TVs, Toilets, and Thresholds: Measuring Household Wealth Comparably Using an Asset-based Index

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Abstract: Asset indices based on durable goods ownership are commonly used to proxy for wealth in surveys lacking detailed income and expenditure data. Yet, the current tools to create these indices are theoretically unfounded, limiting the potential applications for such indices. In this paper, I discuss and extend an existing but little used alternative, the threshold method, pioneered by Ferguson, et al. I use consumer theory based on lexicographic preferences to motivate the use of the index and develop a simple rescaling method to create a wealth index which is comparable across surveys. Using three rounds of LSMS data from Nicaragua, I provide evidence for the method's validity both within and across surveys using expenditure benchmarks. The resulting index performs similarly to the commonly used factor analysis index within surveys, but it offers some improvement in wealth comparisons across surveys when there are few assets common to all surveys.

JEL Codes: I32, D11, O120, C4. Keywords: lexicographic preferences, wealth measurement, asset indices, poverty tracking.

1 Introduction

The accurate measurement of household wealth is critical in many areas of research, as wealth plays an important role as an outcome, a causal factor, and a control. Despite its importance, wealth is an ill-defined concept and therefore difficult to measure. As such, numerous studies have drawn on conrete measures of household income and consumption to capture wealth (Falkingham 2002), but data on income and consumption are often fraught with measurement error and systematic biases associated with recall and sensitivity to questions asked (Scott 1990, Pradhan 2000, Moore 2000). More importantly, accurate income and expenditure data are not collected in many surveys, particularly in developing countries with domestic production and informal transactions and in surveys focused on health and education.

These measurement issues and the expense of implementing lengthy expenditure modules have led to a search for a wealth proxy that is both accurate and easily collectible. The abundance of data on asset ownership and housing characteristics in surveys such as the Demographic and Health Surveys (DHS) have promoted the use of such indicators as proxies for wealth. Although some studies allow assets to enter separately into the multivariate regressions of interest (Sandiford 1995, Montgomery 2000), asset ownership is more commonly combined into a single indicator by a weighting scheme.

Many weighting schemes exist, but I focus my discussion on two key methods: linearly predicted expenditure and factor analysis.[1] Linearly predicted expenditure uses an external dataset with a wealth proxy such as expenditure to derive the optimal weights using a regression of expenditure on ownership. The estimated coefficients can then be used to predict wealth in the data of interest. Factor analysis is a statistical method commonly used to create asset indices (Zeller 2004).[2] Aimed at reducing data into fewer dimensions, factor analysis derives weights that are assumed to represent the underlying processes determining the correlation between asset ownership (Vyas 2006). Specifically, weights are computed using linear combinations which capture the maximum variance shared within the set of variables. Factor analysis advocates have provided some evidence for external consistency, (though issues with urban/rural comparisons exist) but explicitly note the lack of corresponding economic theory (Filmer 2001, Kausar 1999, Vyas 2006).

Linearly predicted expenditure is thus more theoretically pleasing due to the need for few assumptions, while factor analysis is more feasible in most settings. In addition, both

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[1]Additional approaches include using the total number of assets (Jensen 1996, Guilkey 1997, Havanon 1992, Bollen 1995, Gorabach 1998, Razzaque 1990), determining weights by policy analysis and consultation with national experts (Navajas 2000), weighting by asset prices (Dargent-Molina 1994), and weighting based on population ownership levels (Layte 2001, Morris 2000).

[2]Principal components analysis is a similar method that is also used and has been shown to produce results that are highly correlated with factor analysis (Sahn 2000).

methods lack the ability to produce valid wealth rankings across different surveys because both methods require the existence of identical asset indicators across surveys. This inability to create a valid inter-survey wealth index limits the possibilities for micro-level cross-country and intertemporal studies.

In this paper, I present the threshold method, an alternative empirical method pioneered by Ferguson, et al, (2003). In his paper, Ferguson lays out the statistical model and provides some basic empirical validation. Although he claims that the method can be used to promote inter-survey comparability, he restricts his work to developing the initial method and leaves the inter-survey extension for future research. In this paper, I build off his work and make a two-fold contribution. First, I develop an economic model that was previously lacking. Second, I use the underlying theory to develop a simple rescaling method for comparability across populations. I then test the performance of the rescaling using survey data and show that the threshold method enhances comparability (compared to factor analysis) across populations with few common assets.

The paper proceeds as follows: Section 2 presents the theoretical and empirical model. Section 3 describes the data. Section 4 provides evidence for the method's validity within a survey. Section 5 analyzes the performance of the rescaling mechanism in monitoring wealth in a repeated cross section using different asset subsets and compares the index with one created using factor analysis. Section 6 discusses the implications of the empirical results and concludes.

2 Threshold Model

2.1 Behavioral Model and Intuition

I start by introducing a simple model using lexicographic (hierarchical) preferences to motivate the intuition behind the threshold model.[3] The development of an underlying theory is important not only for understanding the empirical specification but for formalizing the implicit assumptions which are often obscured in such statistical processes and for highlighting the limitations of the method. Furthermore, it is precisely the theory which differentiates the threshold method from other statistical methods and allows for the enhanced capacity to compare across populations. Because the estimated parameters have an economic meaning (which is not the case for factor analysis), they can then be used to rescale indices created with differing asset subsets.

