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How strong is the evidence for the existence of poverty traps? A multi-country assessment

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What is Chronic Poverty?

The distinguishing feature of chronic poverty is extended duration in absolute poverty.

Therefore, chronically poor people always, or usually, live below a poverty line, which is normally defined in terms of a money indicator (e.g. consumption, income, etc.), but could also be defined in terms of wider or subjective aspects of deprivation.

This is different from the transitorily poor, who move in and out of poverty, or only occasionally fall below the poverty line.

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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. We also look at the asset accumulation process and test whether this displays non-linearities and non-convexities that could explain why some households experience persistent poverty. We 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. The paper adds substantially to the existing evidence base on this issue.

Keywords: poverty traps, chronic poverty, panel data, parametric and non-parametric estimation

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Contents

1 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 chronically or persistently 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 chronically poor identified in this manner typically have a number of distinct characteristics which might be considered as 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 chronically 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 chronically poor people 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 asset categories identified in the livelihood literature: physical; human; natural; financial; and social (Ellis, 2001). A low level of assets, as well as constituting an important explanation for poverty, could also serve as a good measure of chronic poverty in its own right.

In this paper, we focus specifically 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. We also look at 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 mechanism to test for evidence of the existence of this mechanism across seven panel data sets in five countries from Africa, Asia and Latin America, adding substantially to the existing evidence base on this issue.

This asset-based poverty trap 4mechanism consists in identifying multiple equilibria in the asset accumulation process. Two stable equilibria emerge at high and low levels of assets, as well as an intermediate unstable equilibrium, below which households' asset values converge to the low equilibrium and are trapped into poverty (Carter and Barrett, 2006). Implementing this test using the same methodology for five countries (Bolivia, South- Africa, Tanzania, Uganda and Vietnam), we do not find evidence of the existence of a poverty trap, as defined by Carter and Barrett. It seems that in some cases there is evidence of non-linearities but no evidence of non-convexities, while in other cases, there is no evidence of 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 will be 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.

2 Macro and micro poverty trap mechanisms

2.1 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 rate of technical change. When a country is below its steady state it will converge towards it over time. If the parameter values are the same for all countries, then they display unconditional convergence such that poorer countries will in time catch up with richer countries. When parameters other than technical change differ across countries, the model shows conditional convergence, i.e. convergence in growth rates, but at different income levels.

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. 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 that 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 that 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. A poverty trap 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, geopolitics etc.

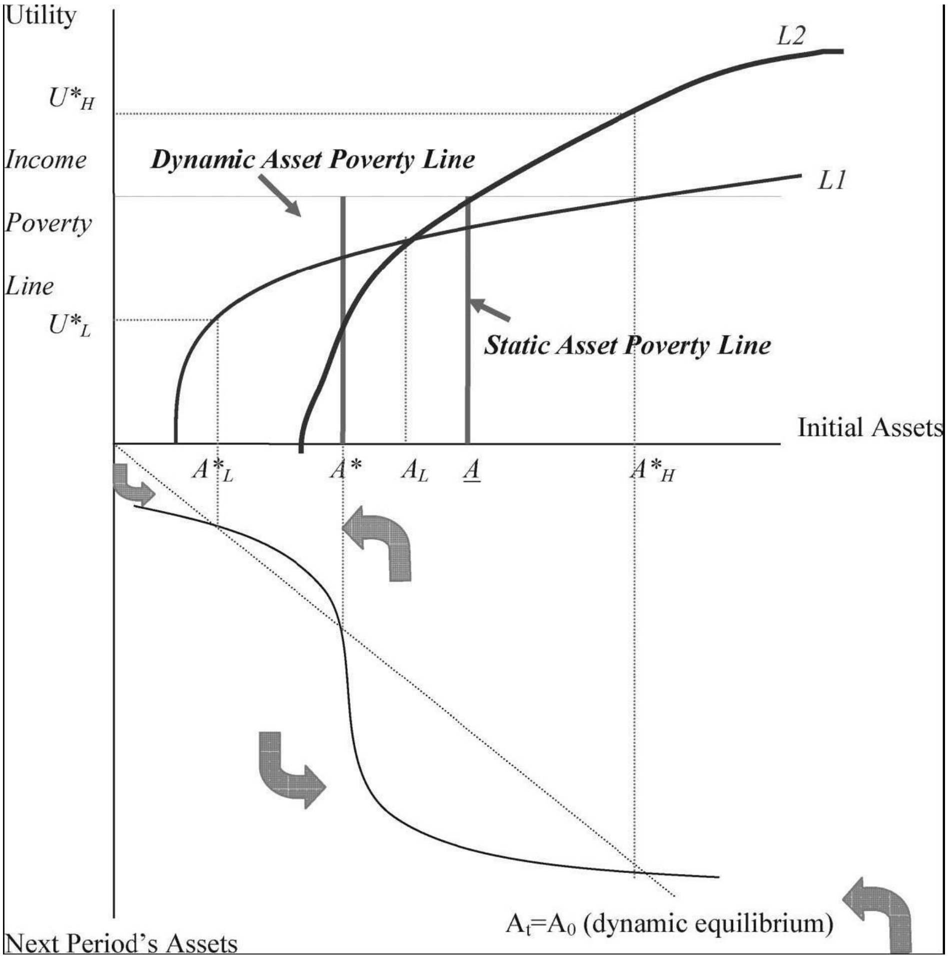
2.2 Poverty trap analysis in a microeconomic setting

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, represented in terms of the relationship between utility and the household's assets (Figure 1). Households with a few assets choose the livelihood strategy L_1, generating a relatively low level of utility; but those with more assets can access the more productive 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.[1]

The curves for the two livelihood strategies will cross at some point, above which 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 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 is lower than the static asset poverty line, though that need not necessarily be the case.

[1] 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 chronically 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 chronically poor are those whose income is frequently below the poverty line, but whose asset holdings are above the asset poverty line.

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



The relationship between this period's assets and next period's assets is graphed in the lower chart. 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.

Analogously 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. But the S-shaped relationship is critical to generating this poverty trap.

2.3 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. 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 of 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 five to six tropical livestock units per capita), but there is much less evidence for S-shaped asset trajectories in Madagascar. Their qualitative investigations support 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, did find evidence of the existence of a poverty trap and an S-shaped 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 wellbeing 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. In the same study, 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 following Sahn and Stifel's (2000) methodology, they look at asset index accumulation over time and did not prove 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 Ethiopia and Pakistan for the former. Likewise, Quisumbing and Baulch (2009) do not find evidence in Bangladesh for poverty traps in relation to land or a range of other household assets. Jalan and Ravaillon (2001) looked at nonlinearities 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.

Starting from this existing evidence, we tried to extend and 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 (Tsimane' in Bolivia).

3 Data used and summary information from data

Testing the evidence for a poverty trap at the household level creates different data requirements. It requires availability of panel data, meaning comparable data on same households collected over different waves. Building a mechanism such as Carter and Barrett's also requires a focus on assets, which as a consequence requires the data sets used to have a large amount of information on different types of assets, e.g. physical, natural, human and financial assets.

