# On the Theory and Measurement of Relative Poverty Using Durable Ownership Data*#

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## ABSTRACT

Clusters in durable goods' ownership data have been used to identify distinct classes in society, especially in cases where expenditure-based class identification methods are impaired by poor data availability or calibration issues. The lowest cluster (or class) in the data is interpretable as the group of households in relative poverty. But why should such clusters exist, and what determines their number?

In this paper, we propose an economic theory of household decision-making that addresses these questions. We develop a dynamic, 3-generation, overlapping-generations model where households must choose between investing in education, which increases subsequent income, and investing in durables, which increases observable wealth and thus increases the probability of finding a high-income marriage partner.

We show that the steady state distribution of household durable expenditures in this model exhibits natural clusters. We also show that the lowest class may be at risk of persistent (relative) poverty even if they are currently above the (absolute) poverty line, because they are unable to take advantage of either the labour market (via education) or the marriage market (via durable accumulation).

The paper's contributions are threefold: (1) we establish a theoretical basis for interpreting household durable ownership data in the context of poverty measurement (2) we validate the use of durables-based mixture models as an empirical tool for identifying relative poverty through the identification of clusters (applied to Indian NSS data, 1993-2005) (3) we build a framework for generating testable hypotheses around the long-run effect of policy changes (e.g. income transfers or education subsidies) on poverty.

## 1. Introduction

The measurement and identification of poverty has long been of special interest to development economists. Intrinsically attached to poverty measurement is the definition of a poverty line – a level of income or expenditure – such that all households that are below this level are identified as 'poor' (Deaton (1997), Ray (1998)). In the absence of data that enables using the poverty line approach – such as when income or expenditure data is unavailable – testing for the presence of assets in households has also been suggested as an alternative method for poverty measurement (Filmer and Pritchett (2001); McKenzie (2005), Stifel and Christiaensen (2007), Filmer and Scott (2008), Montgomery et al (2000), Townsend (1979)).

In the latter category of measuring poverty by asset ownership, some recent papers by Maitra (2016, 2017) have proposed using a mixture model of durable ownership to identify 'classes' in the population. The premise made in this analysis (and that is found to explain the data well) is that there are 3 classes in the population, each with its own density of durable ownership; the lowest class (who own the fewest durables) can then be identified as the (relatively) poor. The motivation for these papers stemmed from attempting to examine what happened to poverty in India over the 1990's, the period following the liberalization of 1991. The National Sample Survey (NSS) data, from which poverty-line-based poverty estimates have traditionally been derived, used a new set of recall periods in the questionnaires in 1999-00 (Deaton and Kozel (2005)) compared with previous years. This led to concerns that the expenditures reported by households (and compared against poverty-line-expenditure) were not comparable in the 1993-94 and the 1999-00 rounds. Since durable ownership data in the survey bypassed the issue of recall periods – being based on a question that asked about durables in use *at the time of* the survey – the mixture approach using durable data provided a method for comparing the size of the lowest class in 1993-94 versus 1999-00. An additional advantage of the mixture approach lay in the fact that it did not necessitate the imposition of an externally set, assumption-based poverty 'line' – the various classes were identified purely based on natural clusters in the data. Of these, the class with the lowest number of durables was, evidently, the class in (relative) poverty.

The immediate questions that motivate this paper arise from observing some clear patterns in Maitra's (2016, 2017) findings for urban India over three rounds of NSS (1993-94, 1999-99 and 2004-05), replicated with interesting variations in our mixture-generated findings for rural India in those same rounds. Why are there clear clusters (or classes) in durable ownership patterns, be it in the rural or urban sectors? What determines the number of clusters – i.e. the existence of 2 versus 3 or 4 classes – of durable ownership? What factors might determine a 'steady state' pattern of durable ownership that returns over time and across sector, despite a temporary displacement (as in urban India in 1999-00)?[1] In other words, what kind of *theoretical* relationship between durable ownership and economic well-being (thence, poverty) could explain what we find about durable ownership patterns in the Indian NSS data?

The answers to these questions are of interest not only to explain the mixture findings for post-liberalization India but for a deeper reason: they would illuminate the underlying economic relationship between durable accumulation and economic well-being, that can inform the process of measuring poverty. While assets have long been used to define and measure economic well-being and poverty (Filmer and Pritchett (2001); Filmer and Scott (2008)), there have, to our knowledge, been few

[1]The specific findings that motivate these questions are: (1) the number of classes that explain durable ownership in rural Indian households is 2 in 1993-94, 3 in 1999-00 and 4 in 2004-05, whereas 3 classes are found in urban India in each period; (2) very similar class definitions are obtained by the mixture process in the 1993-94 urban sector, the 2004-05 urban sector and the 2004-05 rural sector.

attempts to examine *why* or *how* the accumulation of such assets is related with the same. In this paper, we attempt to address the gap in the literature by developing a theoretical model of asset ownership (specifically, durable ownership) over time, *in the context of poverty measurement*. Our immediate goal is to answer the central questions posed above on why there are natural clusters in durable ownership and what drives a long run (steady state) pattern of such ownership. The long-term goal of this paper is to develop a framework for understanding the relationship between durable accumulation and poverty over time; one that can be extended based on specific applications and used to understand the effect of policy changes on durable ownership and poverty in the long run.

We develop an overlapping generations model that incorporates and utilizes three specific characteristics of durable good consumption in India. First, durable items constitute an easily observable component of a household's consumption. We assume, in particular, that the durables owned by a household act as a signal of its social status; higher social status leads to higher income through matching with a "high-quality" spouse of the marriageable generation[2]. Second, durables provide a stream of consumption value over time, so that the observed durable goods owned by a household at any time may have been accumulated over more than one generation. Third, durable goods do not last forever, i.e. they depreciate over time, ensuring a limit on the accumulation effect described above.

In our model, households have two channels for enhancing future income (and

[2]There is ample reference to the norm of arranged marriage prevalent in India, which has also been documented to be a form of social networking by matching (see Maitra (2018), Luke, Munshi and Rosenzweig (2004)). Households care about the social standing of their relatives by marriage, which could be tied to the latter's caste and religion but also the wealth they own. There are certainly mutual visits to the prospective bride's and groom's homes by each party before a marriage is finalized. Connections made by marriage result in transfer and generation of income and wealth (as gifts, dowry, job referrals, etc). In our framework, we conceptualize durable ownership as the observable component of family wealth which influences the quality of connections that can be made through marriage.

potentially escaping poverty) – the labor market and the marriage market. Choosing (costly) education allows a higher expected labor-market return, but spending on additional durables (instead of education) signals a higher social status which increases expected marriage-market return. The optimal choice clearly depends on which of the two expected returns is higher relative to its cost. This depends, in turn, on the quantity of durables already accumulated by older generations in the household, since it is *total* durables in a household at any time that signals its social status. We assume, moreover, that in any period, households must meet a subsistence consumption level ($C$) first, before they can spend on education or durables. The subsistence level $C$ is, therefore, the theoretical counterpart of the (consumption or expenditure) poverty line. Households who earn below $C$ (and who are, therefore, in "absolute poverty") choose 0 durables. Those that have an excess of income beyond $C$ choose high education if it is optimal. The residual income in either case is assigned to durables[3].

The optimal choices made by households in any period can be used to define a stochastic process, which then becomes a data-generating process for observations on durables accumulated by households. Given any set of parameters, we can derive the transition matrix and the steady state distribution of "states" (viz. all possible choices of durable ownership). A synthetic sample of "data" can then be drawn from the steady state distribution. This synthetic sample allows us to examine various aspects of the distribution of durable ownership driven by the labor and marriage-market incentives inherent in our model.

We find that the distribution of durable ownership in the synthetic sample shows

[3]The only savings and investment opportunity in this model is that in human capital (viz. education). Any income in excess of subsistence consumption is spent on durables if investing in human capital is not optimal. High income households may be seen to invest in education (if it is optimal) as well as own non-zero durables.

natural clusters which may be 2, 3 or 4 in number depending on parameter values (Figures 3a-d). These then are the theoretical counterparts of the "classes" that are captured by the mixture model using Indian NSS data. In addition, we are able to demonstrate certain relationships between parameters that are likely to generate different numbers of classes. We do not claim that these relationships are the only explanations for observing different numbers of classes in different populations, but they serve as an example for tests that may be developed to explain the class phenomenon in durable ownership. Our model also provides an explicit framework for predicting the effects of policy changes involving changes in the various parameters.

As an example, here is a situation where there might be 2 classes of durable ownership in a population. Suppose there are two possible levels of income that may be earned – high ($w_H$) and low ($w_L$) – and two possible levels of education to choose from – low (with cost 0) and high (with cost $E$). High education and higher observed durable ownership each leads to a higher probability of receiving $w_H$. Thus, in any period $t$, a household may earn a low income ($2w_L$), a mid-level income ($w_L + w_H$) or a high income ($2w_H$) depending on education level and the durables accumulated (which results in a high-income partner by marriage). We assume that the probability of marriage market success (i.e. matching with a high-income partner) increases with durables owned but not at a constant rate. In particular, there is a generally acknowledged "social standard", say $\beta$, such that the probability of securing a high-income partner increases the most when the household crosses from $(\beta - \epsilon)$ to $(\beta + \epsilon)$ durables (($\epsilon > 0$ and small)[4]. Now suppose that the social standard $\beta$ is high relative to incomes earned ($2w_H$) in a particular society[5]. This makes it hard

[4]We assume, in particular, that the probability of securing a high-income partner is given by the normal CDF $\Phi(\beta, \sigma^2)$, where $\sigma^2$ (an exogenously given parameter) determines the "skepticism" around the belief $\beta$. See Figure 1.

