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

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ABSTRACT

What drives household spending choices on durable goods? Why do consumption classes arise and what determines their number? What does it mean to be poor? In this paper, we propose an economic theory of household decision-making that links these questions. We then use a combination of simulation and empirical techniques to translate the intuition from the economic model into defining, interpreting and measuring relative poverty using durable ownership, in Indian National Sample Survey data (NSS, 1993-94 to 2004-05).

We develop a dynamic overlapping-generations model where households choose between investing in education, which increases subsequent income, and investing in durables, which increases observable wealth (a signal of 'social status') 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, which may be interpreted as 'classes'. Furthermore, we show that certain households – viz. those in the lowest class (i.e., in relative poverty) – may be unable to take advantage of either the labour market (via education) or the marriage market (via durables), offering a new perspective on long-term poverty.

We use the theoretical model as the foundation of a data-generating process for synthetic observations. We then use patterns in the synthetic data to interpret the clusters – identified empirically by a mixture model – in survey data on durable ownership (NSS). This approach is novel and allows us to combine different modes of inquiry – economic theory (OLG), simulation techniques and empirical methods (mixture models) – to inform the purely practical process of poverty measurement.

The paper makes several contributions: (1) we establish a theoretical model linking household income generation and durable choice, patterns in durable goods ownership, class formation, and long-term poverty; (2) we validate the use of durables-based mixture models as an empirical tool for identifying classes (hence, measuring relative poverty); and (3) we build a framework for generating testable hypotheses around the long-run effect of policy changes (such as income transfers or education subsidies) on poverty. Finally, and most generally, (4) we introduce a novel and innovative methodology that combines economic theory, simulations/synthetic data, and empirical methods to understand and measure relative poverty in practice, an approach that can be extended to other applications involving measurement of the observed behaviour of economic agents in complex dynamic settings.

1. Introduction

The measurement and identification of poverty has long been of special interest to development economists. Typically, this involves the definition of a poverty line – a level of income or expenditure – such that all households below this level are identified as 'poor' (Deaton (1997), Ray (1998)). When income or expenditure data is unavailable, testing for the presence of assets in households has 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, Maitra (2016, 2017) uses a mixture model to identify clusters in the total durable ownership patterns of urban households in India. Maitra's mixture analysis finds that there are 3 clusters ('classes') in this population, each with its own distinct density of durable ownership; the lowest class (who own the fewest durables on average) can then be identified as the (relatively) poor.[1] Extending Maitra's analysis to rural households reveals similar clusters in the data: 2 rural classes in 1993-94, 3 in 1999-00 and 4 in 2004-05.

Why do durable ownership data exhibit clusters (or classes) with such a distinct, consistent structure? What determines the number of clusters – i.e. the existence of 3 versus 2 or 4 classes – of durable ownership? What factors might determine

[1] Maitra's (2016, 2017) papers are motivated by an attempt to examine what happened to poverty in urban India in the 1990s, following the economic liberalization of 1991. India's National Sample Survey (NSS) data, from which poverty-line-based poverty estimates have traditionally been derived, used a new set of recall periods in its questionnaires in 1999-00 compared with previous years. This led to concerns that the expenditures reported by households were not comparable between the 1993-94 and 1999-00 rounds (Deaton and Kozel (2005)). 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 poverty 'line' – the various classes were identified purely based on natural clusters in the data.

a ‘steady state’ pattern of durable ownership that re-emerges over time and across sector, despite a temporary displacement (as in urban India in 1999-00)? In other words, what kind of *theoretical* relationship between durable ownership and economic well-being (thence, poverty) could explain the consistent patterns observed in the Indian data?

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 attempts to examine why or how the accumulation of such assets is related with the same. In this paper, we attempt to address this 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 understand why there are natural clusters in durable ownership and what drives the long-run (steady-state) patterns of such ownership. Our larger goal is to develop a framework for understanding the relationship between durable accumulation and poverty over time; one that can be extended to a rich set of applications, including the impact of policy changes in the long run.[2]

To this end, we introduce a novel methodology where we construct a theoretical model that acts as a data-generating process for simulated observations on (optimal, steady state) durable ownership. We draw observations from this data-generating process to generate a synthetic dataset. The patterns observed in the synthetic dataset are then used to interpret patterns observed in the *actual* data from NSS India. This methodology – of connecting micro and macro outcomes using insights

[2]We hope also that our approach will contribute to answering the even larger philosophical question (see Sen (1983)) – how do we measure the lack of capabilities (represented by income) using observations on commodities (durable goods)? Poverty addresses a constraint in income, but asset accumulation is clearly a *choice* that depends on preferences as well as income constraints. The economic model at the heart of our methodology takes the decision-making process of households explicitly into account.

from both empirical and theoretical research – has the potential to greatly improve our understanding of complex development processes in general.

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 higher-quality spouse.[3] 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 potentially escaping poverty) – the labour market and the marriage market. Choosing (costly) education increases the probability of a high labour-market return, while spending on additional durables (instead of education) signals a higher social status which increases the probability of a high marriage-market return. The optimal choice 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 signal its social status. We assume, moreover, that in any period, households must meet a

[3]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), Banerjee, Duflo, Ghatak and Lafortune (2013), 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.

subsistence consumption level first, before they can spend on education or durables. This subsistence level is the theoretical counterpart of the (consumption or expenditure) poverty line. Households who earn below this level (who are, therefore, in "absolute poverty") choose 0 durables. Those that have an excess of income beyond the subsistence level choose high education if it is optimal. The residual income in either case is assigned to durables.[4]

The uncertainty that households face in the labour market is also affected by a latent productivity level (high or low) that each household draws at the birth of each generation. Conditional on the level of education chosen, high-productivity households have a higher probability of obtaining a high labour market return than low-productivity households. Households do not observe the level of productivity they have drawn but they do know the probability of drawing high productivity in each period.

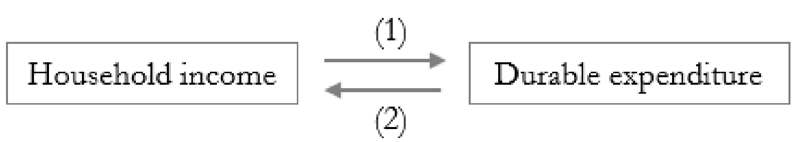
Given the above framework, households' optimal choices in any period can be used to define a stochastic process which then becomes a data-generating process for observations on durables accumulated by households. Given any set of parameters, we can derive the transition matrix and the steady state distribution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

We find that the distribution of durable expenditure in the synthetic sample shows natural clusters which may be 2, 3 or 4 (or higher) in number, depending

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

on parameter values (Figures 3a-c). These 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 our framework allows the development of further tests (both theoretical and empirical) to ascertain which parameters are most likely to explain the durables' class phenomenon in different societies. Our model also provides an explicit framework for predicting the impacts of policy changes that affect the various parameters.

Why do we see clusters in durable expenditure? The answer lies in the *two-way* relationship between household income and durables' choice – (1) the effect of current income on current durable choice, and (2) the effect of durables choice on future income through signaling.



In steady state equilibrium the *same* levels of incomes and durable expenditures must persist over time. But not all feasible or even short-run optimal durable choices are sustainable in steady state. Hence, clusters are formed at the levels of durable expenditures that are reinforced by households' decision-making process in the long run.

We now illustrate this process.

1.1 Why classes? An illustrative example

In any period, a household's total income is the sum of its labour-market and marriage-market incomes. Suppose there are two possible levels of income that may be earned in these markets: high (w_H) and low (w_L). Higher education leads to an increased probability of receiving w_H in the labour market. Similarly, higher observed durable ownership leads to an increased probability of receiving w_H in the marriage market. Thus, a household's total income from both channels in any one period can take three possible values: low L ($= 2w_L$), medium M ($= w_L + w_H$) or high H ($= 2w_H$), depending on education level and durables accumulated.

