The Poor Get Poorer: Tracking Relative Poverty in India Using a Durables-Based Mixture Model

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ABSTRACT

I propose the use of a durables-based mixture model to identify the consumption class structure of a population. The mixture model decomposes the marginal distribution of durables ownership across all households, into three conditional distributions (one each for lower, middle and upper classes), along with their weights in the population distribution, endogenously determining class membership. This approach provides a potentially deeper understanding of the dynamics of classes, in particular the lower class, than can be obtained using poverty lines or PCA alone. It avoids many well-known problems with expenditure data, ameliorates the impact of changing survey designs, and enables an analysis of the behaviour and membership of classes over time. I use the mixture approach to show that the urban lower class in India became smaller but poorer during the 1990s.

Keywords: durable ownership; consumption class; relative poverty; poverty line; mixture model; EM algorithm; Indian poverty

JEL classifications: O10, O12, O15, C14

1. Introduction

I propose the use of a durables-based mixture model to identify the consumption class structure of a population. I then use the mixture approach to examine if poverty in India increased or declined during the 1990s – a much-debated issue in the literature (Deaton and Kozel, 2005).

The motivation for identifying consumption classes is straightforward. At a philosophical level, we care about the well being of *all* and not just a few households in a population. We care about notions of equality and freedom, not just from absolute deprivation but also from relative deprivation. At a practical level, we care about relative poverty and inequality because it could impact (among other things) economic outcomes such as growth rates and productivity and socioeconomic outcomes such as the incidence of crime and social exploitation. An economy is not making use of its full productive potential if a large proportion of its population is deprived of vital resources and choices, and feels exploited (Ray, 1998; Sen, 2000). From this perspective, it seems important both to *define* relative deprivation in a meaningful way so as to be able to target policy to help the needy group, as well as to *evaluate* the effectiveness of such policy.

In this paper I argue that a mixture model is an effective tool for determining a (data-driven) criterion for class membership, and also for identifying consumption classes by this criterion. The approach yields estimates of the size (proportion) of consumption classes as well as a definition of the classes in terms of their different consumption habits.

Consumption (or income) is a commonly used measure of well-being. In addition, most approaches that seek to identify consumption classes – the 'poor', the 'middle class' or the 'rich' (Banerjee and Duflo, 2008; Birdsall et al, 2010; Ravallion, 2010) – use expenditure based measures of consumption, in particular expenditure cutoffs that are assumed to "contain" the class of interest. Indeed there are compelling reasons for using expenditure as a measure of consumption and welfare (Deaton, 1997). However, expenditure data are often unavailable, messy, misremembered and costly to collect. In addition, some surveys (such as the Demograpic and Health Surveys or DHS) do not contain data on expenditure but on assets. To avoid these issues, I use durable ownership as the primary measure of consumption class.

This is not the first time that durables ownership has been used or validated as a measure of consumption and wealth (Filmer and Pritchett, 2001, Montgomery et al, 2000, Lubotsky and Wittenberg, 2006). Filmer and Scott (2008) summarize the extensive literature that focuses on the use of assets as measures of consumption especially when data on expenditure are unavailable, Principal Components Analysis (PCA) being a well-accepted method in this area (Filmer and Pritchett, 2001). I compare the mixture results obtained here with those obtained by using PCA (Filmer and Pritchett's approach). I show that results are largely the same regarding *who* constitutes the classes, but that PCA provides no insight on *how big* the classes are – an advantage of the mixture approach. PCA is not intended as a method of decomposing the marginal distribution of assets into classes while mixture modeling is particularly well suited to this task. This paper therefore makes a significant contribution to the literature on using asset ownership as an identifier of (consumption) class[1].

There are, in particular, two specific reasons for using durables ownership in the current study. First, durables offer a steady stream of utility in future periods making their ownership a natural measure of *long-term* consumption standard (Bar-Ilan and Blinder, 1988, Townsend, 1979). The idea of long-term consumption seems more appropriate for the determination of a consumption 'class' than expenditure, which only captures consumption in the recent past. Second and more importantly, durable ownership is easy to observe and less subject to errors

[1]Note that a mixture approach may be applied to per capita expenditure as well (see Anderson et al, 2014)), but the interpretation of results would then continue to be plagued by the known problems with exenditure data.

in measurement. The durables approach is a particularly useful tool in the dataset I use – the urban sub-sample of the Indian National Sample Survey (NSS), 1999-00. It is widely documented (see Deaton and Kozel (2005) and the references therein) that the expenditure data in this round of the survey are difficult to interpret. Also, the recall periods were changed in the questionnaires of this round. Data on durable ownership are clearly not subject to such errors in reporting.

The (marginal) distribution of durables ownership across individuals can be naturally decomposed using mixture methods into 3 conditional distributions over durables (one each for lower, middle and upper class) and the weights of each of these individual distributions in the population distribution. This decomposition can be estimated at different points in time to allow analysis of the behaviour and membership of classes over time. The approach provides a potentially deeper understanding of the dynamics of classes, in particular, the lower class, than can be obtained using poverty lines and PCA alone[2]. Finally, the identified class structure has implications for expenditure distributions by class.

As a specific example of how the mixture approach provides an important tool

[2] Here is an alternative example of a situation in which a mixture model would work well. Suppose we have earnings data for men and women but that the gender descriptors are lost (or unknown). A mixture model would be a good tool to help decompose the marginal distribution of earnings into conditional distributions for men and women. In the current application the "unknown" descriptor is "consumption class".

for policymakers, I estimate and compare the size of the lower class in India in 1993-94 with that in 1999-00. There was a spate of policy changes liberalizing the Indian economy in 1991. A large basket of goods previously unavailable (or exorbitant) became available to the Indian population, even as Government regulations were eased in favour of more open markets. Growth rates were also higher in this period than before. What happened to poverty during this time is therefore a question of great interest. However, there is no clear consensus on what happened to poverty in the 1990s since a change in recall periods in the National Sample Survey data of 1999-00 has led to non-comparability of responses on expenditure with the previous round (Deaton and Kozel, 2005). A mixture model using durables – such as the one described above – provides an alternative tool to address this issue. Hence, this paper also makes a contribution to the literature that debates the evolution of poverty in India in the 1990s.

I estimate the mixture model of durables for the years 1993-94 and 1999-00 (National Sample Survey data, rounds 50 and 55) and look at the proportion and characteristics of the lower class – or relative poverty – over time. I find that the size of the lower class decreases from 30% in 1993-94 to 20% in 1999-00, suggesting that relative poverty did decline during the 1990's. However, the lower class in the latter year has a significantly (and unambiguously) worse pattern of durable ownership and the proportion of the lower class that is under the official poverty line *increases* slightly over these two periods. This suggests some interesting dynamics in relative consumption during the 1990s, consistent with the idea of an "immiserizing" component of growth during this period (Bhagwati, 1958).

The durables' ownership based mixture model is presented below.

2. Methodology

2.1. Data and Definitions

The data used in the primary analysis comes from the urban sub-sample of the 55th Round of the Indian NSS (1999-00). The $48,924$ households in the sample are asked a battery of questions about their consumption habits and expenditures. For a list of durable items, they are asked to report how many pieces of each good are *in use* at the time of the interview. For each durable, I define 'ownership' as an indicator that at least one piece of the durable is *in use* in the household at the time of interview. The variable of interest Y is the *total* number of durable goods that a household 'owns' (by the above definition) at the time of interview. A mixture model hypothesizes that the density of Y is a weighted sum of densities of individual groups in the population. The goal is, therefore, to identify the distinct groups in the population such that their individual ownership densities or consumption patterns can, when weighted by estimated class-membership probabilities, explain the overall density of Y observed in the sample.

In the following analysis, I use a set of 11 durable goods, which can be placed in three broad categories: recreational goods (record player/gramophone, radio, television/VCR/VCP, tape/CD player), electrical household appliances (electric fan, air conditioner, washing machine, refrigerator) and transport goods (bicycle, motor bike/ scooter, motor car/ jeep)[3][4].

Note from the definition of Y above that the intensity of durable ownership – how many pieces of a certain durable are in use – is *not* incorporated in how ownership is defined. Affluence is measured by the *variety* of services from durables owned, not the intensity of use of individual items. This is due to the fact that intensity of ownership may be higher in larger households not necessarily belonging to a higher class (larger households with more electric fans, for instance); hence including intensity of use in the definition of ownership may inappropriately as-

[3]The data do not allow us to discern the quality of durable goods in use in a household (e.g. models of cars or TVs or makes of audio/ video goods). But, to the extent that goods of higher quality (e.g. plasma TVs versus black-and-white TVs) are owned by households with *more* goods, ignoring durable-quality in the definition of Y is unlikely to impede an appropriate identification of the classes. Footnote 6 makes a similar point.

[4]An earlier working paper version of this article used 12 durable goods in the mixture model. However, in the interest of comparability with the earlier round of data (NSS $50th$ Round, 1993-94) which pools ownership of TVs and VCR/VCPs into one variable, I do the same for the $55th$ Round. Results are the same as in the 12-good model .

cribe higher affluence to larger households (Deaton and Paxson, 1998). Moreover, ignoring the intensity of use does not imply – for example – that households with four cars are treated identically to households with one car. What is important for identifying affluence is the *total* number of *distinct* durables; hence to the extent that households with four cars are also more likely to own a higher *total* number of distinct durables than households with one car, they are more likely to be identified (correctly) as more affluent[5].

Figure 1 presents the distribution of Y – the total number of the 11 durable goods that households own – in the sample[6]. Table 1(a) presents summary statistics for the ownership variables.

The bimodality and positive skewness of the distribution of Y in Figure 1(a) suggest that a mixture model may be an appropriate description of the latent class structure. The objective of the primary analysis is to identify the n distinct classes in the population such that their individual ownership densities or consumption patterns can, in combination, explain a distribution like that in Figure 1(a).

[5] The similarity of mean household size across the different identified classes (see Table 4(a)) seems to reinforce this point suggesting that economies of scale effects are minimized when durables ownership is defined as it is here.

[6] Note that Y – the total number of durable items owned – incorporates a 'natural' weighting of different goods based on the associated level of affluence. For instance, cars occur in households with higher values of Y than radios, since on average cars occur in (more affluent) households with more total durables than do radios.

