If the

3 The Bartlett test consists of measuring the strength of the correlation between variables, with its null hypothesis stipulating that the correlation matrix comes from a sample in which the variables are non collinear. Rejecting the null hypothesis from this test affirms that the variables share at least one common factor that explains their variance. The KMO measure compares the magnitude of the observed coefficients

correlation is strong enough then factor analysis is a relevant technique to define an asset index representing the wealth of the households.

The second step consists in estimating the different coefficients required to construct an asset index, as described by Sahn and Stifel (2000), whose form is as follows:

$$A_i = \hat{\gamma}_1 a_{i1} + ... + \hat{\gamma}_k a_{ik}$$

A_i is the asset index estimated for the i^{th} household in the sample. It is a function of its k different assets, a_{ik}, whose weights γ_k have to be estimated through factor analysis. What is assumed here is that the ownership of the different assets is explained by a common factor and by a unique element whose variance is not correlated across assets (Sahn and Stifel, 2000).

$$a_{ik} = \beta c_i + u_{ik}$$

Both the common variance c_i and its coefficient β are not observed and must be estimated, which is the aim of factor analysis. This estimation enables the construction of a matrix of factor loadings that reflects the relationship between the assets and the common factor, and the common factor would be derived from this unique matrix of factor loadings (Bhorat et al., 2006).

$$c_i = f_1 a_{i1} + f_2 a_{i2} + ... + f_k a_{ik}$$

The welfare is a linear combination of the scoring coefficients f_k of each asset and the asset holdings a_{ik}, such that a large factor score would mean that the asset associated with this score is better able to explain the differences of welfare between households (Sahn and Stifel. 2003).

To finally find out the asset index, the factor scoring coefficients are normalised around the mean and the standard variation of each asset (Sahn and Stifel, 2000; Bhorat et al., 2006).

$$A_i = f_1 (a_{i1} - \bar{a}_1)/\sigma_{a_1} + ... + f_1 (a_{iK} - \bar{a}_K)/\sigma_{a_K}$$

where f_k are the factor scores for each asset, a_k are the mean values of each factor and σ_{a_k} the standard deviations. The asset index is estimated for each household in each year on pooled data.

to the magnitudes of the partial correlation coefficients (Lewis, 1994; Naschold, 2005).

2.2.2 Description of asset information

We tried as much as possible to select assets corresponding to each type of capital which is relevant for household livelihoods. We looked at both the mean values and standard deviations around the mean to do a first selection keeping in mind the different categories of capital as described by Ellis (2001). We also checked whether variables had enough correlation to be used within a factor analysis methodology.

Generally all asset indices include data on animals owned by households, either the number of animals or a dummy if household has a particular animal. Constructing the asset index with VHLSS data, we included the number of water buffaloes, water pigs, poultry, pigs and cattle households own. For the Tsimane' we just included the number of cows households report owning.

Physical assets included in the asset indices can either be used directly to generate output or indirectly through improving households' health or access to information which are used to create output. For instance, constructing KHDS asset indices, sewing machine, hoes and axes are included as tools used respectively in a small business, in agriculture or in timber logging. For the Tsimane' we also included small tools (bows, hooks, knives) they can use directly in hunting or fishing but also mosquito nets and radios. The former helps protect them against diseases, and the latter is the only way they have to receive information about traders, market fairs and whether new seeds are available.

We also took into account diverse measures of education, including the maximum educational attainment and number of literate members in the households (VHLSS), and a dummy whether household has educated or uneducated labourers (KIDS). In the case of the Tsimane' asset index, we included the number of household members who can speak Spanish because Tsimane' households have their own language and only households trading or working outside communities speak Spanish, which potentially gives them better opportunities.

In some cases (TAPS, KIDS, KHDS and VHLSS), we also considered land cultivated by the household, but for UNHS land was not correlated enough with the other assets to be used in the analysis.

We also included dummy variables whether households received remittances (TAPS, UNHS and KHDS) or any transfer income (KIDS).

2.3 Asset indices constructed with pooled asset data

Knowing these different assets, we can proceed with the factor analysis selecting one factor as explaining the common variance in assets. Eigenvalues, screeplots and factor scores are presented in the appendix and a summary of the asset indices is presented below.

In all cases, the asset scores are positive, meaning that the assets used in the factor analysis have a positive relationship with the common factor and the asset index. Looking at some cases, it seems that cattle and goats better explain the differences in asset indices between households when constructing asset indices with KIDS data. Pangas, sickles and the number of literate household members better explain the asset indices with both KHDS panel data while it seems that for UNHS, average education and education of household head are more important. For the TAPS data, holdings of mosquito nets or machetes are more important than holdings of other assets. Finally, in both VHLSS panel data sets, the number of televisions and of cookers better explain the asset indices in all three periods.

An asset index is defined for each household in each period. Table 1 summarises the average values of asset indices in each period for each panel dataset studied. Across cases, different trends are observable through the average values of the asset indices.