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" β, 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).[5]

Note that social status and marriage market success are determined by the total value of durables owned by a household in any period. We assume that durables depreciate completely over two periods; hence the total value of durables is the sum of that accumulated by the current and the previous generation in each household.

We assume that each household must pay a subsistence consumption C in every period. Hence the feasible ranges of durable expenditure in any period for low (L), medium (M) or high income (H) households are given by $[0, 2w_L - C]$, $[0, w_L + w_H - C]$ and $[0, 2w_H - C]$, respectively. Within their feasible range, the optimal level of durables b_t chosen by households will depend on whether choosing high education

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

is optimal in the current period, given the household's income level, the value of durables already accumulated and the (exogenous) returns to education in the labour market.

Finally, we assume there are 2 levels of education that households can choose from: high (with cost $E > 0$) and low (with cost 0). Hence there are 6 total possibilities for optimal durable expenditure choice (b_t) by households in any period, corresponding to the 3 types of household L, M, H above, and their decision whether or not to invest in high education.

Let us now discuss steady state equilibrium outcomes in the above model. Which of the above 6 possible (single period) outcomes are we most likely to observe in a steady state equilibrium? The answer depends on which household incomes (L, M or H) are most likely to occur, and how many durables are likely to be inherited in any period. Clearly, household income and durable inheritance at the beginning of any period t depend on the household's expenditure on education and durables expenditure in the previous period ($t-1$); furthermore, t-period choices – of education level and durables expenditure – determine the initial conditions, and thence, realized income and optimal choices of education/durables in the next period ($t+1$). A steady state equilibrium of this recursive process occurs when the same distribution of incomes and durable expenditures is observed in every period. This requirement of consistency over time does two things – (i) it limits the number of outcomes to those that may be sustained in steady state and (ii) it confers increased mass on these limited outcomes that are sustainable in steady state – which *lead to clustering in durable expenditures.* The number of clusters formed and the levels of durable expenditures observed depend on the nature of income generation via the labour and marriage markets, as well as how these two channels interact. We demonstrate these dynamics in the following examples.

Suppose that the cost of education E is very high, so that none of the 3 types of households find it optimal to invest in high education in any period. This reduces the possible levels of optimal household durable expenditure to 3 from 6.

Let us call these 3 possible (optimal) levels of durable expenditure b_L, b_M and b_H for L, M and H households, respectively. Since the total durables in a household are accumulated over 2 periods of time, there are 9 ($= 3 \times 3$) possible states of (b_{t-1}, b_t) from which total durable expenditure in each household could be derived:

(1) $(b_L, b_L), (b_L, b_M), (b_L, b_H), (b_M, b_L), (b_M, b_M), (b_M, b_H), (b_H, b_L), (b_H, b_M), (b_H, b_H)$

The 9 states above reduce to 5 unique values of total durables accumulated[6]: $(2b_L), (b_L + b_M), (2b_M), (b_M + b_H)$ and $(2b_H)$.

If every household in the economy were subject to the same values of parameters – w_H, w_L, E etc. – then the distribution of total household durables at any time would record a mass at (and only at) each of the 5 (total) values of durables derived above. In other words, the simplified economy we have constructed in the example above could display up to 5 classes of durable expenditure.

Let us now take a closer look at the 5 values of durable expenditure that could prevail: $(2b_L), (b_L + b_M), (2b_M), (b_M + b_H), (2b_H)$.

Recall that in order to spend b_H on durables in a given period, a household must receive a high income in both the labour market and the marriage market. High education increases the probability of receiving a high income in the labour market. Now, some households with low education may still "get lucky" and receive a high income despite their low education. However, the probability of this happening in

[6]The total number of durables in state (x, y) is the same as that in the reversed state (y, x). Furthermore, given that b_L, b_M and b_H come from incomes $2w_L, (w_L + w_H)$ and $2w_H$, respectively, it is straightforward to show that $2b_M = b_L + b_H$.

the same household for two consecutive generations is very low. Hence in an economy where nobody chooses to invest in education, there are not many cases of $2b_H$. That leaves just 4 classes to be observed in the population.

If, in addition, the probability of receiving a high income without education ("getting lucky" in the labour market) is very close to 0 (i.e. education is *effective* in generating labour market income), then even households spending $(b_M + b_H)$ on durables are unlikely to exist. In this case we would observe only 3 classes, corresponding to durable expenditures of $2b_L$, (b_L+b_M) and $2b_M$. Essentially, the high cost and *effectiveness* of education completely blocks one channel of income generation, reducing the number of classes in durable ownership.

Notice the dynamic interplay of choices and outcomes here. A high cost of education reduces the set of spending choices that households may optimally make. But the limited choices also reduce the set of future incomes households can receive which determines subsequent durable choices (the outcomes of interest). The combination of these two effects reinforces certain outcomes and eliminates certain other outcomes in any long-run steady state equilibrium. The limited set of possible steady state outcomes manifests as clusters.

Now suppose that the social standard β is very high and unattainable given the levels of w_H and w_L in a particular society. This makes it hard for households in this society to achieve a high-income partner, and results in the second channel of income generation – the marriage market – being blocked off as well. If this happens when the cost of education is also high, then the probability of observing households with $2b_M$ durables is also suppressed, resulting in just 2 classes in the population, with durables $2b_L$ and $(b_L + b_M)$.[7]

[7] β would be unattainably high if social status is determined by a variable *other* than durable ownership – say, by a household's caste, which is reflected in the residents' names. One can envisage such a situation occurring in close-knit communities where everyone knows their neighbours' "social

A society where β is low compared with w_L (cet. par.) can similarly demonstrate 2 classes, although the levels of durable ownership corresponding to the classes will be higher, since now it is the 2 higher expenditure levels – $(b_L + b_M)$ and $2b_M$ – that are more likely to be observed. When β lies between low and high-income levels, we are likely to find 3 (or even 4) classes instead of 2.

1.2 What does it mean to be 'poor'?

Our theoretical model – illustrated in the examples above – provides an interesting insight on what it means to be 'relatively poor', how relatively poor households differ from those in absolute poverty and, most importantly, why these households warrant the attention of policy makers. Recall that a key feature of the assumption on social standards (β) is that when previously accumulated durable levels are close to $(\beta - \epsilon)$, spending the marginal dollar on durables (and not on education) yields the highest increase in expected future return. This implies that households with accumulated durable levels that are much lower than (or much higher than) β have the strongest incentive to invest in effective education. This further suggests that households who are observed to be accumulating small positive levels of durables instead of spending on education, may be doing so because they cannot afford effective education even in situations where education is their optimal choice.

These "low-income, low-durable" households – who are evidently not in 'absolute poverty' – are nevertheless likely to be *vulnerable* to poverty due to their inability to access either the labour market or the marriage market to improve *long-run* economic well-being. The group of "relatively poor" households ought to include such house-

status" (viz. caste) and durables do not play a role in its assessment. Indeed, we find 2 classes in the mixture for rural households in NSS, 1993-94, where these conditions could plausibly apply. The case of high β represents the counterfactual scenario – when durables-based signaling is 'turned off' – where there may exist at most 2 observed classes in the population.

holds that own a small but non-zero level of durables even when these households appear to be above the absolute poverty line. Indeed, we find this to be true in the empirically obtained definitions of the lowest class in India obtained using mixture estimates (Section 2). This conceptual understanding of 'relative poverty', as can be measured from clustered durables data, constitutes one of the key insights of this paper.

