Distributional dynamics of income in Indian states: Inequality, reallocation, and income transitions

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Abstract:

We study the distribution of income across Indian states for 2014-19 and find significant heterogeneity in income inequality. Particularly concerning in terms of high inequality are states of Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Maharashtra, Gujarat, Punjab, and Haryana – both income shares and real income growth in the bottom decile have declined from 2014 to 2019 in almost all these states. We also find that, across states, while Scheduled Caste and Scheduled Tribe populations and small/marginal farmers and labourers are disproportionally represented at the bottom of income distributions, these groups are most economically impoverished and increasingly vulnerable (due to declining real incomes) in the high inequality states. Using a stochastic model of income growth, we find that states with high inequality are characterized by a negative redistribution of resources from poor to rich, raising concerns about the future of low incomes in these states. The situation is further exacerbated as our model findings also suggest that bottom incomes in the high inequality states show higher likelihood of being stuck in the lowest parts of the income distribution, meaning that a past in deep poverty is highly predictive of a future in deep poverty in these states. Lower inequality states exhibit dynamics that enable greater possibility of movement out of the bottom decile. Overall, given declining real incomes, caste and occupational composition, and risk of persistently deep poverty in the bottom deciles of high inequality states, the most critical concern of economic policy is design of appropriate sustained income support programs for these vulnerable populations.

Keywords: Income, inequality, distribution, states, India, dynamics, sub-national

JEL: D31, O15, D63

1. Introduction

We study the distribution of income in Indian states and explore the dynamics underlying income inequality, especially focusing on changes in bottom incomes over time. While economic inequality has been an animating concern underlying economic policymaking in independent India, the lack of periodic income data has been a significant impediment in understanding the true nature and extent of the phenomenon (Banerjee & Piketty, 2005; Chancel & Piketty, 2019; Deaton & Dreze, 2002; Kohli, 2012; Dev & Ravi, 2007; Sahasranaman & Jensen, 2021). In this context, measurement of inequality in India has been limited to consumption inequality, obtained from the regularly conducted National Sample Surveys (NSS). More recently, the two rounds of the India Human Development Survey (IHDS) provide a nationally representative panel with income data for 2004-05 and 2011-12. Using multiple sources, including tax records, NSS, and IHDS surveys, Chancel and Piketty (2019) constructed the Indian income distribution for 1922-2015, thus producing the longest yet time series of income for India. Using this, they were able to quantify the extent of increase in income inequality since the 1980s, which saw top 10% of incomes increasing their share from 31% of total income in 1981 to 56% in 2015 (Chancel & Piketty, 2019). While these data make possible a study of income inequality at the coarse-grained national level, they still do not provide a representative picture of the income distribution at finer-grained sub-national levels of the state and the district.

At the level of states, the literature on income distributions is sparse, with extant work primarily using NSS consumption data to study consumption inequality across states. Comparing consumption inequality across 17 states in the pre- and post-reform periods (1983-2005), it was found that inequality either increased, or declined at a slower pace, in the post-reform period in most states (Dev & Ravi, 2007). States with low poverty like Kerala, Punjab, and Jammu and Kashmir were found to have higher income and inequality elasticities, implying that continued poverty reduction would require reduction in inequality in addition to growth; while, states with high poverty such as Uttar Pradesh, Bihar, and Madhya Pradesh had low income and inequality elasticity, meaning that growth was more important than redistribution in these states (Dev & Ravi, 2007). Using NSS data for 1999-2000 to 2006-07, consumption inequality was found to increase with rising state incomes (Arora, 2011). Between 1993-94 and 2004-05, intra-state consumption inequality was found have increased in Gujarat, Haryana, Kerala, Orissa, and Punjab (Dubey, 2009). In the absence of income data, non-economic data such as Night Time

Lights have also been used to proxy regional income, and based on this method, southern and western regions of India were found, on average, to have higher income inequality than other parts of the country (Singhal, Sahu, Chattopadhyay, Mukherjee, & Bhanja, 2020). While lack of data constrains our ability to study long-term trends in state-level income, it is now possible to empirically construct and examine recent state-level income distributions using data from the Consumer Pyramids Household Survey (CPHS) - a household panel survey representative at the level of states, which has been capturing income data since 2014.

Using this data, we propose to explore the dynamics of redistribution and income transition occurring in states across India, with a particular focus on the bottom of the income distributions. Our work has three objectives. First, we seek to characterize states based on levels of income inequality, as well as income shares and real income growth at different points in the distribution. Second, we explore the composition of the bottom of state income distributions in terms of caste and occupational profiles, and assess the extent of state contribution to the bottom of the national income distribution. Finally, we model the nature and extent of reallocation occurring within state income distributions and also the corresponding dynamics of income transitions occurring across the bottom of these distributions. We contextualize the heterogeneity of reallocation and transition dynamics across states in view of our empirical assessment of state income distributions.

2. Data and Methods

We use the data from the CPHS pan-India panel household survey of ~170,000 households, collecting monthly data on a range of household-level attributes such as occupation, income, consumption, and demographics. This data, representative at both national and state levels, is available since 2014.

The household income data is the basis we use to construct the income distribution for each state – we do this by adjusting each income by the appropriate weighting factor (provided by CPHS) to ensure apposite representation of all household types in the state's income distribution. Monthly income distributions for each state are obtained by ordering the list of weighted household incomes and dividing this set of incomes into percentiles (100 equi-sized income buckets). Once we construct the monthly percentiles, the annual income distributions for each year and for each state are obtained by adding corresponding monthly percentiles over the 12 months for that year and state.

Having thus constructed the annual income distributions, we compute the income shares of each percentile as the total income in that percentile to the total income in the entire distribution. Given our focus on the bottom of state income distributions and the general problem of under-estimation of top incomes in income surveys, we use the following metric for income inequality: $S_{50\%}/S_{10\%}$, where $S_{50\%}$ is the income share of the bottom half of the distribution and $S_{10\%}$ is the share of the bottom decile of the distribution. In a perfectly equal distribution, this ratio would be 5, but real-world income distributions will have values greater than 5, and the higher the ratio, the greater is the inequality of the income distribution.

Using population weight data from CPHS we compute average annual incomes for each ventile and decile for each state. For the period 2014-19, we calculate the real annual growth rate in average income at each ventile and each decile for each state, adjusting for annual inflation (data obtained from RBI (2021)). These real annual growth rates at each ventile/decile allow us to construct the complete Growth Incidence Curves (GICs) for all states.

We also use the CPHS demographic and occupational data to derive the caste and occupational composition for each ventile/decile for each state, allowing us to examine these characteristics across different parts of the income distribution and across states.

Finally, in order explore the nature and quantum of reallocation occurring within income distributions of states over time, we us a stochastic model of multiplicative income growth with redistribution - Geometric Brownian Motion with Reallocation or RGBM (Berman, Peters, & Adamou, 2017). RGBM models income dynamics using (Eq. 1):

$$dx_i = x_i(\mu dt + \sigma dW_i) - \tau(x_i - \langle x \rangle_N), \text{ where } \langle x \rangle_N = \frac{1}{N}\sum_{i=1}^{n} x_i \qquad (1)$$

dx_i is the change in i's income over dt, μ and σ are the drift and volatility of income, dW_i is the increment in a Wiener process with mean 0 and variance dt, and $\langle x \rangle_N$ is the mean income. τ is the parameter that captures the reallocation of resources within the income distribution and can be interpreted as the cumulative redistribution occurring in an economy. $\tau > 0$ indicates that resources are being transferred down the distribution, and is what we would expect in modern economies with progressive taxation structures; while $\tau < 0$ (especially if prolonged over time) represents the perverse situation of redistributions upwards – from poor to rich.