Table 1: Asset indices in each period (mean and sd)

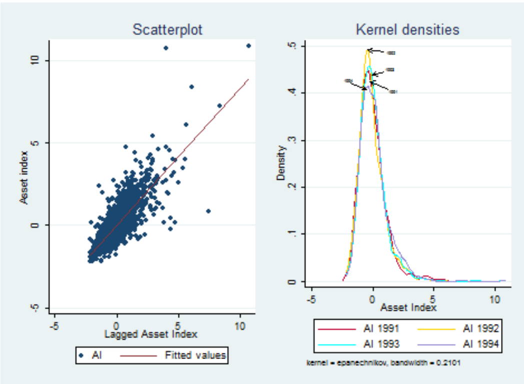
Asset index	KHDS 91-94	KHDS 91-04	KIDS 93-98	UNHS 92-99	VHLSS 02-04	VHLSS 02-04-06	TAPS 02-03-04-05-06
Period 1[4]	-0.009 (1.116)	0.049 (1.204)	-0.118(0.749)	-0.095 (1.004)	0.027 (1.022)	0.037 (1.001)	0.16 (1.07)
Period 2[5]	-0.070 (1.050)	-0.052 (1.065)	0.118 (0.926)	0.098 (1.150)	-0.265 (0.687)	-0.352 (0.586) -	0.14 (1.06)
Period 3	0.037 (1.146)					0.314 (0.827)	-0.094 (1.07)
Period 4	0.111 (1.186)						0.12 (1.21)
Period 5							0.30 (1.10)

4 refers to the first wave of the panel

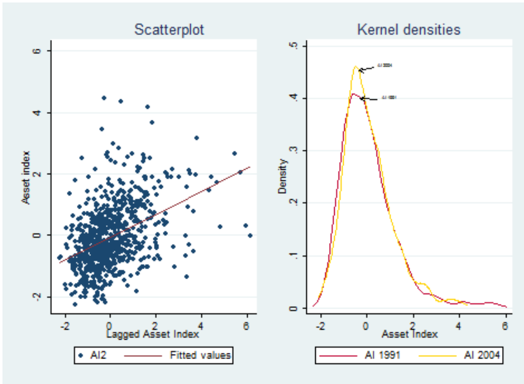
5 refers to the second or last wave of the panel

In most cases, the average value of the asset index increases over time, as in TAPS 02-06, UNHS 92-99, VHLSS02-04 KIDS 93-98 and KHDS 91-94. On the other hand, the asset indices found with KHDS 91-04 are decreasing over time and that for VHLSS 02-04-06 declines between 2004 and 2006.

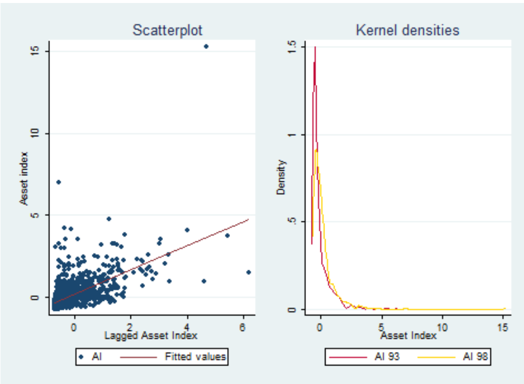
Figure 2: Asset index: scatterplot and kernel densities



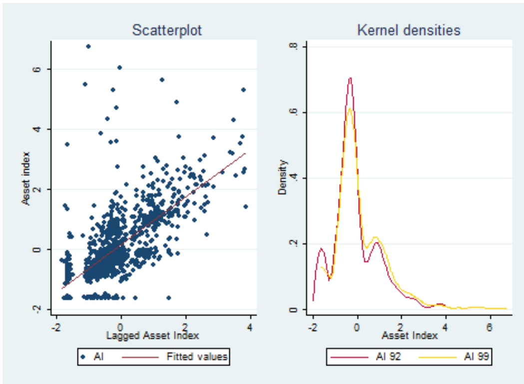
(a) KHDS 91-94



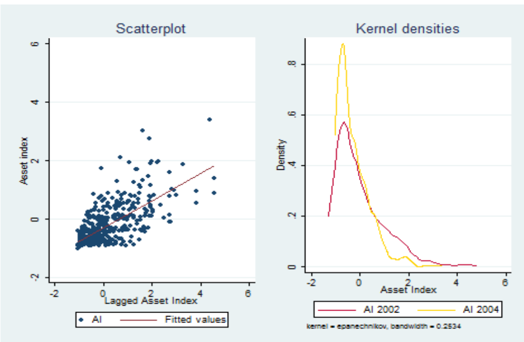
(b) KHDS 91-04



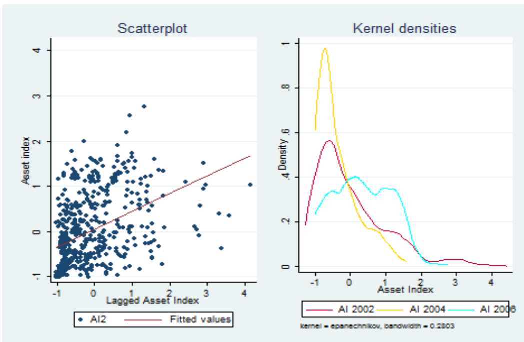
(c) KIDS 93-98



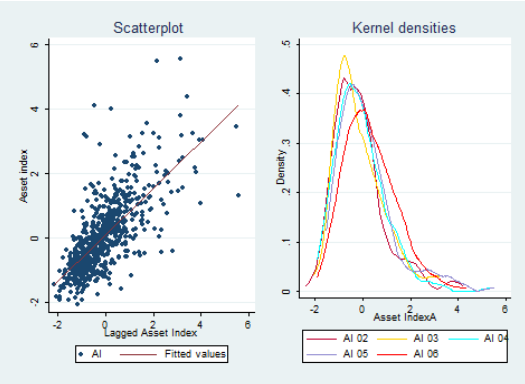
(d) UNHS 92-99



(e) VHLSS 02-04



(f)VHLSS 02-06



(g) TAPS 02-06

The values of the asset index in the current period are plotted against its lagged value in figures 2(a) to 2(g); the densities of distribution in asset index for each period are also plotted.