Note that the application of a finite mixture model requires an assumption about n, the number of classes in the population. I argue that the appropriate number of classes is the *minimum* number of classes that can produce a good fit to the observed density of Y. Else, in the extreme case of allowing each household to be in a class of its own, a perfect fit could easily be obtained. In the present case, I show that a better fit is obtained when three classes are assumed than with two classes (see Section 3.1 and the appendix). Hence, a Three-Component Mixture Model is used to identify the three classes; henceforth referred to as the 'lower', 'middle' and 'upper' class, respectively. Details of the model and the estimation algorithm are provided in Sections 2.2 and 2.3.

Before proceeding to the formal model and estimation algorithm, however, it is useful to discuss why 'durables ownership' is used to identify the classes instead of per capita expenditure (PCE). I do this in the next subsection.

2.1.1. Why 'durables ownership'

Household consumption and wealth is most often measured using household expenditure (Deaton, 1997). While it is a natural and direct measure of consumption, expenditure data can be costly to obtain and are often subject to errors such as recall bias and rounding. Durables ownership data are relatively free of such reporting errors. For the NSS data in particular, recall periods for reporting expenditures were altered in the 1999-2000 round, leading to widespread concerns that expenditures reported in the later surveys may suffer from a systematic recall bias (see the poverty literature summarized in Deaton and Kozel, 2005). Durables ownership information – measured by whether or not certain durables are in use at the time of the survey – is not affected by a change in recall periods and using these would consequently enable reliable comparisons of class characteristics over time.

Several studies have proposed and used durable ownership as a measure of wealth (Filmer and Pritchett, 2001; Montgomery et al, 2000). Consumer durables are a store of utility and assure the realization of a stream of consumption utility in future periods. This characteristic makes durables ownership a natural measure of consumption 'standard', since it represents a permanent, sustainable aspect of consumption (Bar-Ilan and Blinder, 1988). Hence it seems intuitive to use durable ownership to identify consumption 'classes'. In contrast, measures based on total expenditure say relatively little about the 'standard' of living or its sustainability since they refer only to a specific time period in the recent past and may include transitory components as well.

One may argue that a durable good may be acquired using transitory income, which would then make its ownership an inappropriate indicator of (permanent) living 'standards'. However, even if the above is true, it is reasonable to expect that a larger *total* number of durables *in use* – the measure of ownership used herein – is likely to represent a household with higher permanent income, and hence a higher sustainable standard of living. This recommends the use of the total number of durables owned as an indicator of higher permanent living standards, and hence of an increased probability of membership in a higher class.

The approach adopted in this paper uses durables ownership to identify the classes and then examines the PCE-ranges of the individual classes thus identified. It is reassuring to note that the range of PCE implied for the identified classes are in line with the PCE-cutoffs assumed in previous studies (Banerjee and Duflo, 2008; Ravallion, 2010). This suggests intuitively that the current 'dual' approach – of using durables ownership to identify classes instead of PCE – is able to identify classes corresponding to existing researchers' notions about the same. In addition, the mixture approach allows the data to determine the *distribution* of lower (middle or upper) class households over the relevant PCE-range, instead of assuming that *every* household in this PCE-range belongs to the lower (middle or upper) class with certainty, as in the cutoffs-based approach.

2.2. The Three Component Mixture Model

Consider 11 durable goods and let Y represent the total number of these goods that a household owns at the time of interview, $Y \in \{0, 1, 2 \dots 11\}$. Households can belong to one of three classes – 1, 2 or 3 – which are defined by the pattern of durables ownership of members. Assume that a household owns each good with a fixed probability (p_i), which depends on the class ($i = 1, 2$ or 3) to which it belongs. The ordering of the p_i's indicates which i $(= 1, 2, 3)$ corresponds to the lower, the middle and the upper class, respectively, since (by definition) $p_L < p_M < p_U$ (L : lower, M : middle, U : upper). Assume that each good is obtained independently by households. Hence the total number of goods owned by a class-i household follows a binomial distribution with parameters 11 and p_i[7].

Note that the class-specific probability of ownership p_i – which may be interpreted as the probability that a class-i household owns a representative durable good – is assumed to be the same for each good. This is for the following two reasons. First, allowing the probability to vary by class as well as good, viz. p_{ij} $(i = 1, 2, 3;\ j = 1, ..., 11)$[8] would make the mapping of parameters

[7] Allowing dependence in the ownership of different goods would necessitate several additional assumptions on the nature of dependence. Derivation of the density functions ϕ_i in these cases becomes very complex.

Moreover, a binomial distribution is flexible and might provide an accurate approximation to whatever the true discrete distribution might be.

[8] Here j represents a particular durable good, not the total number of durables. Since there

$\{(\pi_i, p_{ij}), i = 1, 2, 3; j = 1, 2, ..., 11\}$ to class $\{Lower,\ Middle,\ Upper\}$ less transparent since there is no longer a clear and intuitive ordering of p_i's that defines the classes. In other words, we would now have to choose some external criterion to compare the vector $(p_{i1}, ...p_{i11})$ across classes $i = 1, 2, 3$ and determine which of these is the lower, the middle and the upper class. Second, it is not the focus of the current analysis to explore the characteristics of the goods j per se (viz. necessary/ luxury items) but to identify the three classes represented by distinct patterns of affluence. A fundamental premise of the current approach is that affluence (and therefore class status) is measured by the *total* number of durables owned. Assuming p_i (and not p_{ij}) provides the simplest tractable framework within which to exploit this premise and generate a transparent mapping of parameters to class[9].

The probability of obtaining an observation y in the sample is given by:

$$P(y; \pi_1, \pi_2, p_1, p_2, p_3) = \pi_1 \phi_1(y; p_1) + \pi_2 \phi_2(y; p_2) + (1 - \pi_1 - \pi_2) \phi_3(y; p_3) \quad (1)$$

where π_i represents the probability that the household belongs to class i and

are 11 durables in the analysis, j can take values $1, 2, ..., 11$.

[9]Note also that postulating a mixture model that allows $p_{ij} (i = 1, 2, 3; j = 1, 2, ..., 11)$ involves the estimation of 35 parameters $(\pi_1, \pi_2, \{p_{ij}\}_{i=1,2,3}^{j=1,...,11})$. It is hard to establish the identifiability of such a model.

$\phi_i(y; p_i)$ represents the (binomial) probability that a class-i household owns y durables. This is a Three-Component Mixture Model (McLachlan and Peel, 2000; Everitt and Hand, 1981).

2.2.1. Identifiability and Observational Equivalence

Before attempting to estimate the binomial mixture model in (1), it is necessary to establish that the model is identifiable. While binomial mixtures in the parameter p need not be identifiable in general (Teicher, 1961), a well-known paper by Blischke (1964) shows that a necessary and sufficient condition for identifiability is $n \geq (2r-1)$, where n is the binomial parameter denoting the number of trials and r is the number of components in the mixture. In the current application, $n = 11$ (the number of durables) and $r = 3$ (the number of classes), so the condition for identifiability is easily satisfied. Hence the model (1) is identifiable.

Note also the issue of observational equivalence known to characterize mixture models in general. This means – for example – that there is no difference observationally, between the parameter vector $(\pi_1, \pi_2, (1-\pi_1-\pi_2), p_1, p_2, p_3)$ and the vector $(\pi_2, \pi_1, (1-\pi_1-\pi_2), p_2, p_1, p_3)$. Observational equivalance makes it hard to uniquely map parameters to class (in the example above: is class 1 the 'lower' class or class 2?). However, the very nature of the current application –

the identification of a lower, a middle and an upper class – provides a natural remedy for the issue, since, obviously, $p_L < p_m < p_U$ (L : lower class, M : middle class, U : upper class). Therefore, the ordering of the p_i-estimates tells us which class is the lower class, which is the middle class and which, the upper class.

2.2.2. Estimation

Having established identifiability, we now proceed to estimation of the mixture model. From (1), the likelihood function can be written as

$$L(y;\pi;p) = \prod_{j=1}^{N}[\pi_1\phi_1(y_j;p_1) + \pi_2\phi_2(y_j;p_2) + (1-\pi_1-\pi_2)\phi_3(y_j;p_3)]$$

where subscript j denotes the household, $j = 1, 2, ..., N$. The log likelihood function is then:

$$\log\ L(y;\pi;p) = \sum_{j=1}^{N}\log\ [\pi_1\phi_1(y_j;p_1) + \pi_2\phi_2(y_j;p_2) + (1-\pi_1-\pi_2)\phi_3(y_j;p_3)] \quad (2)$$

It is hard to obtain closed-form expressions for maximum likelihood estimates of the parameters in (2). The Expectations Maximization (EM) algorithm is a tool used to simplify difficult maximum likelihood problems such as the above (McLachlan and Krishnan, 1996; Dempster et al, 1977; Hastie et al, 2001) and is described in Section 2.3. The importance of the EM algorithm lies in its ability to find a path to the maximum likelihood point estimates where traditional numerical techniques typically fail.

2.3. Implementation of the EM algorithm

Suppose that each household belongs to a particular class and let the dummy variables (δ_1, δ_2) represent the class membership of households, i.e.

$$\begin{aligned}
\delta_{1j} &= 1 \text{ if household } j \text{ belongs to class 1} \\
&= 0, \text{ otherwise} \\
\delta_{2j} &= 1 \text{ if household } j \text{ belongs to class 2} \\
&= 0, \text{ otherwise}
\end{aligned}$$

If class memberships (δ_1, δ_2) were *not* latent variables, then the likelihood and log-likelihood functions could be written as

$$L_{EM}(y, \delta_1, \delta_2; \pi; p) = \prod_{j=1}^{N} \{\pi_1 \phi_1(y_j; p_1)\}^{\delta_{1j}} \{\pi_2 \phi_2(y_j; p_2)\}^{\delta_{2j}} \{(1-\pi_1-\pi_2)\phi_3(y_j; p_3)\}^{(1-\delta_{1j}-\delta_{2j})}$$

$$
\begin{aligned}
\log\ L_{EM}(y,\delta_1,\delta_2;\pi;p) \quad = \quad & \sum_{j=1}^{N}[\delta_{1j}\log\ \{\pi_1\phi_1(y_j;p_1)\} + \delta_{2j}\log\{\pi_2\phi_2(y_j;p_2)\} \quad (3) \\
& +(1-\delta_{1j}-\delta_{2j})\log\{(1-\pi_1-\pi_2)\phi_3(y_j;p_3)\}]
\end{aligned}
$$

It would be easy to find closed-form expressions for maximum likelihood parameter estimates from (3), if class memberships (δ_1, δ_2) were known. Since class memberships are unknown, the EM algorithm computes the *expected* values of (δ_1, δ_2) conditional on the data (call these (γ_1, γ_2)), plugs these into (3) and computes the maximands. The procedure is iterated till convergence is obtained. The steps involved are outlined below (McLachlan and Krishnan, 1996; Dempster et al, 1977; Hastie et al, 2001).

