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Inequality trends and dynamics in India

The bird's-eye and the granular perspectives

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Abstract: India today is achieving per capita growth rates that are historically unprecedented. Poverty reduction has also accelerated. There is concern, however, that this growth is being accompanied by rising inequality. We report on a research project that examines inequality trends and dynamics at the all-India level over three decades up to 2011/12 and contrasts these with evidence at the level of the village, or the urban block. We further unpack inequality to explore dynamics in terms of the movement of people within the income distribution over time. The assessment of mobility is informed both by evidence at the very local level and by aggregate, national-level, trends. Close attention is paid to the circumstances and fortunes of specific population groups. Finally, the study attempts to encapsulate these horizontal inequalities into a measure of inequality of opportunity as captured by inter-generational mobility in education outcomes.

Keywords: inequality, decomposition, welfare dynamics, intra- and inter-generational mobility, India
JEL classification: D31, I31, O15, R13

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1 Introduction

The distribution of income as a topic of attention, analysis, and measurement long occupied a fringe-like status in mainstream economics. In 1997, in his Presidential Address to the Royal Economic Society, Anthony Atkinson noted that the subject appeared to be slowly coming in 'from the cold' (Atkinson 1997). Subsequent decades have provided rich confirmation of this observation. There has been a veritable explosion of interest in and attention to the subject (see for example Atkinson 2015; Milanovic 2016; Piketty 2014; Stiglitz 2012). Multilateral institutions such as the World Bank[1], International Monetary Fund[2] (IMF), and Asian Development Bank[3] have raised flags with respect to the nature and consequences of rising inequality across countries and within countries. The United Nations has also included reduction of inequality as one of the Sustainable Development Goals (SDG).[4] Interest has been spurred in both the developed and the developing world, and a veritable industry has emerged, focusing on the documentation and analysis of inequality trends at country and global level.

In India it can be argued that concerns about income distribution were never really off the radar screen. However, attention in India was historically focused on the lower tail of the welfare distribution—on poverty—rather than on overall income inequality. This would seem appropriate given the very high levels of absolute poverty that prevailed in India over most of the post-Independence period. In recent years, however, as economic growth in India has accelerated, and as absolute poverty rates have started to fall fairly rapidly, there has been a turning also to questions about the distributional impact of India's growth trajectory, about the circumstances of the middle class and how it is being shaped, and about the growing concentration of income amongst the uppermost echelons of society. There are deep concerns about the possible consequences of rising inequality for social stability and the very fabric of society.

An important dimension of inequality in India pertains to widespread horizontal inequalities. India's complex and far-reaching caste structure translates into significantly different opportunities and aspirations amongst different population segments. Religious, gender, and even spatial differences also play a role in shaping welfare opportunities and outcomes. It is important to accommodate these horizontal inequalities into any analysis of the evolution, and determinants, of India's overall income distribution.

This paper reports on a recently completed research project that seeks to inform the debate on inequality in India by offering a 'bird's-eye' view of inequality trends and dynamics at the all-India level over three decades up to 2011/12 and contrasting this with similar evidence at the level of the Indian village, or the urban block. We explore dynamics by attempting not just to report 'snapshots' of inequality at different time periods, but also to trace the movement of people within the income distribution over time. This analysis of income mobility is motivated by the sense that normative views about changes in inequality are likely to vary according to whether a rise in inequality is, for example, characterized by a simple stretching-out of the income distribution—leaving individuals in the same relative position but just further apart in absolute income—or

[1] See World Bank (2016) and Lange et al. (2018).

[2] See IMF (2017).

[3] See Kanbur et al. (2014).

[4] The Sustainable Development Goals (SDGs) adopted by the United Nations General Assembly in September 2015 asks member states to reduce economic inequalities by 2030.

associated with significant 'leap-frogging' upwards and downwards in relative position within the income distribution. Again, our assessment of mobility is informed both by evidence at the very local level and by aggregate, national-level, trends. We attempt throughout to pay close attention to the circumstances and fortunes of population groups defined in terms of characteristics that should not, ideally, be associated with differing outcomes. We provide one attempt to encapsulate these horizontal inequalities into a measure of inequality of opportunity as captured by inter-generational mobility in education outcomes. We acknowledge that we are least able to incorporate India's far-reaching and pronounced gender inequalities into our analysis. This is due to constraints posed by our data, but it represents an important gap that calls for further research.

