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

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ABSTRACT

Poverty measurement using durable ownership data is an attempt to infer income *constraints* by observing consumption *choices*. But what drives household spending choices on durable goods? How do these choices relate to poverty and class? What does it mean to be 'relatively' poor and why should we care to measure it?

In this paper, we propose an economic theory of household decision-making that links these questions using a novel wealth-begets-wealth mechanism. We show that the steady state distribution of total (accumulated) household durable expenditures in this model exhibits natural clusters (classes). Furthermore, certain households may be vulnerable to a long run 'poverty of opportunities', being unable to access any of the channels of income generation available in society.

Our model shows that relative poverty can be understood as the endogenous outcome of an intergenerational process that perpetuates unequal access to opportunities. This finding has novel implications for the measurement of poverty, which has traditionally hinged on definitions that assume exogenous (often arbitrary) cutoffs.

The contribution of this paper also lies in its novel methodology, viz., formulating a theoretical model as the foundation of a data-generating process for synthetic observations, using patterns observed therein to inform the process of poverty measurement. The methodology delivers a framework for generating testable hypotheses around the long-run effect of policy changes (such as income transfers or education subsidies) on relative poverty – an approach that can be applied generally to understand the observed behaviour of economic agents in complex dynamic settings.

1 Introduction

How do consumption classes arise? What determines the number of classes in a given society, and why do classes re-emerge across time and across sector?

Maitra (2016, 2017, 2021) finds that households in India show distinct clusters in the patterns of their durable goods ownership. Using a mixture model, Maitra (2016, 2017) finds three clusters ('classes') in the number of goods owned by urban Indian households in 1993-94, 1999-00 and 2004-05 (NSS). Meanwhile, rural households exhibit two classes in 1993-04, three in 1999-00 and four in 2004-05 (Maitra 2021).

These empirical findings raise some important theoretical questions. What drives household spending on durable goods? Why should such spending exhibit clusters? What can observed consumption *choices* tell us about underlying income *constraints*?

These questions are especially salient in the context of the measurement and identification of poverty. 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).[1] When income or expenditure data is unavailable, household asset ownership has been used as an alternative (Filmer and Pritchett, 2001; McKenzie, 2005; Stifel and Christiaensen, 2007; Filmer and Scott, 2008; Montgomery et al, 2000; Townsend, 1979). Maitra (2016, 2017, 2021) proposes the view that the size of the empirically identified lowest cluster of durable ownership could be an estimate of relative poverty. Understanding the dynamics of durables ownership is therefore valuable for understanding the mechanics of relative poverty and class formation.

We propose an economic theory of household decision making that answers these questions.

In our model, durables are a means of social signaling. Spending on observable durables leads to high social status, which in turn generates income via favourable matches in the marriage market. The alternative is to spend on education, which generates income in the labour market. We find that households that can access either of these income sources – marriage or labour markets – boost their future income generation and hence durable accumulation in the long run; this provides a channel for the 'wealth-begets-wealth' mechanism that often occurs in the literature as the driver of class formation

[1] Multidimensional measures of poverty use multiple indicators and corresponding cutoffs (jointly) to define poverty (Alkire et al, 2015).

(Galor and Zeira, 1993; Banerjee and Newman, 1993).

We further find that some households are unable to generate income from either durable-based signaling, or from investing in education. These households – who then sink into the "lowest" durable cluster – are not just 'relatively' poor; they suffer from a *poverty of opportunities*, which translates into persistently falling behind others in the long run.

Our model incorporates three specific characteristics of durable good ownership in India. First, durable goods constitute an *easily observable* component of a household's consumption. 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.[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 period in an overlapping-generations framework. Third, durable goods do not last forever; they *depreciate over time*, ensuring a limit to this accumulation effect.

Households have two channels for enhancing future income: the labour market and the marriage market. Spending on education increases the probability of a high labour-market return, while spending on additional durables 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.[3]

Households' optimal choices in any period can be used to define a stochastic process which then becomes a data-generating process for observations on household durable expenditures. A synthetic sample of 'data' can then be drawn from the theoretical steady state distribution, which allows us to examine various aspects of the distribution of durable ownership driven by the labour and marriage-market incentives in our model.

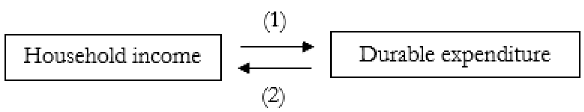
We find that the distribution of durable expenditure in the synthetic sample shows *natural clusters*.

[2]Arranged marriages, the norm in India, have been amply documented to be a form of social networking by matching (Maitra, 2018; Banerjee, Duflo, Ghatak and Lafortune, 2013; Luke, Munshi and Rosenzweig, 2004). Households care about the social standing of their relatives by marriage, of which wealth is an important component; brides' and grooms' families invariably visit each other before a marriage is finalized. Connections made by marriage result in transfer and generation of income and wealth (as gifts, dowries, 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.

[3]Any spending, either on education or durables, occurs only *after* households spends on a 'subsistence' level of consumption – the theoretical counterpart of the absolute poverty line typically used to measure poverty.

These are the theoretical counterparts of the empirical 'classes' in NSS data identified by Maitra's (2016, 2017) mixture approach. In addition, we demonstrate that the relationships between the parameters of our model – which are driven by institutional, behavioral or technological factors – generate different numbers of classes.

Why do we see clusters in total (or accumulated) household durable expenditure? The answer lies in the two-way relationship between household income and durable expenditure – (1) the effect of current income on current durable expenditure, and (2) the effect of current durable expenditure on future income via 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. Some households can afford to invest in durables or education (or both), which leads to higher expected future income, which enables higher future expenditure; they segregate into a cluster exhibiting persistently high (accumulated) durable ownership in steady state. Other households are persistently *left behind* due to an inability to access either of the two channels of income generation. Clusters thus form at the levels of durable expenditures (and incomes) that are reinforced by the households' decision-making process.