3.1 Data used

Panel data required to look at evidence for a poverty trap are still not widely enough collected, but here we obtained seven panel data sets for five countries. This was sometimes a nationally representative sample of the country, and sometimes only a certain category of households within the country.

Nationally representative surveys used are the Uganda National Household Survey, collected in 1992 and again in 1999, and surveying 1,077 households in both years; and the Vietnamese Household Living Standard Survey (VHLSS) 2002-2006. From these data sets we constructed and used the 2002-2004 panels 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 in all three years. We used 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 the 13-year period of 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 between 2002 and 2006 on an indigenous population in Bolivia, the Tsimane' households.

3.2 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 and Felton, 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 may not be 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 the technique of 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).

3.2.1 *Methodology to build an asset index using factor analysis*

Assets potentially cover a wider range of welfare than consumption and income. In this analysis, assets are not only the physical tools households possess, but also the other types of capital the household has: natural; financial; social; and human capital (Ellis, 2001). Using assets to build an index via factor analysis avoids the need for monetary conversion factors and comparability problems, as only quantities of assets or dummies would be considered and asset indices would be built on as similar a basis as possible. Because an asset index is built so as not to have any unit, comparisons over time and spatial comparisons can be more easily undertaken without needing to worry about deators (Sahn and Stifel, 2000; Naschold, 2005).

Building an asset index requires studying the existing correlations between assets and identifying weights for each asset. To define the weights of assets, we have used a factor analysis which corresponds to *'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). The aim of factor analysis is to indicate these unobserved variables, also called underlying factors (Lawley and Maxwell, 1971; Lewis-Beck, 1994). The idea is to keep a single common factor which accounts for a larger part of the variance of the variables looking at eigenvalues and keeping the factor which has its eigenvalue above 1 (Lewis-Beck, 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 are principal components analysis and the principal factor analysis. The difference between both techniques relies on 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 to not fully explain the variance of the variables (Lewis-Beck, 1994; Sahn and Stifel, 2000).

In order to proceed to a factor analysis, the first step is to determine whether the assets share enough correlation that could be explained by one factor. To do so, two tests can be done: the Bartlett's test for sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. 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 to the magnitudes of the partial correlation coefficients (Lewis-Beck, 1994; Naschold, 2005). If this magnitude 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:

$$A_i = \hat{\gamma}_1 a_{i1} + ... + \hat{\gamma}_K a_{iK} \qquad (1)$$

A_i is the asset index estimated for the i 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).

$$a_{ik} = \beta c_i + u_{ik} \qquad (2)$$

Both the common variance c_i and its coefficient β are not observed and must be estimated, which is the aim of a 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).

$$c_i = f_1 a_{i1} + f_2 a_{i2} + \ldots + f_k a_{ik} \qquad (3)$$

The welfare is a linear combination of the scoring coefficients f_k of each asset and the asset holdings a_k; so that a large factor score would mean that the asset associated to 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)

$$A_i = f_1(a_{i1} - \bar{a}_1)/\sigma_{a_1} + \ldots + f_1(a_{iK} - \bar{a}_K)/\sigma_{a_K} \qquad (4)$$

Where f_k are the factor scores for each asset, $\bar{a}_k$ are the mean values of each factor and σ_{a_k} the standard deviations. The asset index would be estimated for each household in each year on pooled data.

3.2.2 *Description of asset information*

We tried as much as possible to select assets corresponding to each type of capital and which are relevant for households to generate their 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 a household has this animal. Constructing the asset index with VHLSS data, we included the number of water buffaloes, water pigs, poultries, pigs and cattle that households own. For the Tsimane' we just included the number of cows that households reported 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 nets protect them against bugs and, as a result, diseases and the radio 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 a 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. This is because Tsimane' households have their own language and tend not to speak Spanish – 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 of whether households received remittances (TAPS, UNHS and KHDS), or any transfer income (KIDS).

3.3 Asset indices constructed with pooled asset data

Knowing these different assets, we can proceed with the factor analysis, selecting only one factor as explaining the common variance in assets. Eigenvalues, screeplots and factor scores are presented in the Appendix and what follows presents the resulting asset indices (Tables 3 to 23).

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. Considering the asset indices with 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 motorbikes 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 asset indices.

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

Asset index	KHDS 91-92-93-94	KHDS 91-04	KIDS 93-98	UNHS 92-99	VHLSS 02-04	VHLSS 02-04-06	TAPS 02-03-04-05-06
Period 1[a]	-0.009 (1.116)	0.049 (1.204)	-0.118 (0.749)	-0.095 (1.004)	0.111 (0.895)	-0.100 (0.812)	-0.16 (1.07)
Period 2[b]	-0.070 (1.050)	-0.052 (1.065)	0.118 (0.926)	0.098 (1.150)	-0.111 (0.683)	-0.290 (0.629)	-0.14 (1.06)
Period 3	0.037 (1.146)					0.391 (0.792)	-0.094 (1.07)
Period 4	0.111 (1.186)						0.12 (1.21)
Period 5							0.30 (1.10)

[a] refers to the first wave of the panel
[b] refers to the second or last wave of the panel

In some cases, we identify an asset index whose average values increase over time, such as in TAPS 02-06, UNHS 92-99, KIDS 93-98 and KHDS 91-94. On the other hand, the asset indices found with VHLSS 02-04, as well as asset indices for KHDS 91-04, are decreasing over time.

When looking at VHLSS 02-06, it seems that asset index decreases between 2002 and 2004 and then slightly increases. We plot the values of the asset index at the current period against its lagged value, and plotted the densities of distribution in asset index for each period (Figure 2a to Figure 2g).

