Long-Term Dynamics of Poverty Transitions in India

Anand Sahasranaman

I use a stochastic model to explore the dynamics of poverty in India from 1952 to 2006 and find that temporal transitions into and out of poverty are common. Model outcomes suggest that transitions out of poverty outnumber transitions into poverty in recent times, but that there is still a nontrivial proportion of individuals transitioning annually into poverty, highlighting the economic fragility of those near the poverty line. There is also a marked persistence of poverty over time, and although this has been slowly declining, past poverty remains a good predictor of current poverty. Particularly concerning in this context are the income trajectories of those in the bottom decile of the income distribution for whom escape from poverty appears infeasible given extant income dynamics. Finally, the dynamics suggest that transitional and persistent poverty are distinct phenomena that require distinct policy responses involving both missing markets and state action.

Keywords: dynamics, income, India, poverty, transition

JEL codes: C63, I32

Anand Sahasranaman: Division of Science, Division of Humanities and Social Science, Krea University, India; and Centre for Complexity Science, Department of Mathematics, Imperial College London, United Kingdom. E-mail: anand.sahasranaman@krea.edu.in. I thank the managing editor and the anonymous referees for helpful comments and suggestions. The Asian Development Bank recognizes “China” as the People’s Republic of China and “Vietnam” as Viet Nam.

I. Introduction

Poverty in India is a deeply explored subject, reflecting the centrality of poverty alleviation in economic policy making since independence. This has meant a keen focus on issues of poverty measurement, the multidimensional impacts of poverty, and the apposite design of economic policy (Ahmed and Bhattacharya 1972; Ninan 1994; Deaton and Dreze 2002; Dev and Ravi 2007; Dhongde 2007; Datt and Ravallion 2009; Kohli 2012; Bhagwati and Panagariya 2013; Kjelsrud and Somanathan 2017; Srinivasan, Bardhan, and Bali 2017).

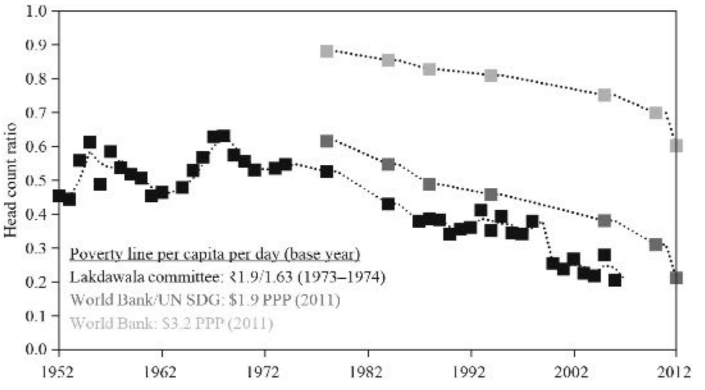
Poverty measurement has largely focused on static descriptors such as the head count ratio (HCR) or the poverty gap index, which are measurements of poverty drawn from extant income or expenditure distributions (Srinivasan, Bardhan, and Bali 2017). These measures are termed "static" because they focus on average properties of the ensemble at any given point in time. However, a more holistic understanding of the phenomenon requires a deeper exploration of long-term dynamical aspects. Our current understanding of the temporal evolution of poverty emerges from a time series of static snapshots of HCR, but this does not provide any information on the time evolution, or dynamics, of poverty, unless poverty is an ergodic process. An ergodic process is one where the ensemble average equals the time average, and the assumption of ergodicity was essential to precisely describe the thermodynamic behavior of gases, where particles undergo Geometric Brownian Motion (GBM) (Peters 2019). On the other hand, studies of household poverty suggest path dependency (nonrandomness) in poverty trajectories and there is therefore no case for assuming ergodicity in this context (Cappellari and Jenkins 2004, Ayllón 2008, Bigsten and Shimeles 2008, You 2011). Exploring the dynamics of poverty—the time evolution of individual income trajectories as they rise above and fall below poverty—becomes critical to enable a comprehensive description and interpretation of poverty trends. Specifically, poverty dynamics pertain to questions on the nature and extent of the transitions of individual income paths across the poverty line as they evolve over long time horizons, as well as to quantifications of the persistence of poverty over time.

Poverty measurement in India has relied on National Sample Survey (NSS) data on consumption because India does not have a regular income survey (Srinivasan, Bardhan, and Bali 2017). This measurement has centered around the poverty line, which is the level of income or expenditure below which an individual is considered poor. India's Planning Commission endorsed the Lakdawala Committee recommendation of a nutritional-requirement-based poverty line definition—specifically, the average level of expenditure required to achieve 2,400 or 2,100 calories per person per day in urban or rural areas, respectively, which worked out to a poverty line of 1.9 Indian rupees (₹) and ₹1.63 (in 1973/74 prices) per day in urban and rural areas, respectively (Expert Group on Estimation of Proportion and Number of Poor 1993, Datt and Ravallion 2009). Datt and Ravallion (2009) used the Lakdawala Committee recommendation as the basis to compute the poverty HCR, which is the fraction of the population under the poverty line, between 1952 and 2006, which makes this the longest available consistent time series of poverty rates for India. The Lakdawala methodology was altered by the Tendulkar Committee, moving away from caloric norms, and instead focusing on expenditure on a basket of goods and services, resulting in a poverty line of ₹32 and ₹26 (in 2011 prices) per person per day in urban and rural India, respectively (Panagariya and Mukim 2014, Expert Group to Review the Methodology for Estimation of Poverty 2009). Additionally, there is the World Bank's global poverty line of $1.9 per person per day at 2011 purchasing power parity (PPP), which is salient because it forms the basis of poverty eradication goals under the United Nations' Sustainable Development Goals (World Bank 2015, World Bank Poverty Data).[1] The World Bank also has a higher poverty line at $3.2 (in 2011 PPP prices) for middle-income countries (World Bank Poverty Data). Figure 1 plots India's HCR for all the poverty lines discussed above, and it is apparent that there has been a systematic, continuous decline in static poverty since the 1980s, with sharp declines evident since 2000.

There is an emerging global empirical literature exploring poverty transitions and the dynamic aspects of poverty (Bigsten and Shimeles 2008; McKernan and Ratcliffe 2002; Haq 2004; You 2011; Imai, Gaiha, and Kang 2011; Jha et al. 2012; Gaiha and Imai 2004). Between 1994 and 2004, households in Ethiopia were found to frequently cycle into and out of poverty, though the probability of exiting decreased with time spent in poverty (Bigsten and Shimeles 2008). Analysis of a panel study of income dynamics data in the United States reveals that the early to mid-1990s were characterized by both high poverty rates as well as increasing fractions of people transiting into and out of poverty, and that such transitions were more likely for persons who experienced major shifts in household composition (McKernan and Ratcliffe 2002). Studying panel data from 1999 and 2001 in Pakistan, Haq (2004) found that while many households entered poverty, fewer households were able to exit, and that school enrollment for children, especially girls, suffered on account of poverty. Poverty was persistent for those who started out poor in the People's Republic of China between 1989 and 2006, and exit from poverty was found linked to

[1]See https://data.worldbank.org/topic/poverty (accessed July 3, 2020).

