Modelling sequencing patterns in asset acquisition: the case of smallholder farmers in three rural districts of Uganda

Elbers, C.; Pouw, N.

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Modelling Sequencing Patterns in Asset Acquisition.
The case of smallholder farmer in three rural districts in Uganda

by

Chris Elbers (VU University Amsterdam), celbers@feweb.vu.nl

Nicky Pouw (University of Amsterdam), n.r.m.pouw@uva.nl

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Abstract
Poor smallholder farmers in Uganda live at or below subsistence level. They are vulnerable to multiple risks and insecurities and have limited access to capital markets and insurance. Their asset base is a reflection of the economic conditions of the farming households. In this article we propose a model to estimate household and individual sequencing patterns in asset acquisition among rural smallholder farmers in Uganda using only cross-section data. The principal assumption underlying the model is that people tend to accumulate assets in a particular dominant order, which could arise from a combination of indivisibilities and missing capital markets. The model is applied to a field-survey dataset consisting of 938 farm households from three districts in Uganda. The assets included are simple count data of household durables, clothing and agricultural tools. The model predicts the distribution of asset ownership, conditional on the number of assets owned. The estimated model predicts highly concentrated conditional distributions, consistent with the assumption of sequencing patterns of asset acquisition. Based on the sequencing patterns the paper proposes a low-cost poverty monitoring instrument using only asset count data.

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1 Introduction

Living standards cannot be separated from livelihoods. People who share the same livelihood are likely to face comparable circumstances (opportunities and constraints) in constructing their livelihoods and, as a result, they can be expected to make close to similar decisions with regard to the accumulation of welfare attributes. *Welfare attributes* are defined as the resources and services that people use to secure and advance their livelihoods (Pouw 2008).[1] They may include physical assets and natural resources, schooling, public transport, housing, good health, food, etc. If a process of accumulation is embarked upon, this can be taken as a sign of households becoming less vulnerable or growing out of poverty. The outcome of accumulation decisions is reflected in people's living standards, and depends on people's individual capabilities, assets, access facilities and services and terms of trade.

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[1] The present article draws upon Pouw (2008) 'The Characterization and Monitoring of Poverty in Rural Uganda'. The approach set forth in this study centers around the three inter-related notions of poverty, vulnerability and destitution.

Consumer budgets of poor households are constrained by lack of (regular) income so that many goods are simply unaffordable to the poor: even at zero consumption levels, marginal utility per monetary unit of these goods is lower than that of the basic necessities a household consumes. Another reason why such corners solutions arise is the indivisibility of consumer durables (e.g. Deaton and Muellbauer 1980). As a result, the solution of the preference model is not necessarily an interior solution, but mixed. If people are destitute, they might consume only the most basic commodities, including food. Moreover, provided no goods are inferior within a given set, the number of different goods consumed will increase as total expenditure increases. The same would be true for welfare attributes: for a given household and a given set of welfare attributes, one would then expect to find a monotonic relationship between the number of attributes owned (or consumed) and per capita expenditure.

The purpose of this article is to estimate a model that predicts sequencing patterns in individual and household acquisition of assets. The model is applied to a sample population including 938 smallholder farmer households in three rural districts in Uganda, namely Kapchorwa, Kabarole and Mpigi district.[2] In terms of economic theory, the order of accumulation indicates the relative additional utility of e.g. household durable goods, given that households seek to maximize their current utility. A dominant pattern across households then suggests that households have similar utility functions. An econometric model will be estimated to predict underlying sequencing pattern within sub-sets of welfare attributes, including household durables, clothing items and agricultural tools. Since the data are a cross-section, any sequencing pattern must be estimated from its impact on the observed distribution of welfare attributes. The main *caveat* for interpreting our results is therefore that there might be other dynamic processes than sequencing patterns that lead to the same distribution of attributes (although we can think of no plausible ones).

If a dominant sequencing pattern can be established within each of the attribute sets and we proceed by the assumption of stable preferences, this would imply that households/individuals can be ranked according to the *number* of different attributes possessed. This would provide us with a short-cut to a welfare ranking and poverty monitoring instrument collecting simple count data in situations where it may be too time-consuming and costly to collect full consumption expenditure data.

[2] The district and sample selection procedures are described in detail in Pouw (2008: Chapter 2).

2 The Sequencing Problem

We observe households *h,* in particular a subset $A_h \subset \Omega$ of attributes owned by the household, where $\Omega = \{1,\ldots,N\}$ denotes the set of all possible attributes. We speculate that the attributes in A_h have been acquired over a period of time following a particular sequence and that the sequencing is similar for different subjects. Hence, two households or individuals with the same *number* of attributes also tend to have the same *type* of attributes. The problem is to reconstruct an underlying 'dominant' sequence order from the data on A_h. This problem is similar to problems of sequencing studied in marketing analysis and data mining. Priority patterns – i.e. certain regularities in the order of accumulation, have been studied empirically by Pyatt (1964), Paroush (1965), McFall (1969), Hebden and Pickering (1974), Kasulis et al. (1978), Kasulis (1979), Clarke and Soutar (1982) with regard to durable goods and financial products. See Dickson et al. (1983) for a good overview of the early works. More recent studies include Mayo and Qualls (1987), Kamakura *et al.* (1991), Knott *et al.* (2002) and Prinzie and Van den Poel (2003), amongst others. These studies have a practical relevance to forecast consumer demand for marketing purposes, as well as theoretical relevance by shedding shed light on the economic theory of consumer demand. Studies on priority patterns are either more descriptive (sequences description) or predictive in nature (use of models). In the case of cross-section data being used, Guttman scales or information on household purchase intentions have been used to assess priority patterns. In the case of time series data, different types of models[3] have been used to predict sequential acquisition - see also Prinzie and Van den Poel (2003). In these models, present ownership (or state of affairs) is often included as a variable to predict future acquisition.