The rest of the paper is organized as follows. In Section 2, we extend Maitra's (2016, 2017) analysis from urban to rural households in India, using data from NSS rounds 1993-94, 1999-00 and 2004-05. 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 Sections 4.2-4.3. Section 5 concludes the paper and underlines its contribution to the literature.

2. Empirical findings

In this section, we 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 ϕ_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

$$P(y) = \pi_L \phi_L(8, p_L) + \pi_M \phi_M(8, p_M) + \pi_U \phi_U(8, p_U) \tag{2}$$

where π_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 (π_L, π_M, π_U) and class-specific ownership probabilities (p_L, p_M, p_U)[8].

Recall that the shape of a binomial distribution – symmetric or positively/negatively skewed – depends on the values of its parameters (n, p). Hence, using the binomial form for ϕ_i in (2) allows us to fit flexible densities of Y within each class/cluster. Maximum likelihood estimates of the specific durable ownership density of each class (p_i) and the size of each class (π_i) then allow us to construct the *predicted* distribution of Y in the entire population based on these estimates, and evaluate the fit of the predicted to the *actual* distribution of Y in the sample. Maximum likelihood estimates of the size of each class (π_i) and the specific durable ownership density of each class (p_i) then allow us to construct the *predicted* distribution of Y in the

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

entire population based on these estimates, and evaluate the fit of the predicted to the *actual* distribution of Y in the sample.

Table 1 presents the estimates of $\{\pi_i, p_i\}$ for urban subsamples in years 1993-94, 1999-00 and 2004-05[9]. 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 ϕ, to which the distribution of durables reverts after an initial adjustment phase in 1999-00.

We extend 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[10].

Yet another interesting finding from the rural results is that in the final year, class definitions (as expressed by p_i) are 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 four important observations from the empirical findings in Tables

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

[10] 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 durable counts 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. Third, 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. Finally, the consistent *structure* of classes we obtain across time and sector suggest that clusters in durable ownership are unlikely to be a purely cosmetic feature of the data – driven, for example, by the discreteness of durable counts – and are instead linked to a deeper, more fundamental process of wealth generation and decision making in households.

The observations above lead to three immediate questions. What feature of the underlying wealth generation process could generate clusters (or classes) in durable ownership patterns? What determines the existence of 3 versus 2 or 4 classes of durable ownership? Finally, what factors could determine a 'steady state' pattern of durable ownership that persists over time, despite displacement?

In the next section, we present a theoretical model of household choice of durable spending that attempts to answer these questions. Our goal is to illuminate the deeper, *economic* connection between wealth generation and durable choice that can explain class formation in durables such as observed in the data. To this end, from this point on, we focus on the durable *expenditure* choices of households. Our results in the next section demonstrate how optimal durable expenditures – which (unlike durable counts) lie within a *continuous* feasible interval – can segregate into classes in steady state equilibrium.

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

$$U(B_t) = C + B_t \tag{3}$$

where B_t is the total value of durables present in the household in t.

Note that B_t includes the durables purchased by period$-t$ parents in period t as well as those accumulated by period$-t$ grandparents in period $(t-1)$, i.e.

$$B_t = b_t + b_{t-1} \tag{4}$$

where b_k indicates the durables purchased in period k by period$-k$ parents. (3) and (4) indicate that when period$-t$ 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 (α_L and α_H, respectively) and (2) whether s(he) has high or low education (e_H and e_L, respectively). The productivity level α_{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 α_L with probability q_L (α_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 value of durables observed to be in use in that household (B_t) – attract partners with higher wage[11]. In particular, we assume that a household 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, β, that is generally acknowledged to mark households of high social standing. The skepticism around this common belief is represented by σ^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 (σ^2) regarding the common social standard β, the lower the increased probability of acquiring a high-wage partner at most levels of accumulated durables

[11]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".

B, around β. An example of a society with low skepticism (or low σ^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 β denotes the social standard and σ^2 denotes the skepticism regarding β. Further, we denote the wage of the parental partner by w_2 and call it the household's 'marriage market income'[12].

Household income in period t can 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, α_{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 particular,

$$I_t(e_{t-1}, \alpha_{t-1}, B_{t-1}) = w_{1t}(e_{t-1}, \alpha_{t-1}) + w_{2t}(B_{t-1}) \tag{5}$$

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,

[12]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.Thus, the model – though motivated by Indian socio-economic conditions – would generalize well to other societies also.

otherwise); $S = (\beta, \sigma^2)$. We assume

$$p(e_L, \alpha_L) = p_1 \tag{6}$$

$$p(e_L, \alpha_H) = p_2 \tag{7}$$

$$p(e_H, \alpha_L) = p_3 \tag{8}$$

$$p(e_H, \alpha_H) = p_4 \tag{9}$$

$$0 < p_1 < p_2 < p_3 < p_4 < 1 \tag{10}$$

where condition (10) – along with our additional assumptions that p_1, p_2 are small and p_3, p_4 are large – indicate that education is *effective* in generating high labour market income.

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:

$$E_t = C + c(e_t) + b_t \tag{11}$$

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 (α_{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 (parents') lifetime utility $[U(B_t) + \delta U(B_{t+1})]$, where δ (ϵ $(0,1)$) 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* value 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:

$$\underset{(e_t,b_t)}{Max}\ U(b_{t-1} + b_t) + \delta U(b_t + b_{t+1}) \tag{12}$$

subject to

$$c(e_t) + b_t \leq I_t(e_{t-1}, \alpha_{t-1}, b_{t-1} + b_{t-2}) - C \tag{13}$$

$$b_{t+1} = I_{t+1}(e_t, \alpha_t, b_t + b_{t-1}) - C - c(e_{t+1}) \tag{14}$$

$$b_t \geq 0 \tag{15}$$

where all durable expenditures in the *continuous* interval $[0, Max\{0, I_t(e_{t-1}, \alpha_{t-1}, b_{t-1} + b_{t-2}) - C\}]$ are *feasible* choices for the household.

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 $(13-14)$. 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 (12) and, (ii) it also increases the potential of higher income (hence, consumption) in the future (14).

It is is easy to see that solving the optimization exercise in $(12)-(15)$ 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[13]:

$$\begin{aligned}(16)\quad &(1+\delta)E + \delta(w_H - w_L)[q_L(p_1 - p_3) + (1-q_L)(p_2 - p_4) + (\widetilde{p} - \widetilde{p}_e)] \\ &\qquad - \delta E\{\Pr(e_{t+1} = E/e_t = e_L) - \Pr(e_{t+1} = E/e_t = e_H)\} < 0\end{aligned}$$

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 (16) encapsulates the heart of our model and has the following interpretation.

Notice that there are three terms on the left-hand side of equation (16). The first term 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

[13]Condition (16) is derived in technical appendix 1.

chosen now remain in the household for two periods (and is discounted by δ for the future).

The second term on the left-hand side of (16) 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 α_L (with probability q_L) or α_H. Thus, the first two terms in the square bracket in (16) 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 (16) captures this effect, viz. the effect of low versus high education on partner's wage, or marriage market income, w_2, via the signal $S = (\beta, \sigma^2)$.

Finally, the third term on the left-hand side of (16) captures the expected loss in future consumption due to future spending on education (i.e. expected future spending on educating the grandchildren of current-generation parents). If choosing low (versus high) education now leads to a path where choosing high education is more likely in the future, then this provides a disincentive for choosing low education now – a feature captured by the third term on the left-hand side of (16).[14]

Recall that, at the beginning of any period t, households vary by their realized income (I_t) and the durables they inherited from the previous generation (b_{t-1}). This implies that condition (16) varies by household only due to the second and third terms on the left-hand side. In the second term, the piece $(\widetilde{p} - \widetilde{p}_e)$ captures the

[14] In steady state equilibrium, future expectations formed in period t – i.e. conditional probabilities $\Pr(e_{t+1}/e_t = e_L)$ and $\Pr(e_{t+1}/e_t = e_H)$ – are perfectly consistent with the distribution of education in households in $(t+1)$ generated by the optimal choices in t. In other words, the expectations that determine optimal choices in t (as per (16)) match the distribution of outcomes in $(t+1)$ that results from these choices.