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[3]The assumption of lexicographic preferences motivates the empirical model, but the validity of this assumption is open to debate. The empirical validity of the index is a separate question independent of any theoretical assumptions.

Under standard theories of consumption, agents compare their preferences using the common denominator of utility which standardly allows for some degree of substitutability between goods. Lexicographic preferences, in contrast, arise when certain needs are hierarchical and distinct, therefore resulting in a lack of substitutability between goods (Drakopoulus 1990). For instance, the need for food is fundamentally different from the need for shelter, and a house cannot be used to satisfy hunger.[4]

To understand the main implications of hierarhical needs, I present a basic model of one household with lexicographic preferences over two goods. Good x_1 represents a primary necessity such as shelther, and good x_2 represents a secondary need such as electricity. When a household makes its consumption decision, the ownership of the secondary good is given a lower priority than the ownership of the primary good. Specifically, in comparing two bundles i and j, $(x_1^i, x_2^i) \succ (x_1^j, x_2^j)$

$$
\begin{aligned}
&\text{if } x_1^j < x_1^i && \text{whatever } x_2^j, x_2^i \\
&\text{or } x_1^j = x_1^i && \text{and } x_2^j < x_2^i.
\end{aligned}
$$

In the context of the threshold index, I use durable goods ownership, where each good takes on a value of 1 when a household owns the good (has access to the service) and 0 when it does not.[5] Thus, using the simple choice rule above with 2 dichotomous goods, there is a complete ordering over the four possible bundles given by $(0,0) \prec (0,1) \prec (1,0) \prec (1,1)$. Likewise, with 3 durable goods, there is a complete ordering given by $(0,0,0) \prec (0,0,1) \prec (0,1,0) \prec (0,1,1) \prec (1,0,0) \prec (1,0,1) \prec (1,1,0) \prec (1,1,1)$, when priorities are highest for the first good and decreasing for the second and third. With N goods where $m > n$ implies that good n is more highly prioritized than good m, I generalize the model using an iterative choice rule. To compare any two specific bundles, $\mathbf{x}^i$ and $\mathbf{x}^j$

Let n=1 Step 1: If $x_n^j \neq x_n^i$, then

$$
\begin{aligned}
x_n^j < x_n^i &\Rightarrow \mathbf{x}^i \succ \mathbf{x}^j \\
x_n^j > x_n^i &\Rightarrow \mathbf{x}^j \succ \mathbf{x}^i
\end{aligned}
$$

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[4]Although the idea of hierarchical needs draws primarily from psychology, it has also been discussed by economic theorists such as Menger (1950) and Marshall (1961). In addition, the idea of basic necessities has been incorporated into the commonly used Stone-Geary utility function where consumption of certain goods takes place only after subsistence levels of basic needs are met.

[5]To include the quantity of goods, such as number of cars, I can use two different dichotomous variables, one representing one or more cars and another repesenting two or more cars. In addition, I can include some categorical variables such as wall materials. I do so by dividing the materials into low quality, medium quality, and high quality and including a variable for medium quality or better and a variable for high quality.

Step 2: Else, $x_n^j = x_n^i$, then update $n = n + 1$ and repeat step 1.

Under these preferences, one can easily solve the consumption decision under a budget constraint. Let $\mathbf{x}^j$ represent a consumption vector with N goods, where the x_n^j component represents ownership of good n. Again, assume that $m > n$ implies that good n is more highly prioritized than good m and ownership is dichotomous. The superscript j captures the ordering of preferences such that $\mathbf{x}^1 \prec \mathbf{x}^2 \prec ... \prec \mathbf{x}^j \prec \mathbf{x}^{j+1} \prec ... \prec \mathbf{x}^J$ where $J = 2^n$ equals the total number of possible consumption vectors. Let M defnote wealth, defined as the amount of household disposable income available for durable goods and services. Let p_n denote the cost of good n. Then, the optimal bundle $\mathbf{x}^*$ is given by

$$\mathbf{x}^j \text{ s.t. } \sum_{n=1}^{N} p_n x_n^j \leq M < \sum_{n=1}^{N} p_n x_n^{j+1}$$

Under the assumption that good 1 is most highly prioritized, any vector where $x_1 = 1$ is preferred to any vector where $x_1 = 0$. Thus, any household with $M \geq p_1$ should choose a bundle such that $x_1^* = 1$. p_1 is therefore a threshold level of wealth at which all households above this threshold should choose to purchase good 1. Likewise, any vector where $x_1 = 1$ and $x_2 = 1$ is preferred to any vector where $x_1 = 1$ and $x_2 = 0$. Thus, any household with $M \geq p_1 + p_2$ should choose a bundle such that $x_2^* = 1$. Again, $p_1 + p_2$ represents a wealth threshold at which all households above this threshold should choose to purchase both good 1 and good 2.[6] Continuing in this manner, there exists a threshold for every good n such that any household with wealth above that threshold should choose $\mathbf{x}^*$ such that $x_n^* = 1$.