When looking at the scatterplots of the current values of asset indices against their lagged values, it seems that there is a concentration around the 45 degree-line. Considering the scatterplot for the asset indices in Kagera 1991-94 (figure 2(a)), it seems that there is not much dispersion in the households' asset index. On the contrary the KHDS panel data over 13 years (figure 2(b)) shows more dispersion. The Kernel densities for asset indices in both panel data sets are quite similar, but the decrease in asset indices between 1991 and 2004 is observable (figure 2(b)).

The scatterplot and Kernel densities also show significant concentration of asset indices in KIDS 93-98 (figure 2(c)), and the levels of asset indices seem to change little over time; the modal value falls but there are more extreme high values in the second period.

The UNHS scatterplot a significant amount of dispersion; unsurprisingly panels covering a longer time period show more dispersion. Here some households with low levels of asset index in the first wave seem to have higher levels of asset index in the second wave, and there are quite a few instances of the reverse phenomenon (the ones at the bottom of the left-hand figure in figure 2(d)). The Kernel density curves show a longer right-hand tail in the second period than in the first period though a lower modal value in the second period.

In the case of VHLSS, the scatterplot covering the shorter time period shows less dispersion than that for 2002-06 (figures 2(e) 6 and 2(f)) . The modal value of the asset index increases between 2004 and 2006 even if the mean value falls. Finally, scatterplots of the asset indices built with TAPS panel data over 5 years (Figure 2(g)) show that there is some dispersion from one year to the other, with both upward and downward mobility being evident. However, Kernel density curves show that there is a rightward shift of the curve in the last years meaning that more households have higher levels of the asset index.

But none of these curves allow us to disprove the presence of non-linearities and discontinuities in the asset accumulation process over time. We therefore seek to test more formally whether the asset accumulation process over time is linear.

3 Tests of a poverty trap with parametric and non-parametric regressions

3.1 Non-linear asset accumulation with parametric and non-parametric specifications

A straightforward approach to analyse a non-linear asset accumulation process is to regress the current asset value against its lagged value with a parametric specification, such as the following polynomial:

$$A_{i,t} = \alpha_0 + \sum_{m=1}^{M} \beta_m A_{i,t-1}^{m} + \gamma Z_{i,t} + T_t + \varepsilon_{i,t}$$

where $A_{i,t}$ are asset holdings of household i at time t with t= 2, ..., T, $Z_{i,t}$ are household characteristics (age of household head, household size, education...) and T_t are time-dummies that take the value 1 if time is t and 0 otherwise (Naschold, 2005).

Identifying a poverty trap consists of showing that some non-linearities occur in the asset accumulation process. But as stated by Naschold (2005), identifying an unstable threshold with a parametric specification requires a large sample. Therefore more flexible non-parametric forms should also be used to estimate the asset accumulation process; here we present results using LOWESS but we have also explored other non or semi-parametric methods.

3.1.1 Parametric regressions: Fourth-degree polynomial

The first approach, in line with some existing studies (Naschold, 2005; Barrett et al., 2006), is to use a fourth degree polynomial regression to estimate the relationship between the change in asset holdings and the asset holdings in the previous period. Using the change in asset index instead of its current value is preferred because there could be some over/underestimation in asset index values which would bias the model. It also allows some individual effects potentially correlated with the lagged values to be eliminated (Jalan and Ravallion, 2001; Naschold, 2005).

$$\Delta A_{it} = \beta_0 + \beta_1 A_{it-1} + \beta_2 A_{it-1}^2 + \beta_3 A_{it-1}^3 + \beta_4 A_{it-1}^4 + \gamma Z_{it} + T_t + \varepsilon_{it}$$

with $\varepsilon \sim N(0, \sigma_\varepsilon^2)$, $1 \leq n \leq N$ and $2 \leq t \leq T$

The change in asset holdings over time is function of a fourth order polynomial of its lagged value $A_{i,t-1}$ and of household characteristics Z_i and time dummies T_t. The age of the household head and its squared value are used to include life-cycle effects in the analysis. The shortness of the survey period means that it is only possible to include a single lag of the asset index in the model.

3.1.2 Non-parametric regressions with LOWESS

In contrast to parametric regression, this approach assumes that the relationship between the asset holdings and their lagged values is unknown and must be estimated by fitting a function *f* through a scatterplot without making any assumptions about its functional form (Ruppert et al., 2003; Naschold, 2005). The following function would be estimated.

$$A_{it} = f(A_{i,t-1}) + \varepsilon_{i,t}$$

with $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ and , $1 \leq n \leq N$ and $2 \leq t \leq T$.

Smoothing the function can be done using Kernel weighted local linear smoothers, Kernel weighted local polynomial smoothers, locally weighted estimator scatterplot smoother (LOWESS), or through splines such as cubic splines, piecewise cubic splines or penalized splines. Here, we opt for LOWESS as being more flexible than other specifications[6] (Naschold, 2005).