[5]One can envisage this happening if the price of procuring or using durables is inordinately high, e.g. due to poor provision of public goods such as good roads or a reliable supply of electricity.

for households in this society to achieve a high-income partner, making the very high household income – $2w_H$ – a rare occurrence. If the cost of education ($E$) is high as well, we may well observe only 2 classes of durable ownership in this society – defined by the level of durables chosen by low-income ($2w_L$) households with no education and that chosen by middle income ($w_L + w_H$) households, also with no education. The durable ownership levels of the few high-income households that are obtained by chance will form the right tail of the upper-class distribution of durables in this setup. A society where $\beta$ is low compared with incomes ($2w_L$) can similarly demonstrate 2 classes, although the levels of durable ownership corresponding to the classes will be higher (since now the 2 higher incomes – ($w_L + w_H$) and $2w_H$ – become more likely to be observed). When $\beta$ lies between $2w_L$ and $2w_H$, we are likely to find 3 (or even 4 classes) instead of 2.

Our findings establish the theoretical underpinnings of natural clusters in durable ownership choices, which confirm that a mixture model – which can identify such clusters – is a valid method for identifying the poorest group in a population. In addition, we show that an interesting feature of the assumption on social standards ($\beta$) is the fact that spending the marginal dollar on durables (and not on education) yields the highest increase in expected future return, when previously accumulated durable levels are close to ($\beta - \epsilon$). This implies that households with accumulated durable levels that are much lower than – or much higher than – $\beta$ have the strongest incentive to invest in education. Hence, households that are observed to be accumulating small positive levels of durables instead of spending on education, are doing so because they cannot afford education even though education is their optimal choice. In other words, these "low-income, low-durable" households are likely to be vulnerable to poverty due

Indeed, we find 2 classes in the mixture for rural households in NSS, 1993-94, where these conditions could plausibly apply.

to their inability to access either the labor market or the marriage market to improve economic well-being. In this sense, the group of "relatively poor" households ought to include those that have a small non-zero level of durables, and not just those that have none (the group in "absolute poverty"). Indeed, we find this to be true in the definitions of the lowest class in the mixture results from India.

The main contribution of this paper is to develop a theoretical framework that explains the relationship between durables accumulation and economic well-being (thence poverty) in a way that directly informs the process of poverty measurement. We demonstrate a potential mechanism – viz. signaling with durables – that could generate clusters in durable ownership data; we also provide an argument for why the lowest cluster observed might contain households who are vulnerable to poverty even when they earn higher than the subsistence consumption level. Our arguments provide a strong justification for using durables-based mixture models to identify classes in a population. The lowest class identified by a mixture model could be reasonably interpreted as the group that is in relative poverty in the population in question.

The rest of the paper is organized as follows. Section 2 presents our empirical findings using the mixture model for rural India using NSS, rounds 1993-94, 1999-00 and 2004-05. We note some interesting parallels (and differences) between our findings for the rural sector versus Maitra's (2016, 2017)) findings for urban India. In Section 3, we present the theoretical model with overlapping generations, and in Section 4, we simulate observations on durable ownership from the theoretical data-generating model. Our main findings connecting the theoretical and empirical results are presented and discussed in Section 4.2; we provide an interpretation of the empirical mixture estimates in the context of our theoretical model in Section 4.3. Section 5 concludes the paper.

## 2. Empirical findings

In this section, we present and extend the results reported in Maitra (2016, 2017) based on the mixture model. Maitra (2016, 2017) uses the urban subsamples of the Indian National Sample Survey (NSS) to document the distribution of total durable ownership in three periods: 1993-94, 1999-00 and 2004-05. This time period is of special interest, since India introduced a substantial liberalization policy in 1991 which resulted (among other things) in the opening up of trade. During this time, therefore, durable goods became more easily available for purchase within the country. Maitra (2016) uses 8 durable goods – fan, radio, television, bicycle, fridge, air-conditioner, motor bike and car – to define a total number of durables ($Y$) observed to be in use in urban households in each of the 3 periods.

The three component mixture model (see Maitra (2016, 2017) for details) postulates the existence of 3 classes in the urban population. Each class $i$ has a class-specific binomial density $\phi_i$ of durable ownership with parameters $(8, p_i)$, where $p_i$ represents the probability with which a class $-i$ household owns a durable in each of the 8 independent draws. Clearly, $p_L < p_M < p_U$, where $L, M, U$ represent the lower, middle and upper classes respectively. The probability of drawing an urban household with $y$ durables is therefore given by

$$P(y) = \pi_L \phi_L(8, p_L) + \pi_M \phi_M(8, p_M) + \pi_U \phi_U(8, p_U) \tag{1}$$

where $\pi_i$ denotes the proportion of class$-i$ households in the urban population. Solving the maximum likelihood problem with an EM algorithm (Maitra (2016, 2017)) yields estimates of the class-proportions $(\pi_L, \pi_M, \pi_U)$ and class-specific ownership probabilities $(p_L, p_M, p_U)$[6].

[6]Mixture models can be plagued by the issue of observational equivalence, which is the general

Table 1 presents the estimates of $\{\pi_i, p_i\}$ for urban subsamples in years 1993-94, 1999-00 and 2004-05[7]. As discussed in Maitra (2016, 2017), a mixture model with 3 classes was able to produce the best fit to the urban data from the years considered (as opposed to 2 or 4 classes). An interesting observation from these estimates is that while the definition of each class (as encapsulated in $p_i$) changes between 1993-94 and 1999-00, it returns very close to the original (1993-94) class-definitions in 2004-05. This suggests the existence of a "steady state" distribution of class-specific densities $\phi$, to which the distribution of durables reverts after an initial adjustment phase in 1999-00.

We repeat the mixture analysis of Maitra (2017) to obtain estimates of $\{\pi_i, p_i\}$ for the rural subsamples of NSS, over the same 3 years – 1993-94, 1999-00 and 2004-05. Interestingly, we find (see Table 2) that in 1993-94, a *two* component mixture model describes the rural distribution better than one with three classes. Three components provide the best fit in 1999-00, but in the final year 2004-05, a model with *four* classes does better than one with two or three[8].

Yet another interesting finding from the rural results is that in the final year, class definitions (as expressed by $p_i$) are once again remarkably similar across rural and urban sectors. This suggests that there may have been some sort of "barrier" between rural and urban sectors in 1993-94 that governed the accumulation of durables in these regions. This barrier seems to have disappeared or at least dissipated by 2004-05, generating very similar class definitions across rural and urban sector households.

We take away three important observations from the empirical findings in Tables

ambiguity surrounding the assignment of estimates to classes (e.g. how do we know that class 1 is L, class 2 is M and class 3 is U?). The problem does not exist in the current application since, by definition L is the class with the lowest $p_i$, U the class with the highest $p_i$ etc. See Maitra (2016) for a detailed discussion.

[7]These estimates are reproduced from Maitra (2017).

[8]LR tests (Greene (2002)) are used to determine the number of classes for each sample.

1-2. First, mixture models do very well in explaining durable ownership data in urban and rural India over three periods of time. This suggests that there are natural clusters in the data representing total durables in a household, which are captured by the mixture model, sometimes with 3 components and sometimes with 2 or 4. Second, there appears to be a steady state in class definitions in urban India, suggested by the very similar class definitions obtained therein in the first and third years. Finally, there is a similarity in class definitions *across* urban and rural India in the final year, suggesting easing of some barrier between the two sectors over the time considered.

The observations above lead to three pertinent questions. Why are there clear clusters (or classes) in durable ownership patterns? What determines the existence of 2 versus 3 or 4 classes of durable ownership? Finally, what factors could determine a 'steady state' pattern of durable ownership that persists over time, despite temporary displacement?

In the next section, we present a theoretical model of household choice of durable spending that attempts to answer these questions.

## 3. The model

Consider an overlapping generations model in which every household is defined by three generations – 0 (child), 1 (parent) and 2 (grandparent). In any period $t$, the earners and decision-makers in a household are the parents (generation 1), while children and grandparents (generations 0 and 2) are dependents. Parents choose the level of education of their children and the amount of durables they wish to purchase, ensuring, first, that a level of subsistence consumption, $C$ ($> 0$), is met. The common household utility of members in any period $t$ is given by

$$U(B_t) = C + B_t \tag{2}$$

where $B_t$ is the total amount of durables present in the household in $t$. Note that $B_t$ includes the amount of durables purchased by parents in period $t$ as well as that accumulated by grandparents in period $(t-1)$. When grandparents pass so do the durables they accumulated when they were parents (in period $(t-1)$).

Household income in any period is the sum of incomes of two parents: one who was born and raised in the household in question and the other that married into the household. The income of the parent born in the household is low ($w_L$) or high ($w_H$) depending on two factors: (1) whether that parent is of low or high productivity ($\alpha_L$ and $\alpha_H$, respectively) and (2) whether s(he) has high or low education ($e_H$ and $e_L$, respectively). The productivity level $\alpha_{t-1}$ of the generation of parents in period $t$ is determined randomly at the time of their birth (in $(t-1)$) and is unobservable. We assume that productivity is $\alpha_L$ with probability $q_L$ ($\alpha_H$ otherwise). Likewise, the education level of the period$-t$ parents is determined by the amount invested in it by *their* parents when they were children, i.e. in $(t-1)$. We denote the wage of the parent raised in the household by $w_1$ and refer to it as the household's 'labour income'.