I now address the problem of inferring household wealth when only $\mathbf{x}^*$ is observed. Under lexicographic preferences, I can use information on ownership to derive the probability that a household has wealth above a given threshold. To illustrate, consider the simple 2 good case. The solutions to the maximization problem are given by

$Case1 : p_2 < p_1$		$Case2 : p_1 < p_2$	
$M < p_2$	$\Rightarrow (0,0)$	$M < p_1$	$\Rightarrow (0,0)$
$p_2 \leq M < p_1$	$\Rightarrow (0,1)$		
$p_1 \leq M < p_1 + p_2$	$\Rightarrow (1,0)$	$p_1 \leq M < p_1 + p_2$	$\Rightarrow (1,0)$
$p_1 + p_2 \leq M$	$\Rightarrow (1,1)$	$p_1 + p_2 \leq M$	$\Rightarrow (1,1)$

I treat each threshold and the information provided from each good separately for the sake of simplicity (although I am ignoring some additional information) and to track closely with the empirical model. Consider the information provided by ownership of good 1 about the

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[6]Note that observation of $x_2^* = 1$ does not necessarily imply that $M \geq p_1 + p_2$ if $p_1 > p_2$. The threshold therefore represents the level of wealth at which the probability of ownership of good n equals 1. Below that level of wealth, the probability of owning good n may still be positive.

household's wealth with respect to the threshold at p_1. In this case, $P(M > p_1|x_1 = 1) = 1$ and $P(M > p_1|x_1 = 0) = 0$. Consider now the information provided by ownership of good 2 with respect to threshold $p_1 + p_2$. $P(M > p_1 + p_2|x_2 = 1) = \frac{P(M>p_1+p_2 \cap x_2=1)}{P(x_2=1)}$ and $P(M > p_1 + p_2|x_2 = 0) = \frac{P(M>p_1+p_2 \cap x_2=0)}{P(x_2=0)}$. If I make assumptions about the distribution of observed ownership vectors, I can calculate the probability of having wealth above/below the threshold given the observed vector. With multiple thresholds, this will lead to a probability distribution over different levels of wealth given the observed vector. Using this latter distribution, one can compute the expectation of wealth conditional on observed ownership.

Using this model and some distributional assumptions, then, one can make infererences about the probable level of wealth underlying an observed ownership vector. Generalizing the model to a population under the standard assumptions that households face similar costs for goods and share common preferences (assumed to be lexicographic), the intuition leads directly to an empirical estimation strategy to calculate thresholds for each good and to use these thresholds to create estimates of household wealth.

Before presenting the estimation strategy, I pause to discuss the empirical implications of the theory. First, there is a threshold associated with each asset which can be interpreted as the level of wealth associated with that good. This interpretation is what allows me to rescale across populations in subsequent sections. Second, as with all asset indices, goods are assumed to have similar meanings across households. This assumption must be considered carefully when placing indices on the same scale. Third, discrimination of wealth across households is driven by the chosen distributional assumptions. In the econometric model, I assume that wealth is distributed normally (broadly consistent with the empirical log normal distribution of expenditure/income), which will tend to overestimate wealth for low ownership households and underestimate wealth for high ownership households under a true distribution that is not normal. Fourth, the theoretical model indicates that proper differentiation requires the inclusion of goods spanning low, medium, and high wealth levels. This implies that an index which lacks higher income assets will provide little information on the upper tail of the wealth distribution. Since asset data focuses primarily on necessities, the threshold index may not be appropriate in higher income settings where asset indicators fail to capture expenditures on luxuries and experiences (such as entertainment).

2.2 Econometric Model

The estimation strategy developed by Ferguson, et al, is as follows.[7] Denote y_i^* as the unobserved wealth of household i, and y_i as a vector of observations on a series of goods and services which take the value of 0 if the household does not possess or have access to the good or service, and 1 if it does. Wealth is assumed to be a linear function of a set of household characteristics X_i' that are observed by the researcher and a term ν_i, which is known to the household but unobserved to the researcher. ν_i is assumed to distributed normally with mean 0 and variance σ_ν^2. N denotes the number of households.

$$y_i^* = X_i'\beta + \nu_i \quad i = 1, ..., N$$
$$\nu_i \sim N(0, \sigma_\nu^2)$$

Let $\tau^a + \epsilon_i^a$ represent the asset threshold for good a for household i, where τ^a represents the average population threshold for that good and ϵ_i^a (assumed to be normally distributed) represents household-specific preferences (costs) for asset a. The latter term allows for heterogeneous priorities across households. Ownership of good a by household i is denoted by y_i^a and is given by[8]

$$
\begin{aligned}
y_i^a &= 0 && if && \text{-}\infty < y_i^* \leq \tau^a + \epsilon_i^a \\
y_i^a &= 1 && if && \tau^a + \epsilon_i^a < y_i^* \leq +\infty \\
\epsilon_i^a &\sim N(0,1) &&&& \forall a
\end{aligned}
$$

Let Ω_0 be defined as the set of all a such that $y_i^a = 0$ and Ω_1 be the set of all a such that $y_i^a = 1$. Under this set-up, the probability of observing response vector y_i conditional on covariates can be written and rearranged using the distributional assumptions as follows:

$$Pr(y_i|X_i, \nu_i) = \prod_{a \in \Omega_0} Pr(-\infty < X_i'\beta + \nu_i \leq \tau^a + \epsilon_i^a) \cdot \prod_{a \in \Omega_1} Pr(\tau^a + \epsilon_i^a < X_i'\beta + \nu_i \leq +\infty)$$

$$Pr(y_i|X_i, \nu_i) = \prod_{a \in \Omega_0} \Phi(\tau^a - X_i'\beta - \nu_i) \cdot \prod_{a \in \Omega_1} (1 - \Phi(\tau^a - X_i'\beta - \nu_i))$$

$$Pr(y_i|X_i) = \int_{-\infty}^{+\infty} \varphi(\nu_i) \prod_{a \in \Omega_0} [\Phi(\tau^a - X_i'\beta - \nu_i)] \cdot \prod_{a \in \Omega_1} [1 - \Phi(\tau^a - X_i'\beta - \nu_i)] d\nu_i$$

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[7]I make two modifications. Ferguson's specification included the stochastic ϵ term in the equation for household wealth, while I interpret the term as idiosyncratic differences in preferences for particular goods and thus place the term on the asset thresholds. In addition, Ferguson presents the ownership probability for a household owning all or no assets, while I generalize the probability to any ownership vector.