LOWESS consists of smoothing the scatterplot ($A_{i,t-1}$, $A_{i,t}$) with $1 \leq n \leq N$ and $2 \leq t \leq T$. At each value of $A_{i,t-1}$, a fitted value is estimated by running a regression in a local neighbourhood of $A_{i,t-1}$ using weighted least squares. The neighbourhoods are defined as a proportion of the total number of observations (Cleveland, 1979; Naschold, 2005). The weight is large if $A_{i,t-1}$ is close to the fitted value, and small if it is not. Therefore the points close to

6 We did try penalized splines and semiparametric penalized splines with TAPS data

$A_{i,t-1}$ play a large role in the determination of the fitted value of $A_{i,t}$ while the ones further away play a smaller role (Cleveland, 1979). *n* weighted local regressions would be estimated at each value of $A_{i,t-1}$ in order to find the smoothed value of $A_{i,t}$ (Naschold, 2005).

3.2 Results from parametric regressions

Table 2 summarises the results found in each case. In all cases, the lagged value of the asset index has a negative and significant effect on the change of asset index over time. It means that the higher is the level of asset index in the previous period, the smaller would be the change in asset index. In other words there is some evidence of convergence.

Table 2: Parametric regressions: fourth degree polynomial of asset change over lagged asset index

VARIABLES	KHDS 91-94	KHDS 91-04	KIDS 93-98	UNHS 92-99	VHLSS 02-04	VHLSS 02-04-06	TAPS 02-06
Lagged AI	-1.114***(0.0308)	-0.706***(0.0618)	-0.626***(0.0542)	-0.234***(0.0602)	-0.496***(0.0614)	-1.426***(-0.08)	-1.071*** (0.08)
Squared lagged AI	0.0179(0.0182)	-0.00746(0.0304)	-0.266***(0.0838)	0.0473(0.0338)	-0.0476 (0.0482)	0.03 (-0.07)	0.0528 (0.04)
Cubic lagged AI	-0.0126**(0.00555)	-0.0126(0.0187)	0.219***(0.0393)	-0.0195(0.0237)	0.0103 (0.0440)	0.06 (-0.06)	-0.00366 (0.02)
Fourth degree lagged AI	0.00128***(0.000391)	0.00175(0.00269)	-0.0289***(0.00462)	0.00301(0.00719)	-0.00101 (0.00820)	-0.01 (-0.01)	-0.00155 (0)
Age household Head	-0.0122(0.0401)	-0.0250***(0.00583)	-0.0107***(0.00311)	0.0102(0.0112)	0.00197 (0.0110)	0.04 (-0.03)	0.0449** (0.02)
Squared age household head	0.000165(0.000370)	0.000243***(6.77e-05)	0.000130***(3.78e-05)	-7.42e-05(0.000105)	-1.39e-05 (0.000104)	0 (0)	-0.000449** (0)
Household size	0.104***(0.0118)	0.131***(0.0133)	0.0430***(0.00533)	0.0669***(0.00829)	0.0322*** (0.0120)	0.03 (-0.03)	0.280*** (0.03)
Education household head	0.0504***(0.0130)	0.0474***(0.00661)					0.02 (0.03)
Dependency ratio	-0.281*(0.148)	-0.108(0.168)	0.000130(0.118)			-0.1 (-0.22)	
minder1	0 (0)	0 (0)	0(0)	0 (0)	0(0)	0 (0)	0 (0)
minder2	0 (0)	0 (0)	0(0)	0(0)	0(0)	-0.569*** (-0.04)	-0.189**(0.07)
minder3	0.0625**(0.0251)					0 (0)	-0.1 (0.07)
minder4	0.126***(0.0288)						0 (0)
minder5							0.170**(0.07)
Constant	-0.720(0.647)	-0.708***(0.136)	-0.0245(0.0995)	-0.408(0.295)	-0.480* (0.277)	-0.46 (-0.85)	-2.902***(0.58)
Observations	2132	598	1132	1070	476	562	580
Number of hhid						281	176
R-squared	0.666	0.539	0.174	0.122	0.55	0.87	0.6

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The key question of interest in these regressions is the significance of the higher order powers in the polynomial. Looking at second-, third- and fourth-degree power of the lagged index, it seems that potentially non-linearities may arise in the asset accumulation processes in the cases of KHDS 91-94 and KIDS 93-98 . However, when plotting the resulting coefficients on the observed range of asset index values there is no evidence of an S-shape curve or of non-convexities.

Considering TAPS 02-06, KHDS 91-04, VHLSS 02-04, VHLSS 02-04-06 and UNHS 92-99, the non-significance of higher degree powers suggests that changes in the asset index over time are linear.

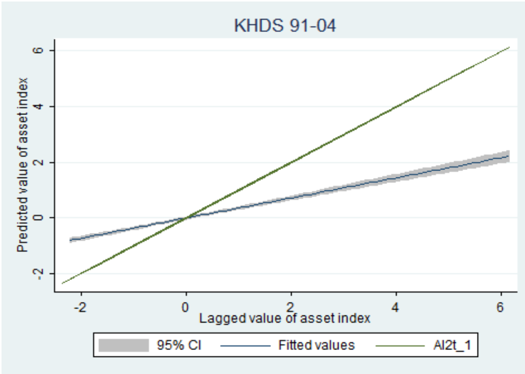
Age has an important effect on asset accumulation in KHDS 91-04, KIDS 93-98 and TAPS. In KHDS and KIDS having an older head of household reduces the increase in asset index but the positive sign of the squared age shows that this reduction is less important when household head grows older, such that the net effect becomes zero at ages, 51.4 and 41.5in respectively . For TAPS 02-06, having an older head of household increases the change in asset index but the negative value of the squared age shows that increase in asset index gets slower when household head grows older, with the overall effect becoming zero at the age of 55.5 years.