In more recent poverty research, we find that the topic of asset accumulation is gaining more attention. Assets make poor households less vulnerable to risks and shocks. Briefly speaking there are two strands of literature in this field. Firstly, studies with a focus on assets and the development of asset indices to complement income and consumption-based measures of welfare (e.g. Adams 1996, Moser 2008, Moser and Felton 2008). Secondly, studies on sustainable livelihoods to determine in which of the five capital dimensions households make progress over time by building-up assets. Much of this work is on-going research at the time of writing-up this article (e.g. Valdivia *et al.* 2008). However, none of these studies on asset accumulation in a poverty context have gone as far as developing a formal model to predict sequencing patterns in asset accumulation.

[4] For example, Markov-type models and the New-Product-To-Buy (NPTB) models.

The study underlying this article was carried out in a widespread poverty context and made use of a single cross section of A_h observations. Discrete choice analysis is particularly important in the case of cross section studies (Deaton and Muellbauer 1980: 346), but can also be useful in the case of (very) poor households with short time-horizons. At an increase of income, poor households can be expected to demand more of all durable goods, rather than less. Basically, what is considered is the decision between ownership and non-ownership of particular attributes (or between consumption and non-consumption in the case of food), which is a discrete choice. Each time a household acquires another durable, it passes certain 'threshold expenditure', representing a certain level of income. At lower income levels, non-ownership is preferred (see also Deaton and Muellbauer 1980: 367). The usefulness of such information in poverty studies is that the presence (or absence) of certain attributes in the household can be taken as a proxy of economic conditions (in the recent past).

3 Data and Model Description

In this section we develop a simple statistical model for analyzing sequencing patterns with a sub-set of the collected cross section data in this study. Out of the seven sets of welfare attributes considered in Pouw (2008), three ranked highest in a principal component analysis.. These are included in the current study: household durables (20 items), clothing and personal items (5 items) and agricultural tools (16 items). The model is estimated for each district separately.[4] The total sample size is 938 households, distributed over Kapchorwa (n=298), Kabarole (n=300) and Mpigi (n=340) district.

We model the household's sequencing decision as a latent variable model. For every household there is a vector of unobserved random variables $(x_1^h,...x_N^h)$, which determines the sequence of acquiring attributes according to the following rule:

Subject *h* acquires attribute *i* before attribute *j* if and only if $x_i > x_j$.[5]

Thus observing A_h reveals that all attributes i in A_h have higher associated x_i^h than attributes not in A_h. By specifying a parametric probability distribution for the latent variables

[4] Pouw (2008, Chapter 3) proposes a simpler two-by-two ranking and testing procedure to establish sequencing patterns, using the McNemar test.

[5] This is a purely descriptive model. If a link with consumer theory is made, the x_i would reflect both the subject's preferences and prices. Thus, these should be constant over the period of acquiring the attributes.

$(x_1^h,\ldots x_N^h)$ we can make inferences on the parameters on the basis of the A_h data and study further model properties. A simple model for the latent variables that leads to an analytical likelihood function is to assume that all x_i^h are independent random variables with an exponential distribution:

$$x_i^h \sim \text{exponential}\,(\lambda_i)$$

Note that the parameter λ_i can alter between attributes, but for a given attribute is the same for different households.[6] From now on we will drop the subject index h if there is no danger of confusion. The assumption that the x_i^h are independent significantly reduces the scope for 'conditional sequencing'. For instance, if x_j and x_k have the same distribution (i.e. the same λ) the presence of i in an attribute set A of size 2 has equal probability regardless of whether the other attribute is j or k. Relationships of the type "presence of j in the attribute set precludes presence of i" would require statistical dependency among the latent variables and therefore cannot be represented in the current model. The probability of observing A rather than another attribute set with the same number of attributes is

$$P(A) = P\left\{\min_{i\in A} x_i > \max_{j\notin A} x_j\right\}.$$

For $t > 0$ write $G_A(t) = P\{\min_{i\in A} x_i \le t\}$, then

$$1 - G_A(t) = P\left\{\min_{i\in A} x_i > t\right\} = \prod_{i\in A} e^{-t\lambda_i} = e^{-t\sum\lambda_i}.$$

In other words, $\min_{i\in A} x_i$ is itself exponentially distributed with parameter $\sum_{i\in A}\lambda_i$ and 1-$G_A(t)$ is the probability of owning a different set A, given that the attribute set owned has the same number of elements Similarly, let $F_A(t)$ denote

$$P\left\{\max_{j\notin A} x_j \le t\right\} = \prod_{j\notin A}(1 - e^{t\lambda_j})$$