[8]The variance of ϵ_i^a is set to 1 out of mathematical convenience.

where $\Phi(\cdot)$ is the cumulative normal distribution, $\varphi(\cdot)$ is the normal probability density function, and the last line is arrived at by conditioning out the random effect ν_i. The integral can be approximated using M-point Gauss-Hermite quadrature[9] and estimation of parameters can be done using standard maximum likelihood methods. [10]

For the posterior estimation, each household is given a prior estimate μ_i based on its covariates and the estimated variance of the unobserved ν_i defined by $\mu_i \equiv X_i'\beta + \nu_i$. The prior estimate is then adjusted using observed ownership levels according to $\Pr(\mu_i|y_i)$ estimated from Bayes' formula:

$$Pr(\mu_i|y_i) = \frac{Pr(y_i|\mu_i)Pr(\mu_i)}{\int Pr(y_i|\mu_i)Pr(\mu_i)d\mu_i} \tag{1}$$

With a set of possible μ_i's, a household's predicted wealth conditional on the observed set of responses is the expected value of μ_i. The way this is implemented is as follows. First, all parameters are estimated using the model including the variance σ_ν^2. This estimated variance is then used to simulate one hundred different values of μ_i^k (where k refers to the simulation) around the predicted $X_i'\beta$ of the latent variable for each household in the sample. $\Pr(\mu_i^k|y_i)$ for each μ_i^k can be derived using the probability specification above. Integrating over all simulated values of μ_i^k for each individual yields the denominator of equation (1). Finally, the predicted wealth is the expected value of μ_i given the previous probability distribution.

$$E(\mu_i|y_i) = \sum_{k=1}^{100} \mu_i^k Pr(\mu_i^k|y_i)$$

2.3   Rescaling procedure

Now, I move past Ferguson's model and turn to the issue of placing indices from different surveys on a comparable scale. Again, the underlying theoretical model allows me to interpret the estimated parameters in a way that is not possible using factor analysis. Using the idea that the estimated thresholds represent wealth levels associated with a specific good, I can use common assets available in different surveys to rescale the index. Under the assumption that these common assets represent the same level of wealth across surveys, I can rescale the index by setting the survey-specific thresholds equal to each other for each common good.

Suppose two surveys include information on good 1 (with a low threshold) and good 2 (with a high threshold), and let τ_a^{sj} represent the estimated cutpoint for good a in survey

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[9]Details found in Ferguson, et al.

[10]The model is operationalized in Stata using the xtprobit command, where each observations is at the household-asset level. Asset thresholds are calculated by including dummies for each good, and a random effect captures the unobserved ν_i.

j. Using these two anchoring assets, I can create an arbitrary common scale by setting $\tau_1^{s1} = \tau_1^{s2} = 0$ and $\tau_2^{s1} = \tau_2^{s2} = 1$. In practice, different surveys often have more than two possible anchoring goods which might be included as anchors. To generalize to several anchoring assets without imposing restrictions, I do so using numerical anchors estimated by the data.

Formalizing this, I depart from the notation above and index the anchoring assets using the subscript a. Let τ_a^{sj} represent the estimated cutpoint for good a in survey j. I assume

$$\tau_a^{s1} = \tau_a^{s2} = \tau_a^{s3} = ... = \tau_a^{sJ} \qquad \forall a$$

Let $\overline{\tau}_a$ be the mean cutpoint for anchoring asset a across the different surveys. Then, I run the following regression separately for each survey j where each observation represents one asset and A represents the number of anchoring assets.

$$\overline{\tau}_a = \tau_a^j \beta^j + b^j \qquad a = 1, ..., A$$

The predictions from this regression give the value of the asset thresholds on the common scale. Applying these coefficients to the household wealth measures places these measures on the common scale. Therefore, the rescaled wealth estimates are given by

$$y_{i,rescaled}^j = y_i^j \hat{\beta}^j + \hat{b}^j$$

3   Data

The data for the analysis comes from 3 rounds of Nicaragua Living Standards Measurement Surveys (LSMS) covering the years 1998/1999, 2001, and 2005. These surveys contain modules on household demographics, housing characteristics, equipment ownership, expenditures, and income. The expenditure and income modules contain detailed information on monetary and in kind costs by category and include agricultural and business transactions. The samples cover 4209, 4191, and 6882 households, respectively. For the purpose of this analysis, I will treat the data as repeated cross sections, though there is a small longitudinal panel.

Asset ownership information is compiled using housing characteristics and equipment ownership, such as housing density, bathroom quality, phone services, and internet. Better quality is determined by those categories which increase in frequency for higher education levels. The dataset contains over 30 potential variables to be used for an asset index. The available data also contain consumption aggregates which are used in this analysis as benchmarks. The details behind the construction of the consumption aggregates can be found on the LSMS website. All monetary measures are presented in 1998 cordobas.