As is apparent from Eq. 1, RGBM models income growth as Geometric Brownian Motion, which yields a broadening lognormal distribution over time, but with a reallocation parameter τ to capture transfers within the distribution. Such a distribution is consistent with empirical observations of distributions of wealth and income, which are generally found to exhibit lognormal or stretched exponential bodies and power law tails (Chatterjee, Chakrabarti, Ghosh, Chakraborti, & Nandi, 2016; Ghosh, Gangopadhyay, & Basu, 2011; Banerjee, Yakovenko, & Di Matteo, 2006; Drăgulescu & Yakovenko, 2001; Souma, 2001).

In order to implement the model, we need to obtain μ and σ for each state. μ is obtained by estimating the exponential fit $\langle x(t)\rangle_N = \langle x(t_0)\rangle_N e^{[\mu(t-t_0)]}$ on a time series of state per capita income data (available for all states at Niti Aayog https://niti.gov.in/state-statistics). Estimating μ in this way, yields the following values for each of the 23 states in our analysis (Tab. 1).

State	$\boldsymbol{\mu}$
Andhra Pradesh	0.0600
Assam	0.0416
Bihar	0.0331
Chhattisgarh	0.0427
Delhi	0.0580
Goa	0.0740
Gujarat	0.0604
Haryana	0.0562
Himachal Pradesh	0.0646
Jammu & Kashmir	0.0446
Jharkhand	0.0420
Karnataka	0.0607
Kerala	0.0736
Madhya Pradesh	0.0452
Maharashtra	0.0567
Odisha	0.0478
Punjab	0.0411
Rajasthan	0.0526
Tamil Nadu	0.0693
Telangana	0.0726
Uttar Pradesh	0.0353

Uttarakhand	0.0795
West Bengal	0.0479

Table 1: *Estimates of drift parameter (μ) for Indian states*

We do not have access to similar, consistent time series of granular data on wages or income or commodity prices across states that would enable us to parametrize σ at the state-level. Given this constraint, we use the same value of σ as we used for the pan-Indian income distribution in Sahasranaman and Jensen (2021), which was estimated using all-India time series data on wholesale prices for staples such as rich, wheat, and jaggery, as well as short-term time series of wages. Thus, we use $\sigma = 0.15$ for all states in the analysis.

Having computed μ and σ, we simulate an initial set of $N = 100{,}000$ incomes from a lognormal distribution such that the modelled cumulative income of the bottom half of the distribution closely matches the observed income of the bottom half in 2014. Once incomes are initialized, Eq. 1 is executed over these $100{,}000$ incomes over $t = 5$ time periods (2014-15 to 2018-19), so that at each time t, the reallocation parameter $\tau(t)$ is obtained by minimizing the distance $|S_{50\%}^{mod}(t) - S_{50\%}(t)|$, where $S_{50\%}^{model}(t)$ is the income share of the bottom half of the simulated income distribution and $S_{50\%}(t)$ the income share of the bottom half of the empirical distribution. This results in a time series of $\tau(t)$ for each state in our analysis and each of these time series describes the dynamics of redistribution for a particular Indian state.

Once we have constructed the time series of income distributions for a state, not only can we assess the dynamics of reallocation as explicated by τ, but also use this synthetic time series of incomes to study the dynamics of income transition in the lower half of the income distribution. Essentially, this analysis will enable us to ascertain the probabilities of transitioning into and out of different points in the distribution. Given our interest in the bottom of the income distribution, we will specifically study transitions across the first decile. This methodology was developed in Sahasranaman (2021), and a detailed exposition can be found there. Given the short time series available to us, we focus on both stickiness to the first decile and escape from the first decile. The escape probability $p_{esc}(t, t_{D1})$ is the probability that an individual has been in the first decile for a spell of at least t_{D1} years (consecutively) at year $t - 1$, given that the individual has transitioned out of the first decile at year t (Eq. 2):

$$p_{esc}(t, t_{D1}) = \frac{N_{1\rightarrow}(t, t_{D1})}{N_{\neg 1}(t)}, \quad (2)$$

where, $N_{1\rightarrow}(t, t_{D1})$ is the number of individuals who have been in the first decile for at least t_{D1} continuous years at year $t-1$ and transitioned out of the first decile at time t; and $N_{\neg 1}(t)$ is the population outside the first decile at t.

Similarly, the persistence probability $p_{stic}(t, t_{D1})$ is (Eq. 3):

$$p_{stic}(t, t_{D1}) = \frac{N_1(t, t_{D1})}{N_1(t)}, \quad (3)$$

where, $p_{stic}(t, t_{D1})$ is the probability that an individual has been in the first decile for at least t_{D1} consecutive years at $t-1$ given that she is in the first decile at year t; $N_1(t, t_{D1})$ is the number of individuals who were in the first decile for a contiguous spell of at least t_{D1} years at time $t-1$ and remain in the first decile at time t; and $N_1(t)$ is the population of the first decile at t. For our analysis, we use $t_{D1} = 1$ and $t_{D1} = 5$, to study stickiness to and escape from the bottom of the distribution at the very short-term and short-to-medium-term time scales.

In previous work, we have simulated the dynamics of redistribution for the Indian income distribution for 1951-2015 and found that the Indian income distribution entered a regime of persistent negative reallocation ($\tau < 0$) post 2000, meaning that there has been a sustained transfer of resources from poor to rich in the past 2 decades (Sahasranaman & Jensen, 2021; Sahasranaman & Kumar, 2020). Using these simulated income distributions for India, we also find that transient or annual transitions into poverty over time are common over time, but that transitions out of poverty outnumber transitions into poverty in recent decades; additionally, poverty is found to be persistent, and despite a gradual decline in persistence over time, a past in poverty remains a good predictor of current poverty (Sahasranaman, 2021).

Our work here gives us the opportunity to explore the dynamics at a lower level of aggregation – states – and attempt to understand the heterogeneity in redistribution and transition dynamics at this scale.

3. Empirical examination of income distribution and inequality of Indian states

We find that income inequality measured as the ratio of income share of the bottom half of the population to the income share of the bottom decile ($S_{50\%}/S_{10\%}$) shows considerable variation across states. In 2019, we find that the states of Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Maharashtra, and Gujarat have ratios of 25 and above, with Uttar Pradesh's ratio at 93 (Fig. 1a, black dashed line). This indicates high levels of income inequality as income share of the bottom decile is dramatically lower than that of the bottom half. On the other hand, the states of Kerala, West Bengal, Odisha, Jharkhand, Assam, and Rajasthan have ratios below 8 (a perfectly equal distribution has a ratio of 5), indicating that the distribution is tighter and that the poorest in the income distribution are, on average, closer to the median of the state than the poorest in states like Uttar Pradesh and Telangana. We also find that the magnitude of income inequality appears to be uncorrelated with the per capita income of states ($R^2 = 0.02$) - for instance, states like Telengana and Maharashtra which have higher than average state per capita incomes as well as states like Uttar Pradesh and Chattisgarh with lower than average state per capita incomes, exhibit high income inequality ($S_{50\%}/S_{10\%} > 25$); while, on the flip side, Himachal Pradesh and Kerala with high state per capita incomes along with West Bengal and Orissa with low per capita incomes exhibit low income inequality (Fig. 1a, dark grey columns).