Figure 1. **Evolution of the Head Count Ratio in India, 1952–2012**



Notes: The temporal evolution of poverty is represented using different measures of the poverty line: The Lakdawala Committee's nutritional norm (black), the World Bank's $1.9 purchasing power parity (PPP) global poverty line for the United Nations (UN) Sustainable Development Goals (SDGs) (dark gray), and the World Bank's $3.2 PPP poverty line (light gray). Poverty clearly shows a declining trend since the 1980s. The dotted lines represent Head Count Ratio moving averages (2-period) over time.
Sources: Datt, Gaurav, and Martin Ravallion. 2009. "Has India's Economic Growth Become More Pro-Poor in the Wake of Economic Reforms?" World Bank Policy Research Working Paper 5103; World Bank. World Bank Poverty Data. https://data.worldbank.org/topic/poverty (accessed July 3, 2020).

education, asset accumulation, migration, and health insurance (You 2011). Analysis of panel data in Viet Nam reveals that vulnerability at the outset of the review period translated into poverty over time and that it also perpetuated poverty; reducing vulnerability would require identification of sources and the creation of appropriate safety nets (Imai, Gaiha, and Kang 2011).

There have also been empirical explorations of rural poverty dynamics in India based on limited panel datasets. A panel study of 240 households between 1975 and 1984 found that severe crop shocks made even relatively affluent rural households vulnerable to lengthy poverty spells in semi-arid southern India (Gaiha and Imai 2004). A panel study of 5,886 rural households between 1999 and 2006 found a high incidence of transient rural poverty to be influenced by the gender of the household head as well as education and land ownership levels (Jha et al. 2012). In a study of chronic poverty in rural India using the National Council of Applied Economic Research panel data for 3,936 households conducted across three rounds in 1970, 1981, and 1998, it was found that among poor households, the chronically poor comprised 43.3% from 1970 to 1981, which declined to 38.6% from 1981 to 1998 (Bhide and Mehta 2005).

As is apparent from this brief survey, most poverty dynamics work from around the world relies on panel data available over short time periods, thus limiting the scope of the analysis and the applicability of findings. My objective here is to take the long view on poverty dynamics for India. In the following section, I attempt to do this by using a stochastic model to construct the Indian income distribution and explore the evolution of aggregate national poverty (including both rural and urban poverty) over 6 decades after independence. Sections III and IV explore the time evolution of individual income paths and isolate the transitions into and out of poverty. These dynamics are characterized probabilistically both in terms of transient short-term transitions across the poverty line as well as long-term trends in the persistence of poverty. Using these modeled probabilistic measures, I study temporal trends in the direction and quantum of both transient and persistent poverty. Section V discusses the results in the context of evidence on poverty alleviation from India. Section VI concludes.

II. Model Definition and Specifications

In previous work on modeling income inequality in India (Sahasranaman and Jensen 2021), we used a stochastic model of GBM with reallocation (RGBM) to explore the nature and extent of redistribution occurring within the income distribution (Berman, Peters, and Adamou 2017). It has been shown using NSS consumption data that the distribution of consumption expenditures for India reveals a lognormal body with a power-law tail (Ghosh, Gangopadhyay, and Basu 2011; Chatterjee et al. 2016). More generally, the evolution of income distributions across countries after the industrial revolution has seen both mean income and income inequality, on average, rising over time (Piketty 2014, Milanovic 2016). This makes the income evolution process ideally suited for exploration using GBM, which generates a temporally widening lognormal distribution. Berman, Peters, and Adamou (2017) used this as the basis for the formulation of RGBM, which is a simple stochastic differential equation with a reallocation parameter (τ) that constructs the income distribution based on multiplicative dynamics and also captures the transfer of resources within the distribution. The change in income x_i of individual i over time dt in the RGBM is obtained as a result of income growth and income reallocation as described in this stochastic differential equation (Berman, Peters, and Adamou 2017):

$$dx_i = \underbrace{x_i(\mu dt + \sigma dW_i)}_{\text{Growth}} - \underbrace{\tau(x_i - \langle x \rangle_N)}_{\text{Reallocation}}, \quad \text{where: } dW_i \sim N(0, dt); \quad \langle x \rangle_N = \frac{1}{N}\sum_{i=1}^{N} x_i. \tag{1}$$

The first term of equation (1) captures the growth in income of individual i, which contains growth due to systemic (μdt) as well as idiosyncratic (σdW_i) factors. Systemic factors include elements like growth, economic environment, and institutions, which impact all participants in the economy, while idiosyncratic factors capture individual aspects such as effort and luck. μ and σ are parameters for drift and volatility of the income distribution. The second term of equation (1) represents the net reallocation of income from individual i and is meant to capture the extent of redistribution inherent in the income distribution. Therefore, the incomes modeled using RGBM are best envisaged as individual net incomes—that is, incomes net of redistributive transfers.

If the reallocation parameter τ is positive, as we would expect in modern economies with progressive redistribution from rich to poor, then there is a net reallocation from i if i's income is greater than the mean income at the time, and a net reallocation to i if i's income is less than mean income. In this scenario, while incomes disperse over time, they remain confined around a rising mean, and the higher the value of τ, the tighter the distribution is held around the mean. If τ were negative, it would imply a perverse reallocation from poor to rich, meaning that there would be a net reallocation from i if i's income is lower than average, and to i if its income were above average. In a regime of prolonged negative τ, incomes diverge exponentially away from the mean, leading to an economy of debtors and creditors.

In this work, I use the Indian income distribution data from Chancel and Piketty (2019) to model poverty dynamics. To the best of my knowledge, the Chancel and Piketty (2019) data are the first consistent long-term time series (1922–2015) of the income distribution for India. In constructing this time series, they acknowledge the inherent data challenges, including issues of underreporting and undersampling in the NSS data, and the use of consumption data from NSS surveys to estimate the income distribution. To work around these constraints, they use both consumption data from NSS surveys and income data from the first two rounds of the India Human Development Survey to construct income profiles. While the use of tax data provides a robust basis to construct the top of the Indian income distribution, they concede the greater uncertainties in estimating informal incomes lower in the distribution. To make income estimates robust, they simulate over 50 scenarios of income distributions over time, and out of these simulations, they choose a base-case income distribution time series, which is found robust to a range of assumptions relating to the data challenges outlined here.

In previous work (Sahasranaman and Jensen 2021), we have used the RGBM model to systematically attempt and reconstruct the bottom half of the income distribution from 1951 to 2015, based on inequality metrics generated from Chancel and Piketty's (2019) data. And it is this distribution constructed using RGBM that I use to study the dynamics of poverty now.