Although there is an additional earlier LSMS round in Nicaragua in 1993, I exclude the earlier data from this analysis due to substantial differences in survey design, which make the consumption aggregates difficult to compare.

Descriptive statistics on asset ownership are shown in Table 1. Ownership levels are generally lower for assets with higher monetary values (given by the estimated values in the right panel of the table), but this is not always the case. For example, there are moderate levels of TV and refrigerator ownership despite being associated with relatively high prices, indicating that preferences are important in determining ownership. I also note that the sets of available variables differ slightly between the rounds, with additional information being collected on cellular phones, CD players, cameras, and video games) in the latter years.

4 Internal consistency

I now apply the threshold method within each survey round and examine the performance of the resulting index. All available variables (23 items in 1998, 24 items in 2001, and 27 items in 2005) are included in the analysis for each round. Figure 1 plots the estimated asset thresholds for each of the three rounds. The scales for each round are not comparable and are only shown on the same axis for general comparison. The results show that basic housing amenities such as electricity and quality construction materials are associated with relatively low levels of wealth. Basic appliances such as stoves, fans, and refrigerators are associated with moderate levels of wealth, and items such as cars, rice cookers, and ovens represent the highest levels of wealth. A visual comparison of the estimated thresholds show that the relative ordering of the thresholds is similar across the three rounds with all items representing similar levels of wealth despite small changes in ranking. The exception is the cellular phone, which represented a high level of wealth in 2001 and only a moderate level of wealth in 2005. This decrease in the estimated threshold can be attributed to lower prices and increased utility associated with cellular phones.

To reproduce the findings in Ferguson's paper, I compare the threshold index to commonly used benchmarks for welfare. As discussed, the concept of wealth is ill-defined and therefore not necessarily very instructive. I therefore compare the threshold index to aggregate per capita household expenditure, the current gold standard measure for wealth or socioeconomic status. Per capita expenditure is likely to capture a more contemporaneous measure of welfare than the underlying wealth which drives asset ownership. Nevertheless, it is one alternative measure of wealth which can be used to assess the performance of an asset index.

In addition, I include comparisons with linearly predicted expenditure and an index

created using factor analysis. The former is the prediction from a linear regression of per capita expenditure on asset ownership (with separate variables for each item) and is included to give a sense of a best-case scenario asset index. That is, linearly predicted expenditure acts as an alternative benchmark which captures how well any asset index might be expected to correlate with per capita expenditure. The factor analysis index is included to assess how well the threshold index performs against the most commonly used existing methods. Factor analysis and principal components analysis have been shown to produce similar results; only one is included in this analysis for the sake of being concise.

Table 2 presents the rank correlation coefficients associated with the application of each method within each round. Using the 1998 data, the alternative asset methods perform similarly when compared against per capita expenditure, with correlation coefficients of 0.53, 0.54, and 0.54 for linearly predicted expenditure, factor analysis, and the threshold method, respectively. Results are similar in the latter two rounds, with a slightly lower correlation for the threshold method in 2001 as compared to linearly predicted expenditure and factor analysis. The correlation between factor analysis and the threshold method is extremely high, ranging from 0.97 to 0.99 between the three survey rounds.

5 Inter-survey comparability: Wealth comparisons in repeated cross sections

To test the performance of rescaling across different surveys, I apply the rescaling technique discussed above to the three rounds to determine how wealth has changed over time. After rescaling, I again compare the estimated threshold index to per capita expenditure, linearly predicted expenditure, and a factor analysis measure. Before presenting the results, I pause to discuss the construction of the linearly predicted expenditure and factor analysis measures in this time series analysis.

When constructing the linearly predicted expenditure and factor analysis measures to provide for a comparable time series analysis, it is necessary to determine the appropriate weights and regression coefficients to be applied across the surveys. Two main options exist: determining appropriate weights using a pooled dataset or applying the weights derived from one dataset to the remaining datasets. In this analysis, I choose to apply the weights derived from the 1998 data to the remaining data from 2001 and 2005 for constructing the linearly predicted expenditure and factor analysis measures. In practice, a researcher would most likely use a predicted expenditure measure when accurate expenditure measures are not available in the dataset of interest but are available in some other dataset. In this case, there

is no potential for deriving weights using a pooled dataset; appropriate weights would be derived from the dataset with expenditure data and then applied to the remaining datasets. When considering a factor analysis index, it is possible to derive weights from a pooled dataset but difficult to defend in a meaningful way. Since factor analysis lacks an underlying theory linking asset ownership to the construction of the index, all factor analysis weights, including through derived within a survey, are difficult to interpret. Deriving weights from a pooled dataset adds an additional layer of complexity, as the relationship between each asset and wealth may differ from survey to survey. Using weights derived from a single dataset avoids the need to make any additional assumptions.

The rank correlation coefficients between each measure and per capita expenditure in the pooled dataset are presented in Table 3. The first rows show the results when the indices are derived using the 23 items which are common in the three rounds. This means that the predicted expenditure and factor analysis measures are constructed with 23 items in every round. The threshold index is first constructed within each survey using all available items and then rescaled using the 23 common items. The correlation coefficients are 0.55, 0.58, and 0.57 for predict expenditure, factor analysis, and the threshold method, respectively.