Household size has a positive effect on the change in asset index in all cases, meaning that larger households tend to accumulate more assets over time. Education has a positive influence in the KHDS regressions and the dependency ratio has a negative and significant effect on the change in asset index for KHDS 91-94.

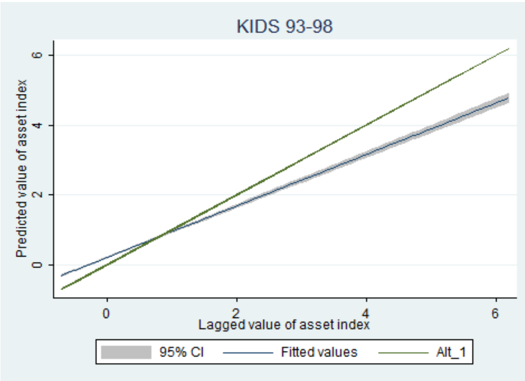
We tried different specifications and obtained similar results. After each regression, we predicted the change in asset index and calculated the predicted current level of the asset index. We have plotted the predicted levels of asset index against their lagged value for each panel data set (Figure 3(a) 9 to 3(g)).

Figure 3: Parametric Regressions

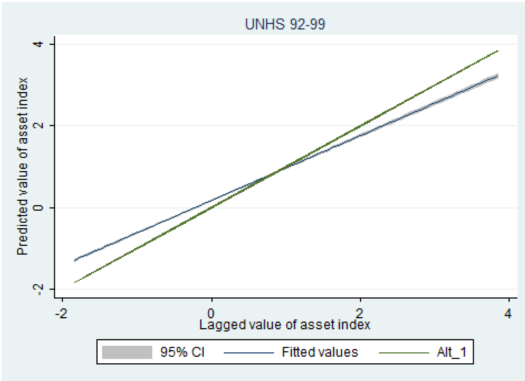
(a) KHDS 91-94



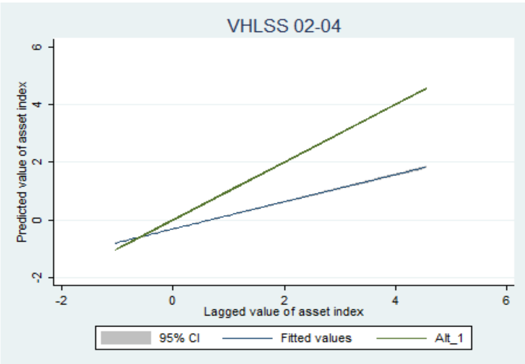
(b) KHDS 91-04



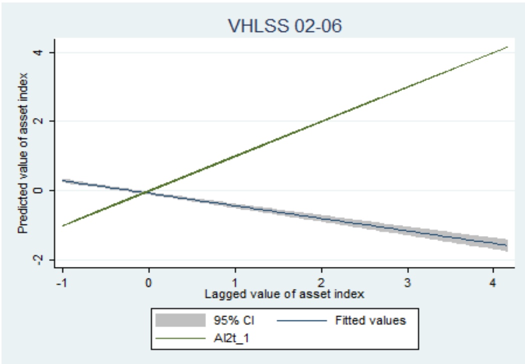
(c) KIDS 93-98



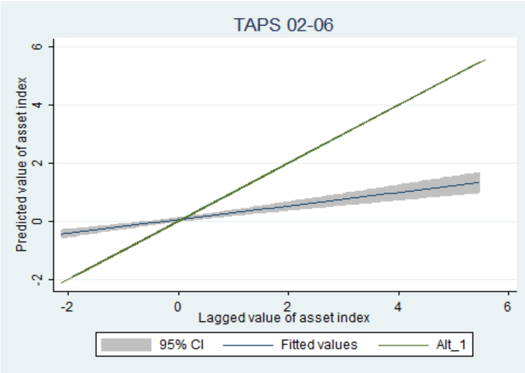
(d) UNHS 92-99



(e) VHLSS 02-04



(f) VHLSS 02-06



(g) TAPS 02-06

Strikingly none of these figures show any evidence of an S-shape curve as Carter and Barrett found. All curves cross the 45 degree line from above at a single point. The points where the curves cross the 45 degree line are at quite low values of the asset index (except in UNHS); there is some evidence of regression to the mean in asset holdings.

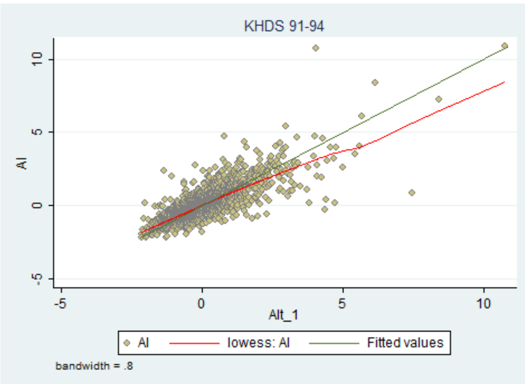
3.3 Results from non-parametric regressions

A non-parametric approach may be more appropriate to seek to find a non-linear relationship. Thus the LOWESS curves obtained for each panel dataset studied are reported below (figure 4(a) to 4(g)).