The inability to access *any* wealth-generation opportunity in the economy makes households in the lowest class susceptible to poverty in the long run. Relative poverty – as observed in the clustered data – is therefore a *poverty of opportunities*, which (we argue) may affect even households that are above the absolute poverty line in any period. Indeed, this phenomenon is expected to be observed as societies become more affluent over time. This conceptual understanding of 'relative poverty' as a 'poverty of opportunities' constitutes one of the key insights of this paper.

What determines the *number* of classes that emerge? The answer depends on how the parameters interact with each other. We demonstrate, for example, how the existence of a generally accepted social standard (for being considered to be "high" status) in a society, and the dissolution of that standard, affects the number of classes, a finding that is corroborated in the empirical results (Maitra, 2016, 2017, 2021).

The contributions of this paper are two-fold. First, we provide an explicit theoretical conceptualization of how observable durable *choices* may be related to household *constraints* over time. Our theoretical model elucidates this relationship, *in the context of poverty measurement*, using key institutional and behavioural features of Indian society – marriage market networks, social signaling, social standards, labour market conditions – along with the inherent nature of durable goods' consumption. This "bottom-up approach" to understanding relative poverty leads to an explicit framework for predicting the long-run effects of policy changes on relative poverty, through changes in model parameters reflecting these systemic features of society.

Furthremore, our model shows that relative poverty can be understood as an endogenous outcome of an intergenerational process; a process that perpetuates an unequal access to opportunities over time. This finding has novel implications for the measurement of poverty, which has traditionally hinged on definitions that assume exogenous (often arbitrary) cutoffs.

The second contribution of the paper lies in the novel methodology used herein. We use an explicit theoretical model as a data-generating process for simulated observations on (optimal, steady state) durable ownership. The patterns observed in the simulated data are then used to interpret patterns observed empirically using NSS data and to propose a methodology (mirroring Maitra, 2016, 2017) for measuring relative poverty from survey data. The benefit of this methodology is that the measurement strategy is linked explicitly to a well-defined theoretical conceptualization of what it *means* to be relatively poor. This approach – of connecting household choices with aggregate patterns using insights from both empirical and theoretical research – has the potential to greatly improve our understanding of complex development processes in general, and our measurement of development outcomes in particular.

The rest of the paper is organized as follows. In Section 2, we present our composite methodology for enumerating the relationship between income generation and durable ownership. Here, we present a theoretical (overlapping generations) model of income generation and durable choice (the data generating process), along with simulated data and explanations of the findings. In Section 3, we discuss what it means theoretically to be relatively poor, and how to measure relative poverty empirically using nationally representative survey data. Section 4 concludes the paper.

2 The Methodology

Our goal is to understand how durable ownership and economic well-being are related in the long run, so that we can use this relationship as a basis for the measurement of relative poverty. The following three components in our methodology allow us to achieve this goal – (1) a theoretical model of income generation and durable choice – the data-generating process for durable ownership data, (2) simulations from this data generating process to generate a synthetic dataset, and (3) an empirical model that permits measurement of relative poverty using durable ownership data from household surveys. The relationship between economic well-being and durable ownership indicated by the explicit model in (1) and (2) allow us to interpret and justify our measurement using survey data in (3).

We present components (1) and (2) of our methodology below. We then argue (in Section 3) using predictions from (1) and (2), that a mixture model (as used by Maitra (2016, 2017)) is an appropriate empirical tool (3) for measuring relative poverty.

2.1 The Model (the Data-Generating Process)

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. C is the theoretical counterpart of the absolute poverty line typically used to measure poverty. The common household utility of members in any period t is given by

$$U(B_t) = C + B_t \tag{1}$$

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

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

$$B_t = b_t + b_{t-1} \tag{2}$$

where b_k indicates the durables purchased in period k by period$-k$ parents. (1) and (2) indicate that when period$-t$ grandparents pass so do the durables they accumulated when they were parents (in period $(t-1)$), viz. durables depreciate over time.

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 a higher wage. 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. Higher accumulated durable ownership B increases the probability of attracting a partner with a high wage, with the rate of increase in probability highest around 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 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'.

Our model of social standing or status and the signal function reflects three observations drawn from social science literature. The first is the well-known idea of 'conspicuous consumption', whereby households consume goods (or leisure) to signal their social status (Veblen (1899)). There are ample references in academic literature (Bhar et al, 2022; Jain, 2020; Chaudhuri et al, 2022; Sharda et al, 2018; Mathur, 2010), but also in popular media, films and fiction (Parikh, 2017; Shanbhag, 2015), to the association of (visible) possessions with social status, in India and elsewhere (Fussell, 1992; Desmichel, 2020; Nelissen and Meijers, 2011).[4] The second observation is the importance of status in marriage partnerships, whereby households/individuals care about the social standing of their partners, and match assortatively into households of similar, ideally high status (Sundie et al, 2011; Kalmijn, 1994). The final observation – connecting status, assortative matching and consumption choice – is the idea that "status implies a *shared, collective standard* of what is worthy of respect" (Ridgeway, 2019; pg. 11; emphasis ours). This idea is core to the definition of 'status' in our model – viz., that it is embodied in a commonly accepted social standard, β, which determines the location of the signal function Φ_S. Note that our generative framework also allows the possibility of departures from a rigidly held social standard (allowing social mobility); this feature is captured in the skepticism parameter σ^2.[5] [6]

[4] *"...everybody says that he is eat up with pride, and I dare say he had heard somehow that Mrs. Long does not keep a carriage, and had come to the ball in a hack chaise."* – Mrs. Bennet, about Mr. Darcy, in *Pride and Prejudice* (Ch. 5, Austen, 1813).

[5] 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 and not just a sense of satisfaction from "keeping up with the Joneses".

[6] Unlike Maitra (2018), we do not explicitly model the matching of partners where the (equilibrium) probability of

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,

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

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

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

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

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

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

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

where condition (8) – 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:

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

matching is determined by the number of agents of all types present in the economy. Rather, we assume that matching is driven by the signaling effect of observable consumption of durables by households. There is evidence of such signaling (and positive assortative mating) in several societies, even those where arranged marriages are not the norm (Sundie et al (2011), Kalmijn (1994), Otterbring et al (2021), Griskevicius et al. (2007), DeWall and Maner (2008), Dunn and Searle (2010)). Thus, the model – though motivated by Indian socio-economic conditions – would generalize well to other societies as well.