Since both linearly predicted expenditure and factor analysis create measures which are weighted sums of the items owned, any inter-survey index constructed using these methods must be restricted to items which are available in all surveys. I reconstruct new measures using varying sets of common assets to examine the sensitivity of each measure to the inclusion of different sets of assets. I do this to cover the different scenarios that might arise when using different datasets of varying construction. The bottom four rows of Table 3 show the results. The 9 common assets included in the second row are chosen based on the variables which are available in the 1993 round of the Nicaragua LSMS. The sets of items included in the remaining rows have been chosen arbitrarily. I exclude items with widely varying ownership levels across surveys as such variables are more difficult to interpret.

When estimation is done with fewer common assets for the predicted expenditure and factor analysis measures, the resulting measures are less correlated with per capita expenditure. The correlation coefficients for the factor analysis measure decreases from 0.58 to 0.42 when reducing the number of common goods from 22 to 2. Similar differences are seen using the predicted expenditure measure. The correlation coefficients for the threshold index shown in the last column range from 0.54 to 0.58 indicating that the threshold index is less sensitive to the number of common assets and have similar levels of performance even with two common assets.

Figure 2 compares the distributions of the different asset measures. The top row shows the measures associated with 22 common assets, the middle row shows the measures associated

with 7 common assets, and the bottom row shows the measures associated with 3 common assets. A visual comparison shows that the different methods result in substantially different distributions even though the correlation coefficients are relatively similar. For predicted expenditure and factor analysis, the distributions become much more lumpy when fewer common goods are included. For the threshold index, the distributions are similar in shape regardless of the number of common assets included since the estimation is done within each survey using all available assets. Instead, the different sets of common assets result in differences in the relative positioning and span of the 1998, 2001, and 2005 distributions.

6 Discussion

Although this analysis should be extended to additional sets of data, the basic results shown here have a host of implications for researchers interested in using asset indices. First, within surveys, the methods perform similarly, indicating that from a empirical standpoint, a more theoretical asset index offers little improvement over the most commonly used statistical indices. On the other hand, one can argue that a more theoretically based index is more appealing from an economic standpoint and has the same empirical performance as the more arbitrary statistical indices.

Second, when comparing wealth across surveys, the different methods perform similarly when considering the correlation with per capita expenditure. For predicted expenditure and factor analysis, lower correlation coefficients are associated with indices created using fewer common goods. This is to be expected, since the indices are created using fewer common goods and thus less variation. The threshold method has similar correlation coefficients regardless of the number of common goods, since the indices are estimated within each survey using all available goods and then rescaled according to the common goods. Regardless, the differences in correlation coefficients both between methods and between different sets of common goods are relatively small. One of the most surprising results is the relatively high level of correlation associated with indices created using data from as few as two goods.

Third, when comparing wealth across surveys, the threshold index results in a smooth distribution when there are a good number of assets available in each survey but few assets common to all surveys. In this case, the factor analysis index provides less discrimination between households when there are few common assets regardless of how many additional variables might be available in each survey. These distributional differences are important when the indices are used to create quintiles or deciles of wealth for use in regressions, as lumpy distributions make the wealth groupings highly sensitive to the choice of cutoff. The difference in performance between the two methods is marginal when the number of common

assets is larger but becomes more important as the number of common assets decreases.

The number of common assets relative to the number of assets available in each survey depends highly on the specific survey instruments used and on the specific inter-survey application. The LSMS instruments are among the most highly consistent surveys available; thus, a researcher would expect to see a larger number of common assets when comparing any two surveys. Other commonly used datasets such as the DHS have fewer assets available overall, due to the non-economic focus of the data collection. Furthermore, there is a base of assets common to most DHS surveys but additional information is often available on country-specific items. Even within consistent instruments such as the LSMS, it is expected the instruments will differ as newer datasets collect information on newly available products such as cellular phones and exclude information on products that are becoming obsolete such as CD players. The fraction of common to total available assets will be smaller when the time span between the earliest and latest datasets is large.

Additionally, although the number of common assets across any two surveys might be of moderate size, the number of assets which should be treated as common is likely to be lower. Within one country over time, an asset may represent highly different levels of wealth due to differences in quality which are not collected in the survey instruments. For example, it is unclear whether or not a television in Nicaragua in the early 1990s represents the same level of wealth as a television in present-day Nicaragua as televisions have progressed from black and white to color to LCD to HI-DEF. Furthermore, the number of common assets in cross-country applications is limited to assets which can be interpreted similarly across different contexts. For example, a bicycle may be a necessity in an area with few alternatives for transportion, while it may be a luxury in other areas. An appropriate asset index whould exclude bicycles as common assets, though data on bicycle ownership might exist in all the datasets.

In conclusion, the theory-based index offers some improvement over the existing asset-based indices in certain applications. The model presented here is a first attempt at introducing theory into the creation of an asset index and has limitations which should be addressed in future work. Specifically, the assumption of lexicographic preferences is restrictive and an alternative model which allows for more flexible preferences would be more realistic and could potentially allow prices to be explicitly incorporated into an asset index.