To implement the RGBM model, Sahasranaman and Jensen (2021) first estimated the drift of the income distribution (μ). The evolution of mean per capita income can be modeled as an exponential fit of the form:

$$\langle x(t)\rangle_N = \langle x(t_0)\rangle_N e^{\mu(t-t_0)}, \tag{2}$$

where $\langle x(t)\rangle_N$ is the mean per capita at any given time t, $\langle x(t_0)\rangle_N$ is the mean per capita income at beginning time t_0, and μ is the drift parameter of this income distribution. Using equation (2) to fit the mean per capita income time series data for India from $t_0 = 1947$ to 2017 provided by Chancel and Piketty (2019), we estimate the drift of the income distribution to be $\mu = 0.0231$.

Second, Sahasranaman and Jensen (2021) attempted to estimate the volatility of the income distribution (σ). In the absence of time series data of requisite granularity on income, we used short-term time series of wages (2013–2019) of monthly granularity for a few professions like construction, harvesting and threshing, ploughing and tilling, animal husbandry, horticulture, and handicrafts. We also used potential proxies such as wholesale prices of staple crops and essential commodities, which are closely related to the economies of the substantial informal workforce in India; these include wheat, rice, and *gur* (or jaggery) for which longer time series of weekly data are available (1993–2012). Finally, given that gold is a prevalent asset in portfolios of Indian households (Prasad et al. 2014), we also estimated σ using gold prices (1979–2019). For each of these time series, we estimated annualized σ as the standard deviation of weekly (for crop, commodity, and gold price data) or monthly (for rural wage data) logarithmic changes of the prices and wages, multiplied by $\sqrt{52}$ for weekly data or $\sqrt{12}$ for monthly resolution of data. Averaging these annualized σ values over all the years in the analysis gave us a consolidated σ for each dataset. Based on the σ obtained for each dataset of crops, commodities, and wages, which range between $0.03 \le \sigma \le 0.17$, we chose $\sigma = 0.15$ as our base case estimate for analysis. We also simulated dynamics for $\sigma = 0.10$ and $\sigma = 0.20$ to explore the robustness of results to the choice of σ.

Finally, we used income inequality time series from Chancel and Piketty (2019), which provided data on the fraction of income earned by the bottom 50% ($S_{50\%}$) of the population between 1952 and 2015, to fit the RGBM model as follows: for $t = 0$, we simulated an initial set of $N = 100{,}000$ lognormally distributed incomes by varying μ and σ such that the cumulative income of the bottom half of the simulated population matched the observed value from the Chancel and Piketty (2019) data ($S_{50\%}(t_0)$). Once incomes were initialized in this manner, we propagated the dynamics for each of the N individuals based on equation (1) (using $\mu = 0.231$, $\sigma = 0.15$), such that the value of the reallocation parameter $\tau(t)$, at any given t, was obtained by minimizing the absolute distance between the simulated income of the bottom half of the distribution at time t and the actual income of the bottom half at t ($S_{50\%}(t)$). This step was repeated for the requisite number of time periods to construct the rescaled income distribution for India from 1951 to 2015.

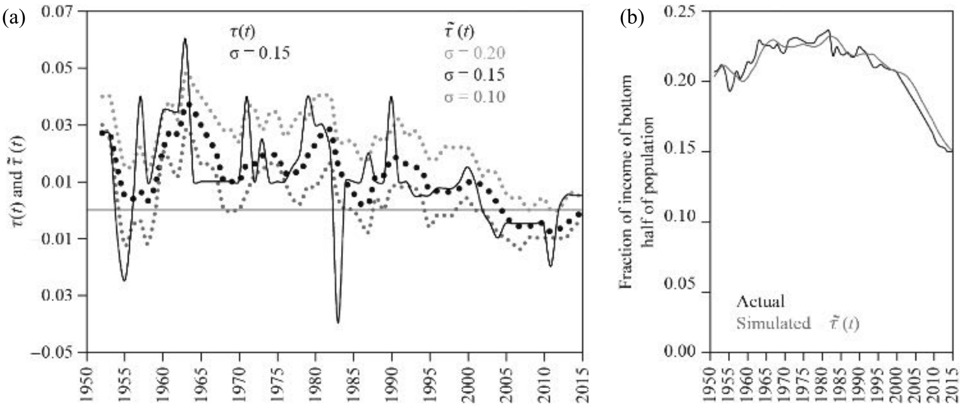
There is evidence of power-law tails for income distributions across the world, including India (Banerjee, Yakovenko, and Di Matteo 2006; Drăgulescu and Yakovenko 2001; Clementi and Gallegati 2005; Souma 2001; Chatterjee et al. 2016; Ghosh, Gangopadhyay, and Basu 2011), and even though the RGBM produces a widening lognormal distribution over time, it is likely to underestimate top incomes in the distribution. However, using the income share of the bottom half of the population, $S_{50\%}(t)$, as the basis to fit equation (1) ensures that our model is consistent for the bottom half of the income distribution, which is my focus in this work.

The resultant time series of $\tau(t)$ is depicted in Figure 2a (thin black solid line), though it could be argued that there is too much year-on-year variation in τ and that actual changes in reallocation are likely to be less abrupt. To adjust for this, we computed an effective reallocation rate $\tilde{\tau}(t)$ as the moving average of the reallocation rate τ over the last 5 periods (t through $t-4$) (Figure 2a, dotted black line). We also presented the temporal evolution of $\tilde{\tau}(t)$ for $\sigma = 0.10$ (Figure 2a, dotted dark gray line) and $\sigma = 0.20$ (Figure 2a, dotted light gray line), which suggest that the nature of dynamics in these scenarios is similar to those in the base case. We verified that the effective reallocation rate was representative of the underlying dynamics by propagating the RGBM model using a time series of $\tilde{\tau}(t)$ and found that the resultant income shares of the bottom half of the population closely matched the empirically observed values $S_{50\%}(t)$ (Figure 2b).

Figure 2a plots both the reallocation and effective reallocation rates for the Indian income distribution from 1951 to 2015, clearly illustrating that, while redistribution in the Indian income distribution was largely progressive (positive τ) over time, it entered a persistently regressive regime (negative τ) starting in the early 2000s, where resources were perversely being redistributed from the poor to rich. In Sahasranaman and Jensen (2021), our focus was on the evolution of the effective reallocation rate and the implications of this significant regime reversal for inequality in India.