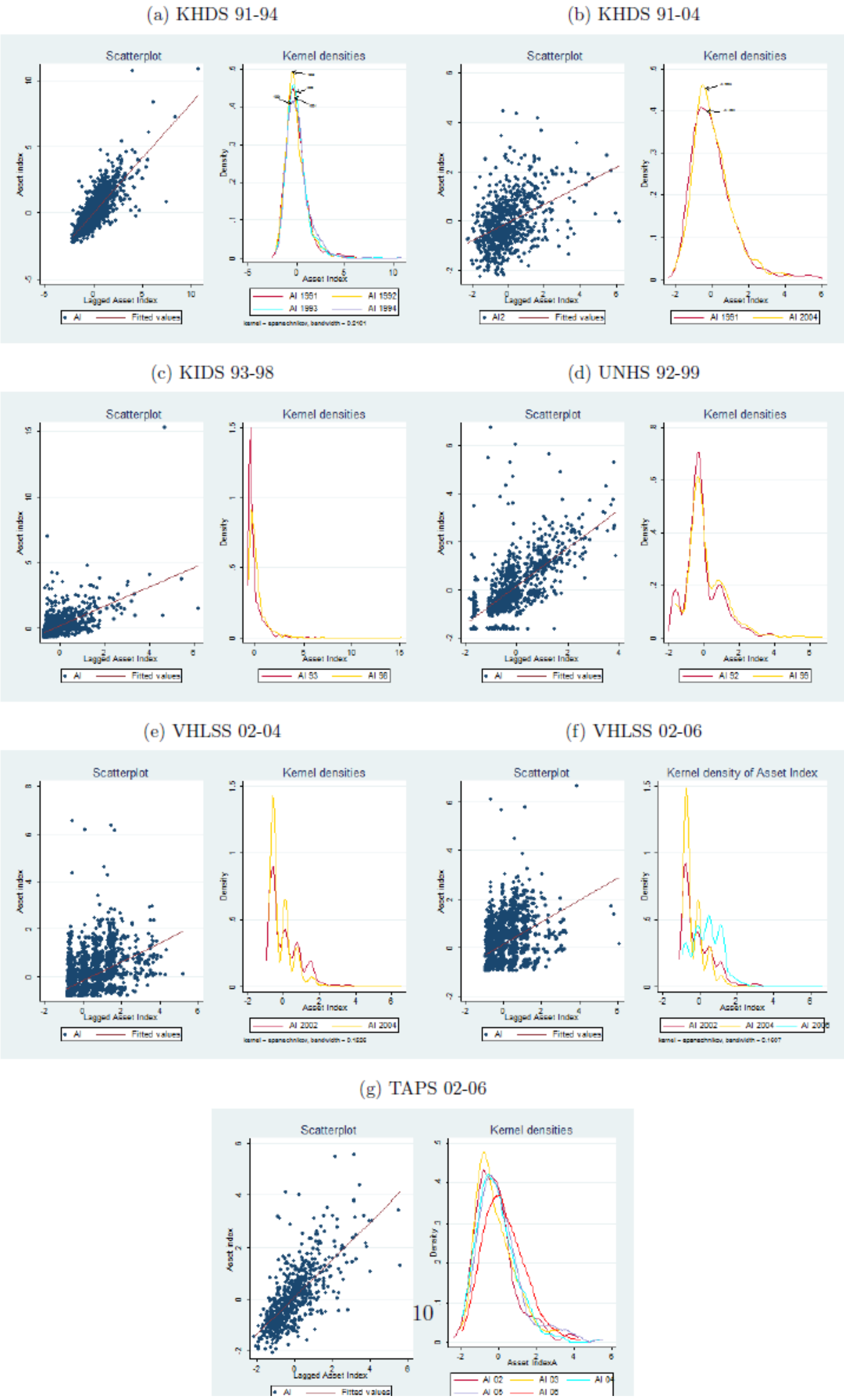
When looking at the scatterplots of the current values of asset indices against their lagged values, it seems that there is a concentration around the 45 degree-line. Considering the scatterplot for the asset indices in Kagera in 1991, 92, 93 and 94 (Figure 2a), it seems that household's asset index does not vary much and there is not much dispersion in the asset index. On the contrary, for the KHDS panel data over 13 years (Figure 2b), there is a little more dispersion from 1991 to 2004, but concentration remains more important than 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 2b).

Scatterplot and Kernel densities with KIDS 93-98 (Figure 2c) show a large concentration of asset indices, and that households tend to have the same levels of asset indices over time. Considering the distribution of Kernel densities, an increase in asset holdings can be observed through a lower modal value in favour of higher levels of asset indices, which result from the existence of extreme values in the second period.

Looking at the scatterplot with UNHS data, there is somehow more dispersion than in the other cases. Some households with low levels of asset index in the first wave seem to have higher levels of asset index in the second wave. However, some households seem to have lower values of the asset index in the second wave (the ones at the bottom of the left-hand figure in Figure 2d). The Kernel density curves show a longer right-hand tail in the second period than in the first period and a lower modal value in the second period. It seems also that, in 1992, more households have asset indices around -1.98 and 1, while in 1999, concentration is only around 1. In the case of VHLSS, scatterplots for both panel data sets (Figures 2e and 2f) seem to have the same pattern, as do the Kernel density curves.

Finally, scatterplots of asset indices built with TAPS panel data over five years (Figure 2g) show that there is some dispersion from one year to the other, but some households have changes either upward or downward in their asset index holdings. 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 asset index. However, neither of these curves allows us to reject the idea that there could be some non-linearities and discontinuities on the asset accumulation process over time. It seems interesting to study the asset accumulation process in order to identify whether or not accumulation of assets over time is linear.

Figure 2: Asset index: scatterplot and kernel densities



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

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

Analysing a non-linear asset accumulation process suggests regressing the current asset value against its lagged value with a parametric specification, which consists of 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 forms would also be used to estimate the asset accumulation process (e.g. LOWESS).

4.1.1 Parametric regressions: fourth-degree polynomial

In line with some existing studies ((Naschold, 2005; Barrett *et al*., 2006)) we 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 supported by the idea that there could be some over/underestimations in asset index values, which would bias the model. It allows to eliminate some individual effects potentially correlated with the lagged values (Jalan and Ravaillon, 2001; Naschold, 2005).

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

$$\text{with } \varepsilon \sim N(0; \sigma_\varepsilon^2) \text{ and } 1 \leq i \leq N \text{ and } 2 \leq t \leq T.$$

The change in asset holdings over time is a function of a fourth order polynomial of its lagged value $A_{i,t-1}$ and of household characteristic 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. Inclusion of only one single lag in the asset index is possible, due to the shortness of the survey period.

4.1.2 *Non-parametric regressions with LOWESS*

Contrary to the 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 on its functional form (Ruppert *et al*., 2003; Naschold, 2005). The following function would be estimated:

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

$$\text{with } \varepsilon \sim N(0;\sigma_\varepsilon^2) \text{ and } 1 \leq i \leq N \text{ and } 2 \leq t \leq T.$$

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 penalised splines. Here, we opt for LOWESS being more flexible than other specifications (Naschold, 2005).[2]

LOWESS consists of smoothing the $(A_{i,t-1}A_{i,t})$ with $1 \leq i \leq N$ 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 $A_{i,t-1}$ 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

[2] We did try penalised splines and semiparametric penalised splines with TAPS data.

estimated at each value of $A_{i,t-1}$ in order to find the smoothed value of $A_{i,t}$ (Naschold, 2005).

4.2 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.

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, KIDS 93-98, VHLSS 02-04 and VHLSS 02-04-06. When plotting the resulting coeffcients on the observed range of asset index values, there is no evidence of an S-shaped curve or of non-convexities.

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

With KHDS 91-04 panel, VHLSS 02-04 and KIDS 93-98 having an older head of household reduces the change in asset index, but the positive sign of the squared age shows that this reduction is less important when the household head grows older; when household heads turn 41.5, 51.4 and 42.4 for, respectively, KIDS 93-98, KHDS 91-04 and VHLSS02-04, their change in asset index would be null. 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; when a household head turns 55.5 years old, they will not increase their change in asset index any more.