The EM Algorithm for a Three-Component Mixture Model

1. Start with initial guesses for the parameters, $(\pi_1^{(0)}, \pi_2^{(0)}, p_1^{(0)}, p_2^{(0)}, p_3^{(0)})$.

2. Expectation (E) step: at the k^{th} step, compute, as follows, the expected values $(\gamma_i^{(k)})$ of class membership, conditional on the data $(y_1, y_2, ..., y_N)$. Since class memberships are binary, $\gamma_i^{(k)}$ is also the estimated probability

that a household belongs to class i, conditional on the data.

$$\begin{aligned}
\gamma_{ij}^{(k)} &= E(\delta_{ij}|(y_1, y_2, ..., y_N; \pi_1^{(k-1)}, \pi_2^{(k-1)}, p_1^{(k-1)}, p_2^{(k-1)}, p_3^{(k-1)}) \\
&= \frac{\pi_i^{(k-1)}\phi_i(y_j; p_i^{(k-1)})}{\pi_1^{(k-1)}\phi_1(y_j; p_1^{(k-1)}) + \pi_2^{(k-1)}\phi_2(y_j; p_2^{(k-1)}) + (1 - \pi_1^{(k-1)} - \pi_2^{(k-1)})\phi_3(y_j; p_3^{(k-1)})}
\end{aligned} \tag{4}$$

$i = 1, 2, 3.$

3. Maximization (M) step: at the k^{th} step, compute the parameters as follows. These are the maximands of the EM-log-likelihood function in (3), when (δ_1, δ_2) are replaced by their expected values conditional on the data.

$$\begin{aligned}
\pi_i^{(k)} &= \frac{1}{N}\sum_{j=1}^{N}\gamma_{ij}^{(k)} \\
p_i^{(k)} &= \frac{1}{11}\left[\frac{\sum_{j=1}^{N}\gamma_j^{(k)} y_j}{\sum_{j=1}^{N}\gamma_j^{(k)}}\right]
\end{aligned} \tag{5}$$

$i = 1, 2, 3.$

4. Iterate steps 2 and 3 (the E and M steps) till convergence is obtained.

As output, the EM algorithm yields the following estimates:

1. $\widehat{\pi}_i$: estimates of the (unconditional) probability that any household belongs to class i; $i = 1, 2, 3$

2. $\widehat{p}_i$: estimates of the probability with which a class-i household owns a durable good; $i = 1, 2, 3$

3. $\widehat{\gamma}_{ij}$: estimates of the (conditional) probability with which household j belongs to class i; $i = 1, 2, 3$; $j = 1, 2, ..., N$

The ownership probabilities $\widehat{p}_i$ and the corresponding class-specific densities $\phi_i(y; \widehat{p}_i)$ answer our motivating question – who are the lower, middle and upper class? – by identifying the distinct ownership patterns of the different classes. Moreover, the estimates of the unconditional probabilities $\widehat{\pi}_i$ – interpretable as estimates of class shares – tell us the sizes of the classes in India. Finally, the estimated (conditional) probabilities of class membership, $\widehat{\gamma}_{ij}$, along with $\widehat{\pi}_i$ and $\widehat{p}_i$, enable an assignment of each household into a particular class. This allows an examination of other class-specific household characteristics such as per capita monthly expenditures.

3. Results and Discussion

3.1. Estimates

The estimates produced by the EM algorithm are presented in Table 3(a) and Figures 2(a), 3(a), 4(a).

The numbers in column *(1)* of Table 3(a) represent the population share of each class, $\widehat{\pi}_i$. The lower class is estimated to constitute 19.8% of urban households. This is the estimate of relative poverty in urban India in 1999-00 – almost 20% of households. The middle and upper classes constitute 59.4% and 20.8% of urban households in 1999-00. Asymptotic standard errors obtained from the information matrix (McLachlan and Peel, 2000) are small, supporting the existence of three distinct classes in the population.

Column *(2)* reports estimates of the probability parameter $\widehat{p}_i$ for each class $i = L, M, U$. Lower class households are found to own a good with 2.6% probability while middle and upper class households own a good with probabilities of 26.5% and 53.6% respectively. Small standard errors support three distinct patterns of durables consumption behaviour[10].

[10] The standard errors are calculated from the standard information matrix (McLachlan and Peel (2000)).

The estimates (standard errors) of the differences are as follows: $\widehat{p}_L - \widehat{p}_U = -0.43$ (0.004), $\widehat{p}_L - \widehat{p}_M = -0.17$ (0.002) and $\widehat{p}_U - \widehat{p}_M = 0.25$ (0.003) ($L \approx Lower;\ M \approx Middle;\ U \approx Upper$).

The mean number of durable goods (out of 11) owned by class-i households is simply $11p_i$ (the mean of the binomial distribution for class i). These estimates are reported in Column *(3)* of Table 3(a). The lower, middle and upper classes are found to own, on average, 0.3, 3 and 6 goods, respectively.

The mean number of goods – or alternatively the probability of ownership p_i – therefore yields a measure of how well class i is doing. By definition of upper, middle and lower class, we have $p_L < p_M < p_U$. In addition, the movement of p_L (or p_M or p_U) over time would indicate how well the lower (or middle or upper) class is doing over time. This makes it possible to make a definitive statement about the well-being of a class *even without knowing the true class membership* of each household.

Figure 2(a) plots the binomial density functions ϕ_i at the estimated parameters $\widehat{p}_i$ $(i = L, M, U)$. The density of the lower class peaks at 0 durables, whereas that of the middle and upper classes peak at 3 and 6 durable goods, respectively.

Figure 3(a) plots the actual relative frequency of observations (Y) in the data along with the predicted values. The figure demonstrates a very good fit to the data. As an analytical exercise, a Two-Component (two classes) Mixture Model was fitted to the data by EM. The results are presented in the appendix (Table 7 and Figure 7). The fit is clearly worse than that of the Three-Component Model.

Hence, three appears to be the minimum number of classes that provides a good fit to the data[11].

Figure 4(a) plots the probabilities $\widehat{\gamma}_i$ that a household belongs to different classes i $(= 1, 2, 3)$ conditional on the number of durables owned. For example, households with low values of Y are most likely to belong to the lower class whereas those with the highest values of Y are almost certain to belong to the upper class. Hence, unlike in previous studies, the current approach places households in different classes with a probability rather than with certainty.

Notice that the computation of $\widehat{\gamma}_i$ allows the placement of households into classes, albeit wth some randomness. Here is an example of how the class assignment is performed. Suppose we estimate $\widehat{\gamma}_{10} = 0.6, \widehat{\gamma}_{20} = 0.1$ and $\widehat{\gamma}_{30} = 0.3$. This means that a household that owns none of the eleven durable goods (i.e. $Y = 0$) belongs to class 1 with probablity 0.6, class 2 with probability 0.1 and class 3 with probability 0.3. Now suppose that in the dataset, there are t observations for $Y = 0$. I then randomly assign $0.6t$ of these households with $Y = 0$ to class 1, $0.1t$ to class 2 and $0.3t$ to class 3. The class assignment will not uniquely assign a

[11] Note that the $3-$class model can predict values of Y upto three places of decimal. It is unlikely that a model with 4 classes will provide a significantly better fit than this, at least for all practical purposes. Moreover, the $3-$class model is parsimonious in the number of parameters to be estimated (5 in total) relative to the $4-$class model (7 parameters). This justifies the choice of the Three-Component Mixture Model in the current study.

household with 0 goods to a class but it will ensure that the ratio of households with $Y = 0$ in class 1 , 2 and 3 are always in the ratio 0.6 : 0.2 : 0.1 (in this specific example).The same procedure may be followed to randomly assign households to classes for each other value of Y $(= 1, 2, ..., 11)$. This method will ensure that we have an assignment of classes to households in the proportion of the class sizes estimated by the mixture model[12].

Assigning a class to each household allows us to then examine how monthly per capita expenditure is distributed for each class[13].

Table 4(a) reports the per capita monthly expenditures (PCE) of households in each assigned class. Note that the ranges of PCE corresponding to different classes are overlapping rather than mutually exclusive, as suggested by the 'cutoffs' approach used in the literature. The fundamental difference between the cutoffs-based approach and the mixture approach lies, therefore, in the postulated distribution of households: the cutoffs-based approach assumes *every* household with PCE in a certain range belongs to a particular class, whereas the mixture

[12] Clearly there is a non-zero probability of assigning a household to a class other than the one to which it truly belongs. There is no way to check or estimate the "misclassification" error because the true class membership of households is unknown. Despite this fact, however, we are able to make definitive statements about the well being of each class – as captured by the parameters p.

[13] I have reported the PCE distribution for a particular assignment of households to classes, as described earlier. There is more than one way of making the assignment, each ensuring consistency with the mixture model estimates. Standard errors of each point of the distribution could then be obtained by looking at repeated assignments and bootstrapping.

aproach identifies each class with expenditures *distributed* over a PCE-range. Consequently, estimates of any class characteristic that is sensitive to distribution could be very different based on which approach is used, even when the range of class expenditures is comparable across approaches[14].

It is interesting to note that the official (urban) poverty line in 1999-00 – Rs. 455 in current rupees – falls at the $29th$ percentile of the PCE distribution of the lower class, almost 30% below the median PCE of the lower class. It seems that urban households in relative poverty – the lower class – are doing better on average than the standard set by the poverty line. This finding could, of course, be a direct result of a general over-statement of expenditures in the survey due to the change in recall periods. It also suggests that PCE may need to be supplemented with other measures less prone to measurement and recall error and related directly to relative well-being in a changing economy.

It is often argued that the poverty line captures the price of purchasing a commodity basket that meets minimum nutritional needs (see Deaton and Kozel, 2005). If this is the case then it is difficult to interpret the fact that a proportion of the middle and upper classes (identified by their ownership of 11 durable goods)

[14]The mean expenditures by class in Table 4 are comparable to those assumed in several studies to mark cutoffs for classes (Banerjee and Duflo, 2008; Birdsall et al, 2010; Ravallion, 2010). However, as emphasized in this paragraph, the estimate of class size could be very different due to sentivity to distribution.

are *not* meeting the minimum nutritional need in terms of PCE. The contradiction could be explained by reporting errors (under-reporting PCE this time) or simply by the fact that PCE captures a component of transitory consumption – both of which re-iterate that expenditure measures are messy and often hard to interpret, especially when used to the identify consumption classes[15]. A mixture model using durables ownership is a good tool to supplement or replace PCE based measures, especially when the latter are not available or misreported.