In this work, I propose to take the effective reallocation rate $\tilde{\tau}(t)$ and the corresponding income distributions generated by the RGBM model from 1951 to 2015

Figure 2. **Temporal Evolution of Reallocation and Inequality, 1951–2015**



Notes: Figure 2a: Evolution of reallocation rates — $\tau(t)$ and $\tilde{\tau}(t)$. Thin black solid line: reallocation rate (τ) over time. $\tau(t)$ is largely positive until 2001 and becomes negative from 2002 to 2012, before becoming slightly positive afterwards. Dotted black line: effective reallocation rate ($\tilde{\tau}$) over time. $\tilde{\tau}(t)$ is positive from 1951 to 2004, and then becomes negative from 2005. Dotted dark gray line: effective reallocation rate ($\tilde{\tau}$) for $\sigma = 0.10$. Dotted light gray line: effective reallocation rate ($\tilde{\tau}$) for $\sigma = 0.20$. Figure 2b: Evolution of income share of bottom half of population. Black line: actual $S_{50\%}(t)$ data based on Chancel and Piketty (2019). Gray line: Modeled inequality obtained by fitting the effective reallocation rate time series $\tilde{\tau}(t)$. Modeled inequality shows close correspondence with actual data.

Source: Sahasranaman, Anand, and Henrik Jeldtoft Jensen. 2021. "Dynamics of Reallocation within India's Income Distribution." *Indian Economic Review* 3 (1): 1–23.

as inputs for exploring the dynamics of poverty in India. Specifically, I am interested in measuring transitions into and out of poverty, as well as persistence of poverty over time.

As a first step, I identify the poverty line of the rescaled income distributions at each period (year), t. The longest consistently available time series for aggregate poverty (rural and urban) in India is the Datt–Ravallion HCR data on poverty between 1952 and 2006 (Figure 1, black) (Datt and Ravallion 2009). However, there are 12 years of missing data (in six distinct blocks) in this period, and these missing data points are computed by assuming linear annual change, thus producing a full 55-year time series on poverty. This is a reasonable approximation because changes in poverty tend to be gradual over short time scales. With this HCR dataset for 1952–2006, I construct the poverty line time series in the rescaled income distribution generated using the RGBM model by finding the appropriate point in the income distribution corresponding to the HCR for each year. For instance, if the HCR for a given year t is $y\%$, then the income at the $y\%$ population point in the ordered income distribution at time t is the poverty line for that year. Once the poverty line time series is thus constructed, I first explore the notion of transient poverty or annual transitions of individual incomes into and out of poverty.

The probability of transitioning out of poverty at time t, $p_{\text{out}}(t)$, is

$$p_{\text{out}}(t) = \frac{N_{P-NP}(t)}{N_P(t-1)}, \tag{3}$$

where $N_{P-NP}(t)$ is the number of individual transitions from below the poverty line at $t-1$ to at or above the poverty line at t, and $N_P(t-1)$ is the total number of individuals below the poverty line at $t-1$.

Symmetrically, the probability of annual transitions into poverty, $p_{\text{in}}(t)$, is

$$p_{\text{in}}(t) = \frac{N_{NP-P}(t)}{N_{NP}(t-1)}, \tag{4}$$

where $N_{NP-P}(t)$ is the number of individual transitions from at or above the poverty line at $t-1$ to below the poverty line at t, and $N_{NP}(t-1)$ is the total number of individuals at or above the poverty line at $t-1$.

$p_{\text{in}}(t)$ and $p_{\text{out}}(t)$ are measures of annual transitions into and out of poverty over time and the time series of these probabilities help us understand the evolution of annual poverty transitions. I also use a composite measure of transition, $p_{tx}(t)$, which is the probability of a transition (up or down) across the poverty line over one period and is defined as

$$p_{tx}(t) = \frac{N_{NP-P}(t) + N_{P-NP}(t)}{N_P(t-1) + N_{NP}(t-1)}. \tag{5}$$

A second set of metrics relate to the persistence of poverty, which estimates the difficulty in climbing out of poverty over longer time periods. I am interested in both stickiness to and escape from spells (or durations) of poverty (d_{pov}), where d_{pov} is at least t_p years long, that is, $d_{\text{pov}} \geq t_p$. First, the escape probability $p_{\text{esc}}(t, t_p)$ is the conditional probability that an individual has been poor for $d_{\text{pov}} \geq t_p$ time periods at time $t-1$, given that the individual is nonpoor at the current time t:

$$\begin{aligned} p_{\text{esc}}(t, t_p) = P(d_{\text{pov}} \geq t_p \mid \text{nonpoor at } t) &= \frac{P(d_{\text{pov}} \geq t_p \cap \text{nonpoor at } t)}{P(\text{nonpoor at } t)} \\ &= \frac{N_{P-NP}(t, d_{\text{pov}} \geq t_p)}{N_{NP}(t)}, \end{aligned} \tag{6}$$

where $N_{P-NP}(t, d_{\text{pov}} \geq t_p)$ is the number of individual transitions from below the poverty line at $t-1$ to at or above the poverty line at t, such that the duration of poverty at $t-1$ is $d_{\text{pov}} \geq t_p$, and $N_{NP}(t)$ is the number of individuals who are nonpoor at time t. For the analysis, I vary $t_p : 1 \leq t_p \leq 10$. Therefore, $p_{\text{esc}}(t)$ is a measure of the persistence of poverty, quantifying the difficulty of escaping poverty, given that individuals have been in a state of poverty for a length of time ($d_{\text{pov}} \geq t_p$).

A second metric for poverty persistence is the stickiness probability, $p_{\text{stic}}(t, t_p)$, which is the likelihood that the individual has been in a spell of poverty for a duration $d_{\text{pov}} \geq t_p$ at time $t-1$, given that the individual is in poverty at time t:

$$p_{\text{stic}}(t, t_p) = P(d_{\text{pov}} \geq t_p \,|\, \text{poor at } t) = \frac{P(d_{\text{pov}} \geq t_p \cap \text{poor at } t)}{P(\text{poor at } t)} = \frac{N_{P-P}(t, d_{\text{pov}} \geq t_p)}{N_P(t)}, \quad (7)$$

where $N_{P-P}(t, d_{\text{pov}} \geq t_p)$ is the number of individuals below the poverty line at $t-1$ who remained below the poverty line at t, such that the duration of poverty at $t-1$ is $d_{\text{pov}} \geq t_p$, and $N_P(t)$ is the number of individuals who are poor at time t.