Drawing on the contribution by Himanshu and Murgai (forthcoming), we start in the next section with a review that assembles and assesses the available evidence on inequality trends and dynamics in India from a variety of perspectives. At the all-India level, inequality is broadly found to have risen between 1983 and 2011/12, particularly in the early 2000s, but to differing degrees depending on the dimension considered and the measurement method employed. The contribution by Elbers and Lanjouw (forthcoming), discussed in Section 3, goes on to interrogate the all-India level evidence with the detailed story of economic development the North Indian village of Palanpur over a period of six decades. They indicate that inequality has also risen in Palanpur—the consequence of a process of structural transformation that can also be discerned at the all-India level. They then draw on a simple model of the village to suggest that this trend may be rather general. The Palanpur study also provides a window on patterns of income mobility, both within and across generations, and points to important changes over time. Prompted by these findings, we return to nationally representative data to enquire into their broader relevance. To pursue these questions with nationally representative data poses challenges that require the application of a variety of methodological fixes. The study by Mukhopadhyay and Garcés Urzainqui (2018), considered in Section 4, shows that local-level inequality (within-village, in rural areas; within-block in urban areas) accounts for the bulk of overall inequality in India; understanding what occurs at the local level is thus important for understanding overall inequality. The importance and direction of change of local-level inequality is, moreover, shown to vary considerably across India's states.

The contribution by Dang and Lanjouw (2018), discussed in Section 5, reveals that nationally representative data also find confirmation of rising intra-generational income mobility over time. This is consistent with the idea that inequality of lifetime income may be lower than what is observed in a given year. However, the evidence also suggests that while poverty has fallen, most of the poor who have escaped poverty continue to face a high risk of falling back into poverty. Moreover, those who remain poor are increasingly chronically poor, and may be particularly difficult to reach via the introduction or expansion of safety nets.

The final study component, by van der Weide and Vigh (2018), which we consider in Section 6, moves on to examine inter-generational education mobility in India. There is little conclusive evidence of improved mobility over time. The study investigates the possible impact of promoting greater inter-generational mobility (thereby reducing the stark inequalities of opportunity that prevail). Not only would such efforts promote social justice, but evidence is presented to show that they could also stimulate inequality-dampening economic growth. A plausible route through which this could occur is via rising education levels, particularly amongst the poor. Section 7 offers some concluding remarks.

2 Inequality levels and trends in India: a bird's-eye view

A study by Himanshu and Murgai (forthcoming) scrutinizes the available evidence from India to present a general picture of rising inequality in recent decades. While the picture is fairly consistent, the patterns are not always equally pronounced across all indicators of well-being. Although Himanshu and Murgai focus on trends based on standard economic indicators of income/ consumption and wealth, they also extend the analysis to examine these by social groups, residence, region, and gender. Using tax data from the World Income Distribution (WID) database they also examine the nature and extent of income/wealth concentration at the top of the income distribution.

Himanshu and Murgai (forthcoming) next look at trends in inequality in human development indicators. They document different dimensions of access and achievements on indicators of health, education, and nutrition. They end by offering some observations on the proximate factors that have contributed to rising inequality in recent decades.