While average income shows no systematic relationship with inequality, it is important to ask the question of whether levels of the lowest incomes in states show a stronger relationship with income inequality. This is also pertinent because, while the analysis thus far gives us a sense of inequality within the income distribution, the picture is incomplete without taking into account the income levels at the bottom of the distribution. For instance, while West Bengal and Odisha have lower inequality than Maharashtra and Gujarat, and Maharashtra and Gujarat have higher per capita incomes – how do the populations at the bottom of these state distributions compare in in actual monetary terms? In order to assess income levels at the bottom, we compute the per capita income of the lowest income deciles in each of the states, and find that this quantity shows exponential decay with income inequality ($R^2 = 0.66$) (Fig. 1b). The states with the highest income inequality have, on average, the lowest per capita incomes for the bottom decile, while states with low income inequalities have higher per capita incomes for this decile (Fig. 1a, light grey columns). The highest income inequality states of Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Maharashtra, Gujarat, and Punjab have the lowest per capita incomes for their first income deciles amongst all states. This analysis reveals a critical distributional aspect of state incomes – that behaviour in different parts of the distribution reveal distinct, even contradictory, dynamics.

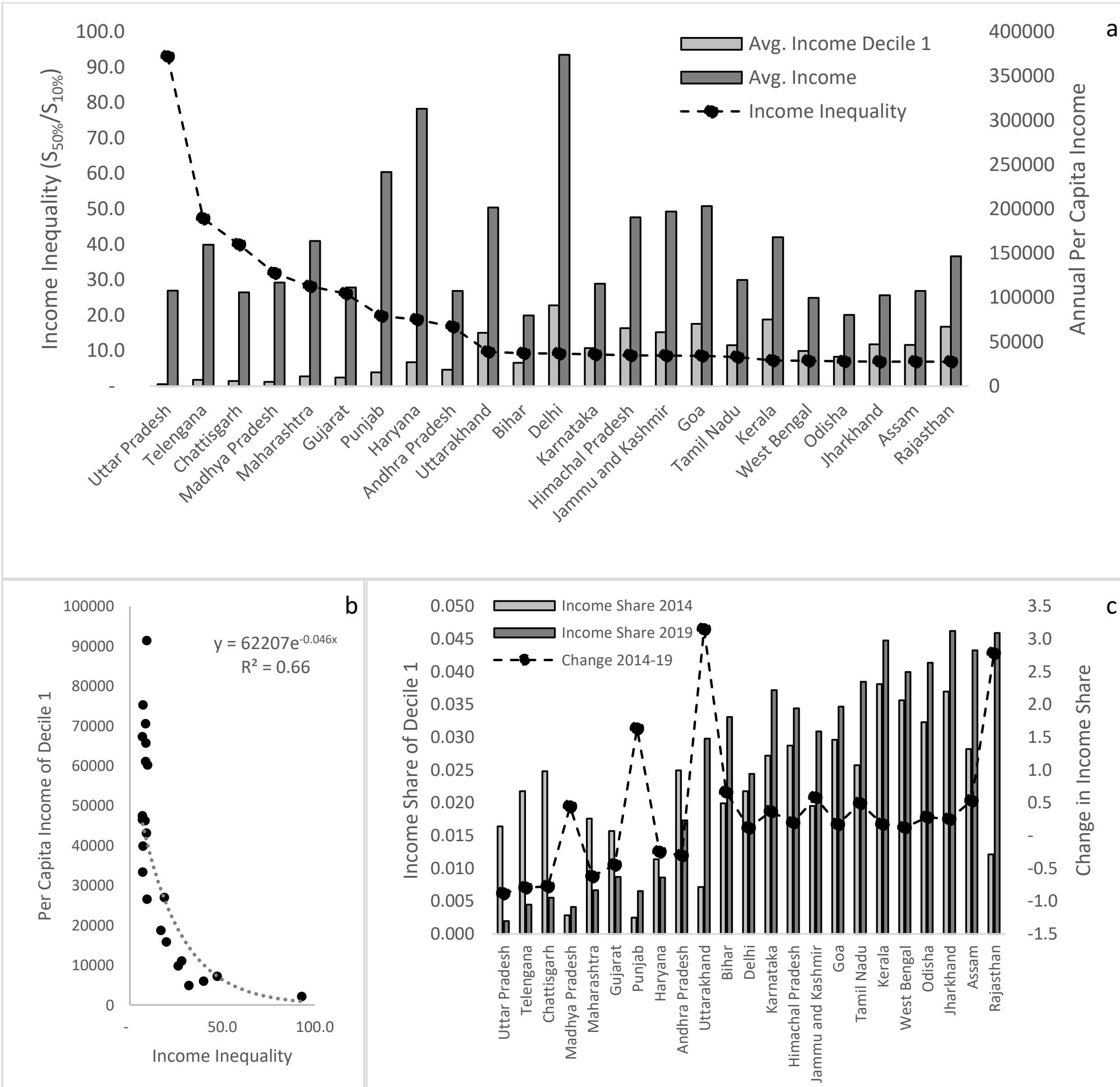

Figure 1: *Income share, Per capita Income, and Income Inequality.* A: Income inequality and per-capita income in Indian states 2019. Income inequality measured as $S_{50\%}/S_{10\%}$ is depicted by the black dots. The dark grey columns and light grey columns represent per capita annual income and per capita annual income of the first decile respectively. B: Per capita annual income of the first decile v. Income inequality (2019) describes an exponentially declining relationship. C: Income share of first decile 2019 and change in income share for first decile 2014-19. Light grey and dark grey columns describe income share of the first decile for states in 2014 and 2019 respectively. Black dots represent the change in income share of the first decile for states between 2014 and 2019.

Such dynamics are brought into sharp relief when we compare states generally regarded as richer (based on overall per capita income), such as Telangana, Maharashtra, Punjab, and Gujarat which have very low levels of per capita incomes for their lowest decile vis-à-vis poorer states like Bihar, Orissa, and West Bengal, whose bottom deciles, we find, have higher per capita incomes than those of the richer states. Therefore, the poorest populations in some of the 'richest' states have lower incomes than the poorest populations in the 'poorer' Indian states, indicating that poverty is deeper in these richer states despite their higher average incomes.

When we study the temporal evolution of income shares of the bottom decile (Fig. 1c), we find that the states with the highest income inequality in 2019 such as Uttar Pradesh, Telangana, Chhattisgarh, Maharashtra, Gujarat not only had the lowest income shares for their bottom deciles in 2019 (Fig. 1c, light grey columns), but also had the sharpest declines in income shares from 2014-19, at -88%, -80%, -78%, -62%, and -44% (Fig. 1c, black dashed line). States with lower inequality, however, all exhibited both higher income shares of the bottom decile and an increase in income share between 2014 and 2019. Thus, the poorest in the high inequality states have also seen a decrease in their relative share of income over time, further highlighting concerns about deepening povertization at the very bottom of the income distribution in these states.