3.1.1. Principal Components Analysis (PCA): A Comparison

Filmer and Pritchett (2001) suggest a durables based measure of wealth that could be used to proxy for expenditure information when the latter is not available. They propose and use the first principal components (PCA) score of a set of durable goods. Ordering this score from low to high they define the lowest 40% of households as the lower, the middle 40% as the middle and the top 20% as the upper class. They acknowledge that this 40 : 40 : 20 division of classes is purely arbitrary and use it for expository convenience.

[15] Some of the dispersion in the class-specific PCE distribution could be caused by outliers. A refinement of the model (see the appendix titled "Truncated Model: A Refinement") is one way to reduce dispersion due to outliers. However, there do exist households in the 1999-00 sample who own a number of durable goods but at the same time report less than poverty line expenditure in the last month.

In this section, I conduct a principal components analysis akin to Filmer and Pritchett (2001) using the same set of durables as in the original mixture. However I define the classes in two ways: (a) the $40:40:20$ division of Filmer and Pritchett (2001) and (b) the $20:60:20$ proportion suggested by the mixture model. The resultant predicted distributions of Y are presented in Figures 5(a)-(b) along with the actual (observed) distribution of Y.

The predicted distributions of Y by class in Figures 5(a)-(b) are derived as follows. As in Filmer and Pritchett (2001), I estimate the first principal component score, order households from lowest to highest scores, then assign households in the lowest 40% to the lower class, the middle 40% to the middle class and the upper 20% to the upper class (20% to lower, 60% to middle and 20% to upper classes, respectively for alternative (b)). In each class thus defined, I then plot the relative number of observations corresponding to each value of Y[16].

Notice, in Figures 5, that the predicted distribution of the variable Y – the total number of distinct durables owned – is invariant to the proportion of classes assumed when using the PCA approach. In other words, whether we assign classes using alternative (a) or alternative (b), the weighted average of observations in

[16] This amounts to using the 'tabulate' command in STATA: *tabulate Y if class==i* (where i can be lower, middle or upper).

each class for each value of Y are quite close to the actual number of observations for that value of Y. This suggests that the first principal components score reflects the same information as contained in the sum of durables Y used in the mixture approach. But the PCA approach does not provide any intuition about the sizes of the classes in the population. In the mixture approach, a maximum likelihood process serves to determine optimal class sizes as well as class ownership densities[17]. PCA is not intended as a method of decomposing the marginal distribution of assets into classes while mixture modeling is particularly well suited to this task.

4. What happened to poverty in India in the 1990s? An Application of the Mixture Model

There is widespread debate about what happened to poverty in India in the 1990s. The Indian economy was subject to a spate of liberalizing policies in 1991. This was followed by high growth rates during the 1990s and an economy that witnessed enormous change in the availability and price of goods and services in the economy. What happened to poverty in this changing environment is a question of great

[17] The invariance has been found to hold for other assumed class size ratios as well. An indepth examination of this phenomenon is beyond the scope of the current paper. It is on the agenda for future research.

interest but there is no clear consensus on the matter. An important reason for the lack of consensus is that the 1999-00 round of National Sample Survey data used different recall periods than the previous (1993-94) round. This led to fear that there was a general over-reporting of expenditures in 1999-00 leading to (erroneous) estimates of lower poverty in the latter year.

The mixture model described above does not rely on expenditure data to identify consumption classes in the 1999-00 survey of NSS. Moreover a change of recall periods should not alter answers to the survey question "how many of the following durable items are in use at the time of the survey". It seems natural therefore to apply the durables based mixture model to see how poverty changed between 1993-94 and 1999-00.

The measures of poverty I will examine are the size and the ownership probability of the lower class. It is important to remember that these are measures of relative poverty because they are identified in relation to two other classes who fare better than the lowest class in terms of durable ownership. The criterion of identification of the lower class is, therefore, endogenously determined by the durables ownership patterns of all households in the data.

Table 3(b) shows estimates from the Three Component Mixture Model of 11 goods conducted using data from the 1993-94 round of NSS. The lower class is found to constitute 30% of urban households in 1993-94, compared with 58% of households being in the middle class and 12% who belong to the upper class.

At first glance, it seems that consumption and well-being has improved unambiguously and across all classes in 1999-00 compared with 1993-94. The size of the lower class has shrunk from 30% in 1993-94 to 20% in 1999-00 suggesting that relative poverty has fallen in the 1990s. Also the size of the upper class has increased suggesting that improvements in well-being have been across the board.

However, a look at the estimates of ownership probabilities indicate how the individual classes have fared over this time. Here it is clear that the lower class fares worse in 1999-00 than in 1993-94. Ownership probability is significantly lower (at level 1%) in 1999-00 than 1993-94 (see LR test results in Table 6) and Figure 6 plots the durables ownership density of the lower class in the 2 years. The worsening of well-being is evident from the increased proportion of lower class households who own no goods and decreased proportions of households owning 1 or 2 goods.

The ownership probabilities of the middle and upper class have increased, suggesting that there have been improvements in well-being in the middle and upper ends of the total ownership distributions.

The ambiguous finding regarding the well-being of the relatively poor group –

the lower class – suggests interesting dynamics of consumption and well-being in the 1990s. In particular it points to the occurrence of an "immiserising growth" in the 1990s, at least for the lowest class, where the proportion of households left behind decreases but the most deprived group find themselves in the direst of circumstances. It will be important for policymakers to identify and track these impoverished households to ensure that they are not left behind as the economy prospers.

In the following paragraph I provide a suggestion for how the information presented above may be used for practical policy. I use the results of Tables 3 and 4 to formulate a "rule" for identifying the most impoverished households who require aid, viz. the social assistance base. This is by no means a unique or an optimal rule by any criterion – but is intended as an example of how the results from the mixture model could inform policy decisions.

Suppose that the official poverty line measures the cost of maintaining a minimum level of nutrition required to survive. The proportion of households that fall under the poverty line may therefore be thought of as a measure of absolute poverty, whereas the lower class are the group of households in relative poverty. The households that lie in the intersection of these definitions – the groups who find themselves in absolute *and* relative poverty – are clearly the most impoverished and should form the core of the social assistance base. The "class" that households belong to are not observable but we do observe durables ownership and we know that 75% of lower class households own 0 durable goods (97% own 0 or 1 good) (see Figure 2(a)). A simple rule for identifying the target group for social policy could then be to assign all households with 0 durables (or $0-1$ durable, depending on the resources available for aid disbursement and the policymakers' tolerance for misclassication errors) and with expenditure below the poverty line to the social assistance base[18].

As mentioned earlier, the rule presented above is not unique or optimal by any criterion. It is a suggestion intended to foment future research that will define and evaluate efficient strategies for identifying truly needy households. This paper demonstrates that the mixture approach using durables is an invaluable tool for informing such research.

[18]Naive calculations from the mixture model (1999-00) show that about 12% of households assigned to the social assistance base (if only 0 durables are included in the rule) will be "non-needy" (i.e. middle or upper class but with expenditure below poverty line) and that 24% of households we wish to assign to the assistance base will be excluded by the decision rule. The proportions are 35% and 2%, respectively, for the decision rule that allows ownership of $0-1$ durables to be included in the assistance base.

5. Summary and Conclusion

I propose the use of a durables based mixture model as a robust tool for identifying and estimating the size of consumption classes, with classes defined by their distinct patterns of durables ownership. In doing so, this paper makes important contributions to two distinct categories in the economic literature.

The first contribution is to the literature that uses assets to measure well-being in the absence of expenditure data. I argue that durables ownership is easy to record and observe and is a natural measure of long-term consumption standard – the underlying determinant of a consumption 'class'. I demonstrate using Indian data that the mixture approach yields a richer probabilistic class definition than that obtained from expenditure-cutoffs-based approaches, using no arbitrary assumptions about who the classes are. Lastly, I show that the mixture approach uses and delivers the same information as a PCA approach (as in Filmer and Pritchett, 2001) on the total durables ownership distribution. The mixture approach yields, in addition, relative class sizes based on an optimization criterion.

The second major contribution of this paper is to the literature that debates what happened to poverty in India in the 1990s. Widespread debate on this question stems from, among other things, a change in recall periods used in the 1999-00 NSS survey, making the expenditure data difficult to compare across the two rounds. I argue that durables ownership is not affected by a change in recall periods, and use the mixture approach as an alternative way to examine what happened to relative poverty in the 1990s. I show that the size of the lower class – or the goup in relative poverty – decreases from 30% in 1993-94 to 20% in 1999-00, and that the size of the upper class increases over time as well. However, the well-being of the lower class – reflected in the probability of ownership of durables – decreases significantly indicating that lower class households, though smaller as a proportion of the population, are significantly worse off in the latter year.

The analysis presented here demonstrates the usefulness of a durables-based mixture approach to identify consumption classes who are the target of policy, to provide context for the definition of a social assistance base and to examine relative poverty and inequality in a population. It is useful to think of the analysis presented here as a metaphor. We think of classes in the abstract and suppose that agents with certain characteristics belong to those classes. The paper tries to identify the classes using the best available data. While there are and will always will be inconsistencies, we do find an empirical model that matches our intuition and is consistent with the data.

It is hoped that further research will investigate how the mixture approach can be used to inform specific policy rules along with their efficiency properties.