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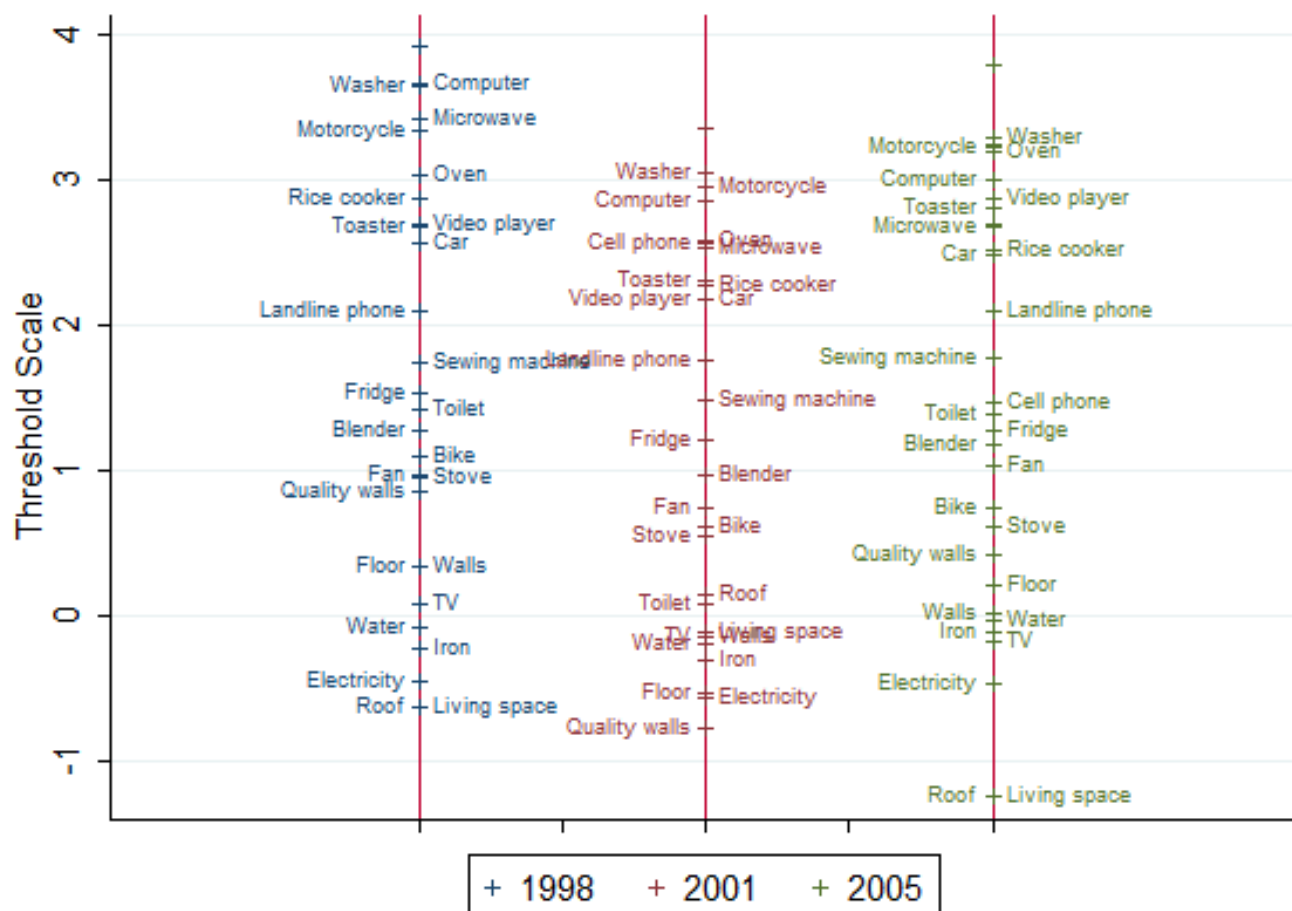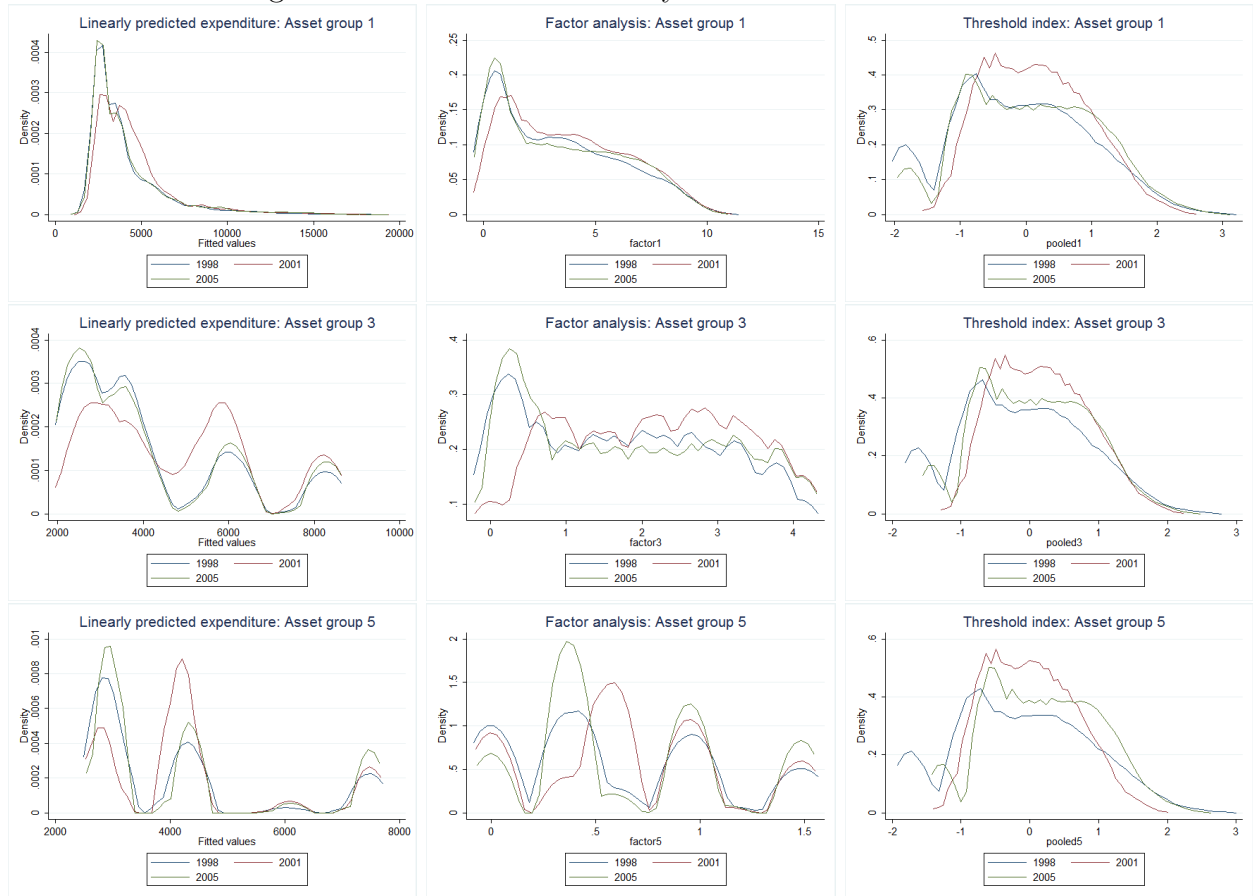# 8 Tables and Figures