[5] This assumption can be relaxed by letting the parameters depend on household characteristics.

with density function $f_A(t) = F'_A(t)$. Then we find

$$P(A) = P\left\{\min_{i\in A} x_i > \max_{j\notin A} x_j\right\}$$

$$= \int_0^\infty P\left\{\min_{i\in A} x_i > t \mid \max_{j\notin A} x_j = t\right\} f_A(t)dt$$

$$= \int_0^\infty (1 - G_A(t)) f_A(t) dt . \qquad (1)$$

The above integral turns out to be analytically solvable. Let $\Omega \setminus A = \{j_1,\ldots,j_s\}$ be the complement of A, and $\mu = \sum_{i\in A} \lambda_i$, then a formula for $P(A)$ is[7]

$$P(A) = \sum_{\delta_{j1}=0}^{1} \cdots \sum_{\delta_{js}=0}^{1} \frac{\sum_{k=1}^{s} \delta_{j_k} \lambda_{j_k}}{\mu + \sum_{k=1}^{s} \delta_{j_k} \lambda_{j_k}} (-1)^{1+\sum_{k=1}^{s} \delta_{jk}} . \qquad (2)$$

Note that all sums in this expression are ratios of sums of the exponential $\lambda_i s$ so that the same value for $P(A)$ results if all $\lambda_i s$ are multiplied by a positive constant. Accordingly, normalize the λ_i by putting $\lambda_1 = 1$.

It is instructive to work out some simple cases of formula (1). Take first the case where only one attribute is missing in the household h, say attribute 2. Then $s = 1$ in formula (2) and $A = \{1,3,\ldots,N\}$, so that

$$P(A) = \frac{\lambda_2}{\lambda_2 + \mu} = \frac{\lambda_2}{\sum_{i=1}^{N} \lambda_i}$$

[7] A different distribution than the exponential distribution could be chosen for the latent variables, but for arbitrary distributions the analogue of equation (1) will not lead to an analytic expression for P(A). This is not as bad as it looks: for large (potential) attribute sets evaluating the sum in equation (2) takes more time than evaluating the integral in equation (1).

the last expression following from the definition of $\mu = \sum_{i \in A} \lambda_i$. This case shows that the higher is λ_2, the higher is the possibility that a household does not have attribute 2. Next, turn to the case of two attributes not in the household, say attributes 1 and 2. This means that in the first draw λ_1 is not selected (out of attributes 1 and 2), and that in the second draw λ_2 is not selected, or *vice versa*.

$$P(A) = \frac{\lambda_1}{\lambda_1 + \mu} + \frac{\lambda_2}{\lambda_2 + \mu} - \frac{\lambda_1 + \lambda_2}{\lambda_1 + \lambda_2 + \mu}.$$

The expression is found to be equal to

$$P(A) = \frac{\lambda_1}{(\lambda_1 + \mu)} \frac{\lambda_2}{(\lambda_1 + \lambda_2 + \mu)} + \frac{\lambda_2}{(\lambda_2 + \mu)} \frac{\lambda_1}{(\lambda_1 + \lambda_2 + \mu)}.$$

Using equation (2) (or equation 1) the likelihood of the observed sets of attributes A_h (given their sizes) can be determined and maximized with respect to parameters λ. The results are discussed in the next section.

4. Presentation and Discussion of the Results

The model parameters are first estimated for the twenty household durables owned by the households in Kapchorwa, Kabarole and Mpigi district. The results for each district are presented in Tables 1-3 below.

Table 1- Kapchorwa: Lambda and ML Estimations for 20 Household Durables

Household durable	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Chairs	1.000	-
Saucepan	1.416	0.649
Beddings	2.668	7.584**
Table	5.033	6.113*
Bed	7.237	2.893
Mat	13.39	29.02***
Pots for cooking and storage	50.33	112.59***
Radio	86.12	23.24***
Hurricane lamp	123.6	10.91***
Flat Iron	176.7	10.53**
Grinding mill/stone	150.5	2.90
Charcoal/paraffin stove	186.9	0.446
Sofa set	475.0	60.64***
Bicycle	505.2	0.260
Sewing machine	883.0	13.41**
Motorcycle	845.0	0.062
Car	1331.3	n.a.
Gas stove	1896.9	n.a.
Television	2448.0	n.a.

Note: For further explanation of the likelihood ratio test, see text. The Chi-square test could not be performed for the items Car, Gas stove, and Television because of too few observations ($n \leq 5$). ***Significant at $p<0.001$; **significant at $p<0.01$; *significant at $p<0.05$.
Source: own calculations, based on Kapchorwa field-survey (2000).

The value 1 at the top of each list is a normalisation. The items are sorted according to decreasing frequency in the data, which (almost always) corresponds to increasing lambda's. A hand mill/grinding stone is an exception to this rule in Kapchorwa and Mpigi – a finding that was also noted in an alternative procedure developed in Pouw (2008). The hierarchy in the durables is clearly visible from the levels in the lambda's. Households acquire beddings, saucepan, chairs, etc. first and much later a lamp, pots for cooking, stove and electric appliances.