While the change in income shares provides us with a sense of the temporal dynamics of the income distributions, we now seek to complete this picture with the change in actual incomes over time. Essentially, how does the average income of the bottom decile change from 2014-19 across all states – do declining income shares still enable for rising real incomes or do we see declining real incomes as well? In order to answer this question, we construct the Growth Incidence Curves (GICs) for all states from 2014-19 and find that the highest inequality states which also saw declines in income share of bottom decile for 2014-19, experienced declines in real income as well (Fig. 3a). Average incomes of the bottom decile fell in Uttar Pradesh, Telangana, Chhattisgarh, Maharashtra, and Gujarat by 34%, 21%, 20%, 16%, and 8% respectively. All other states that saw an increase in income share from 2014-19 also experienced real growth in incomes. The only exception to this trend was Haryana, which saw -25% decline in income share of the bottom decile, yet experienced real income growth of 8% from 2014-19 (Fig. 2a).

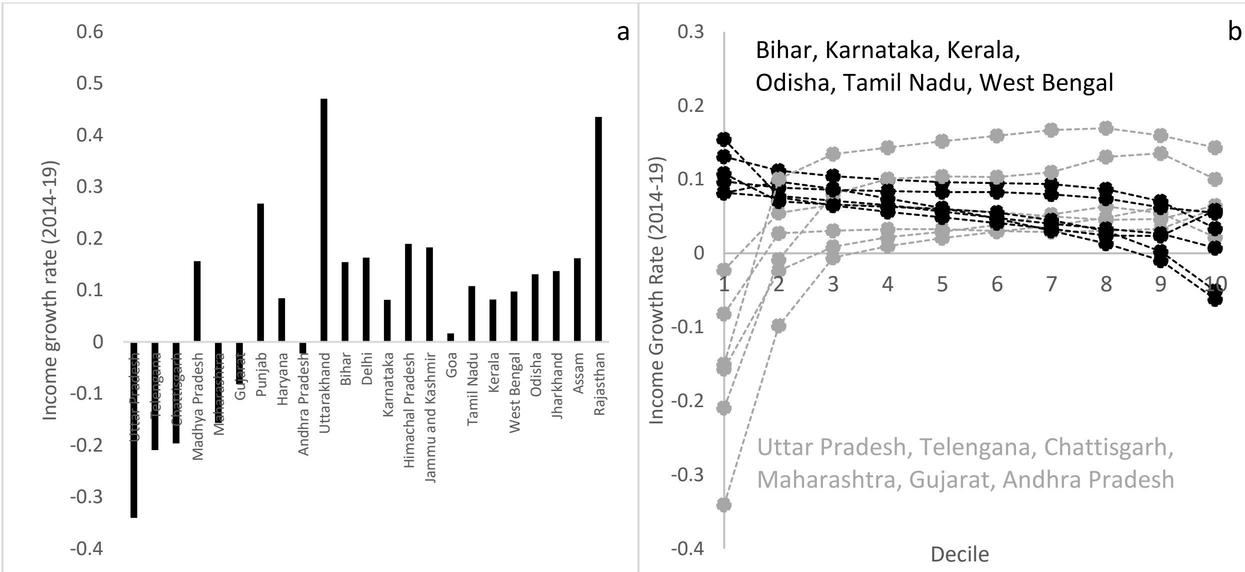

Figure 2: *Growth Incidence Curves*. A: Growth rate of average Decile 1 income across states (2014-19). The highest inequality states, on average, exhibit negative income growth. B: Growth Incidence Curves for states (2014-19). Lower inequality state GICs (black) describe a progressive growth curve with lower incomes exhibiting higher growth rates, while higher inequality state GICs (grey) exhibit a regressive curve with lower incomes having lower (and negative) growth rates.

Fig. 2b provides the complete GICs for a select set of states to illustrate the nature of income growth at different points in the income distribution. For states with lower income inequality, we find that the GICs decline (on average) as we move higher in the distribution, indicating the progressive nature of income growth - with the poorest gaining from highest income growth and richer populations experiencing progressively lower growth (Fig. 2b, black dashed lines). On the other hand, we notice that the nature of GICs for high inequality states is markedly distinct – with the poorest populations experiencing negative growth, and rising growth rates higher in the distribution (Fig. 2b, grey dashed lines). Specifically, the GICs for Uttar Pradesh, Telangana, and Maharashtra reveal that it is not just the bottom decile, but the bottom two deciles (three in the case of Uttar Pradesh), that experience negative real income growth from 2014-19. Therefore, the phenomenon of declining real incomes impacts a quite substantial portion of the income distributions of these three states.

Overall, this analysis of income shares and real income growth across states reveals the heterogeneity in income inequality across states of the nation, and highlights states of most significant concern – Uttar Pradesh, Telangana, Maharashtra, Chhattisgarh, Madhya Pradesh and Gujarat. The high levels of inequality in these states is compounded both by very low levels of real income at the bottom of the distribution and by negative growth rates of these incomes over time in almost all cases. Punjab and Haryana are other states with worrying trends on inequality and income shares of the poorest.

4. Composition of bottom of state and national income distributions

With this understanding in place, we now turn our attention to the composition of the bottom of the state income distributions and the contributions of states to the bottom of the national income distribution. Specifically, we are interested in the caste and occupational characteristics of populations at the very bottom of state income distributions. In a completely random (equal) society, 10% of the population of every caste or occupation would comprise each decile of the income distribution. However, real distribution of castes and occupations reflect historical structural inequities, and this is evinced in the composition of the bottom income deciles. We find that over 10% of the population of historically marginalized communities like Scheduled Caste (SC) and Scheduled Tribe (ST) comprise the bottom decile for all states under consideration, except for West Bengal, Himachal Pradesh, Goa, and Jammu and Kashmir (Fig. 3a). Punjab (26%), Delhi (26%), Haryana (22%), Gujarat (18%), Madhya Pradesh (17%), and Kerala (16%) have the highest proportion of SC and ST populations in their bottom decile (Fig. 3a). We also find that the fraction of SC and ST populations decline as we progress higher in income distributions across almost all states. The trajectory of Upper Caste populations however follows the opposite trend – under-represented in the bottom deciles and over-represented in the higher deciles. Delhi and Kerala are relatively lower income inequality states where both incomes shares and real incomes of the bottom decile - comprising considerable proportions of SC and ST population - have been increasing. On the other hand, Madhya Pradesh, Gujarat, Punjab, and Haryana are amongst high income inequality states and the substantial SC and ST populations in their bottom deciles are beset with rising economic vulnerability.