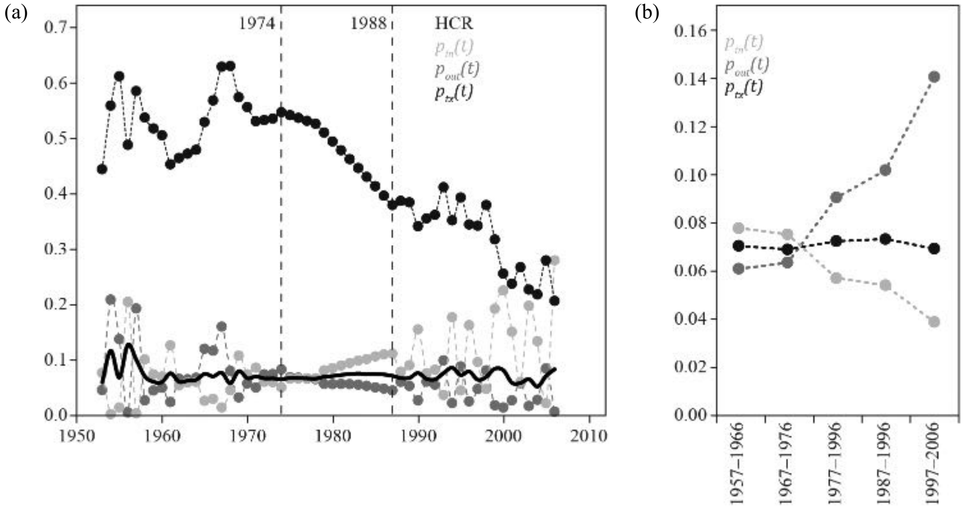
Studying the evolution of p_{esc} and p_{stic} over the period of the dynamics from 1951 to 2006 therefore gives a sense of how India's economic trajectory has impacted the persistence of poverty over time.

III. Dynamics of Poverty Transitions and Poverty Persistence

Using equations (3) and (4) to compute $p_{\text{in}}(t)$ and $p_{\text{out}}(t)$, I find that transition across the poverty line is not uncommon through the entire duration of the dynamics, though there are significant fluctuations in the probabilities of transition in the early and latter part of the dynamics (Figure 3a). Until 1974, there are fluctuations in annual transition probabilities both into and out of poverty; between 1974 and 1988 both probabilities remain stable over time; and after 1988, the transition probabilities again show much higher year-on-year fluctuations. To explore these regimes of behavior, let us juxtapose the evolution of transition probabilities with the evolution of the HCR measure over time. As Figure 3a illustrates, the HCR itself shows fluctuating behavior, rising and falling, in the time periods 1952–1974 and 1988–2006; these fluctuations in the HCR mirror the fluctuations in transition probabilities, with short bursts of rising HCR reflected in rising transitions into poverty $p_{\text{in}}(t)$ and falling $p_{\text{out}}(t)$, and bursts of declining HCR in falling $p_{\text{in}}(t)$ and rising $p_{\text{out}}(t)$. Between 1974 and 1988, when we observe a monotonic decline in HCR, $p_{\text{out}}(t)$ remains consistently higher than $p_{\text{in}}(t)$ through this entire duration (Figure 3a).

There is also strong evidence for a temporal trend in the evolution of transition probabilities over the decades, with two particular aspects standing out (Figure 3b). First, the average annual transitions into poverty, $p_{\text{in}}(t)$, declines over the decades from

Figure 3. **Temporal Evolution of Poverty Transitions, 1952–2006**



Notes: Figure 3a: Evolution of $p_{\text{in}}(t)$ (light gray), $p_{\text{out}}(t)$ (dark gray), and $p_{tx}(t)$ (black). These trajectories reveal that poverty transitions are common, and that overall transitions across the poverty line remain consistent over time. It also appears that transitions out of poverty outnumber transitions into poverty since the 1980s. The evolution of the Head Count Ratio (HCR) (dotted black) offers a concurrent picture of static poverty. Figure 3b: Decadal evolution of average annual $p_{\text{in}}(t)$ (light gray), $p_{\text{out}}(t)$ (dark gray), and $p_{tx}(t)$ (black). On average, probability of transitioning out of poverty increases over time, while that of falling into poverty declines over time.
Source: Author's calculations.

7.8% in 1957–1966 to 3.9% in 1997–2006. At the same time, average annual transitions out of poverty increased from 6.1% in 1957–1966 to 14.1% in 1997–2006. Second, while, on average, $p_{\text{in}}(t)$ was greater than $p_{\text{out}}(t)$ for the first 3 decades after independence, this trend reversed in the late 1970s, with transitions out of poverty consistently higher (and growing) than transitions into poverty (Figure 3b). Even as the overall transition probability (all transitions into and out of poverty) remains remarkably consistent over the decades (Figure 3b), the trends in $p_{\text{in}}(t)$ and $p_{\text{out}}(t)$ indicate that escape from poverty has become a more robust phenomenon over time and is reflective of the declining HCRs since the late 1970s. Prevailing economic conditions at the turn of the century have enabled a greater fraction of individuals to escape poverty, and also correspondingly reduced transitions into poverty. However, it is important to remember that as HCR has been declining and the population of the nonpoor increasing, the fact that (in the most recent decade) about 4% of individuals above the poverty line continued to annually fall into poverty is indicative of substantial fragility of incomes around the poverty line.

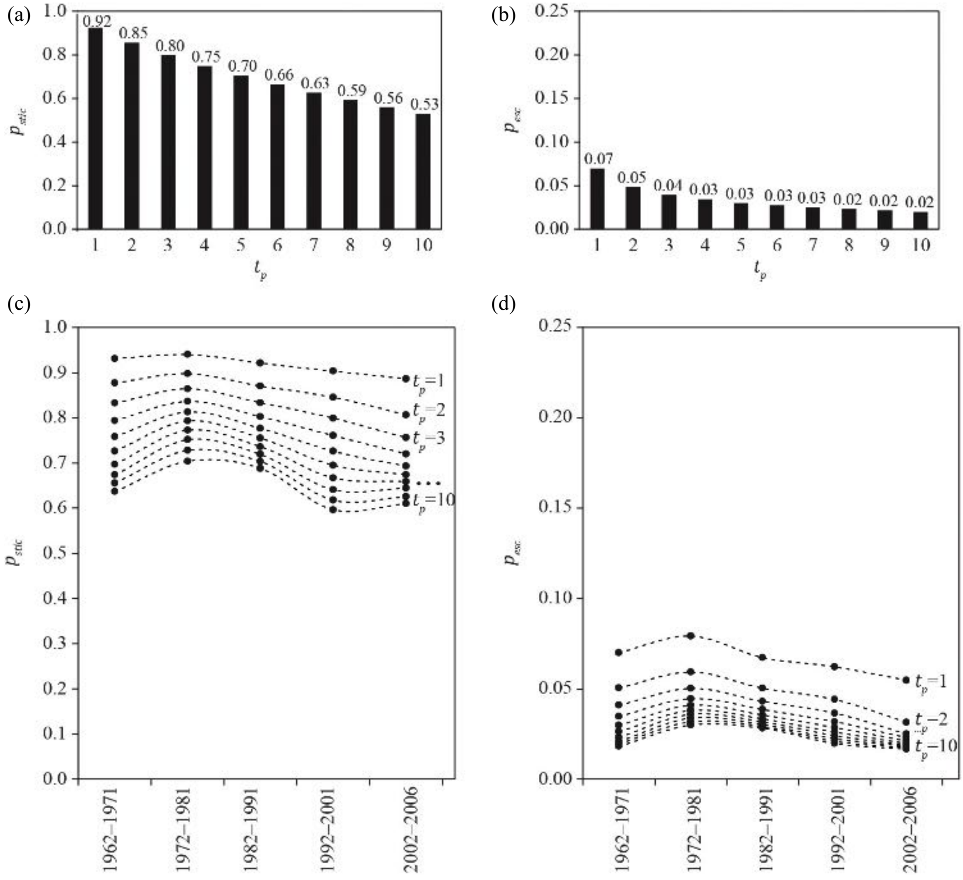
With this understanding of the transient transitions into and out of poverty, I turn to a discussion of the persistence of poverty as revealed by my model. Considering the entire period from 1952 to 2006, poverty is found to be very sticky and hard to escape. My model reveals that the stickiness probability that an individual was poor for at least the last year, given that she is poor in the current year is, $p_{\text{stic}}(t, 1) = P(d_{\text{pov}} \geq 1$ at $t-1 \,|\,$poor at $t) = 0.92$ (Figure 4a). In fact, current poverty appears to be a strong indicator of long-term poverty, with $p_{\text{stic}}(t, 5) = 0.7$ and $p_{\text{stic}}(t, 10) = 0.53$, meaning that given current poverty, there is a probability of 0.7 that the individual has been poor for at least the last 5 years, and a probability of 0.53 that the individual has been poor for at least the last 10 years (Figure 4a).