Table 2- Kabarole: Lambda and ML Estimations for 20 Household Durables

Household durable	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Saucepan	1.000	-
Beddings	1.422	1.084
Bed	5.250	27.57***
Chairs	8.005	3.635
Mat	14.61	29.32***
Table	21.26	5.361*
Hand mill or grinding stone	23.88	0.429
Hurricane lamp	48.28	43.14***
Radio	55.08	1.069
Bicycle	83.85	23.25***
Flat Iron	96.18	1.538
Pots for cooking and storage	101.4	0.854
Charcoal or paraffin stove	249.4	91.62***
Sofa set	336.8	4.894*
Sewing machine	895.8	41.13***
Motorcycle	1173.4	0.870
Car	2081.5	n.a.
Refrigerator	3873.3	n.a.
Television	4650.2	n.a.
Gas stove	4180.5	n.a.

Note: For further explanation of the likelihood ratio test, see text. The Chi-square test could not be performed for the items Car, Refrigerator, Television Gas stove because of too few observations ($n \leq 5$). ***Significant at $p<0.001$; **significant at $p<0.01$; *significant at $p<0.05$.
Source: own calculations, based on Kabarole field-survey (2000)

Table 3 - Mpigi: Lambda and ML Estimations for 20 Household Durables

Household durable	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Saucepan	1.000	-
Mat	1.646	3.572
Beddings	1.805	4.793*
Bed	3.356	9.188**
Radio	10.89	75.17***
Table	15.40	9.788**
Flat iron	18.13	2.490
Chairs	16.66	0.380
Charcoal or paraffin stove	22.23	11.45***
Bicycle	24.01	0.265
Hurricane lamp	26.98	2.694
Pots for cooking or storage	32.13	11.51***
Sofa set	122.7	166.6
Hand mill or grinding stone	112.1	0.175
Motorcycle	201.3	21.92***
Television	229.3	0.419
Sewing machine	272.2	3.320
Car	384.6	13.58***
Refrigerator	476.9	n.a.
Gas stove	3451.3	n.a.

Note: For further explanation of the likelihood ratio test, see text. The Chi-square test could not be performed for the items Refrigerator and Gas stove because of too few observations (n ≤ 5). ***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Mpigi field-survey (2000).

We test the exponential model in two subsequent steps. First, the estimated lambda parameters are tested for their difference by using the likelihood ratio test. Secondly, a Chi-square goodness of fit test is carried out to test the overall predictive capacity of the model.

First, the Likelihood Ratio test is used to assess the significance of difference between two subsequently ranked lambda's in the model. The Likelihood Ratio test compares two alternative nested models – one with and one without restrictions imposed (see e.g. Verbeek

2000: 162). Take the general problem of maximizing a log likelihood function with respect to a *K*-dimensional parameter vector $\theta = (\theta_1, ...\theta_A)$ is

$$\max_{\theta} \log L(\theta) = \max_{\theta} \sum_{i=1}^{N} \log L_i(\theta).$$

A linear restriction on the model can be formulated as $H_0 : R\theta = q$, for some fixed *J*-dimensional vector *q*, where *R* is a *J x K* matrix. The model is now estimated twice: once with the unrestricted maximum likelihood (ML) estimator $\hat{\theta}$ and once with the constrained maximum likelihood estimator $\tilde{\theta}$. The *likelihood ratio* statistic is then computed as

$$\xi_{LR} = 2[\log L(\hat{\theta}) - \log L(\tilde{\theta})],$$

which has a Chi-squared distribution with *J* degrees of freedom under the null hypothesis. If the difference between the restricted and unrestricted version of the model is small (compared to the critical value of Chi-square given the degrees of freedom), the null hypothesis (the restrictions) are not rejected by the data.

The test results are also summarized in Tables 1-3 above. Given that we compare a maximized function subject to a restriction to an unrestricted function, it follows that $\log L(\hat{\theta}) - \log L(\tilde{\theta}) \geq 0$. The procedure followed is that the estimated lamda's with the restriction imposed that lamda 1 and lamda 2 are equal. The resulting likelihood ratio is then compared with the unrestricted likeihood ratio, etc., with the degrees of freedom equal to 1. The likelihood ratio statistic is listed in the third column and significant results are flagged.

Through this procedure, we find that 10 levels can be distinguished in the list of twenty household durables in Kapchorwa, 9 levels in Kabarole and 10 in Mpigi district. Comparing these results with the more pragmatic two-by-two statistical test procedure developed in Pouw (2008: Chapter 3), one additional level is distinguished in the hierarchies of each of the districts, namely between Beddings and Chairs, Saucepan in Kapchorwa, between Mat and Table in Kabarole and between Mat and Beddings in Mpigi district. This indicates that the exponential model is slightly more sensitive in picking up differences between the estimated $\lambda_i s$.