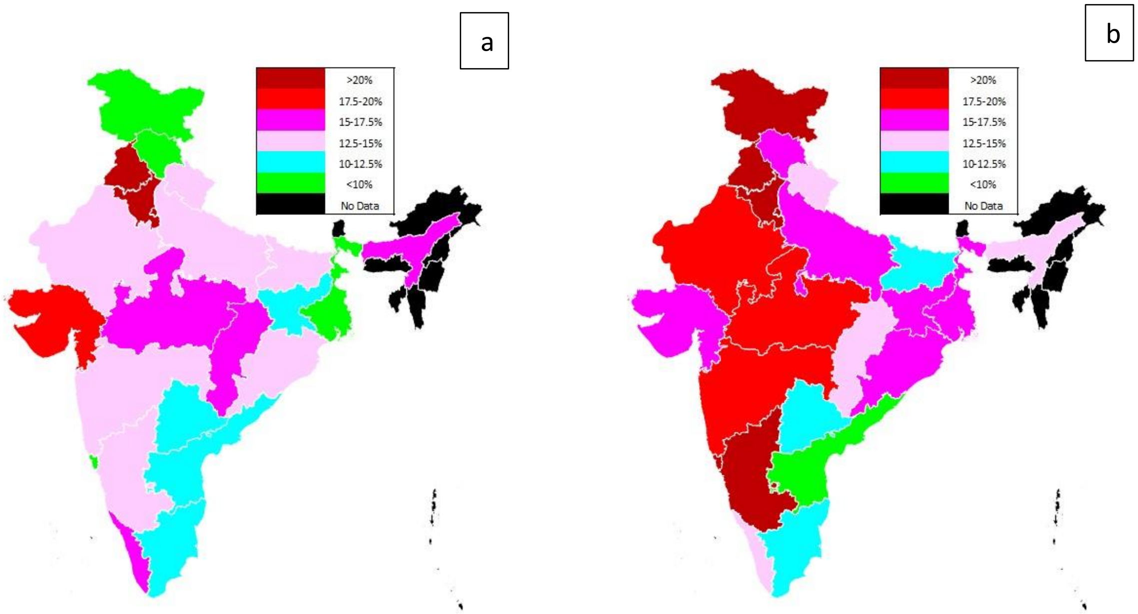

Figure 3: *Caste and occupation in income distribution*. A: Composition of SC/ST castes in the bottom decile of state income distributions (2019). B: Composition of Small/Marginal Farmers & Agricultural and Wage labourers in the bottom decile of state income distributions (2019). Across states, on average, Scheduled Caste and Scheduled Tribe populations as well as small and marginal farmers and labourers (agricultural and wage) are disproportionately represented in the bottom decile of state income distributions.

When we consider the occupations of small and marginal farmers as well as agricultural and wage labourers, once again we find a skewed distribution across the income deciles with the bottom decile of a majority of states accounting for over 15% of these occupations (Fig. 3b). Specifically, we find that the concentration of small and marginal farmers is particularly acute in the bottom deciles of Jammu and Kashmir (37%), Gujarat (35%), Karnataka (24%), Maharashtra (17%), Rajasthan (17%), and Uttar Pradesh (17%), while the bottom deciles of Uttarakhand (69%), Haryana (48%), Delhi (44%), Goa (40%), and Punjab (39%) account for a significant proportion of labourers. Among these states, it is the farmers and labourers in the bottom income deciles of the high inequality states of Gujarat, Maharashtra, Uttar Pradesh, Haryana, and Punjab that present the most significant concern.

Therefore, assessing the caste and occupational make-up of the most economically vulnerable populations across states in India reveals that already structurally discriminated against SC and ST communities as well as small/marginal farmers and landless labour employed in the unorganized sector are disproportionately represented at the very bottom of income distribution across states – and, in particular, their economic condition is becoming increasingly precarious in the high inequality states due to low income shares and declining real incomes. Analyzing the magnitude of vulnerable populations across the six most unequal states of Uttar Pradesh, Telangana, Maharashtra, Chhattisgarh, Madhya Pradesh and Gujarat, reveals the following – from a caste perspective, SC and ST communities comprise 42% of the bottom decile population; and on the basis of occupation, small/marginal farmers and labourers comprise 62% of the bottom decile.

In previous work, we saw that the bottom ventile as well as the 6th and 7th percentiles of the Indian income distribution saw negative real income growth for 2014-19 (Sahasranaman & Kumar, 2020). When we study the contribution of various states to the bottom of the Indian income distribution, we find that 60% of the bottom decile of the Indian income distribution is comprised of populations from four states – Uttar Pradesh (27.5%), Madhya Pradesh (20.2%), Gujarat (6.5%), and Maharashtra (5.5%). On the other hand, Rajasthan, Kerala, Jharkhand, Jammu and Kashmir, Himachal Pradesh, Goa, Delhi, Assam, and Uttarakhand contribute less than 0.5% of the national bottom decile (Fig. 4).

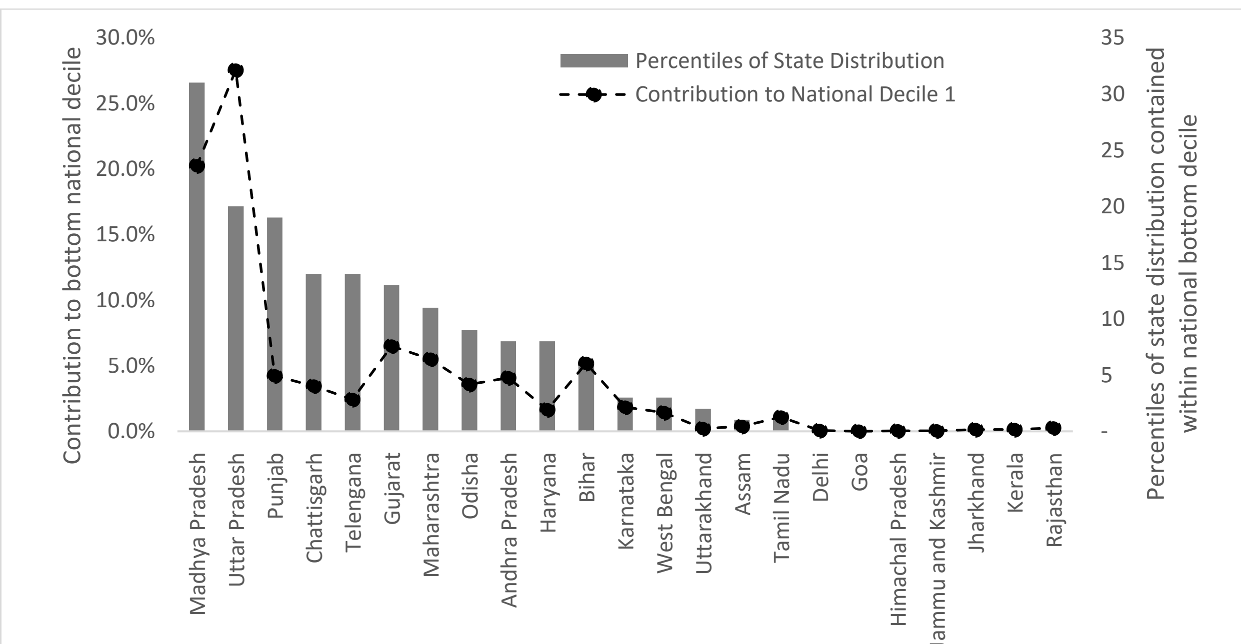

Figure 4: *Composition of national bottom decile by states*. Number of percentiles of state income distributions within the national bottom decile (grey columns) and Proportion of national bottom decile contributed by each state (black dots). Higher inequality states, on average, contribute more to the bottom decile of the national income distribution than lower inequality states.

When we study how this translates in terms of the number of percentiles at the bottom of individual state distributions that are also in the bottom decile of the national income distribution, we find that Madhya Pradesh (31 percentiles) and Uttar Pradesh (20 percentiles) are the most significant contributors. Other states with a substantial contribution are: Punjab (19 percentiles), Chhattisgarh (14 percentiles), Telangana (14 percentiles), Gujarat (13 percentiles), and Maharashtra (11 percentiles). Once again, his composition reiterates our finding that states considered richer based on per capita income like Punjab, Gujarat, Telangana, and Maharashtra are much more significant contributors to the bottom decile of the Indian income distribution than poorer states like Bihar (5 percentiles), West Bengal (3 percentiles), Orissa (9 percentiles), and Jharkhand (1st percentile).