The income of the parent who marries into the household is assumed to depend on the social standing of the household, which determines marriage market success. We assume that marriages are arranged and that households with higher social standing – as measured by the amount of durables observed to be in use in that household ($B_t$) – attract partners with higher wage[9]. In particular, we assume that a household

[9]The literature on the effects of observable (or conspicuous) consumption on well-being and growth mostly assumes that these effects stem from the fact that households care about relative consumption (Becker et al (2005), Friedman and Ostrov (2008), Arrow and Dasgupta (2009), Moav and Neeman (2010), Xia (2010), Alvarez-Cuadrado et al (2011)). We deviate from this literature in the assumption that the observability of durable consumption serves as a 'signal' for the social status of households, which facilitates matching in the marriage market. Thus, observable consumption in our model affects utility through an increase in real household income instead of a sense of satisfaction from "keeping up with the Joneses".

that has $B$ durables in any period will attract a partner with high wage $w_H$ with probability $\Phi_S(B)$, where $\Phi_S(B)$ is the cumulative distribution function of a normal distribution $N(\beta,\sigma^2)$. The latter assumption has the following interpretation (see Figure 1). In any period, there is a certain level of durables ownership, $\beta$, that is generally acknowledged to mark households of high social standing. The skepticism around this common belief is represented by $\sigma^2$. Thus, while higher durable ownership $B$ increases the probability of attracting a partner with high wage, the rate of increase in the probability is highest at the level $(\beta - \epsilon)$ ($\epsilon > 0$, small). Moreover, the higher the skepticism ($\sigma^2$) regarding the common social standard $\beta$, the lower is the increased probability of acquiring a high-wage partner at most levels of accumulated durables $B$, around $\beta$. An example of a society with low skepticism (or low $\sigma^2$) would be one where everyone agrees unanimously on the connection between durables and social standing, such as might be likely in small, close-knit communities in rural settings. Higher skepticism could occur in more anonymous communities such as might exist in urban settings. We will henceforth refer to $\Phi_S(B)$ as the signal function under beliefs $S = (\beta, \sigma^2)$, where $\beta$ denotes the social standard and $\sigma^2$ denotes the skepticism regarding $\beta$. Further, we denote the wage of the parental partner by $w_2$ and call it the household's 'marriage market income'[10].

Household income in period $t$ can, therefore, be written as $I_t(e_{t-1}, \alpha_{t-1}, B_{t-1})$, where $e_{t-1}$ is the education level of period$-t$ parents, $\alpha_{t-1}$ is their (random) productivity level and $B_{t-1}$ is the total number of durables in the household (indicating its social standing) when period$-t$ parents were matched in the marriage market. In

[10]Unlike Maitra (2018), we do not explicitly model the matching of partners where the (equilibrium) probability of matching is determined by the number of agents of all types present in the economy. The assumption here that more durables (or higher observable wealth) leads to higher social standing which in turn leads to more wealth, is no more than an assumption of "wealth begets wealth" where the level of wealth is signalled by the observable consumption of durables by households.

particular,

$$I_t(e_{t-1}, \alpha_{t-1}, B_{t-1}) = w_{1t}(e_{t-1}, \alpha_{t-1}) + w_{2t}(B_{t-1}) \tag{3}$$

where $w_{1t}$ (labour income in period $t$) is $w_H$ with probability $p(e_{t-1}, \alpha_{t-1})$ ($w_L$, otherwise) and $w_{2t}$ (marriage market income in $t$) is $w_H$ with probability $\Phi_S(B_{t-1})$ ($w_L$, otherwise); $S = (\beta, \sigma^2)$. We assume

$$p(e_L, \alpha_L) = p_1 \tag{4}$$

$$p(e_L, \alpha_H) = p_2 \tag{5}$$

$$p(e_H, \alpha_L) = p_3 \tag{6}$$

$$p(e_H, \alpha_H) = p_4 \tag{7}$$

$$0 < p_1 < p_2 < p_3 < p_4 < 1 \tag{8}$$

Household expenses ($E_t$) in any period consist of three components: (1) the subsistence consumption level $C$ that must be met, (2) the investment in education of the generation of children in that period, and (3) the expenditure on durables:

$$E_t = C + c(e_t) + b_t \tag{9}$$

where $c(e_t)$ represents the parental generation's spending on education and $b_t$ is the spending on durables in period $t$. We assume that there are two possible levels of education $e_t$ – high ($e_H$) and low ($e_L$) – and that the cost $c(e_t)$ of providing the same are $E$ ($> 0$) and 0, respectively. We also assume that there are no savings opportunities, so the residual household income after spending $C$ and $c(e_t)$ is used to purchase durable goods.

The timing of income-realization and decision-making is as follows. At the beginning of any period $t$, parents find themselves with (realized) income $I_t$ based on the education level and productivity of one parent $(\alpha_{t-1}, e_{t-1})$, and the wage of the other parent determined by the household's durables level $B_{t-1}$. Given income $I_t$, parents choose their children's education level $e_t$ and the amount to spend on durables $b_t$ in order to maximize their lifetime utility $[U(B_t) + \delta U(B_{t+1})]$, where $\delta$ ($\epsilon$ $(0,1)$) is the discount factor. At the end of period $t$, the current generation of children (with education $e_t$) enters the labor market and earns $w_t$ based on their productivity draw and the education $e_t$ they have received. In addition, the *total* quantity of durables $(B_t = b_{t-1} + b_t)$ in the household in period $t$ determines the wage of their partner by arranged marriage: $w_H$ with probability $\Phi_S(b_{t-1}+b_t)$, $w_L$ otherwise. The sum of own wage and partner's wage determines the household income of the parental generation $I_{t+1}$ in the next period.

The optimization problem of the parental generation in period $t$ can be written as:

$$\underset{(e_t,b_t)}{Max}\ U(b_{t-1}+b_t) + \delta U(b_t + b_{t+1}) \tag{10}$$

*subject to*

$$c(e_t) + b_t \leq I_t(e_{t-1}, \alpha_{t-1}, b_{t-1} + b_{t-2}) - C \tag{11}$$

$$b_{t+1} = I_{t+1}(e_t, \alpha_t, b_t + b_{t-1}) - C - c(e_{t+1}) \tag{12}$$

$$e_t \geq 0,\ \ b_t \geq 0 \tag{13}$$

Notice how the period$-t$ decision variables $(e_t, b_t)$ impact the decision makers' (parents') lifetime utility. The spending on children's education $e_t$ represents a trade-off between current and future consumption, since it involves an expenditure now that increases income (potentially) in the future $(11-12)$. However, the spending on current durables $b_t$ improves consumption now as well as in the future since, (i) it increases direct consumption utility in both periods (10) and, (ii) it also increases the potential of higher income (hence, consumption) in the future (12).

It is is easy to see that solving the optimization exercise in $(10)-(13)$ under the model assumptions reduces to ascertaining which of the two education levels ($e_H$ or $e_L$) generates a higher lifetime utility for the decision maker, conditional on their realized income ($I_t$) and their inherited durable stock ($b_{t-1}$). The residual income after spending on this optimal education level and subsistence consumption is assigned to durables. We can show that households choose the higher education level ($e_H$) if the following condition holds:

$$(1+\delta)E + \delta(w_H - w_L)[q_L(p_1 - p_3) + (1-q_L)(p_2 - p_4) + (\widetilde{p} - \widetilde{p}_e)] < 0 \tag{14}$$

where $\widetilde{p} = \Phi_S(b_{t-1} + I_t - C)$ and $\widetilde{p}_e = \Phi_S(b_{t-1} + I_t - C - E)$ are the values of the signal function under $S = (\beta, \sigma^2)$ when $e_L$ (with cost 0) or $e_H$ (with cost $E$) is chosen, respectively.

Condition (14) has the following interpretation. The first term on the left-hand side captures the increase in direct consumption in both periods if the cost of high versus low education ($E$) is allocated to current durables spending instead of education. The increase in durables consumption lasts for two periods since durables chosen now remain in the household for two periods. The second term on the left-hand side embodies the impact of low versus high education on future income. Choosing the high education level $e_H$ increases the probability of securing the high wage $w_H$ in future (relative to choosing $e_L$), whether the random productivity draw is $\alpha_L$ (with probability $q_L$) or $\alpha_H$. Thus, the first two terms in the square bracket in (14) capture the effect of low versus high education on lifetime consumption through future labour income $w_1$. Choosing $e_H$ has a cost, however, which reduces durables consumption now and, through it, the social standing of the family in the future. This impacts the probability of finding a future partner with a high wage. The last term in the square bracket in (14) captures this effect, viz. effect of low versus high education on partner's wage, or marriage market income, $w_2$, via the signal $S = (\beta, \sigma^2)$.

Note that condition (14) varies by household only due to the last term $(\widetilde{p} - \widetilde{p}_e)$. This term captures the effect of the durables-based signal of the household's social standing on the partner's income, viz. the effect of durables on marriage market outcomes. Labour market incentives are determined completely by pre-specified parameter levels. Given a set of parameters, therefore, the incentive to choose education (and hence current durable expenditure) depends on the amount of durables already accumulated by previous generations.

The model outlined in (2)$-$(14) describes a stochastic process $\{b_{t-1}, b_t\}$, driven by parameters $(w_H, w_L, p_1, p_2, p_3, p_4, \beta, \sigma^2, q_L, \delta, E, C)$. In this straightforward model, total household income in any period $t$ could take one of 3 possible values – $(2w_L)$, $(w_L + w_H)$ or $(2w_H)$. For each of the 3 values of household income, there are 2 possible choices for durable expenditure $(b_t)$, corresponding to whether education level $e_L$ or $e_H$ is chosen in $t$. (The choice of education $e_t$ depends on condition (14).) Thus, in any period $t$, durable expenditure $b_t$ could take one of 6 $(= 2 \times 3)$ possible values. Furthermore, for each of the 6 possible values of $b_t$, there are (similarly) 6 possible values of $b_{t-1}$. These comprise 36 (i.e. $6^2$) "states" that $\{b_{t-1}, b_t\}$ can pass through in any period $t$. Thus, the transition matrix $P$ that governs the movement from $(b_{t-1}, b_t)$

to $(b_{t,} b_{t+1})$ is of order $(36 \times 36)$.