The same procedure is followed for estimating the parameters and test statistics for the attributes category 'clothing and personal items' in each of the three districts. The results are presented in Tables 4-6 below. The items are sorted according to decreasing frequency in the data, which again leads to increasing lambda values. It is found that in Kapchorwa and Mpigi all lambda's are significantly different leading to 5 different levels in the ranking, and in Kabarole no significant difference is found between slippers and shoes, leading to four distinct levels in the ranking. The number of levels found through the Chi-square test procedure is the same as in the hierarchies presented in Pouw (2008) in the cases of Kabarole and Mpigi district. In the case of Kapchorwa district one additional level is found on the basis of the exponential model, namely between a Pair of Shoes and Slippers.

Table 4 - Kapchorwa: Lambda and ML Estimations for 5 Clothing and Personal Items

Item	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Second set of clothing	1.000	-
Pair of shoes	3.224	24.26***
Slippers	4.979	4.861*
Coat	17.93	59.77***
Wrist watch	62.12	53.97***

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Kapchorwa field-survey (2000).

Table 5- Kabarole: Lambda and ML Estimations for 5 Clothing and Personal Items

Item	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Second set of clothing	1.000	-
Slippers	3.225	34.27***
Pair of shoes	3.805	0.755
Coat	8.877	35.48***
Wrist watch	54.75	109.8***

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Kabarole field-survey (2000).

Table 6 - Mpigi: Lambda and ML Estimations for 5 Clothing and Personal Items

Item	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Second set of clothing	1.000	-
Pair of shoes	7.649	41.73***
Slippers	17.73	11.92***
Coat	172.4	149.2***
Wrist watch	574.7	43.20***

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Mpigi field-survey (2000).

Table 7- Kapchorwa: Lambda and ML Estimations for 16 Agricultural Tools

Tool	**Lambda (λ)**	**Likelihood ratio(ξ_{LR})**
Knife	1.000	-
Hand hoe	0.704	(11.01)***
Panga	5.432	18.29***
Ax	9.434	9.758**
Ox plough	37.48	199.6***
Gathering basket	41.51	0.704
Tuchanet (banana leave cutter)	48.08	6.259*
Sickle	60.10	5.009*
Slasher	68.51	0.748
Spade	109.6	21.95***
Rake	134.6	1.796
Digging stick	178.2	11.15***
Hunting or fishing net	171.5	0.216
Pull cart	189.7	0.042
Wheel barrow	214.4	1.323
Tractor	243.1	2.558

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Kapchorwa field-survey (2000).

Table 8- Kabarole: Lambda and ML Estimations for 11 Agricultural Tools

Tool	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Hand hoe	1.000	-
Panga	1.127	1.955
Knife	5.085	48.03***
Ax	10.45	26.12***
Slasher	25.31	63.65***
Spade	45.44	7.12**
Wheel barrow	174.11	95.82***
Rake	244.77	4.60*
Digging stick	500.57	11.47***
Tractor	673.4	1.512
Hunting or fishing net	1003.1	5.204*

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Kabarole field-survey (2000).

Table 9- Mpigi: Lambda and ML Estimations for 14 Agricultural Tools

Tool	**Lambda (λ)**	**Likelihood ratio (ξ_{LR})**
Hand hoe	1.000	-
Panga	0.603	(25.70)***
Knife	2.050	30.62***
Ax	2.423	1.809
Slasher	9.874	182.3***
Spade	18.55	29.86***
Wheel barrow	37.20	31.80***
Tractor	110.1	51.80***
Gathering basket	107.9	0.046
Digging stick	146.0	2.424
Hunting or fishing net	142.5	1.662
Rake	168.8	3.881*
Pull cart	383.1	6.281*
Ox plough	313.6	0.372

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Mpigi field-survey (2000)

Finally, we apply the same estimation procedure to the attributes category ‘agricultural tools’. The results are presented in Tables 7-9. The items are sorted according to decreasing frequency in the data, which again leads to increasing lambda values. On the basis of the Chi-square test results, eight levels can be distinguished in the ranked tools in each of the three districts, despite the fact that the sets are differently composed (note that not all of the 16 tools in Kapchorwa were found to be used in Kabarole and Mpigi district). Compared to the hierarchies of agricultural tools as constructed in Pouw (2008: Chapter 5), the exponential model thus finds the same number of levels in the hierarchy in Kapchorwa district. In Kabarole and Mpigi district, respectively two and one additional level(s) is found on the basis of the exponential model.

The second test carried out is the Pearson Chi-square Goodness-of-Fit (GOF) test of the distributional adequacy of the exponential model. If the set Ω of possible attributes contains N elements, then for each $n \leq N$ the model predicts the frequency distribution over subsets of Ω with n elements. The predicted distributions can be compared to the distributions found in the data. The Pearson test is not suited for outcomes with for which the expected frequencies are small. Therefore we have aggregated all outcomes with expected frequency below 5 into a rest category before performing the test. This is then used as the basis to calculate the critical values of the Chi-square. If the p-value is greater than 0.05, we cannot reject the null hypothesis that there is no difference between the observed values and the model predicted values.