Similarly, looking at escape probability from poverty from 1952 to 2006, the probability of an individual being poor for at least the year before, given that she is nonpoor now, is $p_{\text{est}}(t, 1) = P(d_{\text{pov}} \geq 1$ at $t-1 \,|\,$nonpoor at $t) = 0.07$, meaning that the likelihood that an individual was nonpoor the previous year, given that she is nonpoor in the current year, is 93% (Figure 4b). Both poverty and nonpoverty, therefore, appear to be sticky states for large proportions of individuals, though as seen earlier, there are nontrivial annual transition probabilities from one state to the other for individuals close to the poverty line.

While this analysis suggests significant persistence in poverty, it is useful to study the temporal change in persistence probabilities over the 55 years of study. This is accomplished by a decadal analysis of p_{stic} and p_{esc} (1962–1971, 1972–1981, 1982–1991, 1992–2001, and 2002–2006; I leave out the decade 1952–1961 because there are few transitions to consider for higher t_p values). There appears to be a declining temporal trend in the probability that an individual has been poor for at least t_p years given that she is poor in the current year, across all values of t_p, implying that current poverty is a somewhat poorer predictor of long-term poverty in more recent times (Figure 4c). For instance, $p_{\text{stic}}(1972-1981, 10) = 0.7$ and $p_{\text{stic}}(2002-2006, 10) = 0.61$, meaning that the probability that an individual has been poor for 10 years or more, given that he is poor in the current year, has declined from 0.7 in the 1970s to 0.61 in the 2000s (Figure 4c). Similar declines are apparent for other t_p as well: $p_{\text{stic}}(1972-1981, 5) = 0.81$ and $p_{\text{stic}}(2002-2006, 5) = 0.69$. These findings on reduced persistence of poverty over time are broadly consistent with the empirically observed trends by Bhide and Mehta (2005) for rural India between 1970 and 1998, where they found that the share of chronically poor among the poor population declined from 43.3% for 1970–1981 to 38.6% for 1981–1998.

Despite the decline in stickiness probabilities apparent across all t_p over time, it is important to point out that current poverty remains a significant predictor of long-term poverty; escape probabilities have also shown declines across t_p and over time,

Figure 4. **Persistence of Poverty**



Notes: Figure 4a: $p_{\text{stic}}(1952-2006, t_p)$ shows that poverty remains a very sticky process, with long-term path dependence. Figure 4b: $p_{\text{esc}}(1952-2006, t_p)$ reveals that path dependence also holds for individuals above the poverty line. While stickiness to states of poverty or nonpoverty is apparent, it is also true that transitions occur across states and are an important part of the poverty dynamics. Figure 4c: Temporal (decadal) evolution of $p_{\text{stic}}(t, t_p)$ shows that there is a steady decline in the probability that an individual has been poor for at least t_p years, given that the individual is poor in the current year, across all t_p. Figure 4d: Temporal (decadal) evolution of $p_{\text{esc}}(t, t_p)$ shows that there is a gradual decline in the probability that an individual has been poor for at least t_p years, given that the individual is nonpoor in the current year, across all t_p. Overall, long-term spells of poverty (or being out of poverty) appear to perpetuate themselves.
Source: Author's calculations.

meaning that given an individual is nonpoor in the current year, the probability that she has been poor for at least t_p years before falls over time. This indicates that, over time, being nonpoor in the present time is a consistently better predictor of being nonpoor in the past: $p_{\text{esc}}(1962-1971, 1) = 0.08$ and $p_{\text{esc}}(2002-2006, 1) = 0.05$ (Figure 4d).

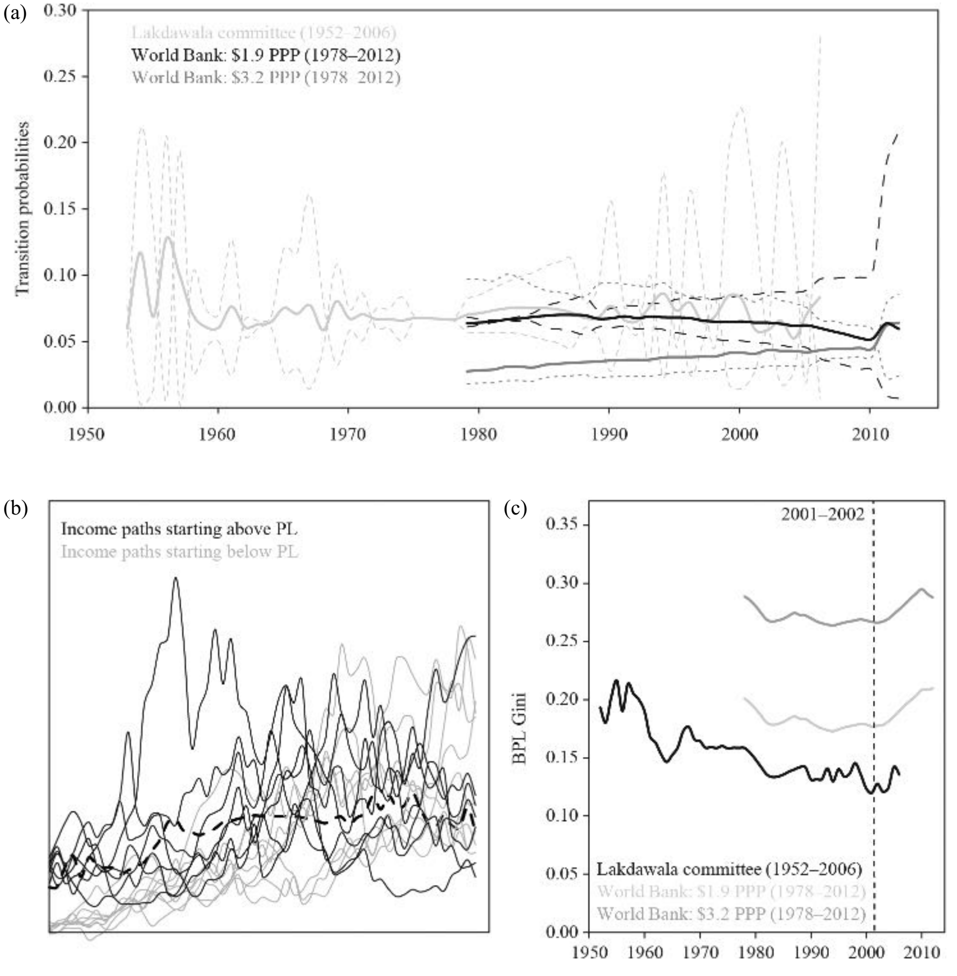
IV. Poverty Lines and Impact on Dynamics