Figure 1: Estimated asset thresholds

Figure 2: Index distributions by method and asset choice

Group 1: 22 common assets.
Group 3: 7 common assets.
Group 5: 3 common assets (water, electricity, toilet)

Table 1: Summary statistics

	Population ownership level			Estimated value (1998 Cordobas)		
	1998	2001	2005	1998	2001	2005
Housing quality and amenities						
Water piped into dwelling	0.52	0.56	0.51			
Electricity	0.61	0.66	0.62			
Toilet	0.18	0.47	0.19			
Quality Walls	0.41	0.54	0.50			
Quality Roof	0.29	0.73	0.40			
Quality Floor	0.67	0.46	0.81			
0.5 rooms or more per capita	0.67	0.55	0.81			
Kitchen	0.43	0.67	0.45			
Kitchen appliances						
Stove	0.27	0.34	0.35	844	721	564
Fridge	0.16	0.18	0.21	2,939	2,304	1,934
Microwave	0.01	0.03	0.04	1,398	937	650
Blender	0.21	0.24	0.23	190	171	154
Toaster	0.04	0.04	0.03	220	184	142
Rice cooker	0.03	0.04	0.05	291	241	194
Oven	0.02	0.02	0.02	360	269	204
Other appliances						
Washer	0.01	0.01	0.01	2,928	2,375	2,280
Sewing machine	0.12	0.12	0.11	761	576	520
Iron	0.56	0.59	0.53	96	92	87
Fan	0.27	0.29	0.26	127	110	105
Air conditioner	0.00	0.01	0.01	3,347	2,144	2,015
Electronics and communication						
Phone	0.09	0.09	0.09			
Cell		0.02	0.17			
TV	0.48	0.54	0.54	1,318	1,125	1,027
CD player			0.04			997
VHS/video player	0.04	0.05	0.03	1,510	1,030	483
Computer	0.01	0.02	0.02	9,477	7,338	4,261
Camera			0.02			1,104
Video games			0.01			678
Transportation						
Bike	0.23	0.32	0.31	465	382	362
Motorcycle	0.01	0.01	0.01	5,688	6,196	7,217
Car	0.05	0.05	0.05	37,439	38,536	36,698

Table 2: Rank correlation with per capita expenditure by survey

1998	Per capita consumption	Linearly predicted expenditure	Factor analysis
Linearly predicted expenditure	0.53	1.00	
Factor analysis	0.54	0.86	1.00
Threshold	0.54	0.85	0.99
2001	Per capita consumption	Linearly predicted expenditure	Factor analysis
Linearly predicted expenditure	0.68	1.00	
Factor analysis	0.65	0.81	1.00
Threshold	0.59	0.70	0.97
2005	Per capita consumption	Linearly predicted expenditure	Factor analysis
Linearly predicted expenditure	0.62	1.00	
Factor analysis	0.63	0.88	1.00
Threshold	0.62	0.87	0.99

Table 3: Rank correlation with per capita expenditure, pooled cross-sections

	Linearly predicted expenditure	Factor Analysis	Threshold index
22 common assets	0.55	0.58	0.57
9 common assets	0.54	0.55	0.56
7 common assets	0.54	0.54	0.56
3 common assets (water, electricity, toilet)	0.50	0.50	0.57
3 common assets (stove, fridge, microwave)	0.52	0.52	0.56
2 common assets (iron, sewing machine)	0.43	0.42	0.58
2 common assets (phone, TV)	0.46	0.46	0.54