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 own expected lifetime utility $[U(B_t) + \delta E_t U(B_{t+1})]$, 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 a wage 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.[7]

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

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

$$subject\ \ to$$

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

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

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

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

[7]Notice the intergenerational impact of household decisions – the income of parents in any period t depends on the investment in their education by their parents (viz. $(t-1)-$parents) and the accumulated durables they have inherited from their parents (b_{t-1}) and grandparents (b_{t-2}).

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 $[(11)-(13)]$. 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).[8]

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 expected 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:[9]

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

$$-\delta E[Pr(e_{t+1} = E/e_t = e_L) - Pr(e_{t+1} = E/e_t = e_H)] < 0$$

where $\tilde{p} = \Phi_S(b_{t-1} + I_t - C)$ and $\tilde{p}_e = \Phi_S(b_{t-1} + I_t - C - E)$ 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) encapsulates the heart of our model and has the following interpretation.

Notice that there are three terms on the left-hand side of equation (14). 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 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 (14) embodies the impact of low versus high education

[8]Note that even though single-period utility is assumed linear (1), lifetime expected utility is non-linear in current decisions, since period$-t$ decisions impact $E_t I_{t+1}$ via probabilities of high income in the labour and marriage markets.

[9]Condition (14) is derived in technical appendix 1.

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 (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. 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 (14) 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.[10]

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 (14) varies by household only due to the second and third terms on the left-hand side. In the second term, the piece $(\tilde{p} - \tilde{p}_e)$ 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. Clearly, $(\tilde{p} - \tilde{p}_e)$ 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 (14) 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 (1) – (14) describes a stochastic process $\{b_{t-1}, b_t\}$, driven by parameters

[10] 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 (14)) match the distribution of outcomes in $(t+1)$ that results from these choices.

$(w_H, w_L, p_1, p_2, p_3, p_4, \beta, \sigma^2, q_L, \delta, E, C)$. 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 (14)). 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).[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 θ_i $(i = 1, 2, ..., 25)$ has, associated with it, an amount of total durables $(b_{t-1i} + b_{ti})$ observed in a household in state θ_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:

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

It can be shown that the stochastic process described above converges to a steady state (Tsokos,

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

[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 play 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 3).

1972).

The next section describes how simulated data on steady-state household durable expenditures can be generated from the model presented above.

2.2 Model Simulations (i.e. drawing synthetic data from the data-generating process)

2.2.1 Drawing samples from the data-generating process

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 for Example 1 – the $x-$axis showing $(b_t + b_{t-1})$, the total accumulated durable spending observed in any time t; and the $y-$axis showing the proportion of households that would be observed in steady state at each level of total durable spending.[13]

Figure 2(a) shows the theoretical steady state distribution – or the data-generating process (DGP) – that corresponds to the 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 household and aggregate outcomes in a complex economic process. In Example 1, we chose arbitrary values of parameters – which define the character

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

of a particular "region" or "community" – and derived its steady state solution. But these theoretical parameters could be "calibrated" to represent any population of interest.[14] Findings from micro-empirical studies, randomized control trials or behavioural experiments 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.[15] Among the various insights such an approach could generate is an indication of the external validity of specific micro-empirical relationships in alternative settings.

2.2.2 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.[16] 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 survey datasets available for analysis, such as the urban (or rural) sub-sample of the NSS.

Let us look at a few more sets of parameters.

Example 2 (Set A)

$w_H \in (80, 120), w_L \in (5, 20), p_1 \in (0, 0.5), p_2 \in (p_1, 0.5), p_3 \in (0.5, 1), p_4 \in (p_3, 1),$

[14] We could think of the parameter values as "equilibrium" values determined by economic forces outside the scope of our model. For example, think of the wage levels as being determined by the economy-wide production function and demand and supply in the labour market. Similarly, the probabilities of earning different income levels in the labour and marriage markets could be envisaged as being derived from a matching process between (1) households and jobs, and (2) households of different income levels in the marriage market, given population growth. In the context of existing macroeconomic models of inequality and class formation (e.g. Galor and Zeira, 1993; Banerjee and Newman, 1993), the steady state equilibrium obtained in their economic "system" would determine the parameter values that initiate our analysis.

[15] For example, incorporating network effects (by ethnic/social group, caste etc) into theories of the macroeconomy and growth (Munshi (2014)). See technical appendix 5 for a discussion of this point.

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

$\beta \in (100, 500), \sigma \in (100, 500), q_L = 0.5, \delta = 0.5, E \in (10, 100), C = 2w_L.$

Figure 3(a) plots the histogram of the pooled sample for the parameters in Set A. (The distribution of each parameter over the specified range is uniform.) The separation of observations into clusters – or durable-spending "classes" – is immediately evident. In this example, the ranges of w_H and w_L do not overlap; this generates the clear separation in the histogram of observations between the lowest class (with 0 durable spending) and the middle and higher classes.

Example 3 (Set B)

$w_H \in (80, 120), w_L \in (5, 80), p_1 \in (0, 0.5), p_2 \in (p_1, 0.5), p_3 \in (0.5, 1), p_4 \in (p_3, 1),$

$\beta \in (100, 500), \sigma \in (100, 500), q_L = 0.5, \delta = 0.5, E \in (10, 100), C = 2w_L.$

Set B 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.

Example 4 (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 is identical to Set B except 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.