For KHDS 91-94 and KHDS 91-04, having a more educated household head has a positive effect on the change in asset index. Household size has a positive effect on the change in asset index in all cases, meaning that having a bigger household encourages a household to accumulate more assets over time. Dependency ratio has a negative and significant effect when looking at the change in asset index for KHDS 91-94 and UNHS 92-99. This means that having more dependants in the household impedes the household to increase its holdings of asset index over time.

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

Strikingly, none of these figures shows an S-shaped curve as Carter and Barrett did. Except for KHDS 91-94 (Figure 3a), VHLSS 02-04 and VHLSS 02-06 (respectively, Figure 3e and 3f), most curves have a positive slope and cut the 45-degree line at one single point.

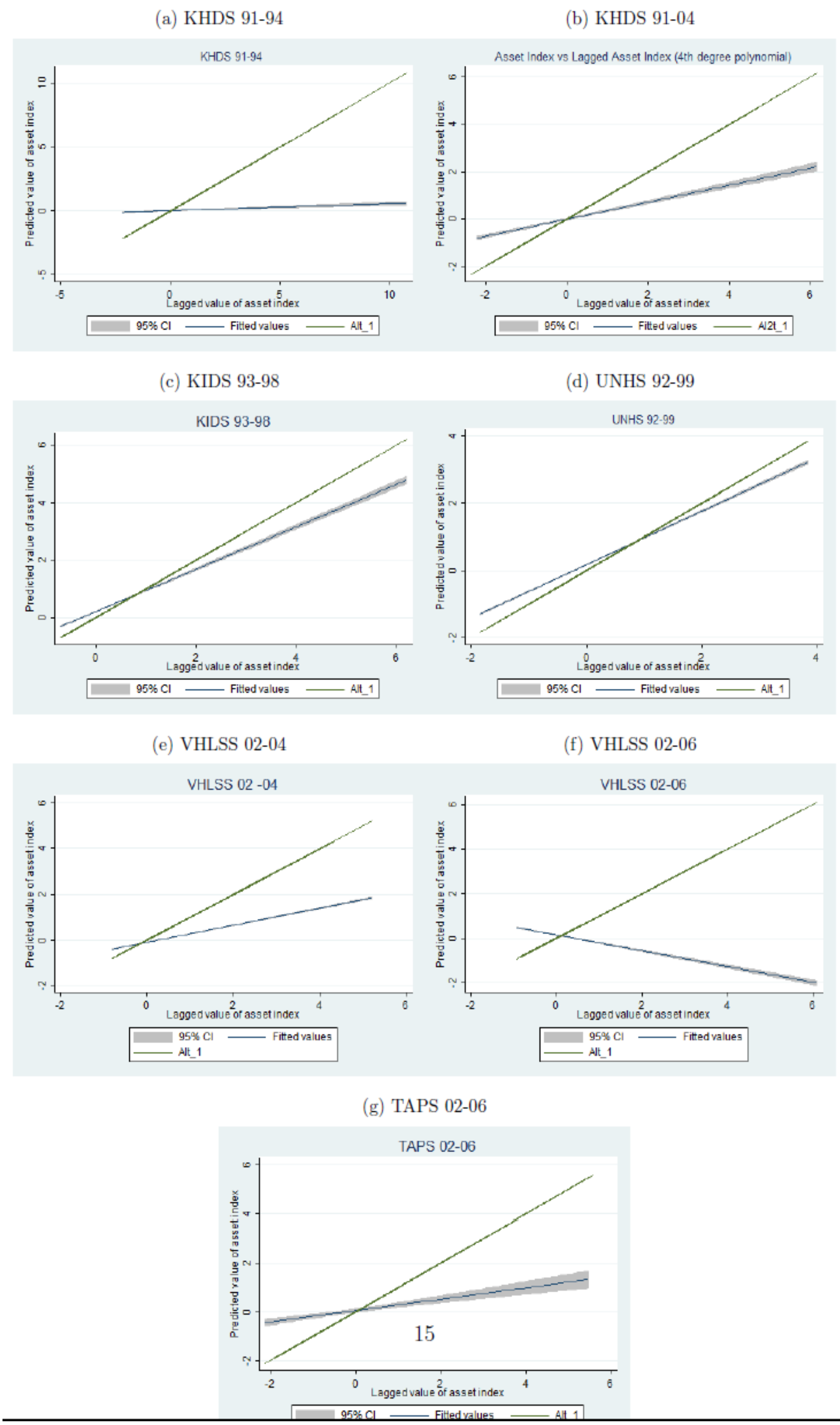
When looking at KHDS 91-94, the curve cuts the 45-degree line at 0 and seems to have a slope equal to 0. The other two aforementioned curves cut the 45-degree line below 0, have a slope equal to 0 and have really small predicted values of asset index.

Table 2: Parametric regressions: fourth degree of 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)	-0.528*** (0.0199)	-1.408*** (0.0290)	-1.071*** (0.08)
Squared lagged AI	0.0179(0.0182)	-0.00746(0.0304)	-0.266***(0.0838)	0.0473(0.0338)	0.184*** (0.0332)	-0.116*** (0.0341)	0.0528 (0.04)
Cubic lagged AI	-0.0126**(0.00555)	-0.0126(0.0187)	0.219***(0.0393)	-0.0195(0.0237)	-0.120*** (0.0226)	0.145*** (0.0256)	-0.00366 (0.02)
Fourth degree lagged AI	0.00128***(0.000391)	0.00175(0.00269)	-0.0289***(0.00462)	0.00301(0.00719)	0.0142*** (0.00373)	-0.0239*** (0.00345)	-0.00155 (0)
Age household head	-0.0122(0.0401)	-0.0250***(0.00583)	-0.0107***(0.00311)	0.0102(0.0112)	0.0101** (0.00442)	0.0217 (0.0145)	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)	-0.000119*** (4.06e-05)	-0.000249* (0.000132)	-0.000449** (0)
Household size	0.104***(0.0118)	0.131***(0.0133)	0.0430***(0.00533)	0.0669***(0.00829)	0.0413*** (0.00527)	0.0413*** (0.0126)	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)			0.0269(0.0318)	
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)	-0.637*** (0.0142)	-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)	-0.586*** (0.117)	-0.247 (0.385)	-2.902***(0.58)
Observations	2132	598	1132	1070	4092	3904	580
Number of hhid	742					1952	176
R-squared	0.666	0.539	0.174	0.122	0.487	0.850	0.6

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

Figure 3: Parametric regressions



Results from non-parametric regressions

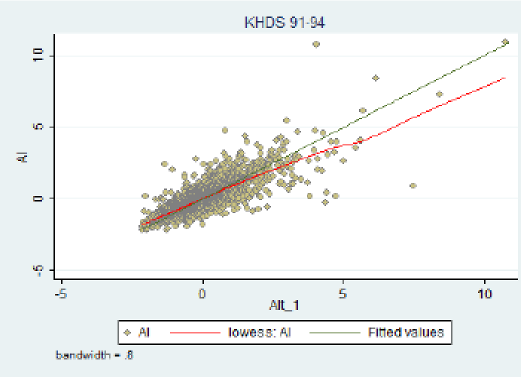
Checking these results with a non-parametric regression form, the LOWESS curves obtained for each panel dataset studied are reported below (Figures 4a to 4g). In most of these curves, a linear accumulation process seems to occur with an upward trend. When looking at KHDS 91-04 (Figure 4b), it seems that the curve has a positive slope until cutting the 45-degree line, then the slope decreases and tends to be close to 0. For KHDS 91-94 (Figure 4a), the LOWESS curve is mainly below the 45-degree line, households are not accumulating asset and there is some concentration [-2; 2].