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Table 1(a): Summary Statistics, Urban Sub-sample, NSS 1999-00, N = 48,924 households

Variable	Mean	Std. Dev.	Min	Max	Remarks
Total No. of Durables Owned (Y)	3.01	2.26	0	11	Variable used in Estimation
If household 'owns':					'1' if household owns at least one piece of the item
Record Player	0.02	0.13	0	1	
Tape Player	0.30	0.46	0	1	
Radio	0.36	0.48	0	1	
TV/VCR/VCP	0.60	0.49	0	1	
Electric fan	0.67	0.47	0	1	
Airconditioner	0.12	0.32	0	1	
Washing machine	0.10	0.30	0	1	
Refrigerator	0.25	0.43	0	1	
Bicycle	0.37	0.48	0	1	
Motor cycle	0.20	0.40	0	1	
Car	0.03	0.17	0	1	
Per Capita Monthly Household Expenditure	1018.72	1535.32	17	205987	48,921 observations

Table 1(b): Summary statistics, Urban Sub-sample, NSS 1993-94, N = 17,467 households (who report durable ownership with no inconsistencies)

Variable	Mean	Std. Dev.	Min	Max	Remarks
Total No. of Durables Owned (Y)	2.28	1.90	0	11	Variable used in Estimation
If household 'owns':					'1' if household owns at least one piece of the item
Record player	0.01	0.106657	0	1	
Tape player	0.25	0.435645	0	1	
Radio	0.49	0.499903	0	1	
TV/VCR/VCP	0.43	0.495035	0	1	
Electric fan	0.61	0.49	0	1	
Airconditioner	0.05	0.22	0	1	
Washing machine	0.05	0.22	0	1	
Refrigerator	0.14	0.35	0	1	
Bicycle	0.16	0.37	0	1	
Motor cycle	0.07	0.25	0	1	
Car	0.01	0.11	0	1	
Per Capita Monthly Household Expenditure	629.04	995.76	11	68559	17,239 observations

Table 2: Total number of durables owned by households (*Y*)

1999-00 (N = 48,924 households)

Y	No. of observations	Relative frequency
0	8,228	0.168
1	6,067	0.124
2	7,596	0.155
3	8,030	0.164
4	6,751	0.138
5	4,910	0.100
6	3,420	0.070
7	2,146	0.044
8	1,194	0.024
9	462	0.009
10	109	0.002
11	11	0.000

1993-94 (N = 17,467 households who report durables wonership without inconsistencies)

Y	No. of observations	Relative frequency
0	3,359	0.192
1	3,703	0.212
2	3,509	0.201
3	2,731	0.156
4	1,863	0.107
5	1,117	0.064
6	678	0.039
7	300	0.017
8	140	0.008
9	51	0.003
10	11	0.001
11	5	0.000

Table 3(a): Lower, Middle and Upper Classes in the Urban Sub-sample, Indian NSS, 55th Round (1999-00), N=48,924 households

Class	Mixture Estimates (Std. Error)		
	(1) Share of Urban Population (*p*)	(2) Probability of Owning a Good (π)	(3) Mean No. of Goods (of 11) ($11p$)
Lower (L)	0.198 (0.004)	0.026 (0.002)	0.29
Middle (M)	0.594 (0.005)	0.265 (0.002)	2.91
Upper (U)	0.208 (0.005)	0.536 (0.003)	5.90

Table 3(b): Lower, Middle and Upper Classes in the Urban Sub-sample Indian NSS, 50th Round (1993-94), N = 17,467 households (who report durables ownership with no inconsistencies)

Class	Mixture Estimates (Std. Error)		
	(1) Share of Urban Population (*p*)	(2) Probability of Owning a Good (π)	(3) Mean No. of Goods (of 11) ($11p$)
Lower (L)	0.299 (0.027)	0.056 (0.006)	0.62
Middle (M)	0.580 (0.018)	0.228 (0.009)	2.51
Upper (U)	0.121 (0.016)	0.483 (0.014)	5.31

Table 4(a): 1999-00 Per capita expenditure, by class (official urban poverty line in current prices: Rs. 455)

Class	Mean	SD	Percentiles											Mean household size
			10	20	**29**	30	40	50	60	70	80	90	99	
Lower	784.32	690.41	315	391	**454**	461	536	631	749	892	1086	1399	2756	4.0
Middle	949.81	1523.15	397	485	557	565	654	753	872	1032	1259	1662	3443	4.6
Upper	1438.81	2003.40	590	741	858	871	1016	1177	1360	1574	1874	2413	5252	5.1

Addendum: Per capita expenditure distribution in the entire sample (1999-00)

Percentile	10	20	30	40	50	60	70	80	90	99
Value	392	490	584	686	801	940	1120	1377	1815	3800

Table 4(b): 1993-94 Per capita expenditure, by class (official urban poverty line in current prices: Rs. 282)

Class	Mean	SD	Percentiles										
			10	20	**26**	30	40	50	60	70	80	90	99
Lower	546.52	669.84	213	258	**282**	298	343	395	460	554	692	999	2415
Middle	597.87	563.88	234	286	316	336	388	447	523	621	779	1128	2504
Upper	976.65	2317.68	336	421	475	508	596	695	820	1005	1266	1661	3759

Addendum: Per capita expenditure distribution in the entire sample (1993-94)

Percentile	10	20	30	40	50	60	70	80	90	99
Value	232	284	336	390	453	535	645	812	1192	2718

Table 5: Principal Components Model, 1999-00 (40% lower class, 40% middle class, 20% upper class)

Class	Mean	SD	Percentiles									
			10	20	30	40	50	60	70	80	90	99
Lower	795.77	1746.47	326	396	460	528	614	724	869	1078	1412	2788.53
Middle	945.95	931.38	441	528	606	687	775	877	1016	1212	1597.50	3390.40
Upper	1582.26	1860.73	723	876	1021	1170	1326	1505	1716	2012	2569	5558.16

Addendum: Per capita expenditure distribution in the entire sample (1999-00)

Percentile	10	20	30	40	50	60	70	80	90	99
Value	392	490	584	686	801	940	1120	1377	1815	3800

Table 6: Likelihood Ratio Test

Mixture estimates of the lower class (reproduced from Tables 3(a)-(b))

	(1) Share of Urban Population (p)	(2) Probability of Owning a Good (π)
1993-94	0.299 (0.027)	0.056 (0.006)
1999-00	0.198 (0.004)	0.026 (0.002)

1993-94

Unconstrained log likelihood (L_U):	-33752.28
Constrained log likelihood (L_C): ($H_1 : p_{L,93} - 0.026 > 0$)	-33996.68
$-2(L_C - L_U)$	**488.79*** **

p < 0.005 (chi-square, 1 d.f.)

Figure 1(a): Distribution of Y, NSS 1999-00

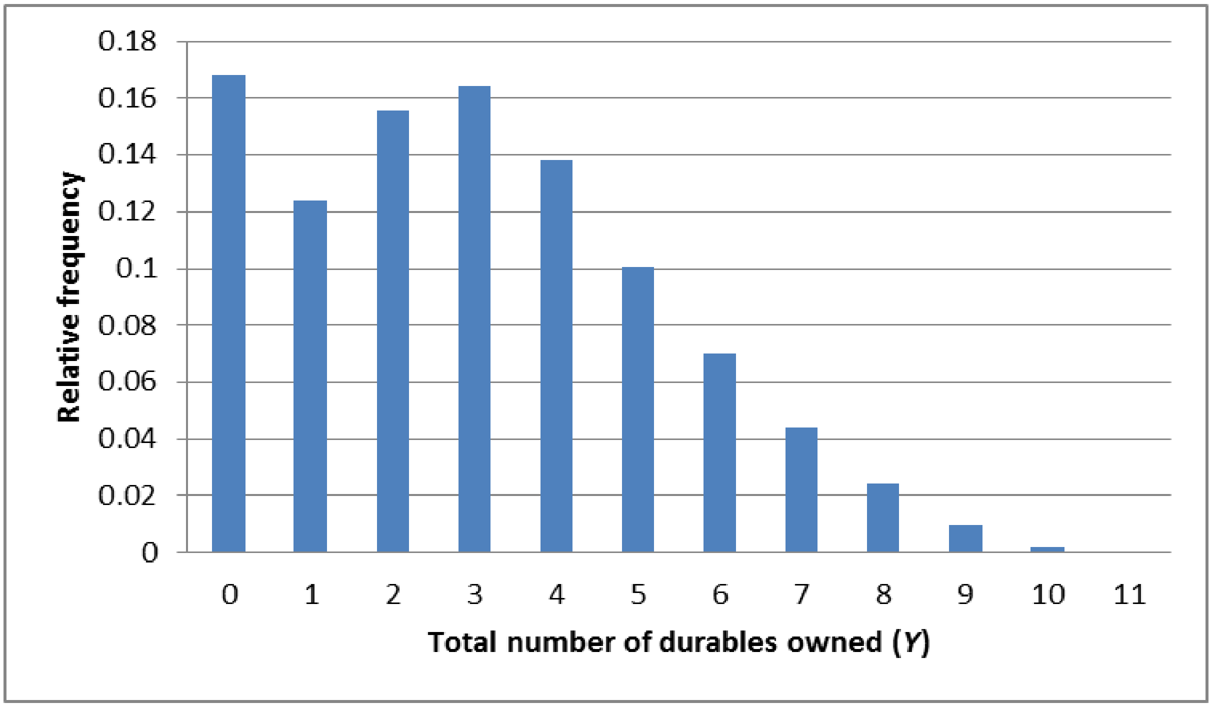


Figure 1(b): Distribution of Y, NSS 1993-94

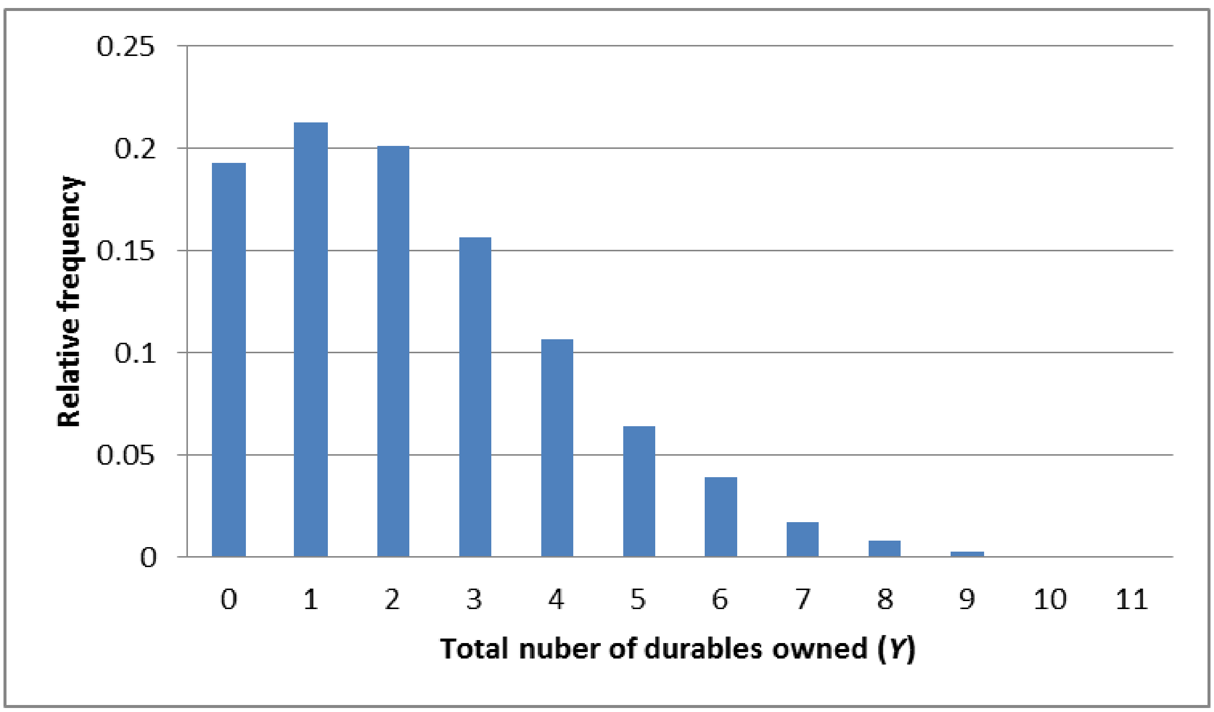


Figure 2(a): Class-specific densities *(φ)* estimated by the mixture model, NSS 1999-00