First, in the case of household durables in Kapchorwa the test is carried out for the biggest groups of households in the frequency distributions, i.e. those owning 6, 7 or 8 different durables. The results are presented in Table 10 below. The same is done for the biggest groups of households in the Kabarole and Mpigi sample. The results are presented in Tables 11 and 12 below. The GOF test accepts the exponential model. In Kabarole, the model is rejected in two out of five cases and in Mpigi in four out of six. However, it should be noted that in those instances where the exponential model is rejected, the observed data follow the predicted pattern even more strongly than expected (see Tables A.1-3 in the Appendix).[8]

[8] Using the exponential distribution for the latent variables therefore leads to expecting a less concentrated distribution over attribute sets than the data show. This suggests using a class of distributions with thinner tails for the latent variables.

Table 10- Kapchorwa: Chi-square Goodness-of-Fit Test for Households Owning 6, 7 or 8 different Household Durables

Number of Durables	Number of households[9]	Chi-square	Critical Value (95% level)	p-value
6	48	21.93	22.66	0.0383
7	65	14.45	22.29	0.2731
8	54	23.31	28.68	0.1394

Source: own calculations, based on Kapchorwa field-survey (2000).

Table 11- Kabarole: Chi-square Goodness-of-Fit Test for Households Owning 7, 8, 9 or 10 different Household Durables

Number of Durables	Number of households[10]	Chi-square	Critical Value (95% confidence level)	p-value
7	34	17.45	36.68	0.7381
8	33	27.37	37.62	0.2405
9	44	27.89	34.36	0.1433
10	34	36.46	35.28	0.0194
11	40	46.64	35.55	0.0016

Source: own calculations, based on Kabarole field-survey (2000).

Table 12- Mpigi: Chi-square Goodness-of-Fit Test for Households Owning 7, 8, 9, 10, 11 or 12 different Household Durables

Number of Durables	Number of households[11]	Chi-square	Critical Value (95% confidence level)	p-value
7	34	21.66	42.74	0.7546
8	33	71.23	47.05	0.0000
9	41	43.77	48.04	0.2856
10	46	59.11	39.84	0.0001
11	43	24.67	21.08	0.0016
12	37	28.87	31.74	0.0007

Source: own calculations, based on Mpigi field-survey (2000).

[6] This amounts to (48+65+54)/298*100%=56% of the households in the Kapchorwa sample.

[7] This amounts to (34+33+44+34+40)/300*100%=61.7% of the households in the Kabarole sample.

[8] This amounts to (34+33+41+46+43+37)/340*100%=68.8% of the households in the Mpigi sample.

The GOF test is also carried out for the other two sub-sets of attributes, clothing and agricultural tools. The results for clothing are presented in Tables 13-15 below. In the case of clothing, the model predicted values are accepted in all cases. The test could not be carried out in the case whereby all individuals own all of the five selected clothing and personal items, as there is no difference between the observed and expected frequencies.

Table 13- Kapchorwa: Chi-square Goodness-of-Fit Test for Individuals Owning 2, 3, 4 or 5 different Clothing and Personal Items

Number of Items	Number of Individuals[12]	Chi-square	Critical Value (95% confidence level)	p-value
2	34	7.344	12.40	0.1963
3	62	3.727	13.45	0.7134
4	88	2.120	9.68	0.8323
5	96	-	-	-

Source: own calculations, based on Kapchorwa field-survey (2000).

Table 14- Kabarole: Chi-square Goodness-of-Fit Test for Individuals Owning 2, 3, 4 or 5 different Clothing and Personal Items

Number of Items	Number of Individuals[13]	Chi-square	Critical Value (95% confidence level)	p-value
2	36	4.854	13.01	0.5627
3	58	5.833	13.60	0.4421
4	94	5.479	9.247	0.3602
5	83	-	-	-

Source: own calculations, based on Kabarole field-survey (2000).

[9] This amounts to (34+62+88+96)/298*100%=94% of the households in the Kapchorwa sample.

[10] This amounts to (36+58+94+83)/300*100%=90.3% of the households in the Kabarole sample.

Table 15- Mpigi: Chi-square Goodness-of-Fit Test for Individuals Owning 2, 3, 4, or 5 different Clothing and Personal Items

Number of Items	Number of Individuals[14]	Chi-square	Critical Value (95% confidence level)	p-value
2	31	21.66	8.099	0.7546
3	75	3.162	9.911	0.5311
4	89	1.629	8.072	0.6528
5	80	-	-	-

Source: own calculations, based on Mpigi field-survey (2000).

Finally, the test results for agricultural tools are presented in Tables 16-18 below. The model is accepted in three out of four frequency groups in Kapchorwa, in only one out of six in Kabarole and none in Mpigi. Again, in looking more closely as to why the test fails it is found that the observed data follow the expected pattern even more strongly than predicted by the model (see Tables A.4-A.6 in the Appendix).

Table 16- Kapchorwa: Chi-square Goodness-of-Fit Test for Individuals Using 3, 4, 5 or 6 different Agricultural Tools

Number of Tools	Number of Individuals[15]	Chi-square	Critical Value (95% confidence level)	p-value
3	41	38.19	15.49	0.0000
4	60	11.13	20.18	0.4323
5	61	17.44	30.37	0.4928
6	41	16.82	29.12	0.4669

***Significant at $p<0.001$; **significant at $p<0.01$; *significant at $p<0.05$.
Source: own calculations, based on Kapchorwa field-survey (2000).