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. Clearly, $(\widetilde{p} - \widetilde{p}_e)$ varies by I_t and b_{t-1} across households. The remaining pieces of the second term, which capture labour market incentives, are determined completely by pre-specified parameter levels. Given a set of parameters, therefore, the *incentive to choose high education* (and hence current durable expenditure) – i.e. whether (16) holds or not – depends on the value of durables *already accumulated* by previous generations. The third term encapsulates the effect on current decisions of the decision-makers' expectations about the future, which too vary based on current realized income and durables inherited from the previous generation.

The model outlined in (3) – (16) 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 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 (optimal) choices for durable expenditure (b_t), corresponding to whether education level e_L or e_H is chosen in t (as per condition (16)). Thus, in any period t, optimal 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 (36×36).

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 (25×25)[15].

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 θ_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 θ_i in period t[16]. 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:

$$x_t P = x_{t+1} \tag{17}$$

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:

$$x^* P = x^* \tag{18}$$

It can be shown that the stochastic process described above does converge to a steady state (Tsokos (1972)).

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

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[15] The individual terms of the (25×25) transition matrix P are provided in technical appendix 2.

[16] 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 play a role in determining the optimality of education (condition (16)). Hence, we retain the 25 states in defining the transition process (16). 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 3).

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 (25×25) transition matrix P and the steady state distribution corresponding to the above parameter values have been derived in technical appendix 4. 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[17].

Figure 2(a) shows the theoretical steady state distribution – or the data-generating process (DGP) – 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). For example, Figure 2(b) plots the histograms of durable expenditures observed in two samples of 1000 observations, drawn independently from the theoretical steady state distribution (the DGP) in Figure 2(a).

Notice how the methodology illustrated in Figures 2(a)-(b) uses a theoretical data-generating process to bridge empirical and theoretical intuition and micro and macro outcomes in a complex economic process. In Example 1, we chose arbitrary values of parameters – which define the character of a particular "region" or "com-

[17] The x axis of Figure 2 shows the 12 unique levels of total durables associated with the 25 states in the stochastic process (17) – (18) (see footnote 16).

munity" – and derived its steady state solution. But these theoretical parameters could be "calibrated" to represent *any* population of interest. Findings from micro-empirical studies or randomized control trials from specific populations could "feed" the calibrations to generate steady state predictions of durable expenditure for those populations. This conceptual approach – and variations thereof – could be used in other development applications as well. Among the various insights such an approach could generate is an indication of the external validity of specific micro-empirical relationships in alternative settings.

4.2 Constructing and examining synthetic datasets

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 $(w_H, w_L, p_1, p_2, p_3, p_4, \beta, \sigma, q_L, \delta, E, C)$. Since it is not clear which specific values of parameters to use for different Indian regions, we follow a strategy of drawing each parameter from a uniform distribution over a given parametric range[18]. Hence, we can derive 1000 data-generating processes or theoretical steady state distributions (such as in Figure 2(a)) each representing a region. 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.

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

[18] Using different parametric ranges does not change the qualitative results.

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 $2 - 4$ classes[19].

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 β is very high compared with the ranges of income (low and high). In Sets A and B, the social standard β 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.

[19]The potentially 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).

How does one interpret the phenomenon of a very high social standard β?

One explanation is that the social status required for marriage market success is determined by a feature *other* than durable ownership. This corresponds to the 'counterfactual' scenario where durables-based signaling is 'turned off' in our model. It is not hard to envisage close-knit rural communities in which the social status of households depends on *caste* revealed in commonly known family names; 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 (as captured by a very high β). In this counterfactual scenario – where caste, not durables, indicates social status – the probability of earning w_H in the marriage market would be very low, leading to the existence of at most 2 classes of durable ownership in the population.

Another factor that could lead to a high β is a high effective price of durables – due to the unavailability of durable goods in markets or high transportation/operational costs (e.g. bad roads, unreliable electric supply). These too are plausible descriptors of conditions in rural India in 1993-94.

Thus, a very high β 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 β 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 β is the only mechanism that could explain a movement from 2 to more 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. Our model exploits the fact that there is a *two-way* link between household income and durable choice. Current income has a direct effect on current durable expenditure, but current durable expenditure also affects future income through signaling. In long-run steady state equilibrium, the *same* levels of incomes and optimal durable expenditures persist over time. Hence, the limited set of durable expenditures that *are* sustainable in the long run are observed with increased probability, while the probability mass on the rest of the durable-expenditure support shrinks; hence we see clusters or classes.

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

We start by deriving (from the mixture estimates of p_i and π_i) the probability $\gamma_L(x)$ that households with x goods belong to the lower class[20]. The results are

[20] *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).

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 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 (16) – the condition under which it is optimal to choose education e_H. The nature of the signaling function $\widetilde{p}$ (and $\widetilde{p_e}$) in Figure 1 imply that households with accumulated durables close to $(\beta - \epsilon)$ are most like to violate condition (16) (thereby choosing low education e_L). This is due to the fact that, for households who have already accumulated close to β 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 β have the strongest incentive to acquire (effective) 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 effective education *even though education is optimal*[21],[22]. In other

[21]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.

[22]An interesting implication of effective education being optimal for poor households is that income increases in these households will be spent on such education even at the cost E (i.e. subsidizing education is not necessary to induce poor households to choose education). Yet another implication of this feature of the model is that education that is neglected (being affordable but considered ineffective) by low-income households could be subsequently adopted if such education is perceived to be effective. The latter is consistent with reports of increased demand for enrollment in English-language schools in India post liberalization (Education World (2005), The Economic Times (2010), Cheney (2005)), along with reports of increased employment of English-speaking youth in international call centers (BBC (2003), Arasu (2008)).

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 effective education) or in the marriage market (due to low levels of accumulated durables). It is in this sense that households that own a small 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[23]. 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[24]. 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.

[23]Note that households with accumulated durables much higher than β 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.

[24]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.

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 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[25].

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. by raising p_3 and p_4 relative to p_1 and p_2)? 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.

[25] 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.

5. Conclusion

This paper develops 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 social status 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 findings 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.

Our methodology is innovative and demonstrates a novel approach to bridge (1) theoretical and empirical intuition and (2) micro and macro outcomes in development applications. Findings from micro-empirical studies and randomized control trials could be used to calibrate parameters in our theoretical framework to generate macro-level predictions. The theoretical framework could in turn inspire research questions for empirical studies to examine to enrich the former's predictive power. Executing both these approaches in tandem will serve to enhance our understanding of complex development issues and how policy may affect outcomes in the service of development. We hope that the framework and insights generated herein will motivate future research on assets-based poverty measurement and related topics in development research.