We now turn our attention to the impact of the definition of the poverty line on the emergent dynamics of transient and persistent poverty. Figure 1 portrays the HCR for India using different measures of the poverty line. In the present analysis, the RGBM model has been fit to Datt and Ravallion's (2009) HCR measures corresponding to the Lakdawala Committee's definition of the poverty line (Expert Group on Estimation of Proportion and Number of Poor 1993). I now fit the model with the World Bank Poverty Data between 1978 and 2012, for poverty lines of \$1.9 PPP and \$3.2 PPP. For years with missing data in the World Bank poverty time series, linear annual change is assumed to produce the complete time series 1978–2012. As is apparent from Figure 1, the poverty line definition as per the Lakdawala Committee is lower than the World Bank's \$1.9 PPP measure, and the World Bank's \$3.2 PPP is the highest among the three poverty lines.

Figure 5a illustrates the evolution of transition probabilities for the different poverty lines chosen. Two stylized facts emerge from the temporal evolution of poverty transitions. First, the higher we go in the income distribution (with different poverty line definitions), transient movements into and out of poverty become scarcer, meaning that increments in poverty line result in poverty becoming more of an absorbing state. The base case (Lakdawala Committee) poverty line reflects both higher absolute levels and the most fluctuations in transition probabilities, $p_{\mathrm{in}}(t)$ and $p_{\mathrm{out}}(t)$, over time. The temporal evolution of overall transition probability, $p_{tx}(t)$, under the base case poverty line, which represented India's national poverty line until recently, largely dominates the transition probabilities under the World Bank poverty lines all through the time frame under analysis, except toward the end of the time frame when there appears to be overlap with the time evolution of the $p_{tx}(t)$ under the \$1.9 PPP poverty line (Figure 5a). The World Bank's \$3.2 PPP poverty line represents the lowest $p_{tx}(t)$ over time, but even in this case, it appears to be converging toward the $p_{tx}(t)$ of the \$1.9 PPP poverty line over time. For instance, values for $p_{tx}(1978-1979)$ under the three poverty lines (base case, World Bank \$1.9 PPP, and World Bank \$3.2 PPP) are 0.07, 0.06, and 0.03, respectively, and the corresponding values for $p_{tx}(2005-2006)$ are 0.08, 0.06, and 0.04 (Figure 5a).

The second stylized fact from the temporal evolution of transitions is that since 1980, while the lower poverty lines (Lakdawala Committee and \$1.9 PPP) show greater probability of moving out of poverty than into it ($p_{\mathrm{out}}(t) > p_{\mathrm{in}}(t)$) over time, the higher poverty line (\$3.2) shows the opposite trend until 2010 with the transition probabilities of movement into poverty being greater than the probability of escaping

Figure 5. **Temporal Evolution of Poverty Transitions, Income Paths, and Below-Poverty-Line Gini**



BPL = below poverty line, PL = poverty line, PPP = purchasing power parity.

Notes: Figure 5a: Evolution of $p_{in}(t), p_{out}(t)$ over time under the Head Count Ratio measures of Lakdawala Committee (envelope with $p_{in}(t)$ and $p_{out}(t)$ in dashed light gray), World Bank \$1.9 PPP (envelope with $p_{in}(t)$ and $p_{out}(t)$ in dashed black), and World Bank \$3.2 PPP (envelope with $p_{in}(t)$ and $p_{out}(t)$ in dashed dark gray); and evolution of $p_{tx}(t)$ for Lakdawala Committee poverty line (solid light gray line), World Bank \$1.9 PPP (solid black line), and World Bank \$3.2 PPP (solid dark gray line) poverty lines. Poverty transitions are, over time, generally higher and show greater variability under lower poverty lines. Figure 5b: Evolution of an ensemble of selected income paths (gray: beginning below poverty line in 1952; black: beginning above poverty line in 1952) from 1952 to 2006 to illustrate the inherent fragility of incomes around the poverty line (thick dashed black line). Figure 5c: Evolution of income inequality of the population below the poverty line (BPL) as measured by the Gini coefficient. Lakdawala Committee poverty line (black line), World Bank \$1.9 PPP (light gray line), and World Bank \$3.2 PPP (dark gray line). Inequality levels are higher for BPL populations under higher poverty lines.

Source: Author's calculations.

poverty ($p_{out}(t) < p_{in}(t)$) (Figure 5a). The vulnerability of populations at and around the poverty line (especially the lower poverty lines), and their risk of cycling through poverty without being able to resiliently escape its effects, is illustrated in Figure 5b by an ensemble of income paths produced by the model, beginning just above and below the Lakdawala Committee poverty line in 1952.

The persistence of poverty also becomes more severe with higher poverty lines, which is essentially indicative of the fact that a past in poverty is progressively more predictive of a future in poverty, the higher the poverty line is within the distribution. For instance, the probability that an individual has been poor for at least 5 years, given that they are poor in the current year, is $p_{stic}(2002-2006, 5) = 0.69$ for the Lakdawala poverty line, while it is $p_{stic}(1998-2007, 5) = 0.79$ for the World Bank \$1.9 PPP poverty line and $p_{stic}(1998-2007, 5) = 0.93$ for the World Bank \$3.2 PPP poverty line.