When looking at VHLSS 02-04 (Figure 4e) and VHLSS 02-06 (Figure 4f), the curves are again cutting the 45-degree line at one single point and households do not seem to have accumulated assets over time. The curves for KIDS 93-98 and UNHS 92-99 (respectively, Figures 4c and 4d) both have 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 which 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.

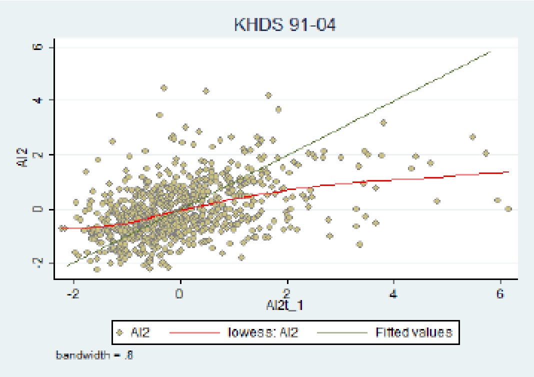
None of the parametric and non-parametric curves show an S-shape in the asset accumulation process and they do not have a Micawber threshold that would keep the household in a poverty trap. The asset accumulation processes seem linear, which is consistent with the result that only the lagged asset index 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.

Figure 4: Non-parametric regressions

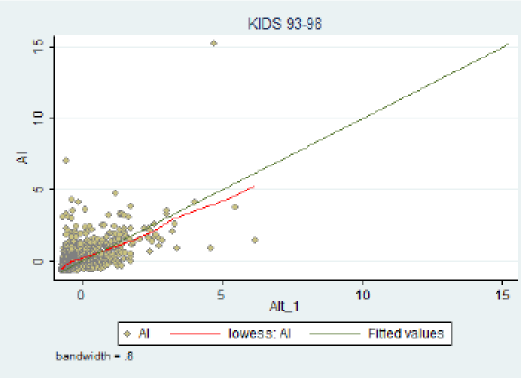
(a) KHDS 91-94



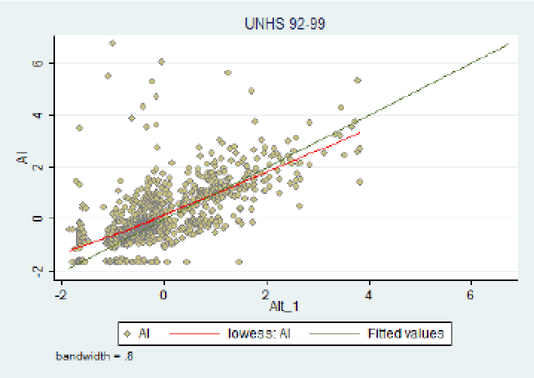
(b) KHDS 91-04



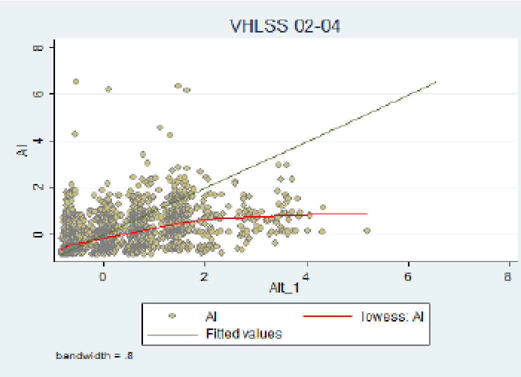
(c) KIDS 93-98



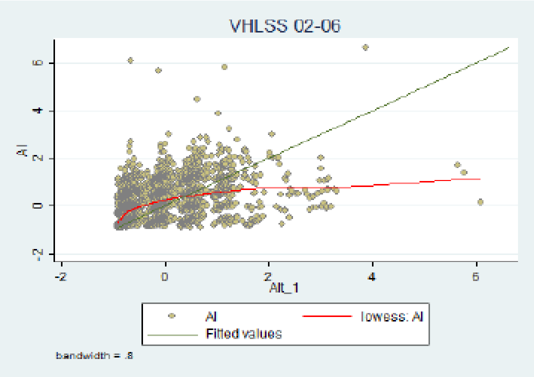
(d) UNHS 92-99



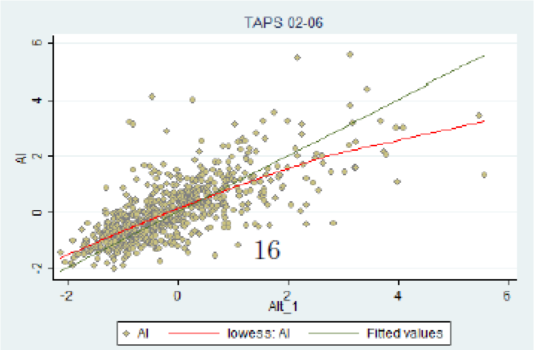
(e) VHLSS 02-04



(f) VHLSS 02-06



(g) TAPS 02-06



5 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 three cases, 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; Quisumbing 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 to recognise the challenges noted above in testing for an asset-based poverty trap and identifying an asset-based poverty trap and, in particular, in finding a non-convexity in an asset accumulation ratio, 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 of a poverty trap (though whether this is an asset-based poverty trap remains an open question).

But, by contrast, in the case of Uganda considered here, there were significant escapes from poverty over the period analysed and there were also quite significant increases in assets, taking nearly 16.5 percent 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 can 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 augmented by this paper, does not support asset-based poverty traps, does not rule out other important mechanisms trapping people in persistent poverty.