To show the existence of clusters in household durable ownership, let us make the additional simplifying assumption that $C = 2w_L$, which implies that households with the lowest income level $(2w_L)$ can barely afford to pay for subsistence consumption; hence they always choose $e_t = e_L$. This reduces the possible values that $b_t$ can take, to 5 (instead of 6). This leads to $5^2 (= 25)$ possible "states" and a transition matrix of order $(25 \times 25)$[11].

Let $\theta_1, \theta_2, ..., \theta_{25}$ denote the 25 possible "states" or values that the process $\{b_{t-1}, b_t\}$ can pass through in any period $t$. Note that each $\theta_i$ $(i = 1, 2, ...25)$ has, associated with it, an amount of total durables $(b^i_{t-1} + b^i_t)$ observed in a household in state $\theta_i$ in period $t$[12]. Furthermore, let $x_t = (x_{1t}, x_{2t}, ..., x_{25t})$ denote the proportions of households in states $\theta_1, \theta_2, ..., \theta_{25}$ respectively, in the population in period $t$ $(0 \leq x_{it} \leq 1, \sum_{i=1}^{25} x_{it} = 1, i = 1, 2..., 25)$. Thus, households' transition through various states of durables expenditure can be written as:

$$x_t P = x_{t+1} \tag{15}$$

Moreover, the steady state distribution of durables expenditures over states $(\theta_1, \theta_2, ..., \theta_{25})$, denoted by $x^* = (x^*_1, x^*_2, ..., x^*_{25})$, will satisfy the condition:

$$x^* P = x^* \tag{16}$$

[11] The individual terms of the $(25 \times 25)$ transition matrix $P$ are provided in technical appendix 1.

[12] Clearly, $(b_{t-1} + b_t)$ is not unique across the 25 states, since any household that has $(b^0, b^1)$ will be observed to own the same amount of total durables as a household with $(b^1, b^0)$. These 2 households would, however, have very different transition probabilities to other possible states since the durables accumulated by grandparents plays a role in determining the optimality of education (condition (14)). Hence, we retain the 25 states in defining the transition process (15). It is easy to show that there are 12 unique values of total durables corresponding to the 25 states of the model (see technical appendix 2).

It can be shown that the stochastic process described above does converge to a steady state (Tsokos (1972)). Recall that our object of interest in this analysis is the total amount of durables in a household in a given period. The theoretical counterpart of this object of interest is $B_t$, the total real expenditure on durables observed in a household in a given period (recall that each state $\theta_i$ $(i = 1, 2, ..., 25)$ corresponds to a specific value of total real durable expenditure). The empirical counterpart, on the other hand, reports on the total *quantity* of durables observed in a household (Section 2). We have no particular theory of durable prices in our theoretical model and are reluctant to invoke assumptions on the same; hence our inferences from the theoretical model will pertain to real durable expenditure, not quantities.

The next section describes how simulation data on household durable expenditure can be generated from the model presented above.

## 4. Simulations & Results

### *4.1 Drawing samples from the data-generating process: an example*

The following example demonstrates how the model above functions as the data generating process from which empirical observations are drawn. Suppose parameter values are as follows.

**Example 1.** $w_H = 100, w_L = 10, p_1 = 0.1, p_2 = 0.3, p_3 = 0.4, p_4 = 0.8, \beta = 150, \sigma = 110, q_L = 0.5, \delta = 0.5, E = 11.5, C = 20.$

The $(25 \times 25)$ transition matrix $P$ and the steady state distribution corresponding to the above parameter values have been derived in the technical appendix. Figure 2(a) plots the derived steady state distribution – the x axis showing $(b_t + b_{t-1})$ ,i.e. the total durable spending observed in any time $t$ and the y axis showing the proportion of households that would be observed with each level of total durables (spending) in the steady state under parameters as in Example 1[13].

Figure 2(a) shows the theoretical steady state distribution – or the data-generating process – that corresponds to given parameters in Example 1. It is possible now to draw samples from a population that is distributed as in Figure 2(a) (i.e. the theoretical steady state distribution). For example, Figure 2(b) plots the histograms of durable expenditures observed in two samples of 1000 observations, drawn independently from the steady state distribution in Figure 2(a).

The process described in Figures 2(a)-(b) – viz. deriving the theoretical steady state distribution and drawing samples from the same – outlines the essence of the simulation exercise we will execute below.

### *4.2 Results*

Suppose that urban (or rural) India is made up of multiple "regions" that correspond to different values of parameters. Suppose there are 1000 such regions. This implies that there are 1000 sets of regional parameters $(w_H, w_L, p_1, p_2, p_3, p_4, \beta, \sigma, q_L, \delta, E, C)$, each of which is assumed to be drawn from a uniform distribution over a given parametric range. Hence, we can derive 1000 data-generating processes or theoretical steady state distributions (such as in Figure 2(a)). Suppose also that the sampling process is able to draw 1000 observations from each of the 1000 data-generating processes. Pooling these observations generates a sample of a million observations from the urban (or rural) sector. This sample is a "theoretical" counterpart of empirical household datasets available for analysis, such as the urban (or rural) sub-sample of the NSS.

[13]The x axis of Figure 2 shows the 12 unique levels of total durables associated with the 25 states in the stochastic process (15) – (16) (see footnote 12).

Figure 3(a) plots the histogram of the pooled sample for the following range of parameters (Set A). (The distribution of each parameter over the specified range is uniform.)

**Example 2.** ***(Set A)*** $w_H \in (80, 120), w_L \in (5, 20), p_1 \in (0, 0.5), p_2 \in (p_1, 0.5), p_3 \in (0.5, 1), p_4 \in (p_3, 1), \beta \in (100, 500), \sigma \in (100, 500), q_L = 0.5, \delta = 0.5, E \in (10, 100), C = 2w_L$.

The separation of observations into clusters – or durable-spending "classes" – is immediately evident in Figure 3(a). Notice that in Example 2 (or Set A), the ranges of $w_H$ and $w_L$ do not overlap; this generates the clear separation in the histogram of observations from the lowest class (with 0 durable spending) and the middle class; and the middle class and the next higher class. Consider a set of parameters – called Set B – which is identical to Set A except that $w_L \in (5, 80)$, i.e. the ranges of $w_L$and $w_H$ *do* intersect. In the histogram corresponding to the pooled sample from Set B (Figure 3(b)), the gaps between the classes appear to close. Moreover, while there is a possibility of there being $3 - 4$ classes in Figure 3(a), the histogram in Figure 3(b) reflects $2 - 3$ classes[14].

Consider a third set of parameters – Set C – as follows.

**Example 3.** ***(Set C)*** $w_H \in (80, 120), w_L \in (5, 80), p_1 \in (0, 0.5), p_2 \in (p_1, 0.5), p_3 \in (0.5, 1), p_4 \in (p_3, 1), \beta \in (500, 3500), \sigma \in (100, 500), q_L = 0.5, \delta = 0.5, E \in (10, 100), C = 2w_L$.

Set C differs from Set B only in that the social standard $\beta$ is very high compared with the ranges of income (low and high). In Sets A and B, the social standard $\beta$

[14]The fewer observable clusters or "classes" in Figure 3(b) could be driven by the fact that allowing the ranges of $w_H$ and $w_L$ to intersect lowers the overall dispersion between the same (i.e. low and high wages) in Set B (compared with Set A).

lay within the achievable range of incomes in the labour and marriage markets. The histogram corresponding to Set C in Figure 3(c) shows a shrinkage in the proportion of higher levels of durable spending and a separation into 2 rather than 3 clusters. This situation is akin to the mixture estimates we obtain in rural India in 1993-94.

How does one interpret the phenomenon of a very high $\beta$? One explanation could simply be that the price of owning durable items is extremely high in rural areas due to high transportation or operational costs (e.g. bad roads, unreliable electricity supply). Another explanation could be that durables are *not* an effective signal for marriage market success in rural India. It is not hard to envisage close-knit rural communities in which the social status (e.g. caste) of households is common knowledge; this would weaken any additional information that observable consumption (such as durable ownership) could provide about a household's social standing. In order for durable spending to matter beyond what is already known about each other, it would have to be inordinately high.

Thus, a very high $\beta$ in rural India could explain the difference in mixture results between urban and rural India in 1993-94. The convergence to similarly defined classes in rural and urban India in 2003-04 could indicate a lowering of $\beta$ in rural India to meet urban standards. The easier availability of durable goods post-liberalization leading to an effective fall in prices facing rural customers would appear to be an obvious explanation for this effect. Another factor in play could be greater geographical mobility, leading to greater social anonymity and the emergence of durable ownership as a more effective signaling mechanism. We do not claim, however, that a lowering of $\beta$ is the only mechanism that could explain a movement from 2 to 3 classes in rural India. There could be alternative pathways (represented by shifts in other parameters) that could generate effects that match what we find in the empirical data.

The more robust finding from the current analysis is the fact that household durable spending data exhibits natural clusters or "classes" when generated by the model in Section 3. The model exploits some intrinsic characteristics of durable goods – viz. their observability and the fact that they can be accumulated over time (before they depreciate completely). These characteristics coupled with the fact that durables serve as a signal for social standing, hence marriage market outcomes, are able to generate "classes" of durable spending.

Given the findings above, the mixture model seems like a natural choice of process for identifying classes – in particular, the lowest class – in durable ownership.

But, *who* are the households that constitute the lowest cluster in our economic model, and why should we care about them? Are households in the lowest cluster vulnerable to poverty in any way or simply disinterested in owning durables? How do we interpret the probabilistic nature of the empirical mixture estimates in the light of findings from the theoretical model? In the next section we discuss answers to these questions, in the context of the empirical results from Indian NSS.

### *4.3 Interpreting the mixture estimates based on the economic model*

In this section, we interpret the empirical mixture estimates (Tables 1-2) in the light of predictions from the theoretical model of Section 3.