2.1 Monetary inequality

Himanshu and Murgai (forthcoming) begin by looking at standard indicators of consumption, income, and wealth. Consumption data underpin most of the debates around economic living standards in India. Since the 1950s the National Sample Survey Organization has fielded a series of national household surveys suitable for tracking household consumption. Himanshu and Murgai draw on the 'thick' rounds (with larger sample sizes) of the NSS surveys to examine trends between 1983 and 2011/12 (the most recent available round). Their inequality measures are based on the Mixed Recall Period (MRP) consumption aggregates that are the basis of India's official poverty estimates.[5]

Table 1 reports Gini indexes between 1993/94 and 2011/12 after correcting for spatial cost-of-living differences using the deflators implicit in India's official poverty lines. Non-availability of deflators for the 1980s prevents the authors from reporting inequality figures for 1983 based on real expenditures. Based on the available figures, consumption inequality at the all-India level can be seen to have risen moderately since the early 1990s. The trend increase is more marked when based on the variance of log of consumption expenditure—which gives higher weight to inequality at the lower tail of the income distribution. The increase was sharpest between 1993/94 and 2004/05 and most pronounced in urban areas.

Figure 1 reports the Gini index of income inequality from the 2004/05 and 2011/12 India Human Development Surveys (IHDS). The IHDS is a nationally representative household panel survey that collects comprehensive information on both consumption and income. Estimates based on this survey indicate that income inequality in India was about 0.54 in both 2004/05 and 2011/12, with a marginal increase during this period.[6] IHDS-based estimates of consumption inequality are lower than estimates of income inequality but, as in the NSS, show an increase over time. It is

[5] Most NSS consumption rounds collect data using a Uniform Recall Period (URP) of 30 days for all consumption items. A mixed recall period (MRP) aggregate with longer (365 days) recall for some (mainly non-food) items was introduced, alongside URP consumption, in the mid-2000s. For earlier years, Himanshu and Murgai (forthcoming) reconstruct a comparable MRP aggregate using the unit-record data.

[6] Corrected for spatial price differentials, the Gini coefficient of real incomes is 45.3 in 2005 and 45.9 in 2012.

noteworthy that estimates of income inequality place India amongst the highest inequality countries internationally.

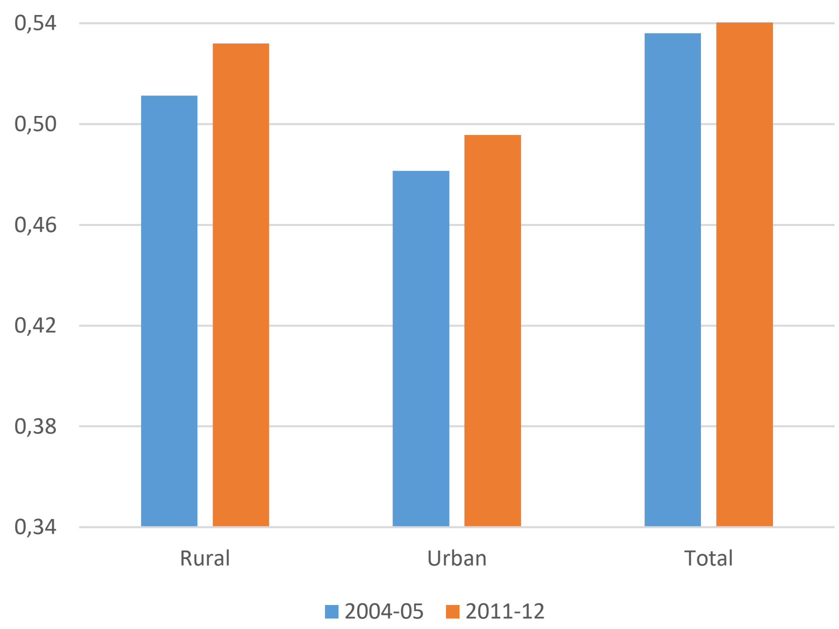
Table 1: Inequality trends in real consumption expenditure