[11] This amounts to (31+75+89+80)/340*100%=80.9% of the households in the Mpigi sample.

[12] This amounts to (41+60+61+41)/298*100%=68.1% of the households in the Kapchorwa sample.

Table 17- Kabarole: Chi-square Goodness-of-Fit Test for Individuals Owning 2, 3, 4, 5 or 6 different Agricultural Tools

Number of Tools	Number of Individuals[16]	Chi-square	Critical Value (95% confidence level)	p-value
2	30	9.968	11.68	0.0761
3	48	15.22	15.56	0.0550
4	82	6.58	16.28	0.5826
5	58	34.19	16.73	0.0000
6	44	30.99	17.96	0.0003

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Kabarole field-survey (2000).

Table 18- Mpigi: Chi-square Goodness-of-Fit Test for Individuals Owning 2, 3, 4, 5 or 6 different Agricultural Tools

Number of Tools	Number of Individuals[17]	Chi-square	Critical Value (95% confidence level)	p-value
2	36	57.20	14.97	0.0000
3	48	18.66	18.25	0.0283
4	96	17.43	18.25	0.0654
5	68	22.89	18.30	0.0065
6	45	47.59	22.65	0.0000

***Significant at p<0.001; **significant at p<0.01; *significant at p<0.05.
Source: own calculations, based on Mpigi field-survey (2000).

5 Conclusion

In this article a latent variable model was developed to predict sequencing patterns in acquisition of welfare attributes. The empirical data used are a cross-section of three sub-sets of asset data – household durables, clothing and personal items, and agricultural tools. The model parameters were estimated at the individual and household level for each of the three districts covered in the field-survey. The estimated parameter values confirm the pre-supposed sequencing pattern. The hierarchy in the data is clearly visible from the levels in the estimated parameters for all three sub-sets of attribute data. Subsequently, the model was tested in two steps. First, a Likelihood Ratio test was used to assess the significance of difference between the estimated parameters. The test results subscribe to earlier findings with regard to the established hierarchies in Pouw 2008. However, in a number of cases one

[13] This amounts to (30+48+82+58+44)/300*100%=87.3% of the households in the Kabarole sample.
[14] This amounts to (36+48+96+68+45)/340*100%=86.2% of the households in the Mpigi sample.

additional level in the hierarchy was distinguished on the basis of the model. This leads us to conclude that the model is slightly more sensitive in picking-up differences than the simple two-by-two test Chi-square test for measure of distance as developed in Pouw (2008). Second, a Goodness-of-Fit test was carried out to test the adequacy of the exponential model. The test results were positive as well (for those frequency categories that could be included in the tests); in those instances where the null hypothesis was rejected it was found that the observed values followed the implied sequencing pattern even more strongly than the expected values. We therefore conclude that the model generally worked well to detect sequencing patterns in asset acquisition by poor smallholder farmers in Uganda, in the case of three selected districts.

The caveats to this model concern the implicit assumptions of constant prices, the possible inclusion of inferior goods and the fact that we take into account only presence of certain assets, but not their number. The first caveat requires more research by using time series data, including information on price changes, to test whether sequencing patterns are consistent to price variations. The second caveat would require the inclusion of (more) higher income groups to see whether certain goods become inferior at higher levels of welfare.[18] The third caveat could be addressed by collecting additional information on number of assets and take into account household size and composition effects.

As to the wider application of the underlying notion of sequencing patterns in asset accumulation in poverty research, the findings indicate that in any asset index or underlying survey instrument developed it would make sense to choose assets intelligently. There are categories of assets that are representative of different welfare levels. If one wants to take into account the heterogeneity below the poverty line, one has to include different categories of ‘poor people’s assets’ instead of ‘rich people’s assets’ only. Moreover, when taking into account people’s productive assets (e.g. agricultural tools) the choice of assets should reflect the dominant form of livelihoods of the people concerned. This might well lead to the development of regional asset indices as, in the case of Ugandan smallholder farmers, agricultural production patterns and ecological patterns can differentiate substantially across region. Furthermore, the approach would enable a rapid welfare assessment of people’s productive asset base and dynamics over time if time series data are made available. This would shed light on the different kinds of livelihood strategies adopted and potential ‘pathways out of poverty’.

[18] The field-survey underlying this research collected self-categorizations into five welfare groups: (i) the extremely poor/destitute; (ii) the poor; (iii) middle category; (iv) slightly better off; and (v) comfortable. Only 0.96% categorized themselves as “comfortable” and 4.7% as “slightly better off”. The focus on rural smallholder farmers in this study does not lead to a representative sample of the total population.

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Appendix

Table A.1
Kapchorwa: Observed and Expected Frequencies for Households Owning 6 Different Durables

Expected values (n=6)	Observed values (n=6)
23.44	36
2.135	0
0.662	0
2.683	0
1.120	1
0.544	0
1.849	0
0.771	0
0.970	1
0.513	1
7.184	0
2.683	0
1.120	9

Source: own calculations, based on Kapchorwa field-survey (2000).