We derive (from the mixture estimates of $p_i$ and $\pi_i$) the probability $\gamma_L(x)$ that households with $x$ goods belong to the lower class[15]. The results are presented in Table 3. Notice, for instance, that households that have $0-2$ durables in $2004-05$ (both sectors) are likely to belong to the lower class with a somewhat large non-zero probability. However, these probabilities are not close or equal to 1. This means that *not all* households that have $0-2$ durables belong to the lower class either. Can the

[15] *It is easy to show that* : $\gamma_L(x) = \frac{\pi_L \phi_L(p_L,x)}{\pi_L \phi_L(p_L,x)+\pi_M \phi_M(p_M,x)+\pi_U \phi_U(p_U,x)}$ (See Maitra (2016, 2017).

theoretical model in Section 3 provide an intuition for probabilistic estimates such as these? The answer – discussed in detail below – is yes.

First, let us outline who belongs to the lower class (the relatively poor) and if (and how) these households are different from those in absolute poverty. In our economic model, households in "absolute poverty" are those that barely earn the subsistence consumption level $C$ in any period, and are, hence, likely to own 0 durables. It makes sense for these households to be included in the lowest class, since households in absolute poverty must also find themselves in the group of relatively poor (i.e. the lowest cluster). In the examples above (Sets A-C), we have assumed that subsistence consumption is equal to low-level incomes, $C = 2w_L$, in all regions from which data is drawn. Figure 3 shows clearly that, in these cases, the lower class (in relative poverty) includes households that have *no* durables. Thus, low-income households – all of whom have 0 durables and are in absolute poverty – are also the the likely group of the "relatively poor" in this population. Therefore, under the simplified assumptions made above, the groups of households in "absolute" and "relative" poverty may be roughly the same – viz. households that are too poor to afford a basic subsistence consumption. In general, however, there may be some regions in the population where $C > 2w_L$ and others where $C = 2w_L$. In the former case, our theoretical model predicts that some low-income households will be observed to accumulate a small (positive) number of durables. Indeed, the empirical results for rural and urban India (Table 3) indicate that lower-class households may own $0, 1$ or 2 durable goods. In other words, we may have some low-income households with 0 durables (i.e. households in absolute poverty) but some that own more. This raises the question: in what sense could households with small positive levels of durables be considered to be "poor" (albeit in a relative sense), even when their incomes are above the (consumption) poverty line?

Our theoretical model provides an interesting insight on low-income households' vulnerability to poverty, even when their incomes are above the poverty line. A household may be considered to be vulnerable to poverty if it is unable to access either of the two channels for high-income ($w_H$) generation – viz. the labour market or the marriage market. Now consider (14) – the condition under which it is optimal to choose education $e_H$. The nature of the signaling function $\widetilde{p}$ (and $\widetilde{p_e}$) imply that households with accumulated durables close to $(\beta - \epsilon)$ are most like to violate condition (14) (thereby choosing low education $e_L$). This is due to the fact that, for households who have already accumulated close to $\beta$ durables, the additional dollar spent on durables is more likely to increase future income (by procuring a high-income spouse), than that spent on education. This means also, that households whose accumulated durable levels are much *lower* (or much higher) than $\beta$ have the strongest incentive to acquire education (since, at their current level of owned durables, spending the marginal dollar on durables is not likely to increase expected marriage-market income by much *more* than it already is, relative to spending it on education). But this means that households who are observed to own a small positive level of durables may be doing so because they cannot afford education *even though education is optimal*[16][17]. In other words, households with small positive levels of durables may be vulnerable to poverty since they are unable to generate high income either in the labour market (due to being unable to afford education) or in the marriage market (due to low levels of accumulated durables). It is in this sense that households that own a small

[16]Note that for education to be optimal, $E$ must be sufficiently small. However, as long as $E > 0$ there will be some levels of $2w_L(> C)$ such that households with that income find it optimal to choose education but cannot afford to do so.

[17]An interesting implication of education being optimal for poor households is that income increases in these households will be spent on education even at the cost $E$ (i.e. subsidizing education is not necessary to induce poor households to choose education). This is consistent with reports of increased demand for enrolment in English-language schools in India post liberalization (Education World (2005), The Economic Times (2010), Cheney (2005)), along with increased employment of English-speaking youth in international call centers ( BBC (2003), Arasu (2008)).

amount of durables could be interpreted as being vulnerable to poverty – i.e. being in "relative" poverty – even when they are not in absolute poverty[18]. This finding is certainly reflected in the empirical results for rural and urban India, which show that the lower class may contain households with $0-2$ durable goods (Table 3).

Why then are *all* households with $0-2$ durable goods *not* considered to be vulnerable to poverty (and hence be considered to be "relatively poor"? The answer to this question lies in the fact that not all households with a small positive number of durables may come from low-income households. For example, we might observe, say $x$ durables ($x > 0$, small) in low-income households from some regions (who would prefer to choose education if they could afford it) or middle-income households in other regions (for whom education may or may not be optimal). In the former case, the households would be clearly considered to be vulnerable to poverty but this is not so clear in the latter situation. The mixture approach is able to capture this fact in its probabilistic assignments of class conditional on durable ownership[19]. Thus, the durables-based mixture approach recommends itself once more as a reasonable process for identifying and understanding relative poverty in a population, including the size and characteristics of the most vulnerable households.

In a poor and developing nation, the group of households in relative poverty (the lowest class) may have a large intersection with the group of households in absolute poverty. When this is the case, the durables-based mixture approach could be used to approximate the group of absolutely poor households, without necessitating the

[18]Note that households with accumulated durables much higher than $\beta$ may be unable to afford (optimal) education too if they are unlucky enough to draw a low income in the current period. However, the previously accumulated quantity of durables acts as a buffer for poverty as it gives them a relatively high probability of marriage market success in the next period.

[19]Note also that some households that have 0 durables may also be middle-income households who can just afford education (and hence accumulate 0 durables). These households would not belong to the category of the absolute or relatively poor. This phenomenon too is captured by the mixture model in its probabilistic assignment of household to class, conditional on durable ownership.

imposition of an externally determined "poverty line". This is useful especially when data on income or expenditure are hard to obtain or compare over time. As a country develops and incomes grow, however, we might expect the group of households in relative poverty to diverge from the group in absolute poverty. We could then use the mixture model described above to capture and visualize the divergence and how it changes during the development process[20].

In addition to explaining the phenomenon of classes and relative poverty, the model framework described in Sections 3-4 could provide a valuable tool for understanding policy effects on durable accumulation (and hence on relative poverty). Here are some questions, beyond the scope of this paper, that could be answered using our approach. Could poor households be jolted out of their poverty by a policy of providing free education ($e = 0$ for households with income $2w_L$)? Would providing free education be sufficient for poverty reduction or would we need to ensure also that the education is *effective* in securing a job (e.g. raise $p_2$ and $p_3$)? How would the effect of providing free education to the poorest households differ from that of giving them an income subsidy? We hope our framework will be useful to development researchers as well as practitioners for answering questions such as these and more.

## 5. Conclusion

We show, in this paper, that durable accumulation data generated from a theoretical model of marriage-market signaling exhibits natural clusters interpretable as classes. The mixture model – used in earlier research to measure relative poverty in urban India in the 1990s – is, therefore, an ideal framework for identifying classes in durable accumulation data. We argue, using intuition from the theoretical model,

[20]Could we "estimate" an expenditure-based relative-poverty line based on households in the lowest cluster identified by the durables-mixture model? This and related questions are subjects of our ongoing research.

that the lowest class identified by a mixture model – interpretable as the relatively "poor" – are the most vulnerable to poverty even when they are able to earn more than the poverty-line subsistence income. This is because these households are unable to access high incomes either through the labor market or social networks such as the marriage market. The theoretical framework developed herein is also a valuable tool for identifying policy effects, which will allow us to test and answer important development questions such as those pertaining to the role of free education or subsidy to the poor.

The main contribution of this paper is, therefore, that it establishes a vital link between the theoretical relationship between durable accumulation and poverty, and the practical process of measuring poverty using durable ownership data. We hope that the framework and insights generated herein will motivate future research on assets-based poverty measurement, including the role of policy in alleviating the same.

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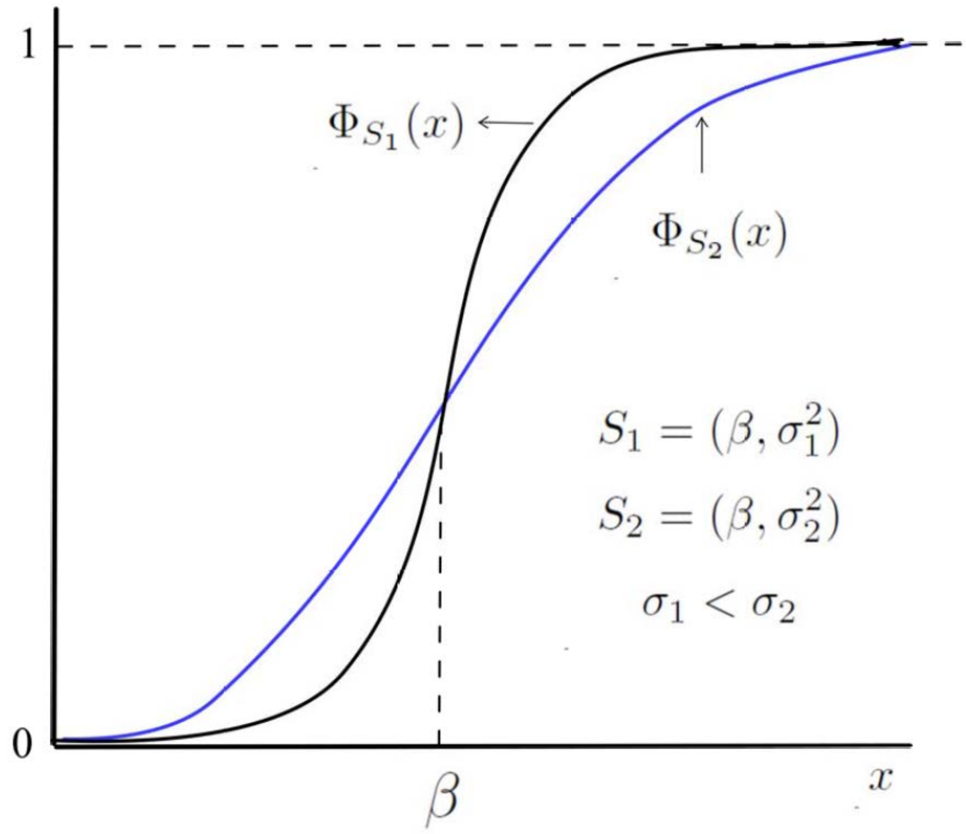


Figure 1: The Signal Function, normal c.d.f. $\Phi_S(x)$

Assumption: $\Phi_S(X)$ (where S = (β, σ)) represents the probability that the marriageable generation in a household with durables β will find a partner that earns the high wage, when skepticism around the belief β is given by σ.