5. Dynamics of reallocation and transition in state income distributions

We execute the RGBM algorithm described in Section 2 for all states in the analysis, to uncover the dynamics of reallocation occurring within each state's income distribution. We find close correspondence between the modelled outcomes on income shares for the bottom 5 deciles and empirically observed shares across all states. Given this agreement between model and empirics, we turn to the dynamics revealed by the reallocation parameter τ for the high inequality states – Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Maharashtra, Gujarat, Punjab, and Haryana. As Fig. 5 demonstrates, out of the 5 time periods under consideration (2014-15 to 2018-19), τ is negative for 2 to 3 periods for each of these states and is either negative or close to 0 in 2019, implying that these states appear to be constantly at the cusp of negative reallocation – a situation where resources are transferred from the bottom of the distribution to the top, rather than from top to bottom as we would expect in a modern, progressive economic system.

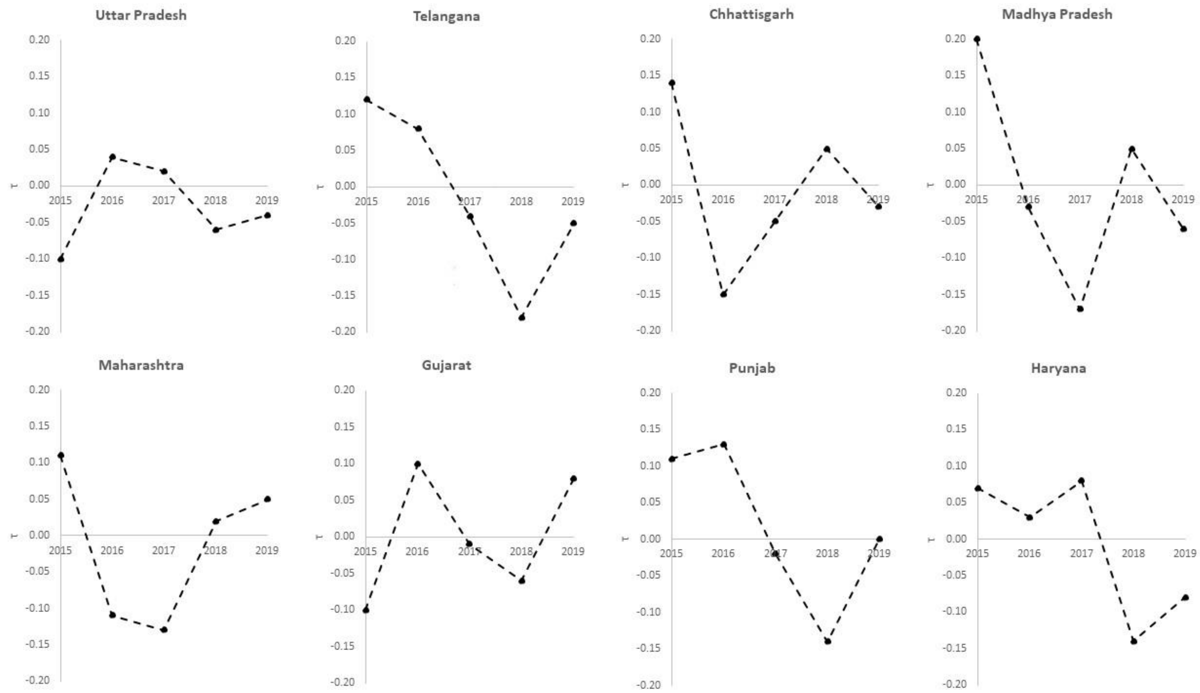

Figure 5: *Evolution of τ for high inequality states*. τ is negative for 2 or 3 years out of the 5 under consideration, implying that reallocation is hovering at or below 0 on average. This raises concerns for the direction of reallocation going into the future.

Prolonged negative reallocation over time is a cause for significant concern because that would indicate the real risk that incomes in the distribution are diverging and that the poor are being driven into deeper poverty, while enabling the rich to become even richer. We see evidence of such a trend in the GICs for the high inequality states, with the bottom decile seeing real income declines over 2014-19 for almost all of these states (Fig. 2a); the concern emerging from the dynamics of τ is the possibility of such a trend continuing into the future. Indeed, prior work has highlighted the concern that the Indian income distribution as a whole has been in a regime of negative reallocation since the early 2000s, with the possibility that the bottom decile of the distribution has seen negative income growth since then (Sahasranaman & Jensen, 2021; Sahasranaman & Kumar, 2020).

For low inequality states, the general trend of τ is positive, meaning that resources are transferred, as we would expect, from richer to poorer in the distribution (Fig. 6). This is also reflected for 2014-19 in the positive growth rates of bottom decile incomes for these states.

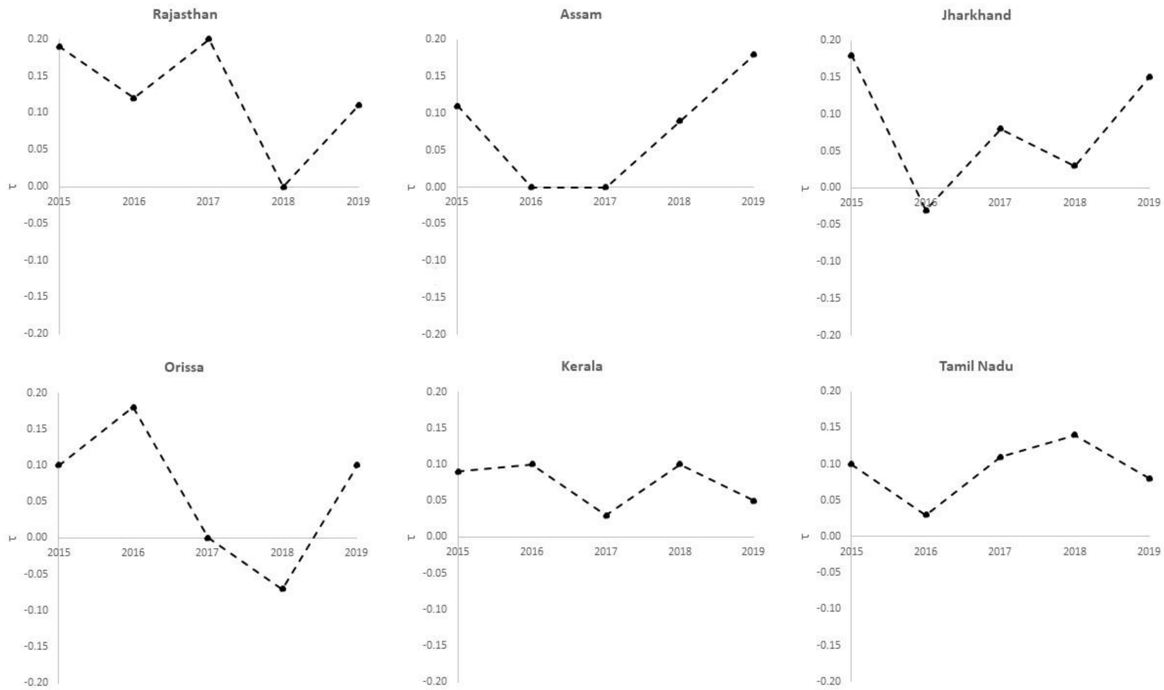

Figure 6: *Evolution of* τ *for low inequality states*. τ is generally positive over time, indicative of a progressive trend in redistribution of resources.