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Figure 1: The Signal Function

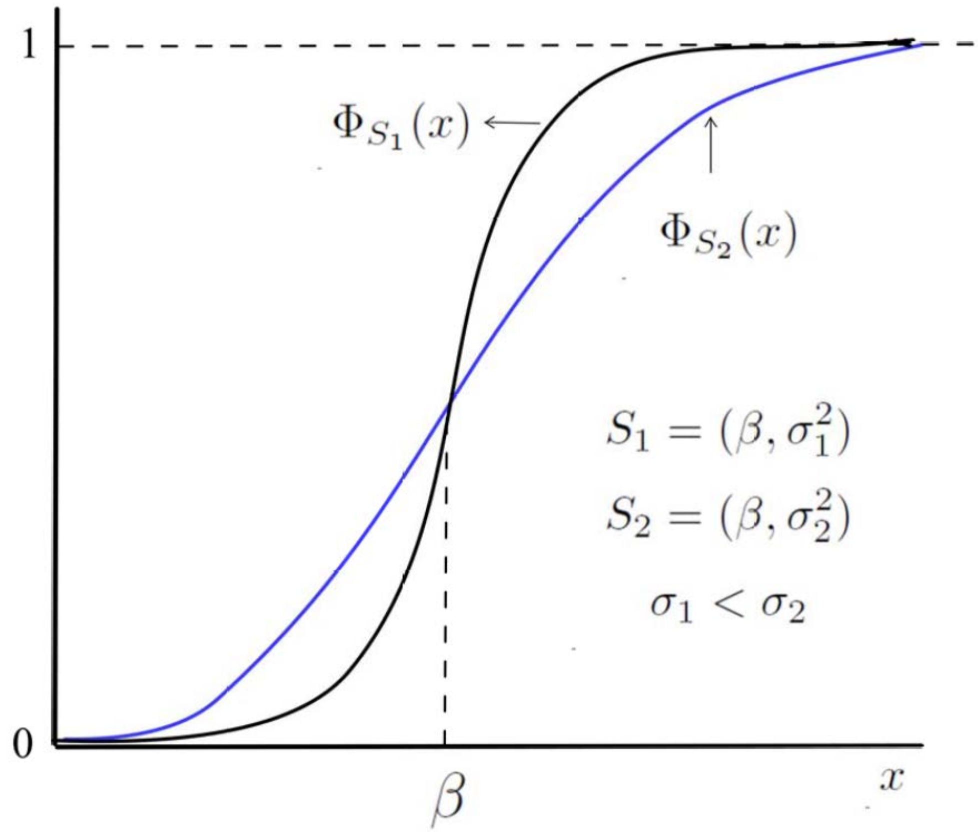


Figure 1: The Signal Function, normal c.d.f. $\Phi_S(x)$

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

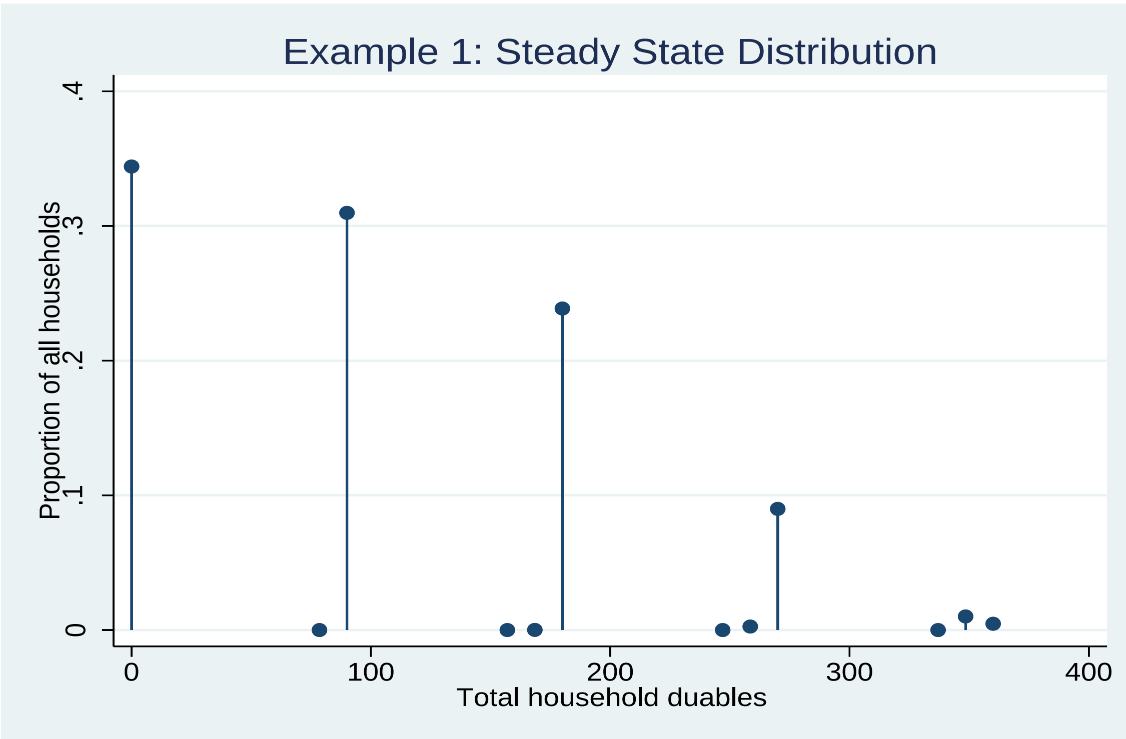
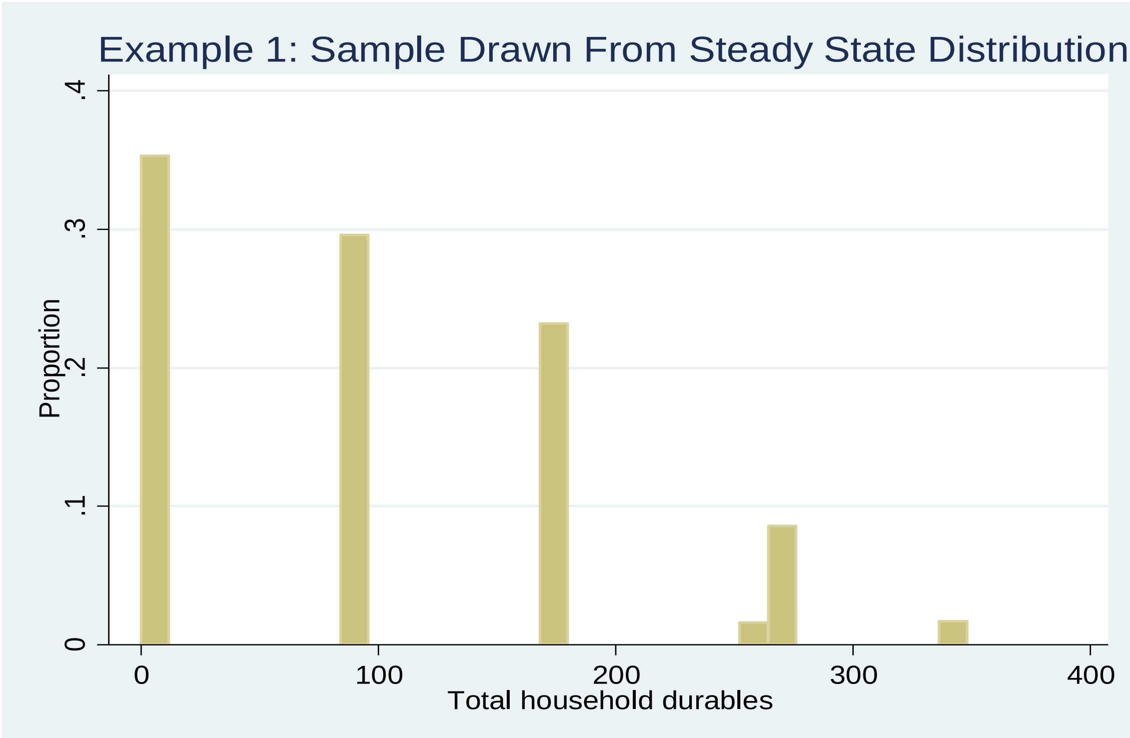


Figure 2(b): Histograms from samples independently drawn from the theoretical distribution in Figure 2(a)