6 Appendix factor analysis

6.1 KHDS 91-94

Table 3: Factor analysis/correlation

Factor analysis/correlation — Number of obs. = 2917
Method: principal factors — Retained factors = 1
Rotation: (unrotated) — Number of params = 14

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.63864	2.01143	0.9095	0.9095
Factor2	0.62721	0.19942	0.2162	1.1257
Factor3	0.42778	0.30342	0.1474	1.2731
Factor4	0.12437	0.06774	0.0429	1.3160
Factor5	0.05662	0.02544	0.0195	1.3355
Factor6	0.03118	0.05796	0.0107	1.3463
Factor7	-0.02678	0.00965	-0.0092	1.3370
Factor8	-0.03643	0.03158	-0.0126	1.3245
Factor9	-0.06801	0.03810	-0.0234	1.3010
Factor10	-0.10611	0.04588	-0.0366	1.2645
Factor11	-0.15199	0.00569	-0.0524	1.2121
Factor12	-0.15768	0.04905	-0.0544	1.1577
Factor13	-0.20674	0.04410	-0.0713	1.0865
Factor14	-0.25083	.	-0.0865	1.0000

LR test: independent vs. saturated: chi2(91) = 6227.91 *Prob > chi2* = 0.0000

Figure 5: Screeplot of eigenvalues

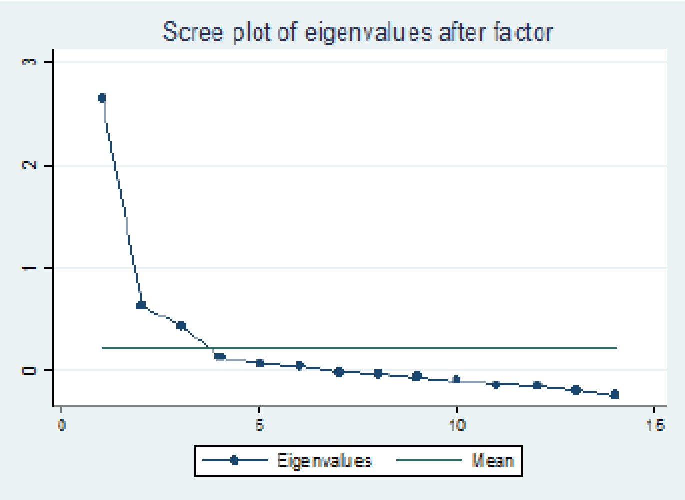


Table 4: Factor loadings

Variable	Factor1	Uniqueness
bicycle	0.3322	0.8896
sewing machine	0.2233	0.9501
hoes	0.5660	0.6796
axes	0.4981	0.7519
pangas	0.6702	0.5508
sickles	0.6348	0.5970
mundu	0.2959	0.9124
other tools	0.4395	0.8069
nb read	0.6304	0.6026
max grade	0.4151	0.8277
dummy received remittances	0.1340	0.9820
goat	0.3241	0.8949
cattle	0.2673	0.9285
shamba area (ha)	0.1136	0.9871

Table 5: Factor scores

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

6.2 KHDS 91-04

Table 6: Factor analysis/correlation

Factor analysis/correlation				Number of obs. = 2917
Method: principal factors				Retained factors = 1
Rotation: (unrotated)				Number of params = 14

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.82009	2.17158	0.9124	0.9124
Factor2	0.64851	0.27076	0.2098	1.1222
Factor3	0.37775	0.16722	0.1222	1.2445
Factor4	0.21053	0.10308	0.0681	1.3126
Factor5	0.10745	0.10613	0.0348	1.3473
Factor6	0.00132	0.02362	0.0004	1.3478
Factor7	-0.02230	0.02504	-0.0072	1.3405
Factor8	-0.04733	0.03409	-0.0153	1.3252
Factor9	-0.08142	0.04711	-0.0263	1.2989
Factor10	-0.12853	0.02517	-0.0416	1.2573
Factor11	-0.15370	0.02127	-0.0497	1.2076
Factor12	-0.17497	0.04658	-0.0566	1.1510
Factor13	-0.22155	0.02349	-0.0717	1.0793
Factor14	-0.24504	.	-0.0793	1.0000

LR test: independent vs. saturated: chi2(91) = 3064.28 $Prob > chi2 = 0.0000$

Figure 6: Screeplot of eigenvalues

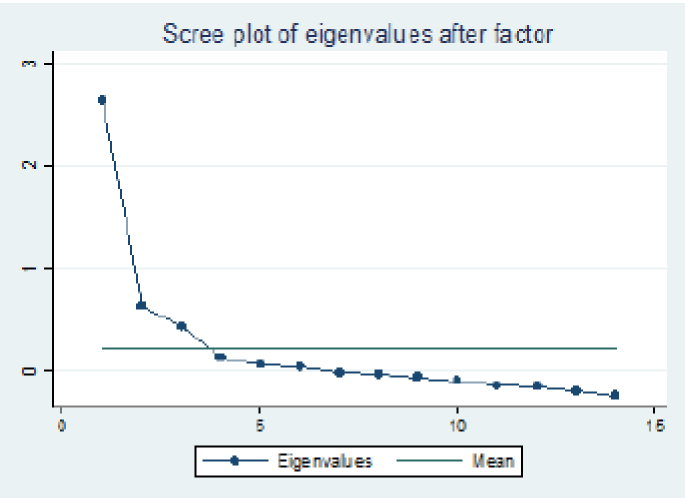


Table 7: Factor loadings

Variable	Factor1	Uniqueness
bicycle	0.4510	0.7966
sewing machine	0.3317	0.8900
hoes	0.4662	0.7826
axes	0.4790	0.7706
pangas	0.6368	0.5945
sickles	0.5945	0.6466
mundu	0.3252	0.8942
other tools	0.3695	0.8634
nb read	0.5985	0.6418
max grade	0.3515	0.8765
dummy received remittances	0.0982	0.9904
goat	0.3278	0.8925
cattle	0.3847	0.8520
shamba area (ha)	0.5584	0.6882

Table 8: Factor scores

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

6.3 KIDS 93-98

Table 9: Factor analysis/correlation

Factor analysis/correlation — Number of obs. = 2264
Method: principal factors — Retained factors = 1
Rotation: (unrotated) — Number of params = 11

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.78800	1.36744	0.9452	0.9452
Factor2	0.42057	0.14325	0.2223	1.1676
Factor3	0.27732	0.14139	0.1466	1.3142
Factor4	0.13593	0.09193	0.0719	1.3861
Factor5	0.04399	0.02703	0.0233	1.4093
Factor6	0.01697	0.02101	0.0090	1.4183
Factor7	-0.00404	0.07933	-0.0021	1.4161
Factor8	-0.08337	0.09292	-0.0441	1.3721
Factor9	-0.17629	0.05592	-0.0932	1.2789
Factor10	-0.23221	0.06309	-0.1228	1.1561
Factor11	-0.29530	.	-0.1561	1.0000

LR test: independent vs. saturated: chi2(55) = 2851.57 *Prob > chi2* = 0.0000

Figure 7: Screeplot of eigenvalues

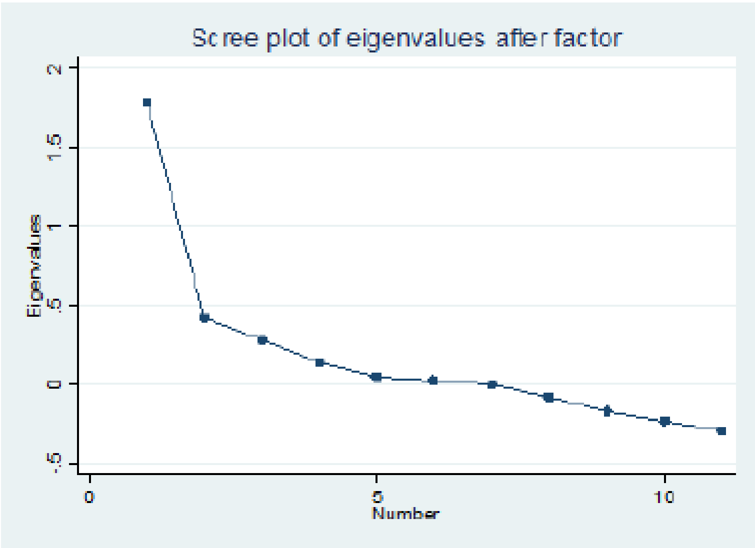


Table 10: Factor loadings

Variable	Factor1	Uniqueness
educated labour	0.0426	0.9982
non-educated labour	0.4568	0.7913
cattle	0.7011	0.5084
sheep	0.1997	0.9601
goats	0.6108	0.6269
pigs	0.1588	0.9748
poultry	0.5400	0.7084
plot size	0.0710	0.9950
farm equipment dummy	0.2985	0.9109
farm tool dummy	0.4691	0.7800
transfer	0.2048	0.9580