**Figure 2(a): Steady state distribution of household durables, derived for parameters as in Example 1**

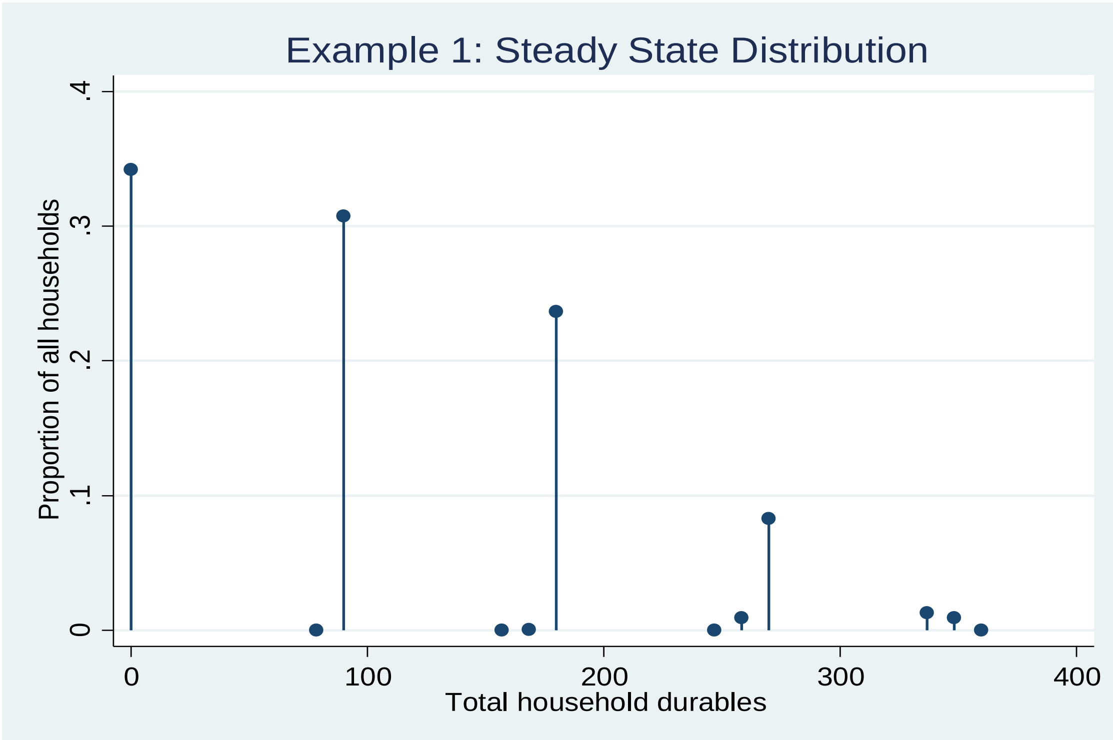
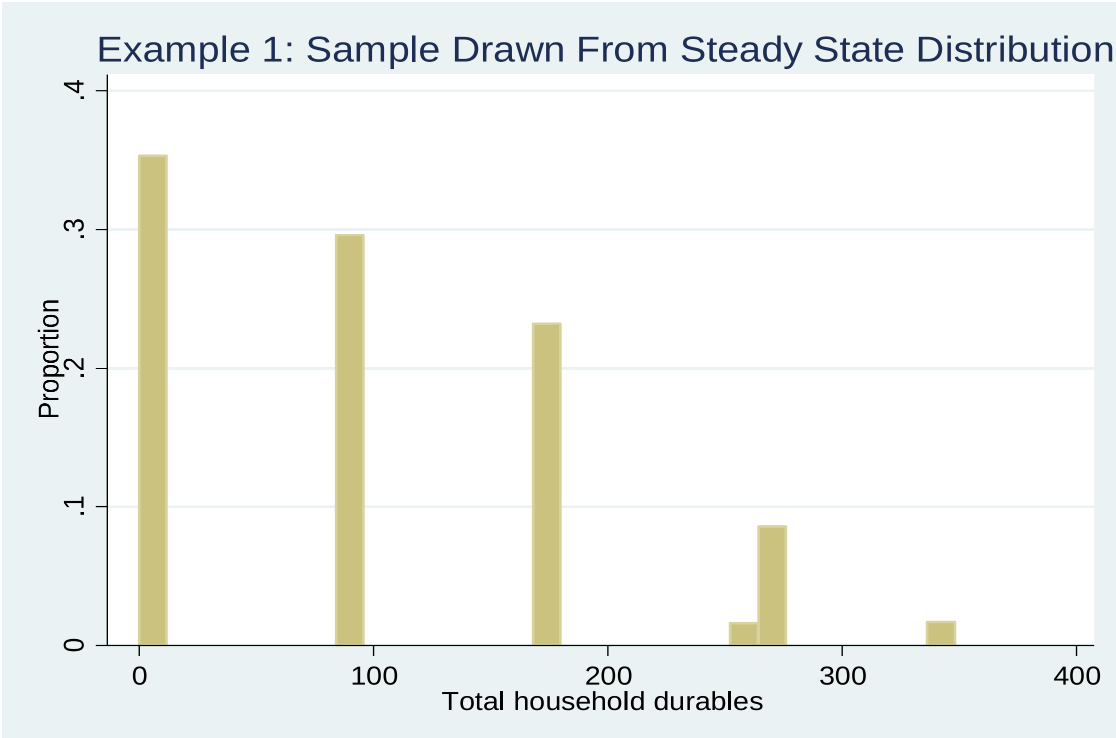


**Figure 2(b): Histograms from samples independently drawn from the theoretical distribution in Figure 2(a)**

**Sample 1**




**Sample 2**

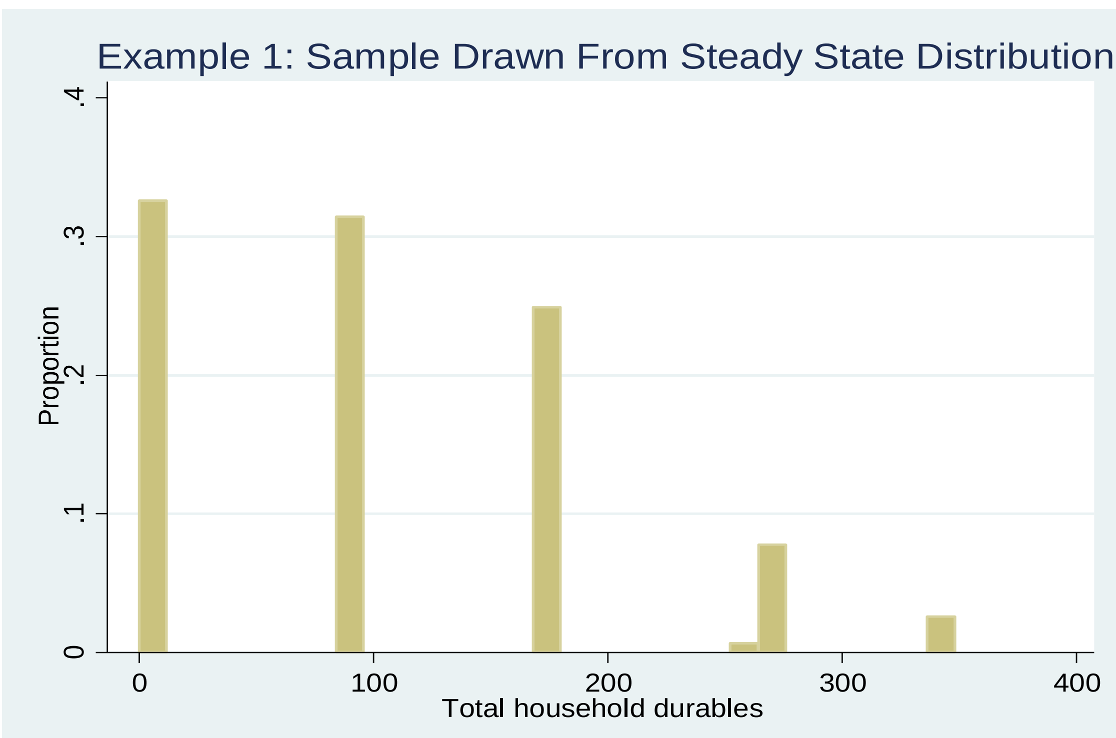


**Figure 3(a): Pooled sample from data generated using Set A parameters (Example 2)**

(wH and wL ranges do not intersect, beta is within attainable income range)