Sample 1



Sample 2

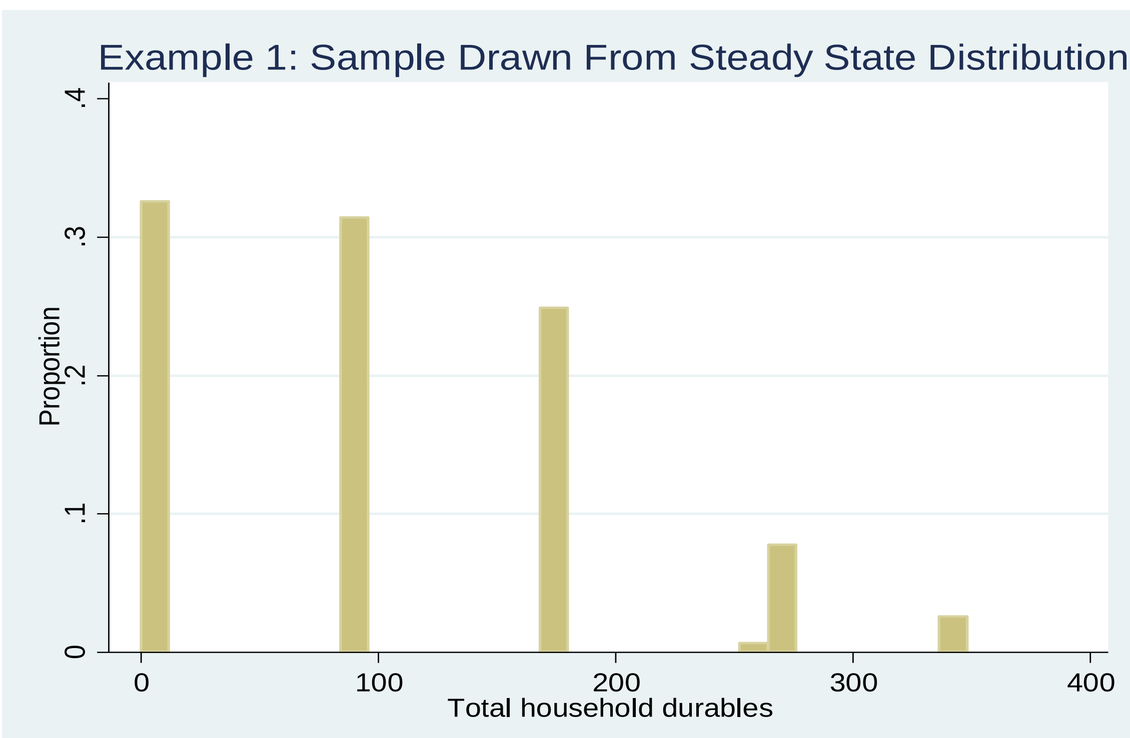


Figure 3(a): Pooled sample from data generated using Set A parameters (Example 2)
(wH and wL ranges do not intersect, beta is within attainable income range)

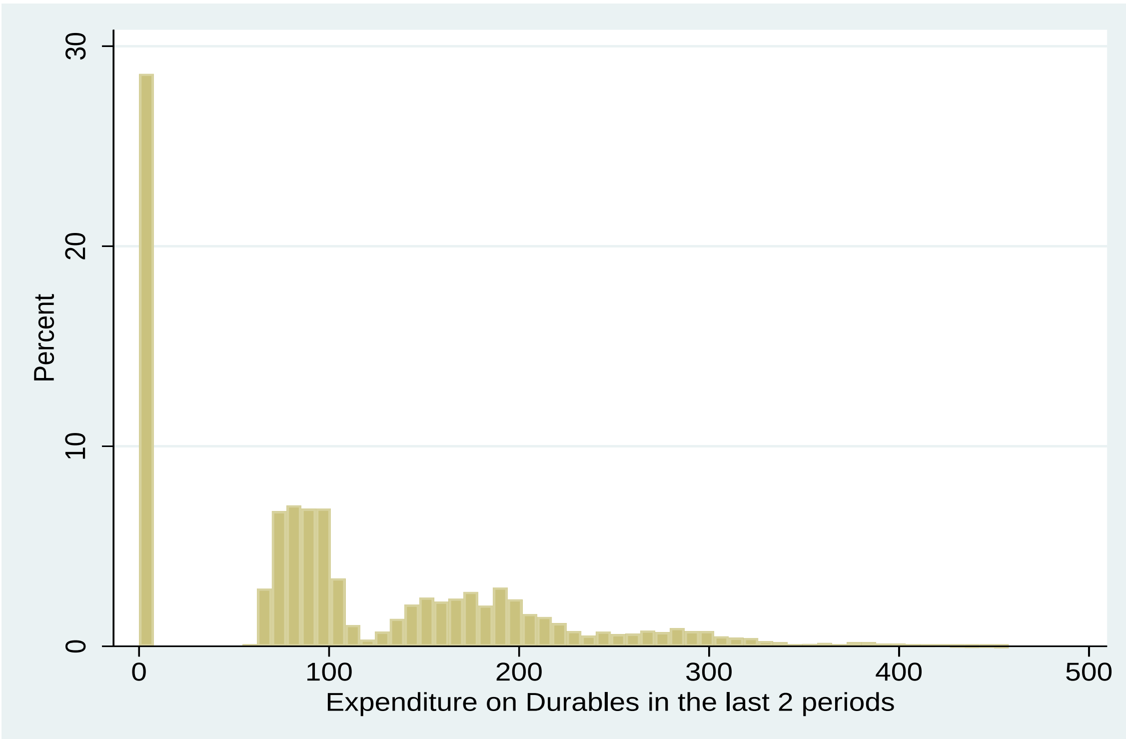


Figure 3(b): Pooled sample from data generated using Set B parameters
(wH and wL ranges do intersect, beta is within attainable income range)

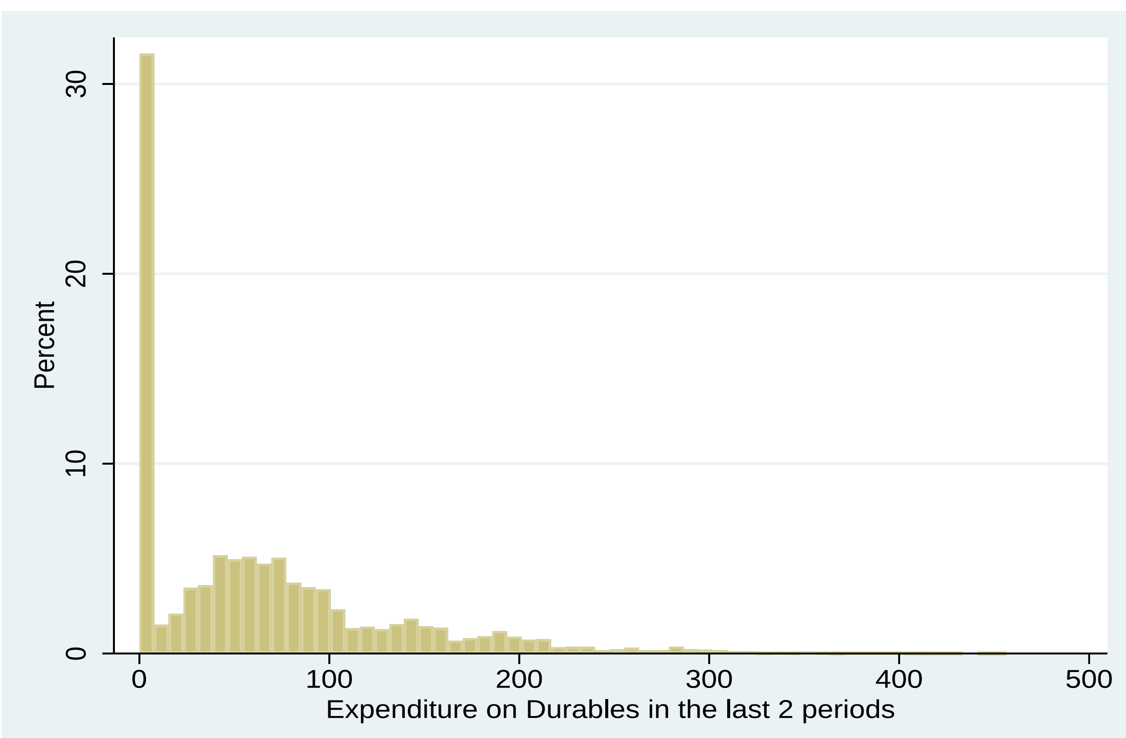


Figure 3(c): Pooled sample from data generated using Set C parameters (Example 3) (wH and wL ranges do intersect, beta is very high)