Given these distinct redistribution dynamics across high and low inequality states, we study the income transitions across the first decile to better understand the stickiness of lowest incomes and their ability to transition higher in the income distribution. We find that incomes in the bottom decile of the highest income inequality states tend to have a higher probability of remaining in the bottom decile over time (Fig. 7). For instance, the persistence probability $p_{stic}(t, 1)$, which is the probability that an individual has been poor for at least the past year given that they are poor currently, is 0.89 for Uttar Pradesh, 0.88 for Maharashtra, 0.87 for Gujarat, 0.85 for Haryana and Madhya Pradesh, and 0.83 for Telangana, when compared to lower stickiness probabilities for states like Rajasthan (0.71), Kerala (0.75), Karnataka (0.76), Tamil Nadu and Odisha (0.77) (Fig. 7a). This dynamic indicates that persistence of individuals in short-term poverty over time is worsened by higher levels of income inequality.

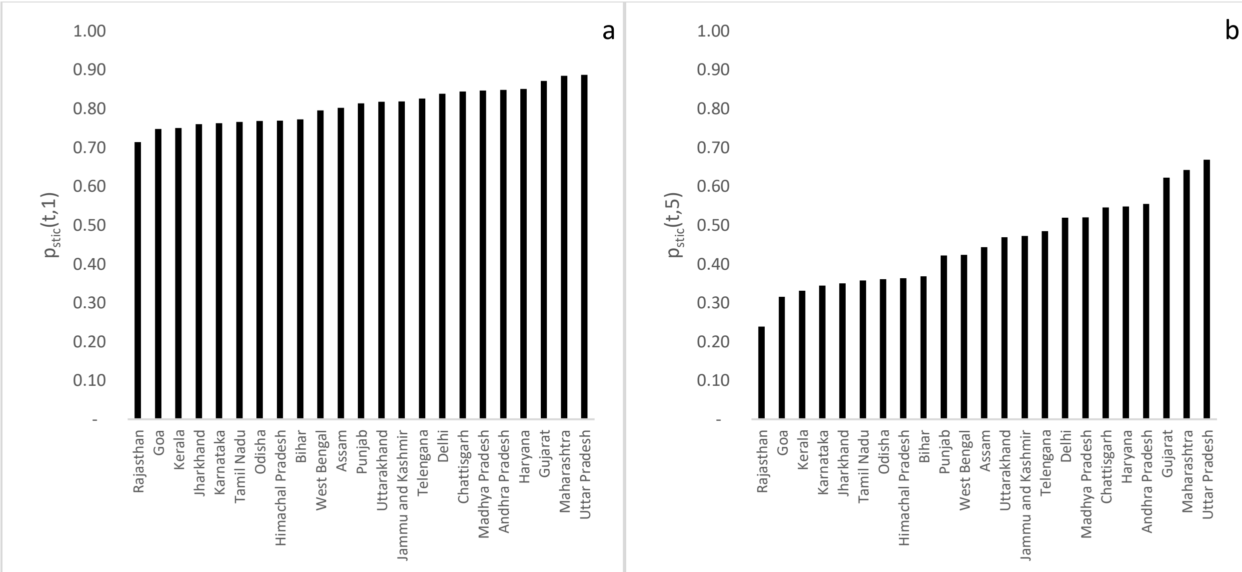

Figure 7: *Persistence probabilities across states*. A: $p_{stic}(t,1)$ is generally high across states, but with an increasing trend from lower to higher inequality states. Persistence is higher in higher inequality states. B: $p_{stic}(t,5)$ also shows the same trend, but there is a clear difference between low and high inequality states. Long term persistence of low incomes is much more likely in high inequality states.

This dynamic between income inequality and stickiness of low incomes is brought into sharper relief when we consider the persistence probability $p_{stic}(t,5)$ - the probability that an individual has been in the first decile for at least the past 5 years continuously given that they are in the first decile currently - which reveals once again that individuals in lower inequality states tend to have much lower persistence probabilities than those in high inequality states (Fig. 7b). Rajasthan, Kerala, and Tamil Nadu have $p_{stic}(t,5)$ of 0.24, 0.33, and 0.36 respectively, when compared to Uttar Pradesh, Maharashtra, and Gujarat which have persistence probabilities of 0.67, 0.64, and 0.62 respectively. These trends with $p_{stic}(t,1)$ and $p_{stic}(t,5)$ therefore reveal that the greater a state's inequality, the greater is the likelihood of stickiness of incomes to the bottom of the income distribution.

Next, we consider the probability of transitioning out of the first decile given time spent in the first decile and find that this probability is very low, with $p_{esc}(t,1) < 0.035$ and $p_{esc}(t,5) < 0.016$ for all states under consideration (Fig. 8). Despite this general outcome, there is still an observable trend of individuals in the lowest decile of high inequality states having a lower probability $p_{esc}(t,1)$, on average, of transitioning out of the first decile – Rajasthan has $p_{esc}(t,1) = 0.032$ which is more than double of Uttar Pradesh with $p_{esc}(t,1) = 0.013$ (Fig.

8a). Similar outcomes are visible for escape probabilities given$t_{D1} = 5$, with Karnataka's $p_{esc}(t, 5) = 0.015$, over 5 times that of Maharashtra with $p_{esc}(t, 5) = 0.003$ (Fig. 8b). Thus, there is a distinct difference in escape probabilities $p_{esc}(t, 1)$ and $p_{esc}(t, 5)$ for high and low inequality states, with increasing income inequality and longer t_{D1} making it progressively more difficult to transition out of the bottom decile.

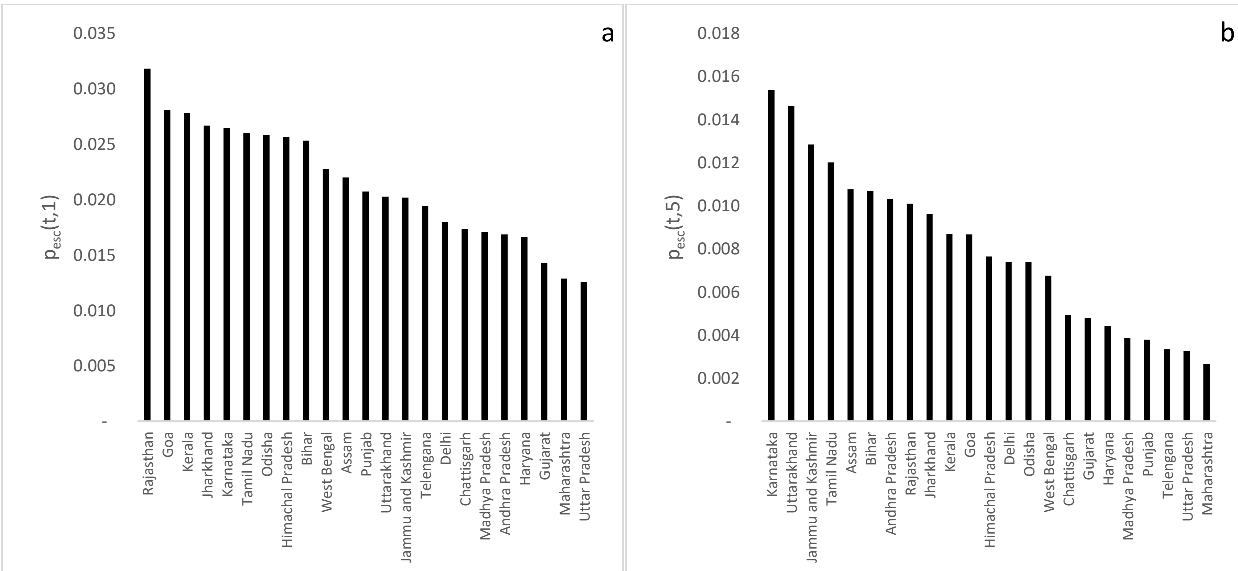

Figure 8: *Escape probabilities across states*. A: $p_{esc}(t, 1)$ is generally low across states, but with a decreasing trend from lower to higher inequality states. Escape probability is higher in lower inequality states. B: $p_{esc}(t, 5)$ also shows the same trend, but there is a clearer difference between low and high inequality states.

