



The poor get poorer: Tracking relative poverty in India using a durables-based mixture model

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ABSTRACT

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

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1. Introduction

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

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

In this paper I argue that a mixture model is an effective tool for determining a (data-driven) criterion for class membership, and also for

identifying consumption classes by this criterion. The approach yields estimates of the size (proportion) of consumption classes as well as a definition of the classes in terms of their different consumption habits.

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

This is not the first time that durables ownership has been used or validated as a measure of consumption and wealth (Filmer and Pritchett, 2001; Lubotsky and Wittenberg, 2006; Montgomery et al., 2000). Filmer and Scott (2008) summarize the extensive literature that focuses on the use of assets as measures of consumption especially when data on expenditure are unavailable, Principal Components Analysis (PCA) being a well-accepted method in this area (Filmer and Pritchett, 2001). I compare the mixture results obtained here with those obtained by using PCA (Filmer and Pritchett’s approach). I show that results are largely the same regarding who constitutes the classes, but that PCA provides no insight on how big the classes are — an advantage of the mixture approach. PCA is not intended as a method of

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decomposing the marginal distribution of assets into classes while mixture modeling is particularly well suited to this task. This paper therefore makes a significant contribution to the literature on using asset ownership as an identifier of (consumption) class.¹

There are, in particular, two specific reasons for using durables ownership in the current study. First, durables offer a steady stream of utility in future periods making their ownership a natural measure of long-term consumption standards (Bar-Ilan and Blinder, 1988; Townsend, 1979). The idea of long-term consumption seems more appropriate for the determination of a consumption ‘class’ than expenditure, which only captures consumption in the recent past. Second and more importantly, durable ownership is easy to observe and less subject to errors in measurement. The durables approach is a particularly useful tool in the dataset I use – the urban sub-sample of the Indian National Sample Survey (NSS), 1999–00. It is widely documented (see Deaton and Kozel (2005) and the references therein) that the expenditure data in this round of the survey are difficult to interpret. Also, the recall periods were changed in the questionnaires of this round. Data on durable ownership are clearly not subject to such errors in reporting.

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

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

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

consistent with the idea of an “immiserizing” component of growth during this period (Bhagwati, 1958).

The durables’ ownership based mixture model is presented below.

2. Methodology

2.1. Data and definitions

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

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

Note from the definition of Y above that the intensity of durable ownership – how many pieces of a certain durable are in use – is not incorporated in how ownership is defined. Affluence is measured by the variety of services from durables owned, not the intensity of use of individual items. This is due to the fact that intensity of ownership may be higher in larger households not necessarily belonging to a higher class (larger households with more electric fans, for instance); hence including intensity of use in the definition of ownership may inappropriately ascribe higher affluence to larger households (Deaton and Paxson, 1998). Moreover, ignoring the intensity of use does not imply – for example – that households with four cars are treated identically to households with one car. What is important for identifying affluence is the total number of distinct durables; hence to the extent that households with four cars are also more likely to own a higher total number of distinct durables than households with one car, they are more likely to be identified (correctly) as more affluent⁵.

Fig. 1 presents the distribution of Y – the total number of the 11 durable goods that households own – in the sample⁶. Table 1 and Table 2 present summary statistics for the ownership variables.

The bimodality and positive skewness of the distribution of Y in Fig. 1 suggest that a mixture model may be an appropriate description of the latent class structure. The objective of the primary analysis is to

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

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

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

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

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

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

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