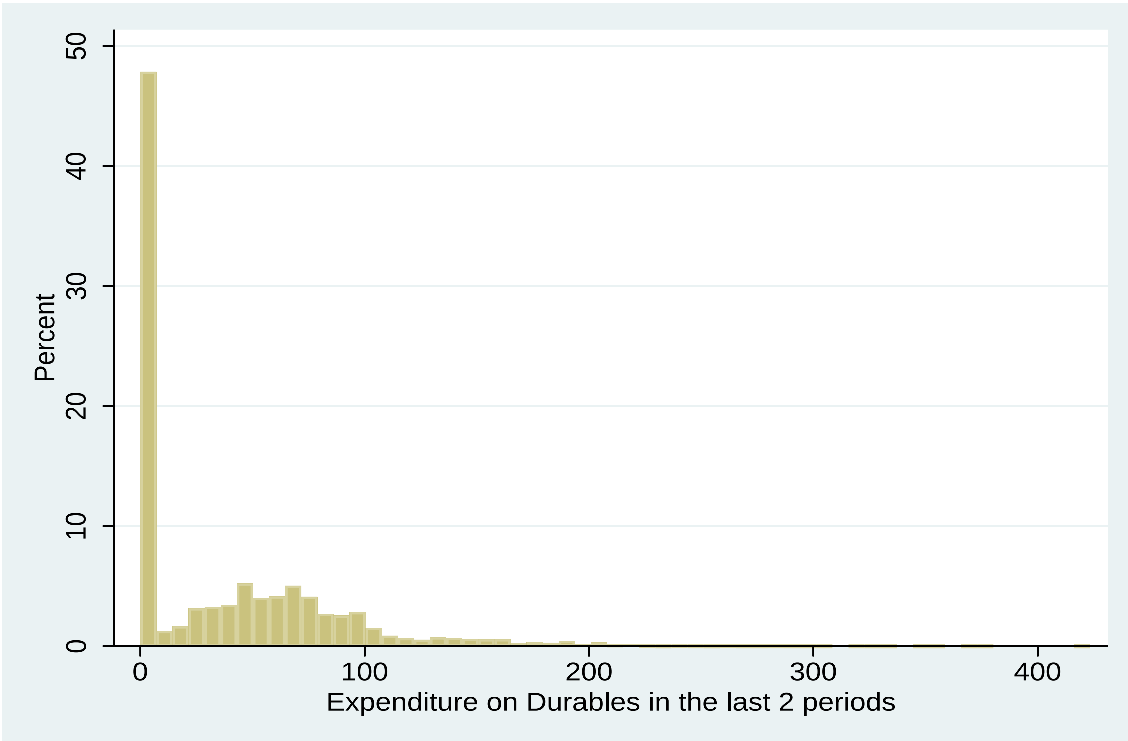
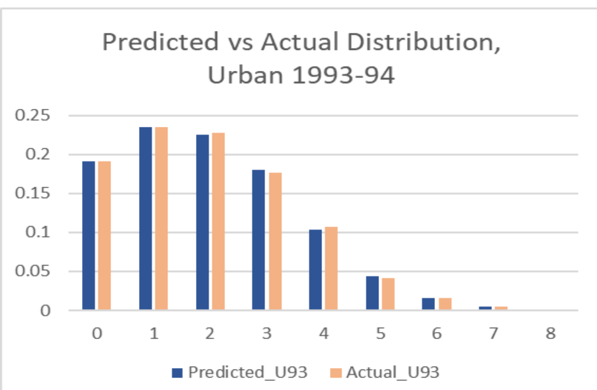
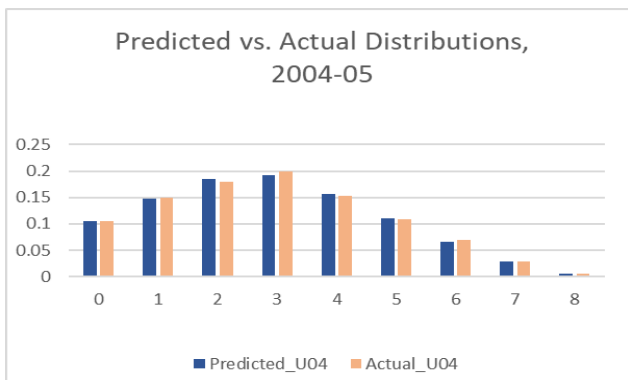
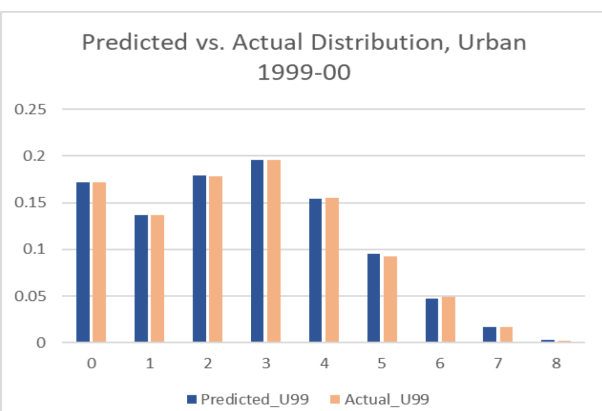


Table 1: Mixture results, Urban subsamples of NSS

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	



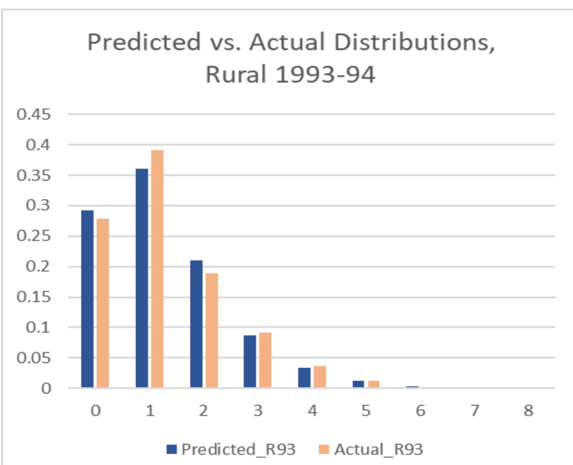


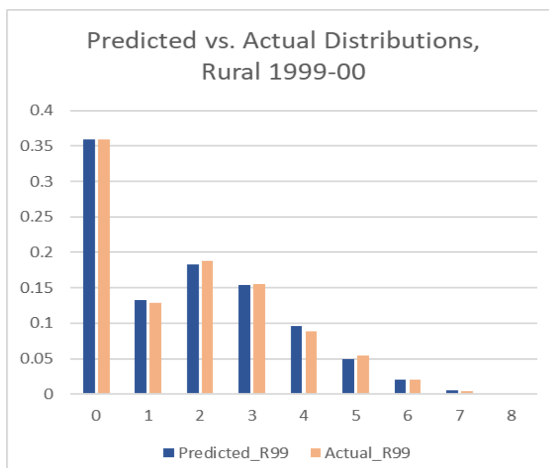


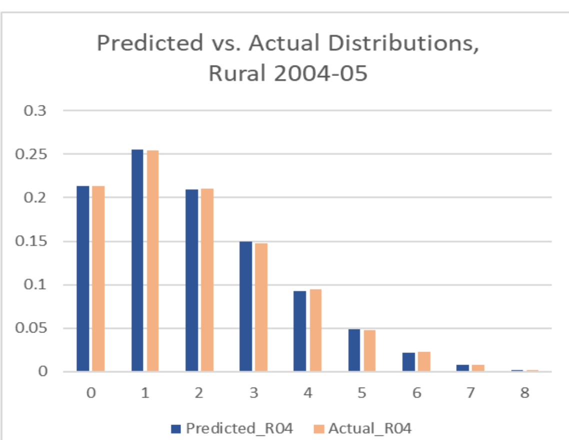
* see Data Appendix IIa for graphs of the mixture-estimated class-specific densities.