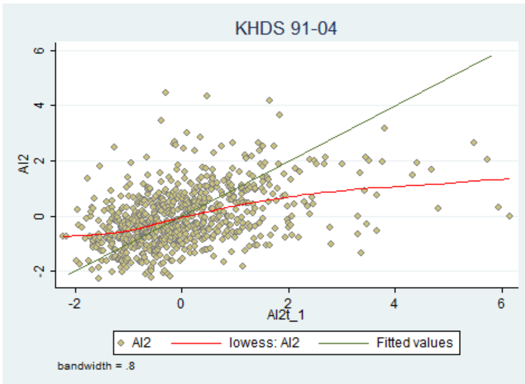
In most of these curves, a linear accumulation process seems to occur with an upward trend. When looking at KHDS 91-04 (figure 4(b)) it seems that the curve has a positive slope until cutting the 45-degree line, after which the slope decreases and becomes close to 0.

For KHDS 91-94 (figure 4(a)), the LOWESS curve is mainly below the 45-degree line, households are not accumulating assets and there is some concentration [-2;2].

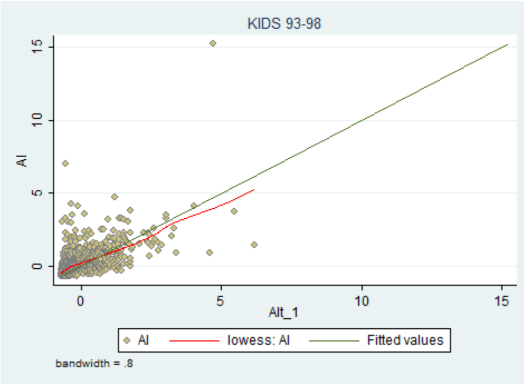
Figure 4: Non-parametric regressions



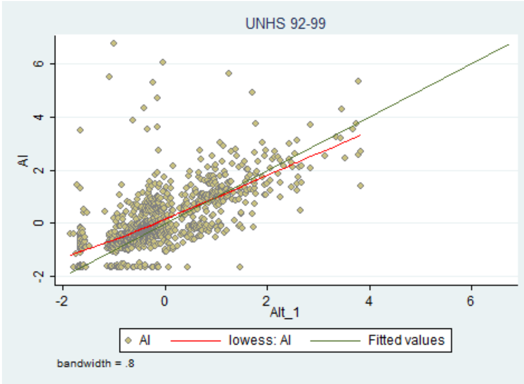
(a) KHDS 91-94



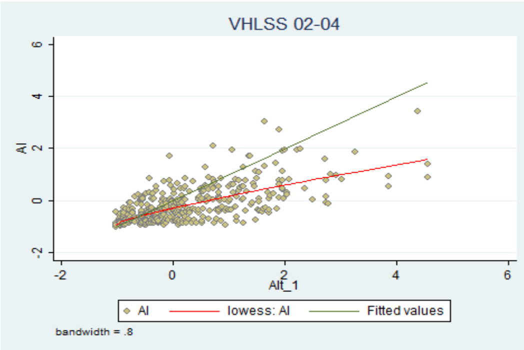
(b) KHDS 91-04



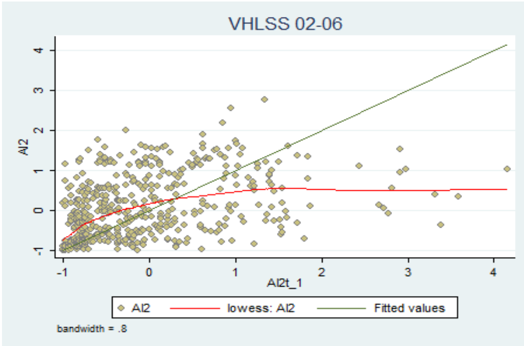
(c) KIDS 93-98



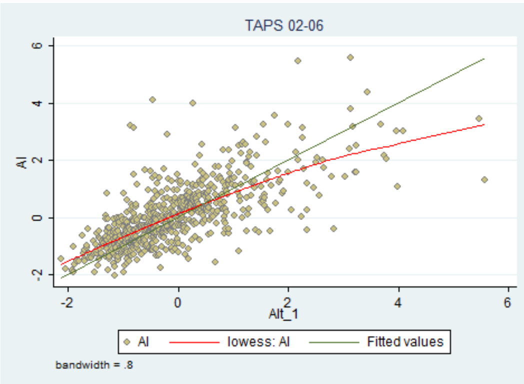
(d) UNHS 92-99



(e) VHLSS 02-04



(f) VHLSS 02-06



(g) TAPS 02-06

When looking at VHLSS 02-04 (figure 4(e)) and VHLSS 02-06 (figure 4(f)), the curves are again flat and households do not seem to have accumulated assets over time.

The curves for KIDS 93-98 and UNHS 92-99 (respectively figure 4(c) and 4(d)) have both positive slopes, but while households in KIDS 93-98 seem not to accumulate assets (the LOWESS curve staying below the 45-degree line), households in UNHS 92-99 who have low levels of the asset index seem to accumulate assets. But after cutting the 45-degree line at

[0.9;1.4], UNHS households do not accumulate assets.