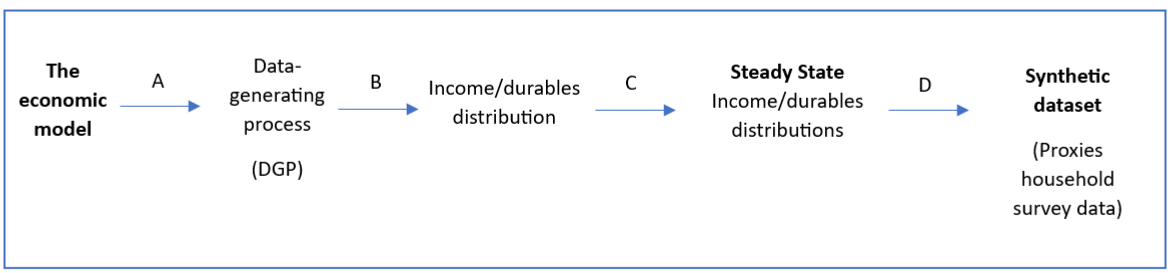
We present these examples (parameter sets) to illustrate that it is the *interaction of parameters* that determines the dynamics of class formation and specifically the number of clusters generated in the data. We can calibrate these parameters using exogenous inputs (empirical studies, RCTs, behavioural experiments) to make predictions about specific populations; more interestingly, we can evaluate the impact of policy changes by tweaking the parameters corresponding to those changes and simulating their steady state outcomes.

Note that in every case, the lowest cluster represents households who cannot access either labour or marriage markets; furthermore, the lowest class is self-identified (in the synthetic dataset) by the data-generating process and steady state dynamics. We will return to this point in Section 3.

2.2.3 Why classes, and how many?

There are two ways to approach the answers to the questions – why do classes form and how many? The first approach – presented in this subsection – stems from a broad, methodological perspective. The second approach (in subsection 2.2.4) is presented from the perspective of a specific example that demonstrates the *physical* process of cluster formation.

The infographic below presents a bird's eye view of the methodology proposed in this paper. Why do we see (a certain number of) clusters of total durable ownership in the synthetic data, when these are generated by our postulated economic process?



Let us ignore the economic model for a moment, and focus on the relationship between the data generating process (DGP) and the distribution of income over time, viz. step (B) in the above infographic. Consider two economies in which total income I_t in period t lies in the interval (a, b), $a > 0$. Suppose that the DGPs for income follow certain "rules" – (1) in economy 1, incomes I_t are drawn (uniformly) from $U(a, b)$ in every period t, but (2) in economy 2, all households who earn $I_{t-1} \geq d$, earn $I_t \sim U(d, b)$; all households $I_{t-1} < d$, earn $I_t \sim U(a, d)$; $(a < d < b)$. The DGP "rule" for economy 2 is, therefore, akin to one that exhibits a *wealth-begets-wealth* mechanism over time.

Suppose we simulate incomes in each economy – 1000 observations from each economy over 1000 time periods, $t = 1, ..., 1000$ – where observations are governed by the rules specified above. Figures

4-5 present the results.

If incomes evolve according to the rules specified, then the income distribution in any given period t will be virtually indistinguishable in economy 1 (Fig. 4(a)) and economy 2 (Fig. 4(b)). However, consider the *sum* of incomes drawn in the last 2 periods, in economy 1 and 2 (Figs 5(a)-5(b)). We see the clear emergence of *clusters in two-period incomes* in the economy where a mechanism akin to wealth-begets-wealth prevails (economy 2), even though the distribution of incomes in any *single* period is identical (and uniform) in both economies. This finding – viz. that when wealth begets wealth, clusters might be observed in *total* household durables *accumulated* from repeated draws of income over time – constitutes the *foundational motivation* for this paper; and our assumptions governing the signal function $\Phi_S(\beta, \sigma^2)$ in the marriage market (Section 2.1).

Consider now a third economy – Economy 3 – where the (pseudo) wealth-begets-wealth rule exists in a different format: all households in Economy 3 who earn $I_{t-1} \geq d$ earn $I_t \sim U(d-\epsilon, b)$; all households $I_{t-1} < d$, earn $I_t \sim U(d+\zeta, b)$, $\epsilon, \zeta > 0$. We can see the distribution of the sum of incomes over 2 periods exhibits a third (middle) cluster (Fig. 6).

Notice that the examples in Figures 4-6 are based purely on the interaction of distributions governed by pre-specified rules (operating through step (B)). There is no economics in the generation of these findings; neither can we glean any economic information by observing the clusters formed, since these were generated by arbitrary rules about income generation. This purely distributional exercise is important, however, becauses it demonstrates that the "parameters" and "rules" specified by the modeller as "inputs" – such as the presence and degree of overlap (e.g. ϵ, δ) or the distributions of incomes governing the DGP (e.g. uniform or otherwise) – have a clear role to play in how and where the clusters form.[17] It also shows that the generative approach inherent in our methodology – captured in step (B) – can, in principle, be made very complex by adding to the "inputs" and assumptions about these inputs (e.g. parameters, distributions, rules).[18] It is critical, therefore, to weigh the benefits of adding complexity to the model (viz. richer outcomes) against the cost of doing so (viz. rapidly increasing computational intensity/time to solution; obfuscation of the relationship between inputs and outcomes).

[17]It is trivially possible, in fact, to *generate* clusters in the sum of incomes by *assuming* clusters (i.e.non-uniform distributions) in the income distribution rule!

[18]See technical appendix 5 for more discussion of this point.

Let us now turn our attention to the first step (A) – the model specified in section 2 – which provides an *economic* rationale for the "rule" that powers the DGP. Our goal here is to specify the *most parsimonious model* in input parameters and in distributional assumptions governing the parameters. To do so, we postulate 2 channels of income generation (the labour and marriage market) in which only 2 wages (high or low) – may be earned, and only 2 education levels (high or low) may be chosen.[19] Our only distributional assumptions about the wage parameters are that (1) higher education (and productivity) leads to a higher probability of the high wage in the labour market; and (2) more total household durables lead to a higher probability of the high wage in the marriage market.[20] Moreover, while an explicit wealth-begets-wealth mechanism is assumed in the marriage market – via the signaling function – agents have an alternative opportunity of income generation (viz. the labour market). They can *choose* how to allocate their resources and differentially access the available opportunities. Since durables passed down across generations do not last forever, even households with high durable levels (above the social standard) have an incentive to participate in the labour market. Thus, the clustering mechanism injected in the model dynamics integrates a direct wealth-begets-wealth effect (the signal function), offset by the presence of (and freedom to *choose*) alternative opportunities, in the labour market.