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	







* see Data Appendix IIb for graphs of the mixture-estimated class-specific densities.

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 I: Distribution of Total Durables Owned, NSS India

1993-94

Total Durables Owned	urban Freq	urban Rel Freq U	rural Freq	rural 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	

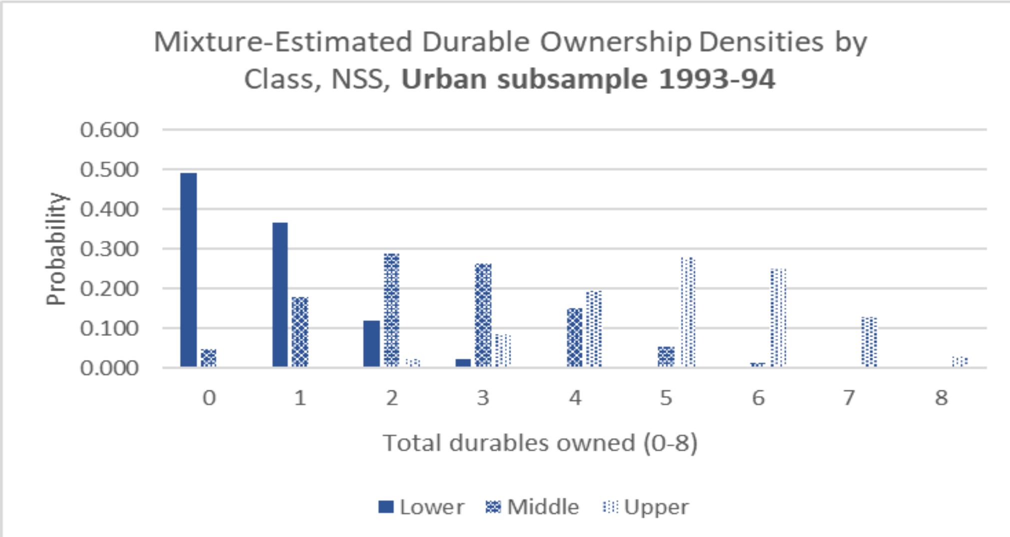
1999-00

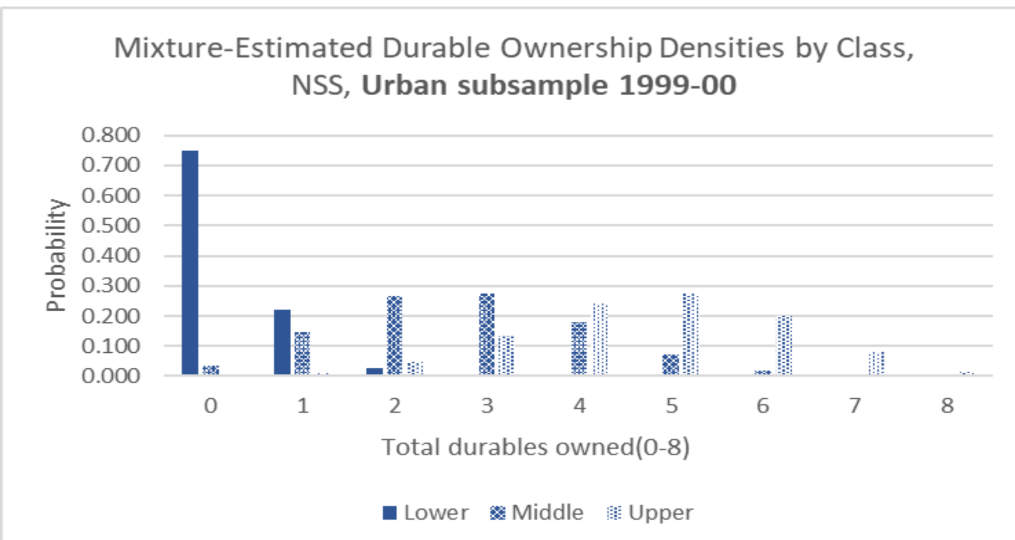
Total Durables Owned	urban Freq	urban Rel Freq U	rural Freq	rural Rel Freq R
0	8419	0.172	25618	0.359
1	6692	0.137	9220	0.129
2	8743	0.179	13400	0.188
3	9600	0.196	11124	0.156
4	7592	0.155	6275	0.088
5	4540	0.093	3907	0.055
6	2413	0.049	1440	0.020
7	806	0.016	339	0.005
8	119	0.002	62	0.001
Observations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

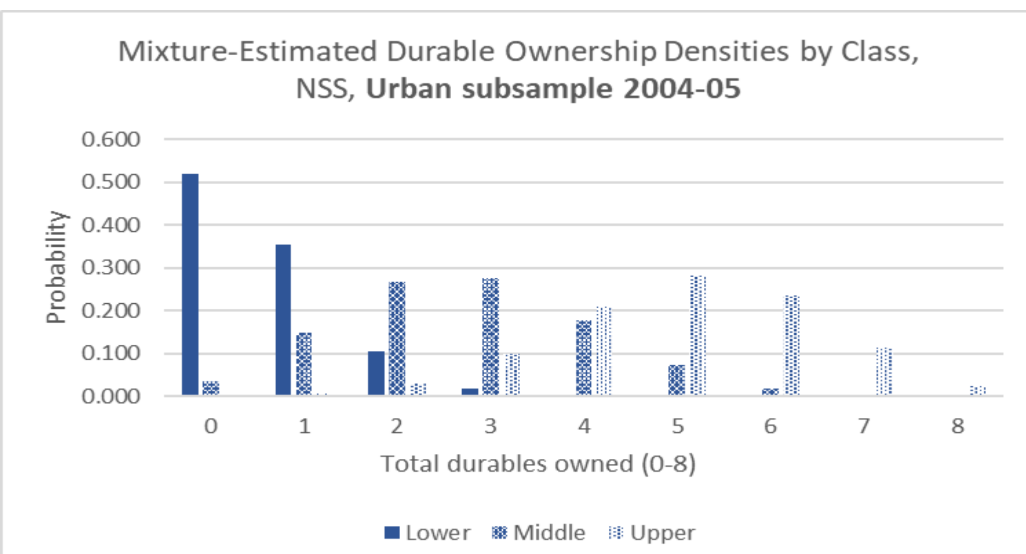
2004-05

Total Durables Owned	urban Freq	urban Rel Freq U	rural Freq	rural 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	

Data Appendix IIa: Mixture-Estimated Class-Specific Durable Ownership Densities -- Urban







Data Appendix IIb: Mixture-Estimated Class-Specific Durable Ownership Densities -- Rural