Table 11: Factor scores

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

6.4 UNHS 92-99

Table 12: Factor analysis/ correlation

Factor analysis/correlation — Number of obs. = 2147
Method: principal factors — Retained factors = 1
Rotation: (unrotated) — Number of params = 8

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.12867	1.35843	0.8511	0.8511
Factor2	0.77024	0.58388	0.3080	1.1591
Factor3	0.18636	0.17800	0.0745	1.2336
Factor4	0.00836	0.08686	0.0033	1.2370
Factor5	-0.07850	0.03419	-0.0314	1.2056
Factor6	-0.11270	0.04135	-0.0451	1.1605
Factor7	-0.15405	0.09338	-0.0616	1.0989
Factor8	-0.24743	.	-0.0989	1.0000

LR test: independent vs. saturated: chi2(28) = 4534.47 $Prob > chi2 = 0.0000$

Table 13: Factor loadings

Variable	Factor1	Uniqueness
education head	0.7991	0.3615
mean education	0.7984	0.3625
max education	0.8840	0.2185
land	0.0549	0.9970
cow	0.0878	0.9923
bike	0.2051	0.9579
other equipment	0.0679	0.9954
media equipment	0.1175	0.9862

Figure 8: Screeplot of eigenvalues

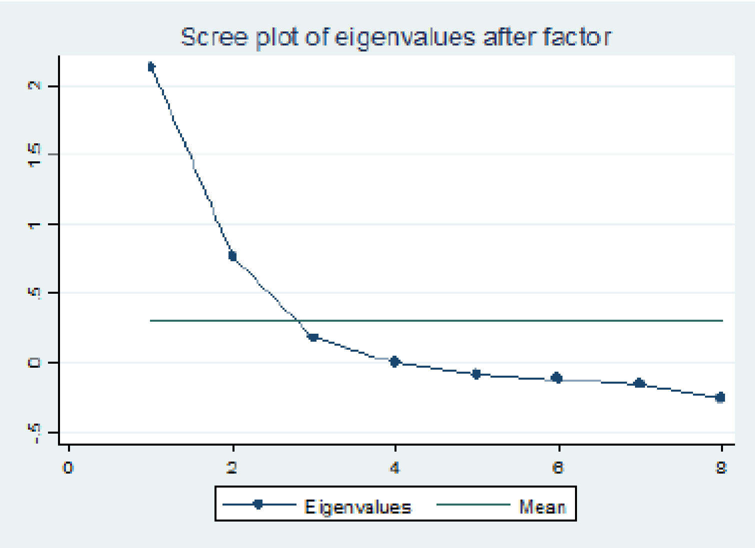


Table 14: Factor scores:

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

6.5 VHLSS 02-04

Table 15: Factor analysis/ correlation

Factor analysis/correlation — Number of obs. = 8184
Method: principal factors — Retained factors = 1
Rotation: (unrotated) — Number of params = 11

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.36004	1.10240	1.2317	1.2317
Factor2	0.25764	0.18170	0.2333	1.4650
Factor3	0.07594	0.03574	0.0688	1.5338
Factor4	0.04020	0.04346	0.0364	1.5702
Factor5	-0.00326	0.01877	-0.0029	1.5672
Factor6	-0.02202	0.01198	-0.0199	1.5473
Factor7	-0.03400	0.01447	-0.0308	1.5165
Factor8	-0.04847	0.08294	-0.0439	1.4726
Factor9	-0.13141	0.05872	-0.1190	1.3536
Factor10	-0.19013	0.01019	-0.1722	1.1814
Factor11	-0.20032	.	-0.1814	1.0000

LR test: independent vs. saturated: chi2(55) = 5912.00 *Prob > chi2* = 0.0000

Figure 9: Screeplot of eigenvalues

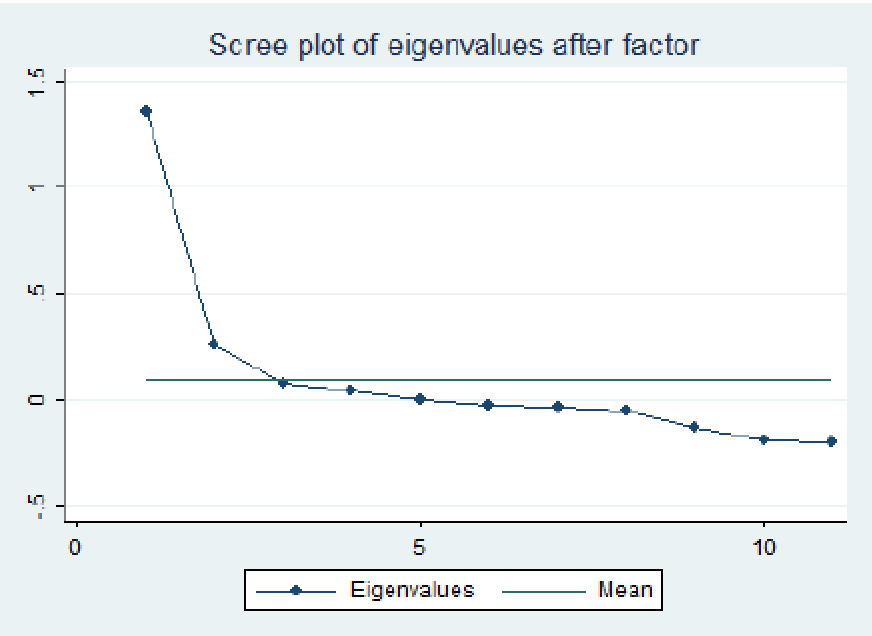


Table 16: Factor loadings

Variable	Factor1	Uniqueness
number literate members	0.1505	0.9774
rice machine	0.0119	0.9999
car	0.0747	0.9944
trailer	0.0024	1.0000
plough	0.0004	1.0000
motorbike	0.3591	0.8710
bicycle	0.2004	0.9598
sewing machine	0.2231	0.9502
television	0.6457	0.5831
gas cooker	0.5374	0.7112
electric cooker	0.6380	0.5930