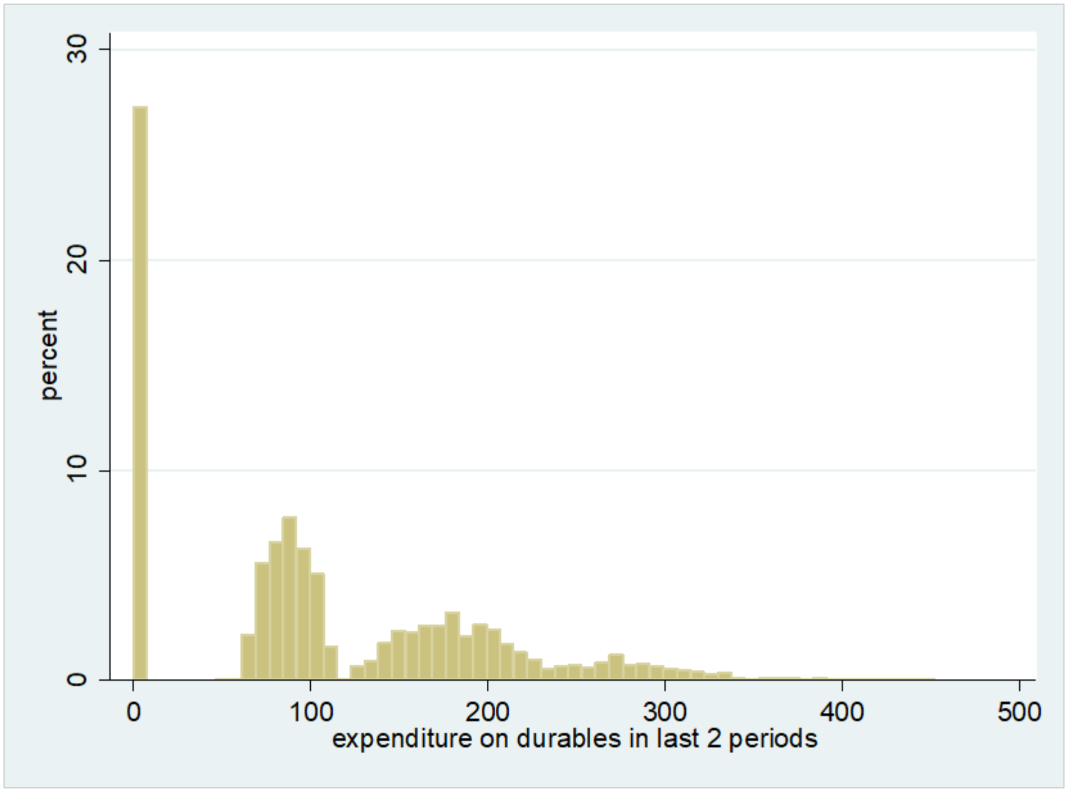



**Figure 3(b): Pooled sample from data generated using Set B parameters**

(wH and wL ranges intersect, beta is within attainable income range)

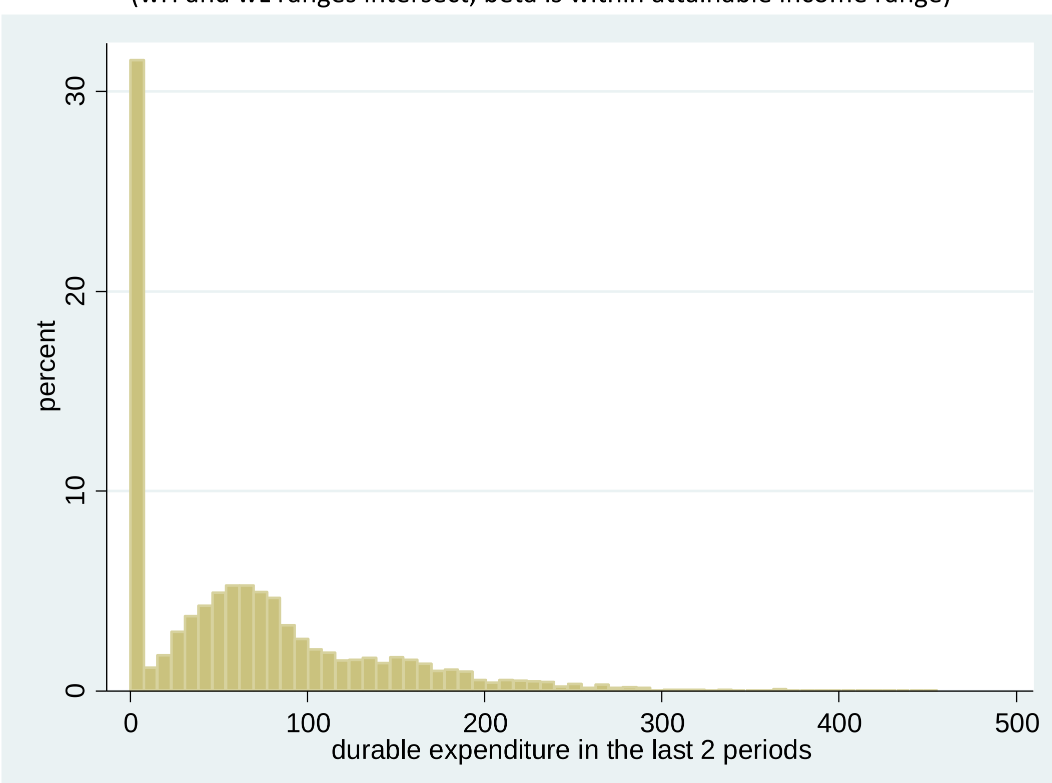


**Figure 3(c): Pooled sample from data generated using Set C parameters (Example 3)**

(wH and wL ranges intersect, beta is very high)

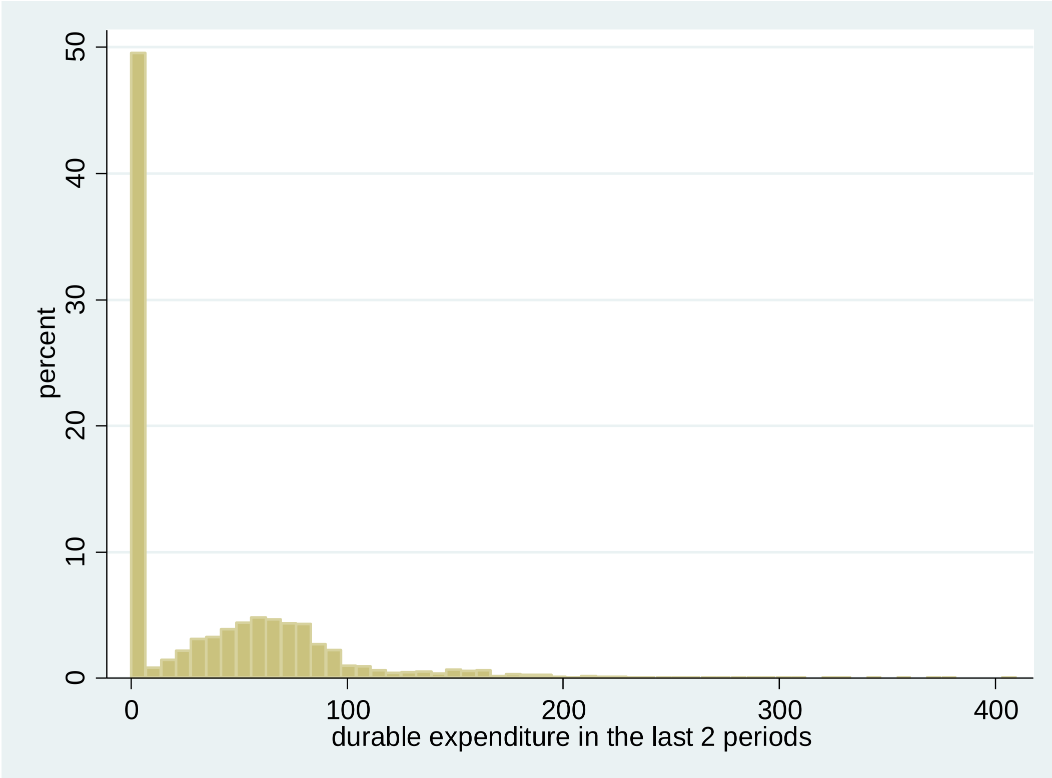
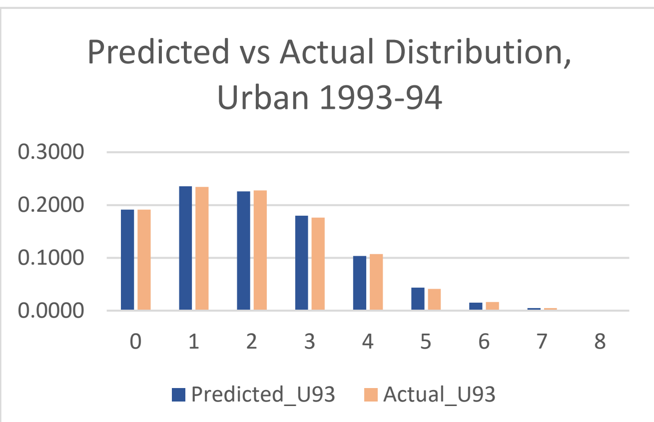
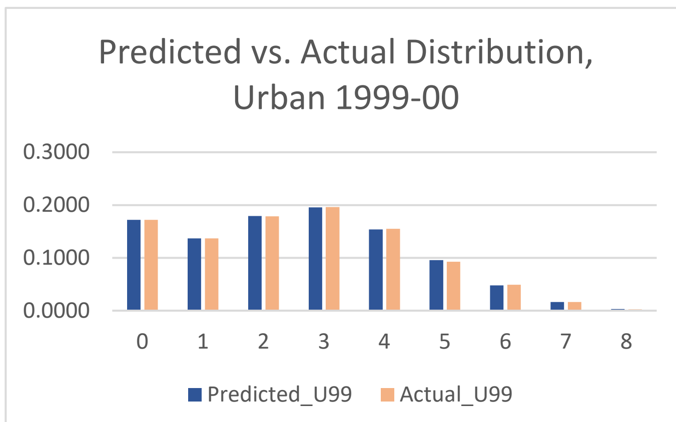