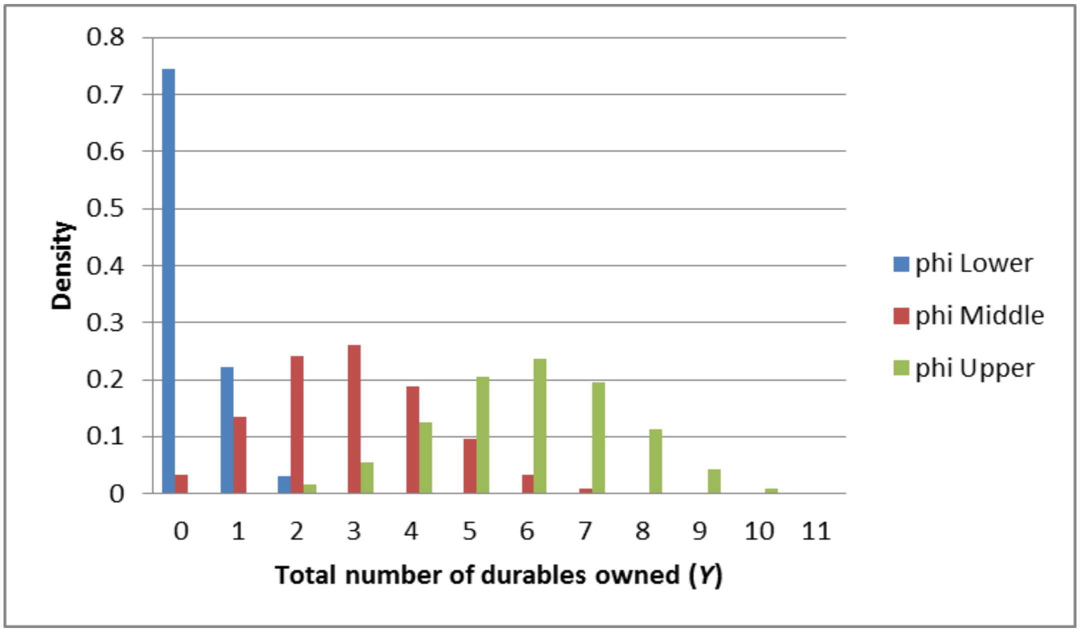


Figure 2(b): Class-specific densities *(φ)* estimated by the mixture model, NSS 1993-94

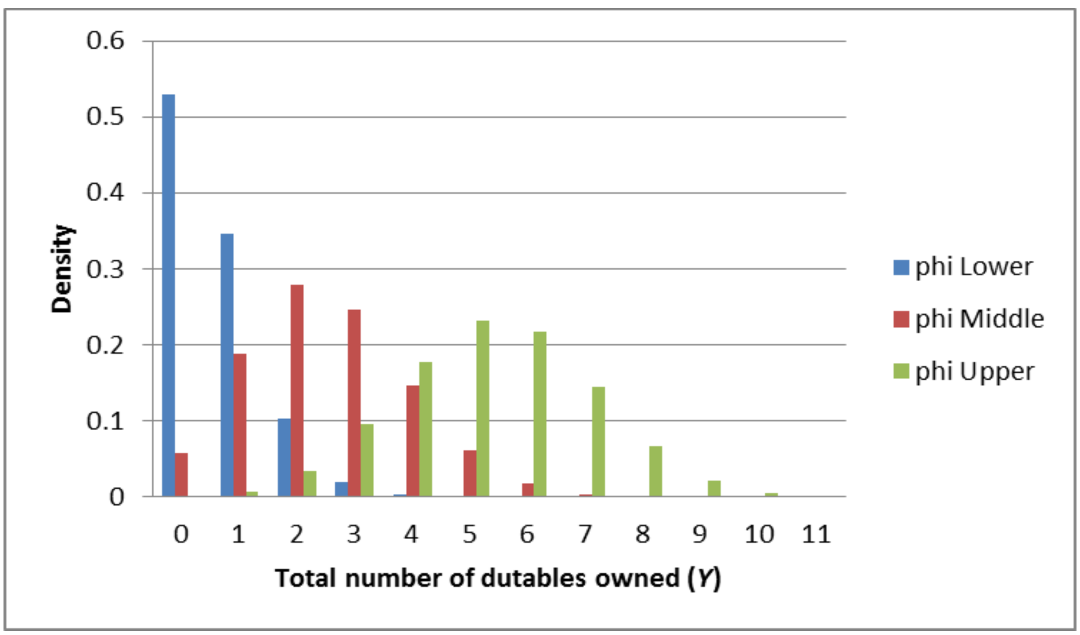


Figure 3(a): Observed vs. (mixture) predicted distribution of Y, NSS 1999-00

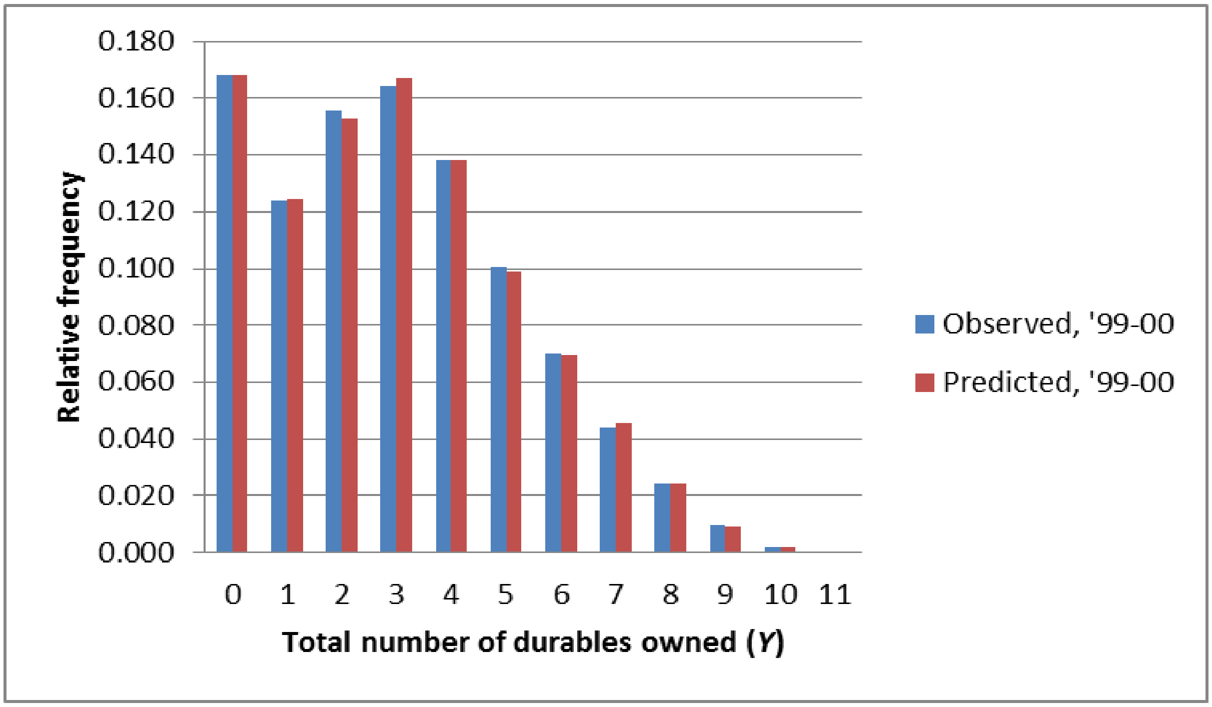


Figure 3(b): Observed vs. (mixture) predicted distribution of Y, NSS 1993-94

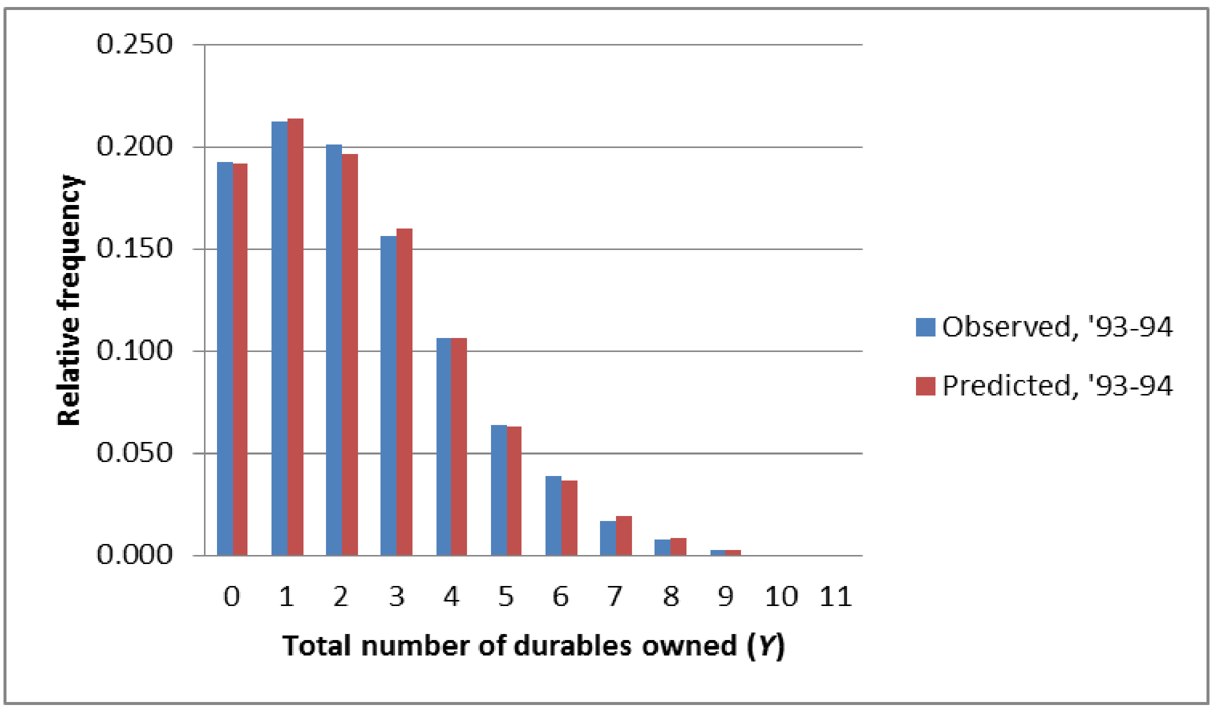


Figure 4(a): (Mixture) Estimated probability of belonging to each class (γ), NSS 1999-00