None of the parametric and non-parametric curves show an S-shape in the asset accumulation process and they do not have a Micawber threshold that would keep household in a poverty trap. The asset accumulation processes seem linear which is consistent with the result that only the lagged asset index up to a first-degree power are significant in some cases (TAPS 02-06, KHDS 91-04 and UNHS 92-99). In the other cases, the parametric regressions show that there could be some non-linearities because the lagged values of the asset index at a third- and a fourth-degree power are significant but the plots do not show these non-linearities.

4 Conclusion

The analysis on this paper does not find evidence for asset based poverty traps in any of the seven data sets from five countries. The parametric regressions do not show evidence of even much non-linearity in two cases where higher order powers of the lagged asset index are significant, and in the other four show no evidence of non-convexity in the plausible range of asset index values. The non-parametric LOWESS curves also do not find evidence of non-convexity in many cases. These seven cases support what has been found in a number of recent studies of individual countries (Naschold, 2005; Quisimbing and Baulch, 2009; Schindler and Giesbert, 2010) and we even cannot find evidence for a poverty trap using the same KwaZulu Natal data set previously analysed by Adato et al. (2006).

It is important though to recognise the challenges noted above in testing for and identifying an asset-based poverty trap, and in particular in finding a non-convexity in an asset accumulation process, but the fact that we cannot find this across seven panel data sets to add to other studies does raise a serious question about whether an asset-based poverty trap applies in many cases.

Some of the strongest evidence for poverty traps seems to have come from studies where households rely principally on one asset category, livestock. In these studies the authors were able to identify a non-convexity and hence a Micawber threshold, in the relationship between current and past asset levels. But it seems that when assets are reliant on many households they are much less likely to be caught in a poverty trap. Having many assets may give households more flexible livelihood options and enable them to develop more diversified livelihood portfolios or to respond to shocks more effectively. It seems that most such households are much less likely to be caught in asset-based poverty traps.

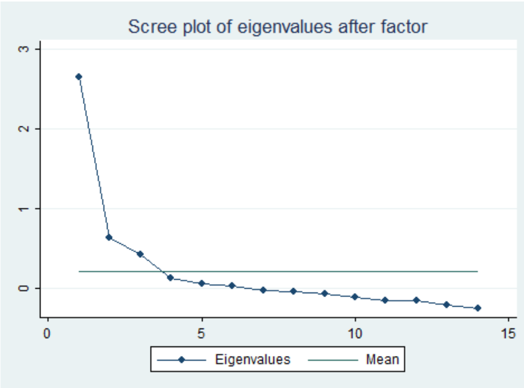
This is not to say that households may not be persistently poor. For example in the TAPS data set analysed here there is strong evidence to think that these households fall a long way below any plausible poverty line for Bolivia, and that even if households are slowly accumulating assets, the rate of accumulation is so slow that this will not take them out of poverty in their lifetimes. For KIDS according to Adato et al. (2006) there seemed to be quite strong qualitative evidence, and some quantitative evidence, of a poverty trap (though whether this is an asset-based poverty trap remains an open question). But we do not find a poverty trap in this same case.

But by contrast in the case of Uganda considered here, there was significant escapes from poverty over the period analysed and there were also quite significant increases in assets taking nearly 16.5% out of asset poverty. To some extent that reflected the favourable circumstances of that decade and was partly reversed for a short period later, but in this period few were caught in poverty traps.

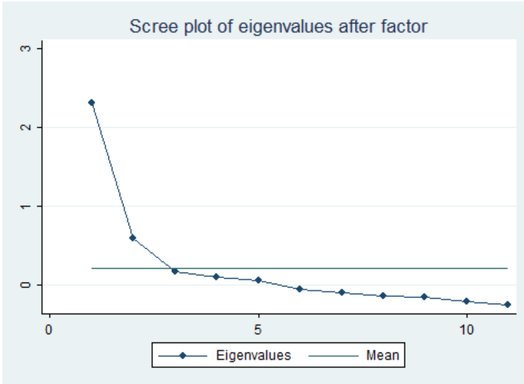
The results of this paper do not therefore rule out poverty traps in general, nor that large numbers of households find themselves in persistent poverty. Even if an asset-based poverty trap mechanism is not supported here, poverty traps may still come about for significant numbers of households via other mechanisms, reviewed comprehensively by Duclos and O'Connell (2009). Lagging regions, discrimination, political economy motivations and many other factors van generate poverty traps and may well be in operation in many of these cases (e.g. TAPS). The fact that now a large body of evidence, significantly added to in this paper, now does not support asset-based poverty traps, does not rule out other important mechanisms trapping people in persistent poverty.