The economic model (step (A)) serves to power an economically meaningful period-wise DGP (step (B)) that generates the income (and durables') distributions in the economy in each period. We focus now on *steady state equilibrium* in this economy, viz. one where the same distribution of states (durables) persists over time, and where households' expectations about future opportunites are fulfilled in each period. We see that clusters emerge in steady state equilibrium because some income/durable levels cannot be sustained in the long run under the conditions of our model. Thus the nature of the steady state clusters – which respond to changes in "policy" parameter values – holds economic information about the households that constitute the clusters and their access to economic opportunities.

[19]Note from the above discussion on step (B), that clusters occur in cumulative incomes (hence, in accumulated durables) even when single-period incomes are distributed uniformly over a continuous range of values. Hence, it is not the simplifying assumptions of the model (viz. two wages, two education levels etc) that generate the clustering impetus of the wealth-begets-wealth mechanism.

[20]Technical appendix 5 presents potential generalization of the model, with more than 2 wage and education levels. Each of these cases necessitates additional assumptions about the education-wage and the durables-wage distributions governing income generation. The assumed distributions play a role in and of themselves in the outcomes observed.

It should be noted here, that the fact of cluster (or class) formation in the long run is not a new or recent finding in development literature (Galor and Zeira, 1993; Banerjee and Newman, 1993). What is novel, however, is the derivation of clusters within a framework that informs the measurement of poverty. To make this connection with measurement, the final step (D) in our methodology is crucial. In this step, we draw a synthetic "dataset" from a population in steady state (powered by (A)-(B)-(C)), much as a statistician would draw a random sample from a population of households. The synthetic dataset is, therefore, a direct counterpart of a survey dataset of representative households. That the lowest cluster in the synthetic dataset represents households in a poverty of opportunities, suggests that identifying the lowest cluster from survey data might be an appropriate measure of relative poverty in the economy in question. This new approach to understanding poverty not only provides an alternative way to measure poverty without imposing arbitrary cutoffs, but also a means of informing where poverty cutoffs are set in applications of the traditional approach.

2.2.4 Intuition of the Model

In this section we turn to the *physical* process of cluster formation. Our goal is to work out the intuition of the model and how it collapses multiple possible expenditure levels into a smaller set of clusters.

Recall that a household's total income in any period can take three possible values – low L $(= 2w_L)$, medium M $(= w_L + w_H)$ or high H $(= 2w_H)$. Also, 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 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. The number and nature of the 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. For specificity, we use the following examples to demonstrate these dynamics.

Suppose that the cost of effective 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:

$$(b_L, b_L), (b_L, b_M), (b_L, b_H), (b_M, b_L), (b_M, b_M), (b_M, b_H), (b_H, b_L), (b_H, b_M), (b_H, b_H) \tag{17}$$

The 9 states above reduce to 5 unique values of total durables accumulated:[21] $(2b_L), (b_L+b_M), (2b_M)$, $(b_M + b_H)$ 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

[21] 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 $2b_M = b_L + b_H$.

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 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 in the number and the nature/location of the 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.[22]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 $(b_L + b_M)$.

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

[22] In such a society, the social status required for marriage market success may be determined by a feature *other* than durable ownership. This corresponds to the counterfactual scenario where durables-based signaling is 'turned off' in our model.

low and high-income levels, we are likely to find 3 (or even 4) classes instead of 2.

The above discussion illustrates the mechanism of cluster or class formation in total durable expenditure data generated by the economic model in Section 2. We now ask the question: *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 truly vulnerable to poverty or simply disinterested in owning durables? The answer is key to our understanding of what it means to be relatively poor.

3 Relative Poverty and Mixture Models: From Theory to Measurement

3.1 Relative Poverty as Poverty of Opportunity

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.

A key feature of the assumption on social standards β (Figure 1) is that when previously accumulated durable levels are close to β, spending the marginal dollar on durables (and not on education) yields the highest increase in expected future return. This implies, conversely, 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. And yet some households are nonetheless observed to be accumulating small positive levels of durables instead of spending on education. One explanation for this behaviour is that they cannot afford effective education, even in situations where education is their optimal choice.[23] [24] [25]

[23]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.

[24]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).

[25]Note that households with accumulated durables much higher than β may also be unable to afford (optimal) education if they are unlucky enough to draw a low income in the current period. However, the previously accumulated quantity

These "low-income, low-durable" households – who are evidently not in 'absolute poverty', since they can afford some durables and are hence above the subsistence-consumption 'poverty line'[26] – are nevertheless likely to be *susceptible to poverty in the long run.*They are unable to access income-generating opportunities in either the labour market or the marriage market to improve their economic status; they suffer from a *poverty of opportunities*. This poverty of opportunities renders them systematically vulnerable, and at risk of being permanently left behind – an attribute that goes to the heart of the definition of (relative) poverty as an indicator of true deprivation, more than any criterion based on income or wealth alone.

This conceptual understanding of 'relative poverty' as a poverty of opportunities constitutes a key insight of this paper. We now apply this understanding to the measurement of relative poverty from clustered durables data from surveys.

3.2 Estimating Relative Poverty with Mixture Models using Durable Ownership Data

Relative poverty is typically measured using a relative-poverty line, which is an income or expenditure (x) cutoff defined as a percentage of $r(x)$, $r(x)$ being some notion of a standard of living (mean, median or other quantile) of the $x-$distribution (Foster, 1998). The specific cutoffs can be somewhat arbitrary. Also, it is not clear why households (and only those households) identified by cutoffs-based definitions should be considered deprived.

Our theoretical model suggests a defining feature of relative poverty – *a poverty of opportunities* – that is clearly linked to long-run vulnerability and deprivation. We show, moreover, that households who experience such a poverty of opportunities are characterized by the fact that they are in the lowest cluster of durable expenditure. It remains only to devise an empirical method to identify such households using durable ownership data; mixture models are ideally suited to this task (McLachlan and Peel, 2000; McLachlan and Krishnan, 1996).

Previous empirical work has used mixture models of durable ownership to identify the size of the

of durables acts as a buffer for poverty as it gives them a relatively high probability of marriage market success in the next period.