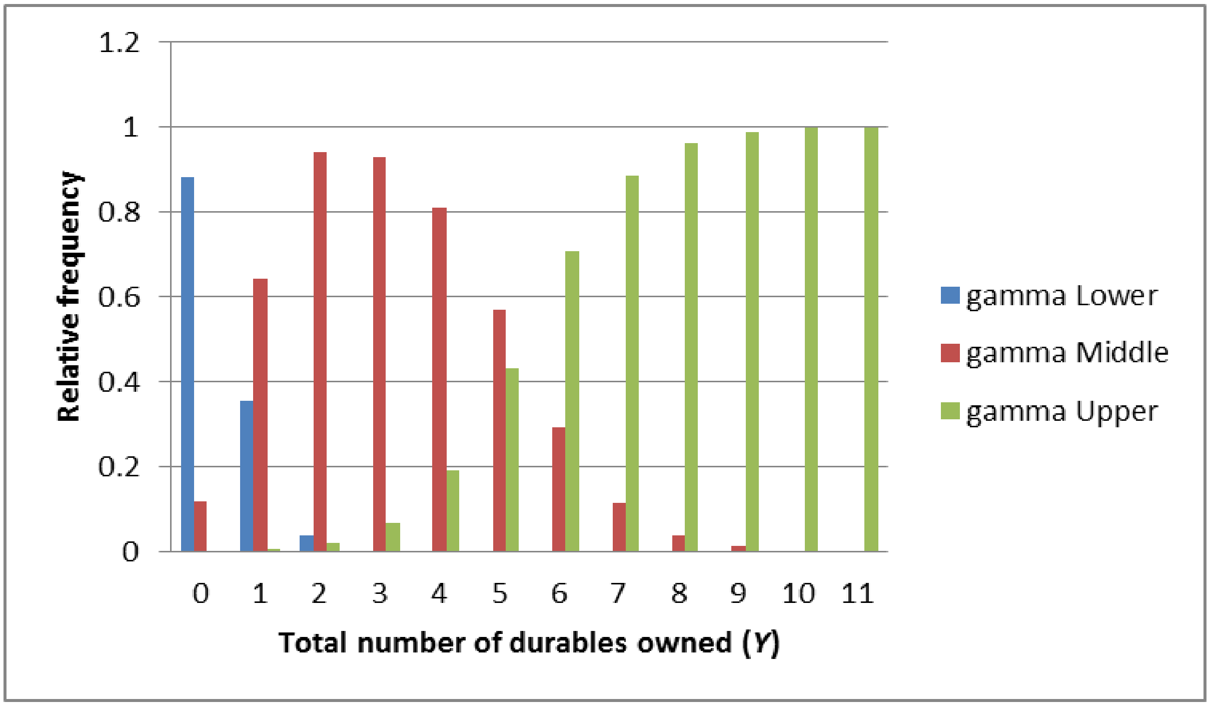


Figure 4(b): (Mixture) Estimated probability of belonging to each class (γ), NSS 1993-94

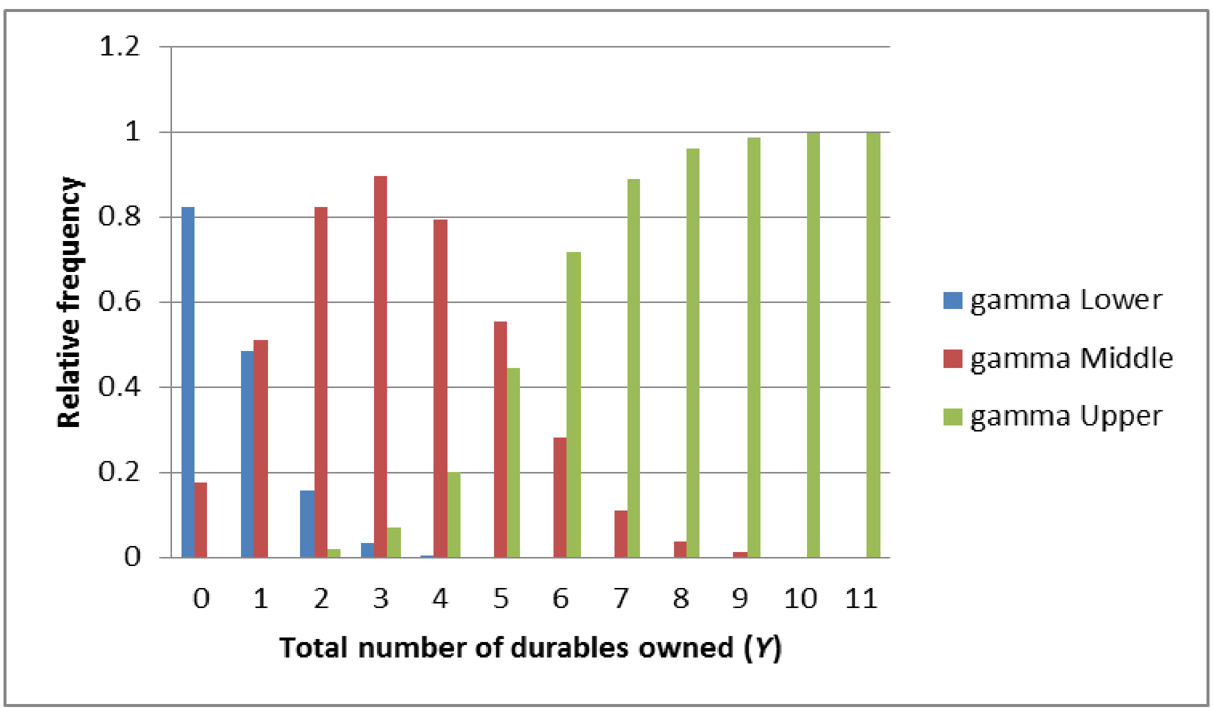


Figure 5(a): Observed vs. (Principal Components Analysis) predicted distribution of Y, NSS 1999-00
Assumed class sizes: 40% lower, 40% middle, 20% upper (Filmer & Pritchett (2001))

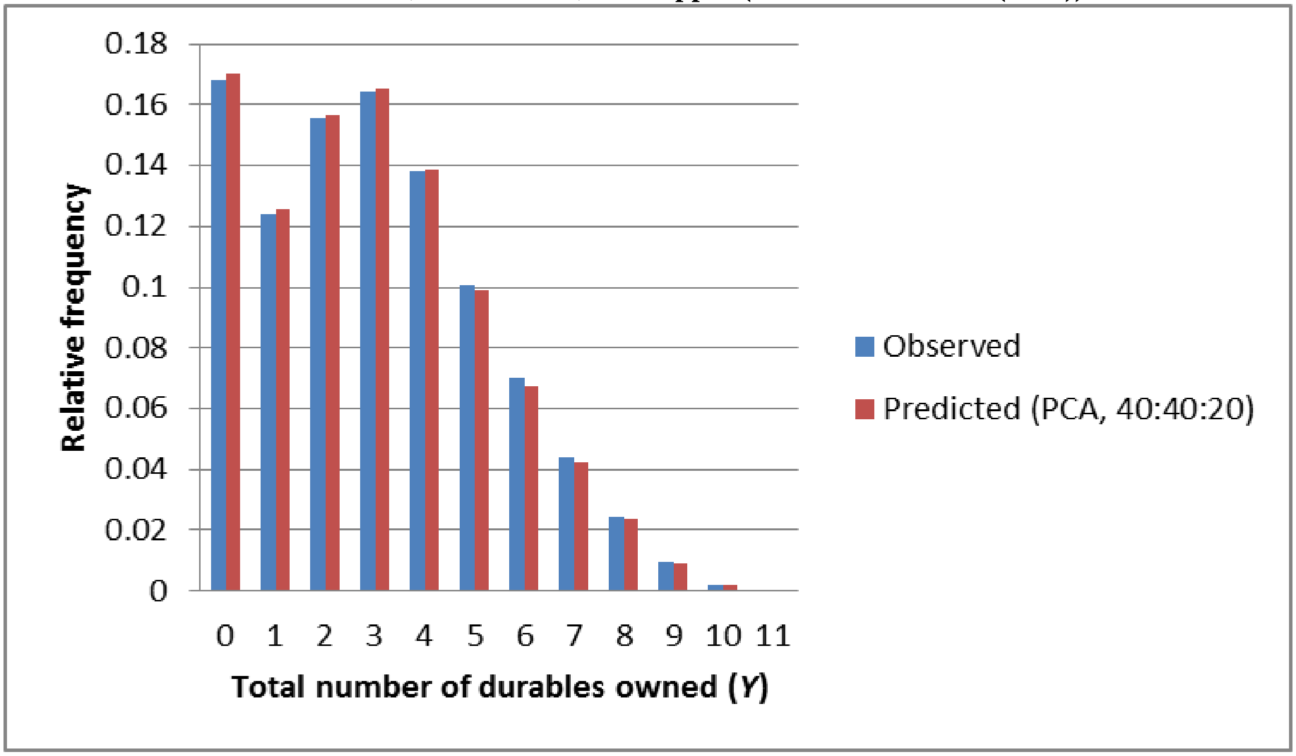


Figure 5(b): Observed vs. (Principal Components Analysis) predicted distribution of Y, NSS 1999-00
Assumed class sizes: 20% lower, 60% middle, 20% upper (Three Component Mixture estimates)