Finally, I explore the evolution of income inequality within the poor population—the population below poverty line (BPL)—to estimate the nature of distributional change in this vulnerable part of the distribution. The Gini coefficient is found to be higher for higher poverty lines, and the evolution of the Gini coefficient over time maintains this relative ordering (Figure 5c). While the Gini coefficient for the BPL population under the Lakdawala poverty line shows, on average, a declining trend over time, it shows initial declines followed by substantial increases after 2001–2002 for the World Bank poverty lines. For instance, in 1978, the Gini coefficients for the incomes of the BPL population under the three poverty lines (base case, World Bank \$1.9 PPP, and World Bank \$3.2 PPP) were 0.18, 0.2, and 0.29, respectively. By 2000, BPL inequality had decreased across all poverty lines (BPL Gini of 0.15, 0.18, and 0.27, respectively); however, while the BPL Gini coefficient under the Lakdawala poverty line was 0.16 in 2006, it had returned to its high 1978 levels for the World Bank poverty lines by 2012 at 0.21 and 0.29, respectively. This indicates that the income distributions under higher poverty lines reflect the divergence of the higher-end of poor incomes away from those at the very bottom of the distribution. These trends are of particular concern, as they potentially reflect the sustained povertization of the poorest of the poor—the bottom decile and bottom percentile. This is supported by our previous results on sustained real income losses at the bottom of the Indian income distribution since 2000 (Sahasranaman and Jensen 2021).

V. Discussion

Our model suggests that transitions into and out of poverty are common through the entire review period from 1952 to 2006, albeit with significant variations over time, and the limited empirical findings on transient poverty appear to be in broad concurrence with these findings. There is, for instance, a recognition that escaping from poverty in India is a fragile process, and many studies have examined the phenomenon of households transitioning into poverty as a consequence of multiple factors such as health shocks, agricultural productivity shocks, and social expenses (Flores et al. 2008, Mohanty et al. 2017, Selvaraj and Karan 2009, Shahrawat and Rao 2012, Keane and Thakur 2018, Naik 2009, Brey and Hertweck 2019, Krishna 2006, Krishna et al. 2005). Out-of-pocket expenses on health are identified as one of the most significant reasons for households slipping into poverty (Krishna 2006), with estimates that the additional population pulled into poverty due to such expenses increased from about 26 million during 1993–1994 to about 39 million during 2004–2005 (Selvaraj and Karan 2009). This increase in the number of individuals falling into poverty is found to be largely drawn from those just above the poverty line; the poorest quintile in the above-poverty-line population experienced a poverty headcount increase of 17.5% (Shahrawat and Rao 2012). Indeed, it is estimated that if out-of-pocket expenditure were not considered consumption and included as necessary expenditure, it would have pushed 50 million people below the poverty line during 2011–2012 (Keane and Thakur 2018). Even those households that are able to cope using mechanisms such as debt to tide over short-term health shocks face significant long-term poverty risks on account of servicing the high-cost debt and depleted stocks of wealth to weather future shocks (Flores et al. 2008). The multidimensionally poor in poorer regions are also found more likely to face catastrophic health shocks and, by definition, least able to afford health services (Mohanty et al. 2017).

Given rural India's dependence on the annual monsoons for crop harvests, it has been found that the occurrence of droughts is associated with transitions into poverty, especially in places where failure of rainfall is compounded by irrigation failure as well (Krishna 2006). In the event of severe crop shocks, even richer rural households are vulnerable to spells of poverty (Gaiha and Imai 2004). Regional droughts are found to have important distributional consequences in the medium run, with the decline in the real incomes of agricultural workers making them vulnerable to poverty (Brey and Hertweck 2019). In addition to risks associated with health and weather shocks, expenditures on social functions, weddings, and funerals are also observed to push individuals and households into poverty (Krishna 2006). These findings suggest that transient poverty is a significant economic phenomenon driven by specific event risks related to health and weather, as well as predictable but unplanned social expenditure.

Evidence on persistent poverty suggests that structural factors such as social group, land ownership, infrastructure, market access, and informal debt are drivers of this phenomenon (Mehta and Shah 2003, Flores et al. 2008, Bhide and Mehta 2005, Deshingkar 2010). Individuals in socially marginalized communities, such as Scheduled Caste and especially Scheduled Tribe populations, are found to be disproportionately represented in the chronic poor (Bhide and Mehta 2005, Mehta and Shah 2003).[2] Land is the only private asset, in addition to local public infrastructure, that is found significantly correlated with poverty persistence (Bhide and Mehta 2005, Mehta and Shah 2003). The rise of household debt to tide over health emergencies or social functions—especially from informal, high-cost sources—is a source of long-term risk that could be keeping households poor over prolonged periods of time (Flores et al. 2008, Krishna 2006).

An understanding of poverty based simply on static metrics like the HCR gives us no insight into the nature and extent of poverty dynamics that we have seen. Our model outcomes highlight the fact that both transient and persistent poverty are nontrivial aspects of emergent dynamics that occur over differing time scales, and therefore possibly demand distinct strategies to combat their impacts.

Given the importance of single event impacts on causing transient poverty, and our ability to categorize these primarily as health and weather risks, there is a need for effective risk management tools to counter them. The poverty impacts of completely predictable social expenditures (e.g., functions, weddings), on the other hand, require financial planning and saving tools. Essentially, these solutions call attention to the need for access to functioning financial markets that enable low-cost, efficient, and scalable insurance, investment, and savings solutions.

Addressing the causes of persistent poverty will, however, require active state intervention. Issues of land, infrastructure, and market access require a combination of long-term legislative action and administrative implementation to be meaningfully addressed over time.

VI. Conclusion

I model the long-term dynamics of poverty in India using a simple stochastic model, RGBM. Using income inequality data to fit the model, we study trends in both transient and persistent poverty for the period 1952–2006.

[2]Scheduled Castes are communities within the framework of the caste system who have historically faced deprivation, oppression, and isolation. Scheduled Tribes are communities that have been historically distinguished by geographic isolation and socioeconomic neglect. These categories are recognized by the Constitution of India, which incorporates a number of safeguards for the protection of the rights of these communities.

I find that both transient and persistent poverty are significant emergent phenomena of India's poverty dynamics. The transition probability of individuals moving into and out of poverty annually shows significant fluctuation over time but is primarily driven by higher fractions of individuals moving out of poverty and fewer transitions into poverty over time. While this is a desirable outcome, it is important to recognize that incomes around the poverty line remain fragile, with recent trends revealing that close to 4% of individuals slip into poverty annually.

Studying the persistence of poverty, we find that over time, the likelihood of an individual having been poor for a long duration, given that they are poor at present, has been declining. Even as persistence is declining, this decline has been slow, and the persistence of poverty remains significant. For instance, the likelihood that an individual was poor for 10 years, given that he or she is currently poor, declined from 0.7 in 1972–1981 to 0.61 in 2002–2006, undoubtedly indicating progress but also highlighting that current poverty remains a reliable predictor of long-term past poverty.

I also explore the impact of the definition of the poverty line on poverty dynamics and find that transient poverty becomes less pronounced as the poverty line is increased; correspondingly, the persistence of poverty also appears to increase.

The distinct dynamics of transient and persistent poverty also potentially require disparate strategies to counter them. Transitions into poverty appear to be driven by event shocks due to health or weather-related risks; the availability of well-functioning financial markets for insurance and savings will be essential to the mitigation of these risks. Countering the systemic causes of persistent poverty such as land, infrastructure, and market access, on the other hand, requires concerted, long-term action by the state.

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