[26]This phenomenon is reflected in the empirical results for rural and urban India, which show that the lower class may contain households with $0-2$ durable goods (Maitra, 2016, 2017, 2021).

lowest class of durable ownership in India (Maitra, 2016, 2017, 2021) using nationally-representative survey data (NSS). The mixture approach delivers a data-driven criterion for class identification based on natural patterns in the data, without imposing an arbitrary, researcher-defined criterion of *who* constitutes the lowest class.

Specifically, the mixture model (see appendix) estimates the size and density of durable ownership of the lowest class. The estimated size (proportion) of the lowest class provides a measure of the extent of relative poverty, interpreted as a poverty of opportunities. The mixture approach also estimates the probability that any household belongs to the lowest class – i.e. of being relatively poor – conditional on its level of durable ownership. These estimates permit a ranking of households by relative poverty (albeit probabilistically) based on their durable ownership levels.[27]

It is important to note the difference in the *approach* to poverty identification that is being proposed here versus existing approaches. Typically, poverty is identified by imposing conditions – mainly as cutoffs – on characteristics that will identify poor households, including in multidimensional measures of poverty. In our approach, we first identify poor households (facing a poverty of opportunity) – based on the lowest cluster in the durable ownership data – and then examine the multidimensional indicators that characterize these households (see Maitra (2016, 2017, 2022)). The current approach may thus be seen as a *dual* to the existing one, and may even be used to inform the standard appoach in the process of setting the appropriate cutoffs for poverty identification (see Maitra (2022)).

We have provided, in the previous section, an economic rationale for why and how households that are identified as being in the lowest class are in relative poverty. A mixture model is a natural tool for measuring relative poverty, backed now by a theoretical framework for understanding how durable choices and poverty are connected in the long run.[28]

[27] The appendix provides a brief outline of a three-component mixture model (McLachlan and Peel, 2000; McLachlan and Krishnan, 1996) – as used in Maitra (2016, 2017, 2021, 2022) – to estimate the size and characteristics of the lowest class of durable ownership in India (NSS, 1993-2005). A more detailed treatment of mixture models as applied to the problem of measuring and interpreting relative poverty (as poverty of opportunities) may be found in Maitra (2021).

[28] Note that our theoretical framework models durable *expenditure*, predicting clusters in durable expenditure in the long run. The mixture model identifies classes using a count of durable *ownership*. See Maitra (2016, 2017, 2021) for a discussion.

4 Conclusion

This paper develops a theoretical framework that explains the relationship between income generation, durables accumulation and economic well-being in a way that directly informs the process of poverty measurement. The key insights that emerge are as follows.

Clusters in total (accumulated) durable ownership data may be generated by an intergenerational "wealth begets wealth" mechanism in wealth-generating channels. Households in the lowest cluster of durables can be seen to be at a risk of persistently "falling behind", owing to an inability to access wealth-generation opportunities that others can access, be it in the labour or the marriage market. In this sense, households in the lowest cluster of durable ownership are in "relative poverty". Furthermore, there may well exist households who consume above the absolute poverty line, but are at the same time in relative poverty (in the lowest class), i.e. they battle a poverty of opportunities. The findings provide a strong justification for using durables-based mixture models to identify classes using a nationally representative sample of household-level data (Maitra, 2016; 2017; 2021).

Our theoretical framework draws from key technological, institutional and behavioural features of Indian society to understand why and how some households persistently "fall behind" others. In doing so, it delivers an explicit framework for predicting the effect on relative poverty of policy changes – as captured in parameter changes – that affect these systemic features of society. Furthermore, our composite methodology is innovative and demonstrates a novel approach to bridge (1) theoretical and empirical intuition and (2) household and aggregate outcomes in development applications. Findings from micro-empirical studies, randomized control trials and behavioural experiments could be used to calibrate parameters in our theoretical framework to generate predictions at a more aggregated level. The theoretical framework could in turn inspire research questions for empirical studies and behavioural experiments 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.

Appendix: A Three-Component Mixture Model of Durable Ownership

Let Y represent the total number (out of n) durable goods that a household owns at the time of interview, $Y = 0, 1, 2, ..., n$.[29] Households belong to one of three (latent) classes – $1, 2$ or 3 – which are defined by specific within-class densities of Y. A Three-Component Mixture Model (McLachlan and Peel, 2000) postulates the following:

$$f(y) = \pi_1\phi_1(y; p_1) + \pi_2\phi_2(y; p_2) + \pi_3\phi_3(y; p_3) \tag{18}$$

where $f(y)$ is the density of Y in the population, $\phi_i(y; p_i)$ is the binomial density of Y within class i (parameters: n, p_i) and π_i represents the proportions of class i $(= 1, 2, 3)$ in the population $(\pi_1 + \pi_2 + \pi_3 = 1)$.

Use the Expectations Maximization (EM) algorithm for likelihood maximization of (18) (McLachlan and Krishnan, 1996) to obtain estimates: $\hat{\pi}_1, \hat{\pi}_2, \hat{p}_1, \hat{p}_2, \hat{p}_3$.[30] Using Bayes' Law, estimate the probability that any household with y durables belongs to class i: $Pr(class = i/Y = y) = \frac{\hat{\pi}_i\phi_i(y,\hat{p}_i)}{\hat{\pi}_1\phi_1(y,\hat{p}_1)+\hat{\pi}_2\phi_2(y,\hat{p}_2)+\hat{\pi}_3\phi_3(y,\hat{p}_3)}$; $i = 1, 2, 3$.

Summary of results (Table 1 from Maitra, 2017), Table 2 from Maitra, 2021); LR tests (Greene, 2002) used to determine the number of classes).

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	

[29] In Maitra (2017, 2021), $n = 8$, viz. fan, radio, tv, ac, fridge, bike, motor bike, car.

[30] The ordering of the $\hat{p}_i$'s indicates which i $(= 1, 2$ or $3)$ corresponds to the lower, the middle and the upper class, respectively, since (by definition) $p_L < p_M < p_U$ (L: lower, M: middle, U: upper).