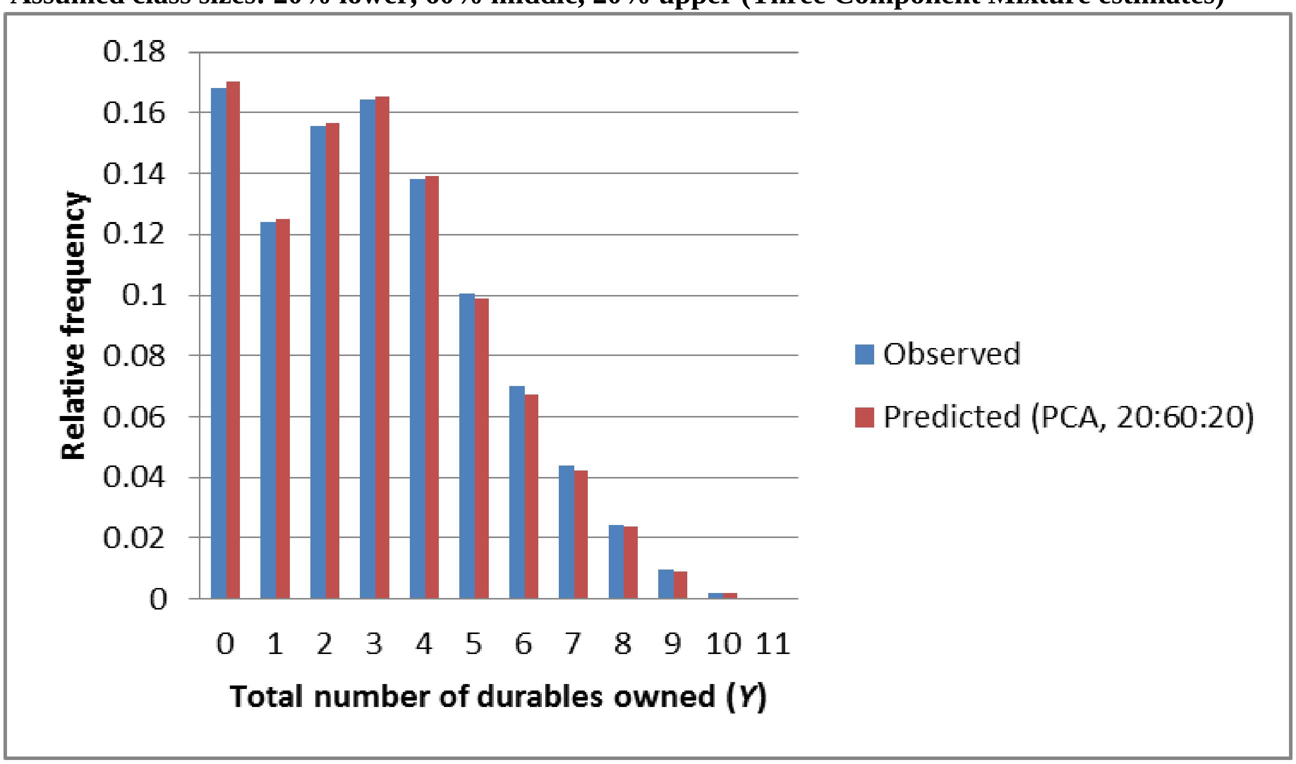
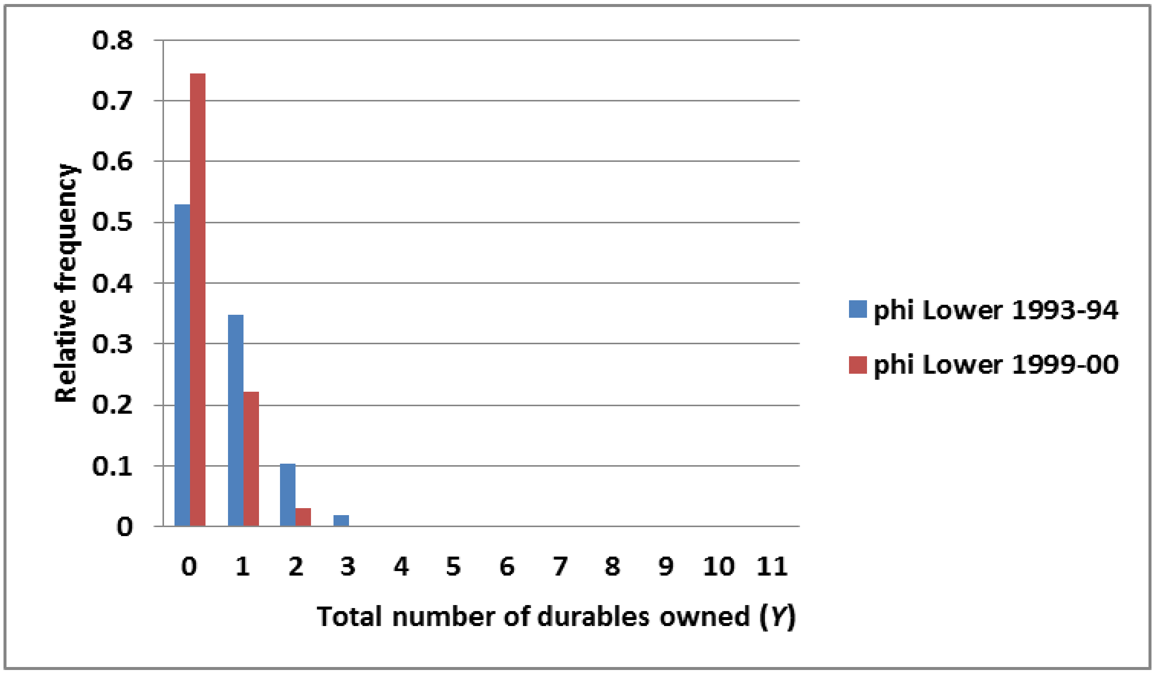


Figure 6: Durable ownership density of the lower class in India, 1993-94 vs. 1999-00

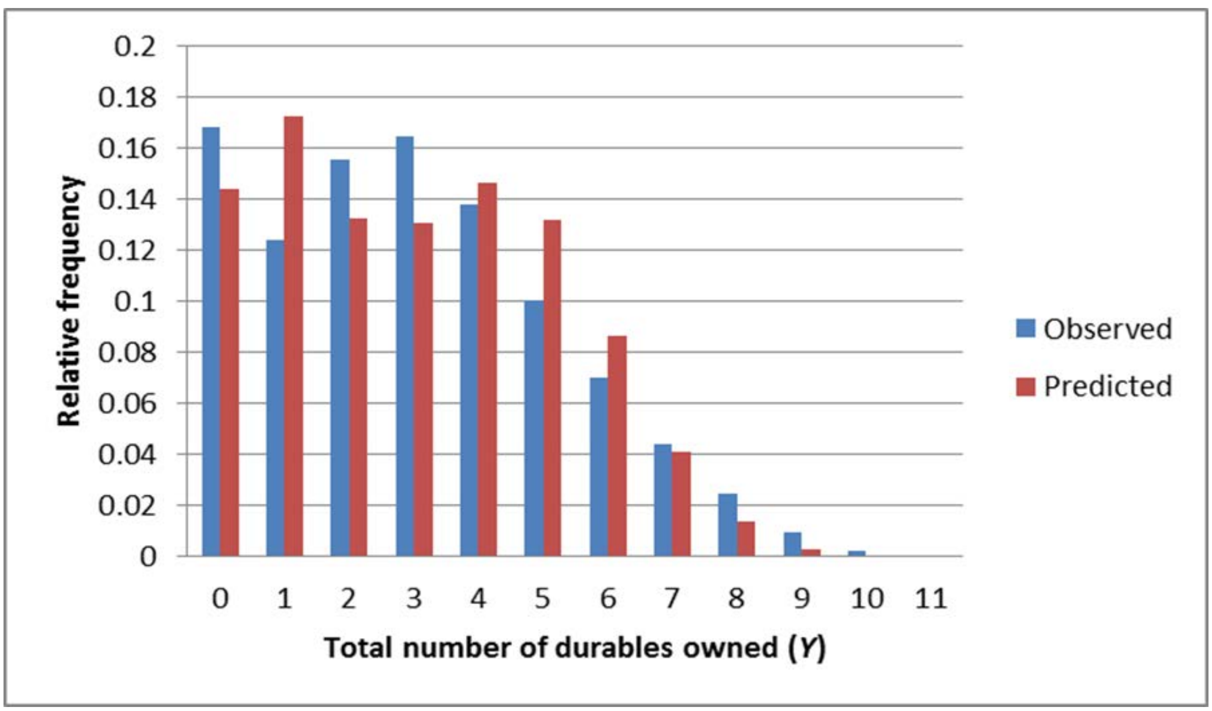


Appendix: Two-Component Mixture Model, NSS 1999-00

Table 7: Lower and Upper Classes in the Urban Sub-sample, N = 48, 924 households

Class	Mixture Estimates		
	(1) Share of Urban Population (*p*)	(2) Probability of Owning a Good (π)	(3) Mean No. of Goods (of 11) ($11p$)
Lower	0.404	0.091	1.00
Upper	0.596	0.398	4.37

Figure 7: Two-Component Mixture Model: Observed vs. predicted distribution of Y, NSS



Appendix: Truncated Model: A Refinement (Footnote 15, Page 25)

Table 8(a): Lower, Middle and Upper Classes in the Urban Sub-sample, Indian NSS, 55th Round (1999-00), N = 48,924 households, 11 goods[a]

	Mixture Estimates[a] (Std. Error)		**Characteristics of Ownership Distribution**	
Category (Class)	*(1)* Share of Urban Population	*(2)* Probability of Owning a Good	*(3)* *Range of total goods owned*	*(4)* Expected No. of Goods (of 11)
Lower (L)	0.2090 (0.005)	0.0181 (0.001)	0, 1, 2	0.2
Middle (M)	0.5987 (0.005)	0.2423 (0.003)	1, 2, … , 6	2.7
Upper (U)	0.1922 (0.007)	0.5179 (0.005)	4, 5, … , 12	5.7

Table 8(b): Predicted Y from the truncated model (vs. Observed)[a]

	Relative frequency	
Y	Predicted	Observed
0	0.168	0.168
1	0.123	0.124
2	0.156	0.155
3	0.162	0.164
4	0.138	0.138
5	0.096	0.100
6	0.068	0.070
7	0.042	0.044
8	0.028	0.024
9	0.013	0.009
10	0.004	0.002
11	0.001	0.000

[a]The truncated (mixture) model allows each class i to own a different number of goods (n_i). It contains all the information from the non-truncated mixture model but provides a cleaner separation of the marginal distribution of Y into conditional distributions; hence it is an easier tool of reference for policy makers and practitioners. Refer to the working paper version for details. The very good fit to observed Y is an indicator of the accuracy of the truncated model.