The dynamics of persistence in and transition out of the first decile naturally raises the question of why there exists a systematic relationship between these probabilities and income inequality. One possible explanation for this could be the nature of distribution of incomes within the first income decile. In high inequality states, by definition, the distribution of incomes is wider than the narrower distributions of low inequality states. We posit a similar distributional pattern within the first income decile itself - meaning that in high inequality states we would expect that there are more individuals with very low incomes ($\rightarrow 0$) than for lower inequality states, thus creating a wider distribution of income within the first decile of high inequality states. In order to test this hypothesis, we compute the Income Gap (an application of the Poverty Gap Index) for each state (Eq. 4):

$$I_g = \frac{1}{N} \sum_{j=1}^{q} \left(\frac{i_{D1} - x_j}{i_{D1}} \right), \qquad (4)$$

where, I_g is the income gap; N is the population of the system; i_{D1} is the income level at the first decile; q is the population of individuals at or below i_{D1}; and x_j is the income of the individual j. The Income Gap I_g can be interpreted as the average percentage shortfall in income from the first decile income level, and higher values of I_g indicate greater average distance from the first decile income level. We would expect that the high inequality states have higher values of I_g than lower inequality states, indicating the greater average distance between incomes in the first deciles and i_{D1} in these states. We find that this indeed is the case, with the highest inequality states of Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Maharashtra, Gujarat, Punjab, and Haryana also exhibiting the highest Income Gaps (Fig. 9).

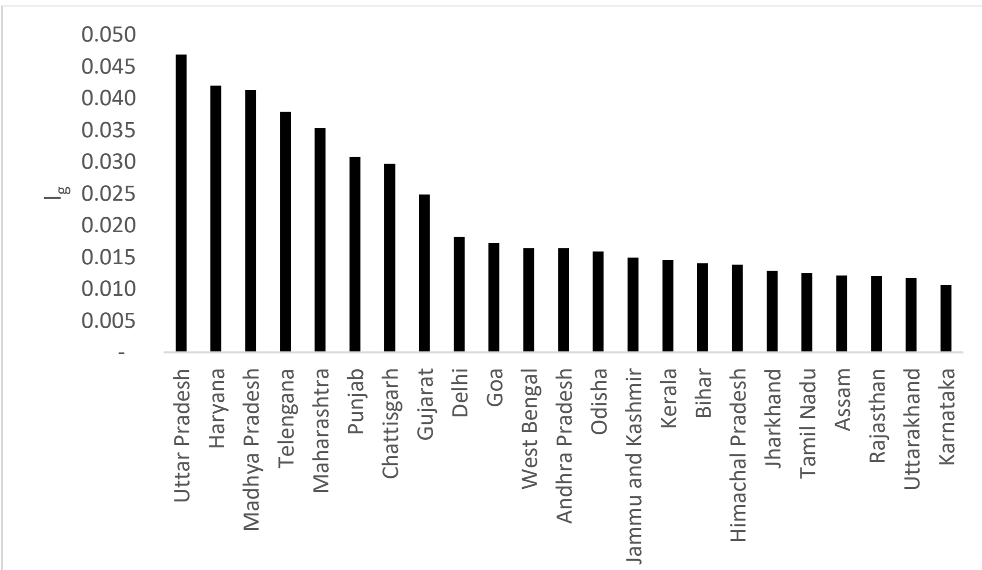

Figure 9: *Income Gap across states*. I_g is higher for higher inequality states and indicates that the lowest incomes in the bottom decile in these states are so low as to have little likelihood of transitioning beyond the first decile.

Therefore, the nature of distribution of incomes within the first decile offers a candidate explanation of the relationship between income inequality and the dynamics of persistence of incomes in the bottom of the income distribution. This has direct implications for the depth of poverty in high inequality states vis-à-vis low inequality states, because it suggests the possibility of increasing povertization of those at the bottom of high inequality state income distributions. Already, we see that many high inequality states have experienced negative real income growth in their bottom deciles for 2014-19, and our model outcomes suggest that the threat of deepening poverty due to reducing real incomes remains most stark for these high inequality states going into the future as well.

High inequality states are confronted with the dual challenge of rising income disparities as well as deepening poverty at the bottom of the distribution. We have shown that many of these states have high proportions of socially and economically vulnerable groups such as SC and ST communities, as well as farmers and labourers comprising the bottom of their income distributions. It has been argued that the rural poor have been at the receiving end of deep structural challenges manifested in the form of agrarian distress and informal wage employment in rural India (Vakulabharanam & Motiram, 2011; Suri, 2006; Reddy & Mishra, 2008; Vaidyanathan, 2006). Given declining real incomes in the high inequality states from 2014-19 and the further risk of prolonged income loss, state action will be essential to countering these dangerous trends. While long-term improvements will require sustained investment by these states on health, educational, and economic infrastructure (Ghosh & De, 2004; Rao, Shand, & Kalirajan, 1999), responses to the immediate challenge of declining incomes will require enhancing livelihood security through sustained income support programs for those at the bottom of their income distributions.

6. Conclusion

We study the income distributions of Indian states for 2014-19, with a particular focus on the income dynamics at the bottom of these distributions, and find a high degree of heterogeneity amongst states in terms of trends in income inequality. Specifically, the states of Uttar Pradesh, Telangana, Chhattisgarh, Madhya Pradesh, Gujarat, Maharashtra, Punjab, and Haryana are found to have high levels of income inequality. We find not only that income shares of the bottom deciles in almost all these states are decreasing over time, but also that real incomes are declining at the bottom of the distribution. Additionally, the most vulnerable populations – Scheduled Caste and Scheduled Tribe communities as well as agricultural and wage labourers – are disproportionately represented at the bottom of income distributions, meaning that it is these populations bearing the brunt of decreasing income shares and declining real incomes.

We model state income distributions using the RGBM framework to understand the nature of reallocation occurring within state distributions, and find evidence of negative reallocation in the high income inequality states. This concords with the emergence of declining incomes in the bottom of these distributions, but also raises concerns about continued declines in the future as well. With these income distributions constructed using RGBM, we also explore the dynamics of transition into and out of the first decile over time. We find that incomes in the first decile of high inequality states show much lower probabilities of transition out of this decile than lower inequality states. The cause for greater stickiness to the bottom decile in high inequality states is potentially related to the distribution of incomes within the first decile, with high inequality states having larger numbers of incomes close to zero than lower inequality states. This points to a significant problem of deepening povertization in high inequality states, and will require prompt policy action to ensure sustained livelihood support for households impacted by these dynamics.

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