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Figure 1: The Signal Function

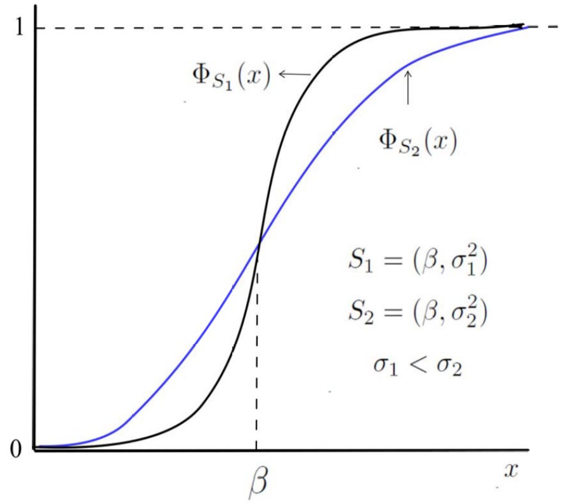


Figure 1: The Signal Function, normal c.d.f. $\Phi_S(x)$

Assumption: $\Phi_S(X)$ (where $S = (\beta, \sigma)$) 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

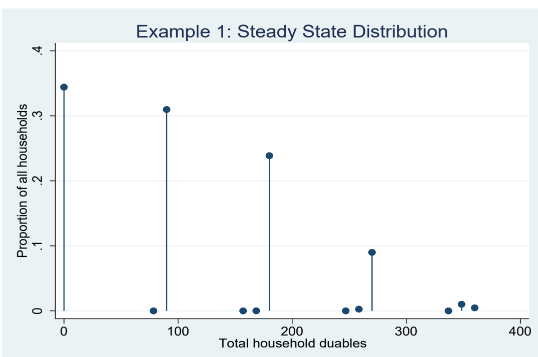
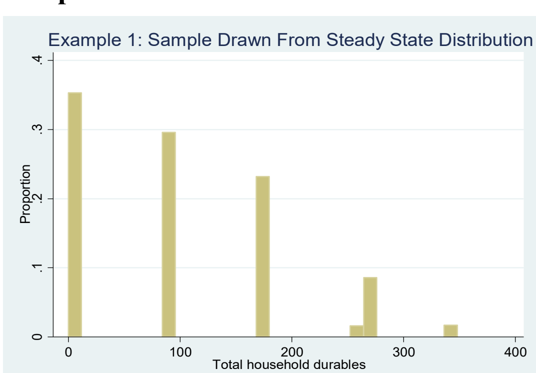


Figure 2(b): Histograms from samples independently drawn from the theoretical distribution in Figure

Sample 1



Sample 2

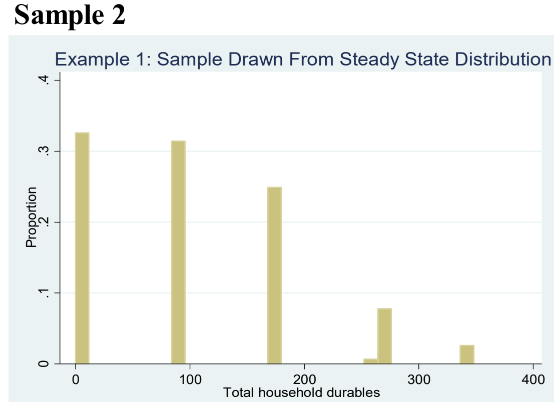


Figure 3(a): Pooled sample from data generated using Set A parameters (Example 2)
(wH and wL ranges do not intersect, beta is within attainable income range)

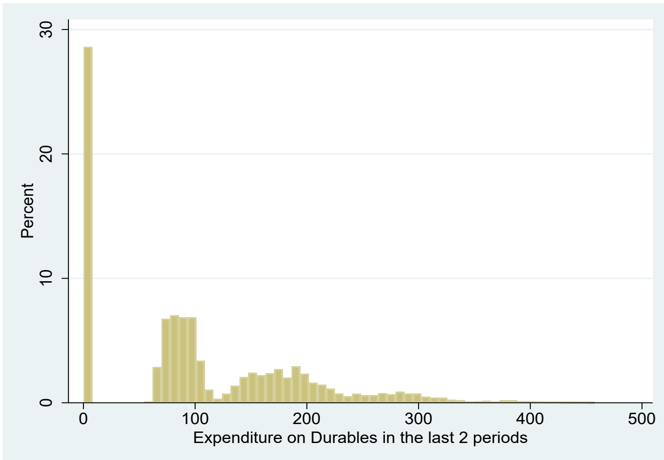


Figure 3(b): Pooled sample from data generated using Set B parameters
(wH and wL ranges do intersect, beta is within attainable income range)

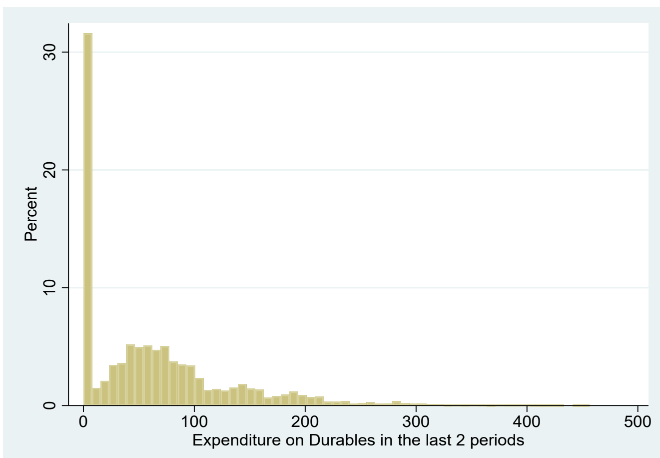
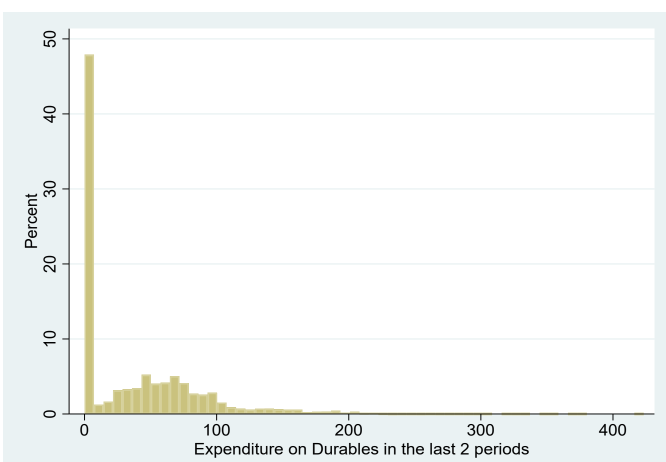