**Table 1: Mixture results, Urban subsamples of NSS**

| Year | | Class proportion | Binomial ownership probability |
|---|---|---|---|
| 1993-94 (urban) | Class 1 | 0.323 | 0.085 |
| | Class 2 | 0.647 | 0.313 |
| | Class 3 | 0.029 | 0.643 |
| | Observations | 17239 | |
| | Likelihood | -30493.9 | |
| 1999-00 (urban) | Class 1 | 0.200 | 0.035 |
| | Class 2 | 0.621 | 0.341 |
| | Class 3 | 0.179 | 0.590 |
| | Observations | 48924 | |
| | Likelihood | -95047.9 | |
| 2004-05 (urban) | Class 1 | 0.161 | 0.079 |
| | Class 2 | 0.603 | 0.340 |
| | Class 3 | 0.235 | 0.627 |
| | Observations | 43356 | |
| | Likelihood | -86451.9 | |



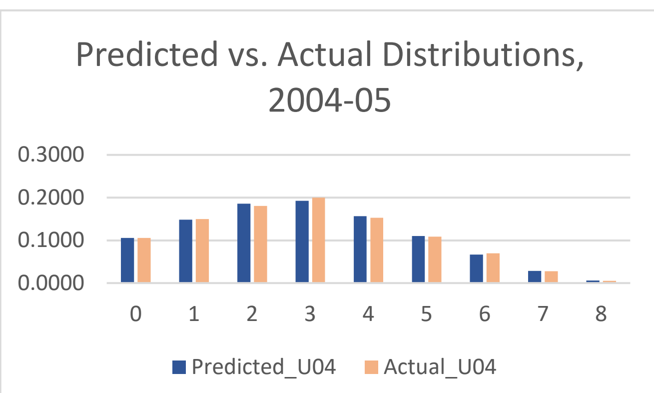
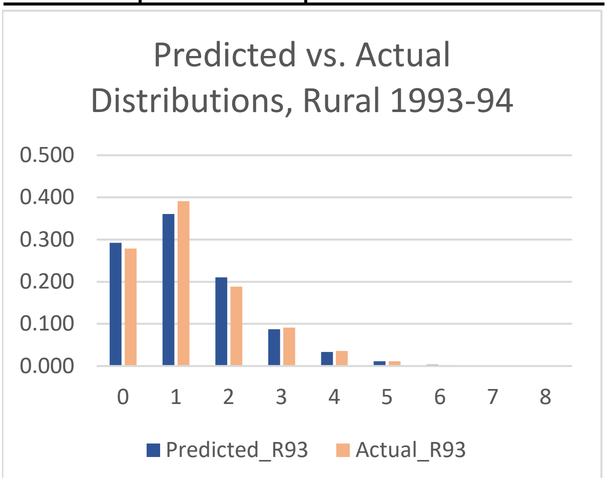
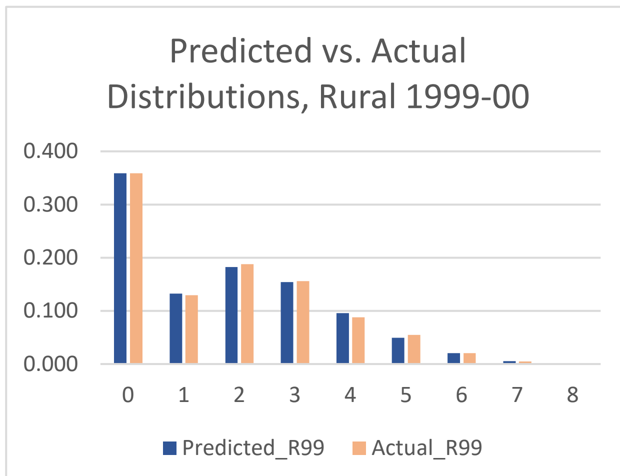



**Table 2: Mixture results, Rural subsamples of NSS**

| Year | | Class proportion | Binomial ownership probability |
|---|---|---|---|
| 1993-94 (Rural) | Class 1 | 0.880 | 0.130 |
| | Class 2 | 0.120 | 0.359 |
| | Observations | 17452 | |
| | Likelihood | -25273.3 | |
| 1999-00 (Rural) | Class 1 | 0.316 | 0.000 |
| | Class 2 | 0.554 | 0.274 |
| | Class 3 | 0.131 | 0.523 |
| | Observations | 71385 | |
| | Likelihood | -122760.65 | |
| 2004-05 (Rural) | Class 1 | 0.247 | 0.075 |
| | Class 2 | 0.355 | 0.182 |
| | Class 3 | 0.345 | 0.363 |
| | Class 4 | 0.053 | 0.633 |
| | Observations | 75941 | |
| | Likelihood | -135842.2 | |



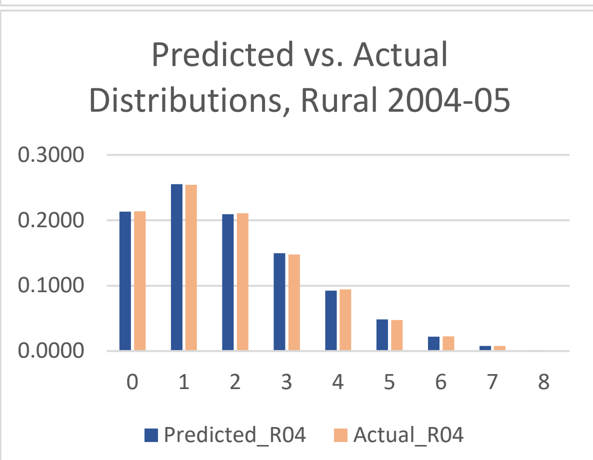



**Table 3: Probability of lower-class membership by durables owned, NSS, 1993-04, 1999-00, 2004-05***

| Total No. of Durables Owned (x) | Probability that household with x durables belongs to the lower class | | | | | |
|---|---|---|---|---|---|---|
| | 1993-94 | | 1999-00 | | 2004-05 | |
| | urban | rural | urban | rural | urban | rural |
| 0 | 0.832 | 0.988 | 0.871 | 0.879 | 0.793 | 0.624 |
| 1 | 0.502 | 0.957 | 0.320 | 0.000 | 0.386 | 0.336 |
| 2 | 0.170 | 0.857 | 0.031 | 0.000 | 0.092 | 0.116 |
| 3 | 0.040 | 0.615 | 0.002 | 0.000 | 0.015 | 0.026 |
| 4 | 0.008 | 0.299 | 0.000 | 0.000 | 0.002 | 0.004 |
| 5 | 0.001 | 0.102 | 0.000 | 0.000 | 0.000 | 0.001 |
| 6 | 0.000 | 0.029 | 0.000 | 0.000 | 0.000 | 0.000 |
| 7 | 0.000 | 0.008 | 0.000 | 0.000 | 0.000 | 0.000 |
| 8 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 |

* Derived from mixture estimates reported in Tables 1 & 2.

**Data Appendix: Distribution of Total Durables Owned, NSS India**

**1993-94**

| Total Durables Owned | urban | | rural | |
|---|---|---|---|---|
| | Freq | Rel Freq U | Freq | Rel Freq R |
| 0 | 3296 | 0.191 | 4869 | 0.279 |
| 1 | 4044 | 0.235 | 6831 | 0.391 |
| 2 | 3924 | 0.228 | 3282 | 0.188 |
| 3 | 3041 | 0.176 | 1589 | 0.091 |
| 4 | 1843 | 0.107 | 629 | 0.036 |
| 5 | 716 | 0.042 | 205 | 0.012 |
| 6 | 279 | 0.016 | 39 | 0.002 |
| 7 | 80 | 0.005 | 7 | 0.000 |
| 8 | 16 | 0.001 | 1 | 0.000 |
| Observations | 17239 | | 17452 | |

**1999-00**

| Total Durables Owned | urban | | rural | |
|---|---|---|---|---|
| | Freq | Rel Freq U | Freq | Rel Freq R |
| 0 | 8419 | 0.172 | 25618 | 0.359 |
| 1 | 6692 | 0.137 | 9220 | 0.129 |
| 2 | 8743 | 0.179 | 13400 | 0.188 |
| 3 | 9600 | 0.196 | 11124 | 0.156 |
| 4 | 7592 | 0.155 | 6275 | 0.088 |
| 5 | 4540 | 0.093 | 3907 | 0.055 |
| 6 | 2413 | 0.049 | 1440 | 0.020 |
| 7 | 806 | 0.016 | 339 | 0.005 |
| 8 | 119 | 0.002 | 62 | 0.001 |
| Observations | 48924 | | 71385 | |

**2004-05**

| Total Durables Owned | urban | | rural | |
|---|---|---|---|---|
| | Freq | Rel Freq U | Freq | Rel Freq R |
| 0 | 4565 | 0.105 | 16218 | 0.214 |
| 1 | 6486 | 0.150 | 19315 | 0.254 |
| 2 | 7831 | 0.181 | 16002 | 0.211 |
| 3 | 8670 | 0.200 | 11215 | 0.148 |
| 4 | 6623 | 0.153 | 7173 | 0.095 |
| 5 | 4721 | 0.109 | 3611 | 0.048 |
| 6 | 3020 | 0.070 | 1712 | 0.023 |
| 7 | 1217 | 0.028 | 583 | 0.008 |
| 8 | 223 | 0.005 | 112 | 0.002 |
| Observations | 43356 | | 75941 | |