Table 17: Factor scores

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

6.6 VHLSS 02-04-06

Table 18: Factor analysis/ correlation

Factor analysis/correlation Number of obs = 5856
Method: principal factors Retained factors = 1
Rotation: (unrotated) Number of params = 13

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.34742	1.12202	1.2348	1.2348
Factor2	0.22540	0.12279	0.2066	1.4413
Factor3	0.10261	0.07214	0.0940	1.5353
Factor4	0.03047	0.00557	0.0279	1.5633
Factor5	0.02491	0.01500	0.0228	1.5861
Factor6	0.00991	0.01762	0.0091	1.5952
Factor7	-0.00771	0.00365	-0.0071	1.5881
Factor8	0.01136	0.01238	-0.0104	1.5777
Factor9	-0.02375	0.04147	-0.0218	1.5559
Factor10	-0.06522	0.08888	-0.0598	1.4962
Factor11	-0.15410	0.03667	-0.1412	1.3549
Factor12	-0.19078	0.00578	-0.1748	1.1801
Factor13	-0.19655	.	-0.1801	1.0000

LR test: independent vs. saturated: chi2(78) = 4168.69 Prob>chi2 = 0.0000

Figure 10: Screeplot of eigenvalues

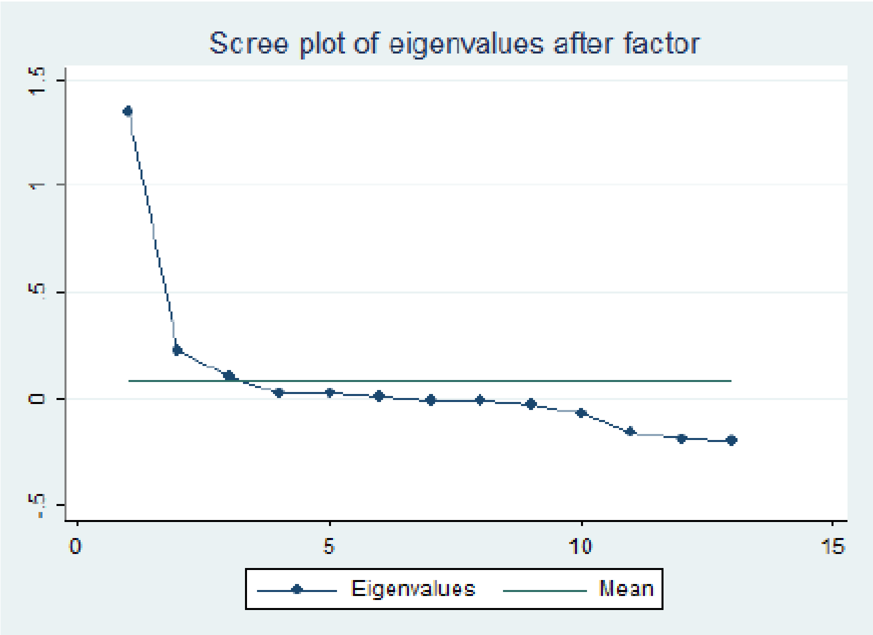


Table 19: Factor loadings

Variable	Factor1	Uniqueness
number literate members	0.1552	0.9759
agricultural land	0.0762	0.9942
buffaloes	0.0409	0.9983
car	0.0798	0.9936
trailer	0.0201	0.9996
plough	0.020	0.9996
motorbike	0.3752	0.8593
bicycle	0.1484	0.9780
sawing machine	0.0278	0.9992
sewing machine	0.1621	0.9737
television	0.6350	0.5967
gas cooker	0.5575	0.6892
electric cooker	0.6362	0.5952

Table 20: Factor scores

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

6.7 TAPS 02-04-04-05-06

Table 21: Factor analysis/correlation

Factor analysis/correlation — Number of obs. = 870
Method: principal factors — Retained factors = 1
Rotation: (unrotated) — Number of params = 17

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.71410	2.70345	0.7959	0.7959
Factor2	1.01066	0.47873	0.2166	1.0125
Factor3	0.53193	0.22753	0.1140	1.1265
Factor4	0.30440	0.06685	0.0652	1.1917
Factor5	0.23755	0.11913	0.0509	1.2426
Factor6	0.11842	0.07890	0.0254	1.2680
Factor7	0.03952	0.03596	0.0085	1.2765
Factor8	0.00357	0.02701	0.0008	1.2772
Factor9	-0.02344	0.02751	-0.0050	1.2722
Factor10	-0.05095	0.02502	-0.0109	1.2613
Factor11	-0.07597	0.02074	-0.0163	1.2450
Factor12	-0.09671	0.04845	-0.0207	1.2243
Factor13	-0.14516	0.05694	-0.0311	1.1932
Factor14	-0.20210	0.00992	-0.0433	1.1499
Factor15	-0.21201	0.02055	-0.0454	1.1044
Factor16	-0.23256	0.02228	-0.0498	1.0546
Factor17	-0.25484	.	-0.0546	1.0000

LR test: independent vs. saturated: chi2(136) = 3246.72 $Prob > chi2 = 0.0000$

Table 22: Factor loadings

Variable	Factor1	Uniqueness
axe	0.5847	0.6581
bike	0.3118	0.9028
bow	0.5488	0.6988
canoe	0.3286	0.8920
cow	0.2032	0.9587
hook	0.6264	0.6076
knife	0.6825	0.5342
machete	0.7359	0.4584
mosquito net	0.7432	0.4477
net	0.4197	0.8238
radio	0.4404	0.8061
rifle	0.2467	0.9392
shot gun	0.3764	0.8583
size plot	0.4562	0.7919
gift	0.1662	0.9724
nb speak Spanish	0.2399	0.9424
dummy math	0.0810	0.9934

Figure 11: Screeplot of eigenvalues

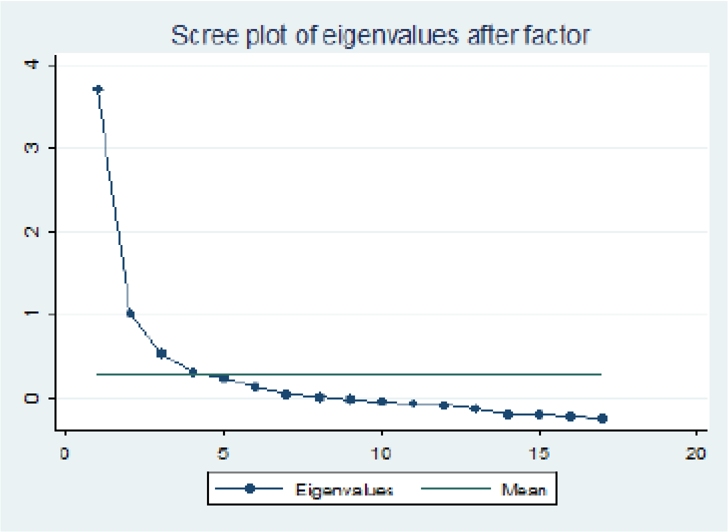


Table 23: Factor scores

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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