Figure 3(c): Pooled sample from data generated using Set C parameters (Example 3)
(wH and wL ranges do intersect, beta is very high)



<u>Economy 1</u>:

Data Generating Process: Income in every period is drawn from uniform(1000, 10000)

<u>Economy 2</u>:

Data Generating Process: t-income is drawn from uniform(6000,10000) if (t - 1)-income >= 6000;
t-income is drawn from uniform(1000, 6000) if (t - 1)-income < 6000

Figure 4(a): Economy 1, Single-Period Incomes

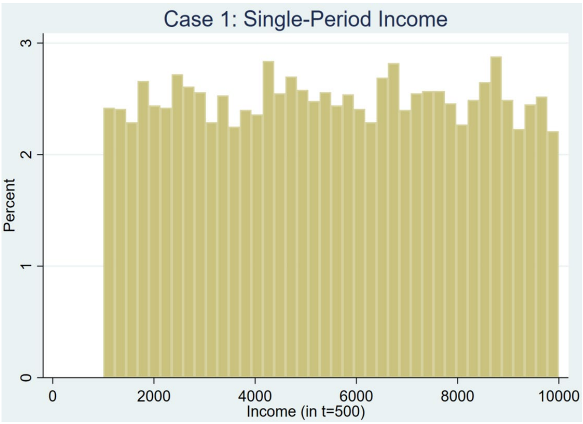


Figure 4(b): Economy 2, Single-Period Incomes

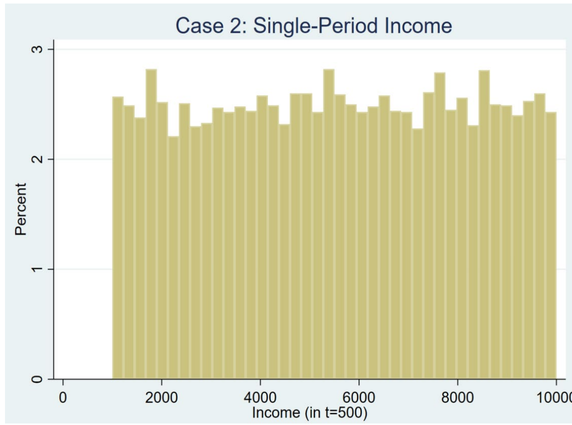


Figure 5(a): Economy 1, Two-Period Incomes

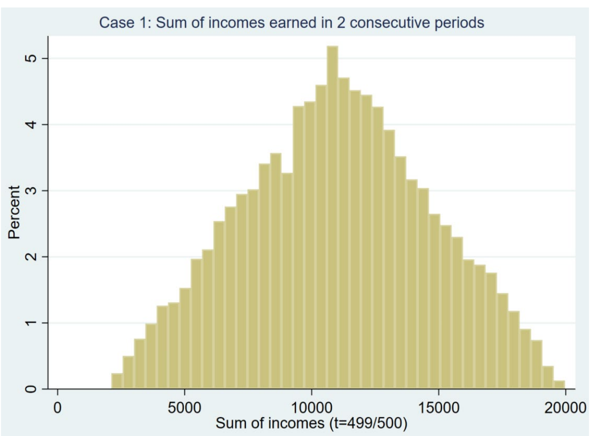


Figure 5(b): Economy 2, Two-Period Incomes

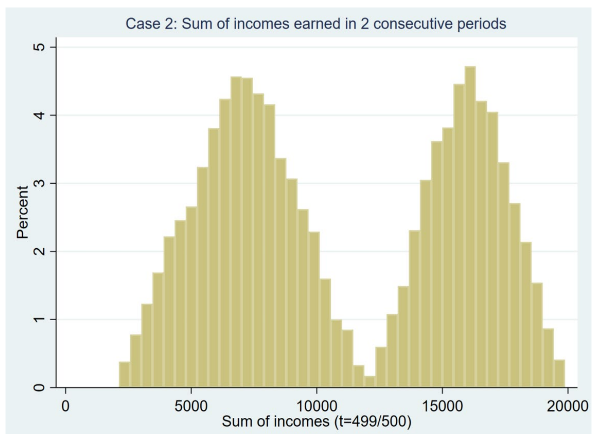
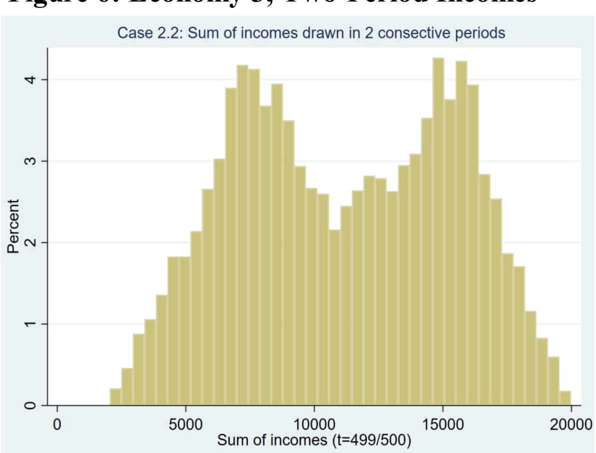


Figure 6: Economy 3, Two-Period Incomes



<u>Economy 3</u>:

Data Generating Process:

t-income is drawn from uniform**(5000,10000)** if (t - 1)-income >= 6000;

t-income is drawn from uniform**(1000, 7000)** if (t - 1)-income < 6000