Table A.2
Kabarole: Observed and Expected Frequencies for Households Owning 10 and 11 Different Durables

Expected values (n=10)	Observed values (n=10)	Expected values (n=11)	Observed values (n=11)
2.857	4	4.112	5
2.422	3	3.874	4
2.268	4	1.247	0
0.610	1	0.785	0
0.348	1	3.327	7
1.497	0	1.070	1
1.402	0	0.674	5
0.378	2	1.007	1
1.187	1	0.635	0
1.295	3	2.114	1
1.212	2	0.678	1
1.026	2	0.427	0
0.633	0	0.638	0
0.611	2	0.402	0
0.572	0	0.547	2
0.485	1	1.839	3
0.542	1	0.589	1
0.507	0	0.555	0
0.429	0	0.476	0
0.368	0	0.886	1
0.344	2	0.787	0
13.01	5	0.537	1
		12.79	7

Source: own calculations, based on Kabarole field-survey (2000).

Table A.3

Mpigi: Observed and Expected Frequencies for Households Owning 8, 10, 11 and 12 Different Durables

Expected values (n=8)	Observed values (n=8)	Expected values (n=10)	Observed values (n=10)	Expected values (n=11)	Observed values (n=11)	Expected values (n=12)	Observed values (n=12)
1.160	1	2.122	1	3.285	11	5.438	13
0.807	0	1.855	7	2.706	1	1.063	5
0.729	0	1.508	1	0.443	1	1.212	1
0.621	0	1.699	0	0.516	0	0.468	1
0.483	0	1.382	7	2.381	1	0.880	0
0.895	1	1.207	0	0.454	0	1.004	0
0.808	3	1.234	3	2.190	2	0.388	1
0.689	0	1.003	0	1.609	2	0.777	2
0.536	3	0.876	0	1.761	1	0.887	1
0.563	0	0.803	0	1.481	0	0.716	0
0.480	0	1.354	3	1.031	0	0.817	1
0.373	0	1.101	0	25.14	24	0.529	2
0.433	0	0.962	0			0.604	0
0.337	0	0.881	0			0.578	0
0.734	0	0.639	1			0.659	0
0.663	3	1.133	0			0.487	0
0.565	0	0.921	0			0.556	0
0.439	1	0.804	0			0.389	0
0.461	1	0.737	0			19.55	10
0.393	0	0.534	1				
0.355	2	0.587	0				
0.512	1	0.782	2				
0.436	2	0.635	1				
0.340	0	0.555	0				
0.394	0	0.508	1				
0.491	1	20.18	18				
0.444	1						
0.378	3						
0.343	0						
17.14	10						

Source: own calculations, based on Mpigi field-survey (2000).

Table A.4

Kapchorwa: Observed and Expected Frequencies for Individuals Using 3 Different Agricultural Tools

Expected values (n=3)	**Observed values (n=3)**
20.91	22
11.44	3
1.183	0
0.941	1
0.663	1
1.408	2
2.005	1
2.452	11

Source: own calculations, based on Kapchorwa field-survey (2000).

Table A.5

Kabarole: Observed and Expected Frequencies for Individuals Using 2,3,5 and 6 Different Agricultural Tools

Expected values (n=2)	Observed values (n=2)	Expected values (n=3)	Observed values (n=3)	Expected values (n=5)	Observed values (n=5)	Expected values (n=6)	Observed values (n=6)
19.50	17	25.24	37	27.00	20	24.12	27
3.880	9	11.50	4	14.49	17	5.242	1
1.288	2	3.113	3	1.940	0	3.117	1
3.434	2	0.990	0	0.965	4	0.791	4
1.138	0	2.449	2	5.839	3	2.855	2
0.760	0	0.653	0	0.771	1	1.693	2
		2.171	0	2.818	10	1.160	0
		0.579	0	0.621	0	0.687	0
		1.310	2	3.560	3	0.562	3
						3.771	4

Source: own calculations, based on Kabarole field-survey (2000).

Table A.6

Mpigi: Observed and Expected Frequencies for Individuals Using 2, 3, 4, 5 and 6 Different Agricultural Tools

Expected values (n=2)	**Observed values (n=2)**	**Expected values (n=3)**	**Observed values (n=3)**	**Expected values (n=4)**	**Observed values (n=4)**	**Expected values (n=5)**	**Observed values (n=5)**	**Expectec values (n=6)**	
15.12	9	16.73	16	51.30	57	30.16	37	18.28	
3.824	16	13.99	14	11.15	7	14.89	6	8.250	
3.037	7	1.992	1	4.364	1	5.476	4	1.372	
6.570	1	0.560	0	1.139	3	3.467	1	1.433	
5.228	1	3.961	10	9.373	10	1.258	0	0.724	
0.377	1	0.553	1	3.665	4	2.923	7	0.767	
1.289	0	6.636	1	2.705	4	1.060	1	0.502	
0.566	1	0.931	1	1.052	2	0.851	0	4.219	
		0.773	0	4.510	0	1.416	0	0.696	
		1.868	4	1.757	0	6.500	12	0.727	
				4.997	8			1.004	
								0.847	
								6.181	

Source: own calculations, based on Mpigi field-survey (2000).