Appendix: Eigenvalue plots and factor scores

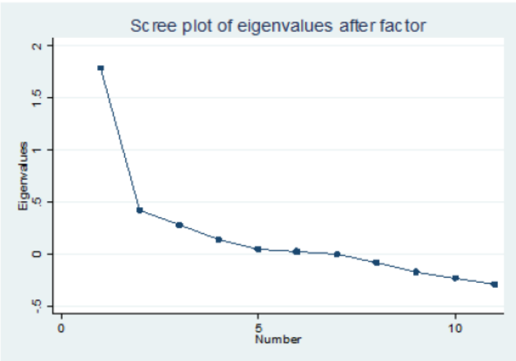
a Eigenvalue plots



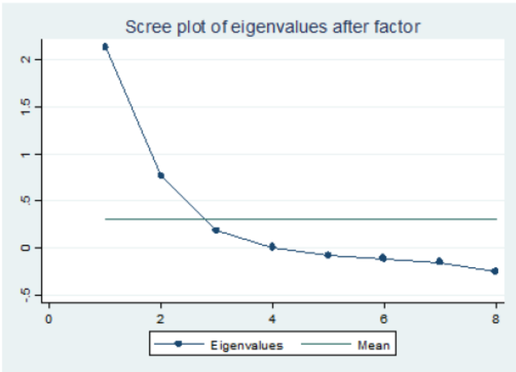
(a) KHDS 91-94



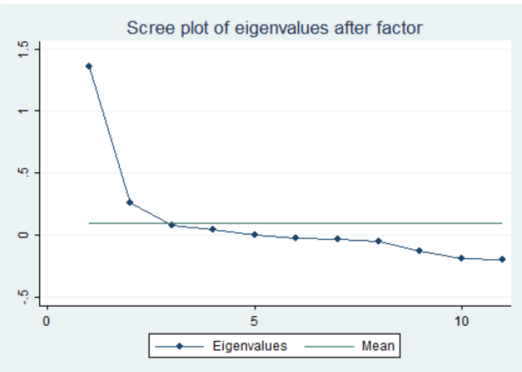
(b) KHDS 91-04



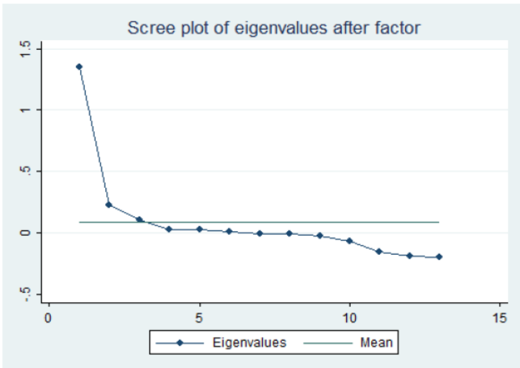
(c) KIDS 93-98



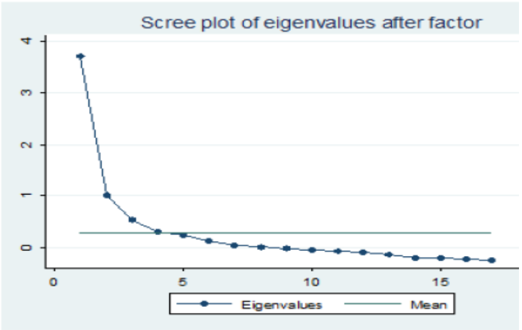
(d) UNHS 92-99



(e) VHLSS 02-04



(f) VHLSS 02-06



(g) TAPS 02-06

b Factor scores

Table A.1: KHDS 91-94

Variable	Factor1
Bicycle	0.09582
sewing machine	0.06030
hoes	0.21370
Axes	0.16997
Pangas	0.31221
sickles	0.27284
Mundu	0.08323
other tools	0.13977
nb read	0.26848
max grade	0.12869
dummy received remittances	0.03501
Goat	0.09294
cattle	0.07388
shamba area (ha)	0.02953

Table A.2: KHDS 91-04

Variable	Factor1
bicycle	0.14458
sewing machine	0.09520
Hoes	0.15214
axes	0.15874
Pangas	0.27356
Sickles	0.23481
mundu	0.09288
other tools	0.10931
nb read	0.23816
max grade	0.10242
dummy received remittances	0.02532
Goat	0.09381
Cattle	0.11533
shamba area (ha)	0.20723

Table A.3: KIDS 93-98

Variable	Factor1
educated labour	0.01101
non-educated labour	0.17256
Cattle	0.34730
Sheep	0.05552
Goats	0.24548
Pigs	0.04191
Poultry	0.19291
plot size	0.02173
farm equipment dummy	0.09694
farm tool dummy	0.17866
Transfer	0.07055

Table A.4: UNHS 92-99

Variable	Factor1
education head	0.30809
mean education	0.30694
max education	0.56393
land	0.00768
Cow	0.01233
bike	0.02984
other equipment	0.00951
media equipment	0.01660

Table A.5: VHLSS 02-04

Variable	Factor1
number literate members	0.06112
rice machine	0.00415
Car	0.02801
Trailer	0.00091
Plough	0.00101
Motorbike	0.13808
Bicycle	0.07303
sewing machine	0.08342
Television	0.33566
gas cooker	0.23719
electric cooker	0.32554

Table A.6: VHLSS 02-04-06

Variable	Factor1
number literate members	0.06384
agricultural land	0.02690
Buffaloes	0.01306
car	0.02789
Trailer	0.00755
plough	0.00777
motorbike	0.14709
Bicycle	0.05363

sawing machine	0.00950
sewing machine	0.05857
Television	0.32541
gas cooker	0.25496
electric cooker	0.32519

Table A.7: TAPS 2002-06

Variable	Factor1
axe	0.14333
Bike	0.05572
Bow	0.12669
Canoe	0.05943
Cow	0.03420
Hook	0.16634
knife	0.20611
machete	0.25900
mosquito net	0.26783
Net	0.08220
Radio	0.08814
rifle	0.04237
shot gun	0.07076
size plot	0.09294
Gift	0.02758
nb speak Spanish	0.04107
dummy math	0.01315

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