	Gini coefficient of consumption expenditure					
	Nominal MPCE			Real MPCE		
	Rural	Urban	Total	Rural	Urban	Total
1983	0.27	0.31	0.30	n/a	n/a	n/a
1993/94	0.26	0.32	0.30	0.25	0.31	0.28
2004/05	0.28	0.36	0.35	0.27	0.36	0.31
2009/10	0.29	0.38	0.36	0.27	0.38	0.32
2011/12	0.29	0.38	0.37	0.27	0.37	0.33
	Variance of log of consumption expenditure					
	Nominal MPCE			Real MPCE		
	Rural	Urban	Total	Rural	Urban	Total
1993/94	0.20	0.31	0.26	0.19	0.29	0.23
2004/05	0.22	0.39	0.32	0.21	0.37	0.26
2009/10	0.24	0.42	0.35	0.21	0.40	0.29
2011/12	0.25	0.41	0.36	0.21	0.39	0.29

Notes: Real mean per capita expenditures (MPCE) are MRP consumption estimates corrected for cost-of-living differences across states, between rural and urban areas, and over time, using deflators implicit in the official poverty lines.

Source: Himanshu and Murgai (forthcoming).

Figure 1: Income inequality in India

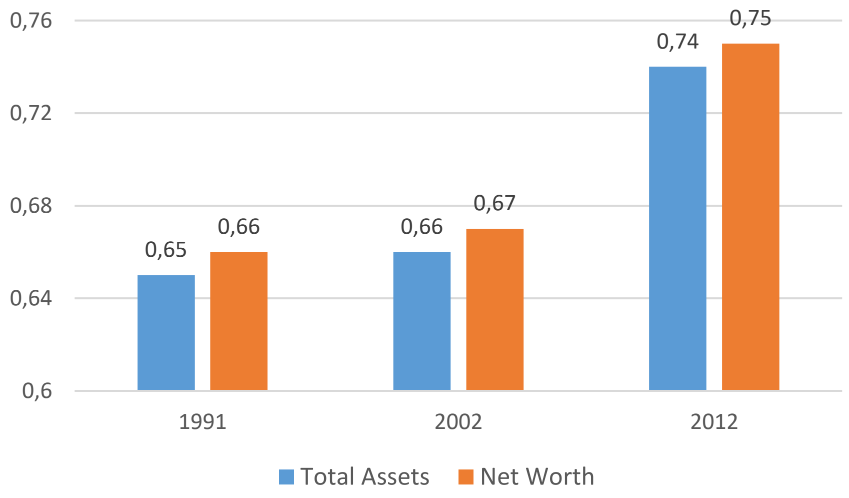


Source: Himanshu and Murgai (forthcoming).

The distribution of wealth provides a complementary perspective on consumption and income inequality. The All India Debt and Investment Surveys (AIDIS), conducted in 1991, 2002, and 2012 by the NSSO, collected information on the asset holdings and debt of households. The

AIDIS provide information on physical quantities of assets (land, buildings, agricultural machinery, vehicles, debt, etc.) and their value. These are a useful source of information with the caveats that values of assets are self-reported, and there may be under-reporting, particularly by richer households. Even so, wealth data point to much higher levels of inequality than either consumption or income data. The Gini coefficient based on AIDIS data for wealth (asset holdings) rises from 0.66 in 1991 and 0.67 in 2002 to 0.75 in 2012 (Figure 2).[7]

Figure 2: Gini coefficient of wealth (asset holdings)



Source: Authors' calculations based on AIDIS data.

As suggested above, an important note of caution in assessing survey-based levels and trends in inequality is that household surveys may not capture well the economic status of richer households. This seems particularly problematic with (NSS) consumption-based analysis in the light of the growing gap over time between aggregate consumption from the NSS surveys and private consumption in the national accounts (NAS). There are good reasons why the two aggregates should differ (for instance, due to differences in definition) but the gap in India is particularly large.[8] It is difficult to know how much of the gap is due to errors in NAS consumption versus NSS survey methods, with evidence of errors on both sides. To the extent that under-reporting of consumption or non-compliance is likely to be greater amongst the rich, inequality would be under-estimated.

An emerging set of studies attempt to overcome the limitations of survey data on the rich by drawing on income tax data, in combination with household survey-based income or consumption data, to examine the changing shares of income accruing to rich households across a range of countries. For India, Chancel and Piketty (2017) have extended an earlier analysis by Banerjee and Piketty (2005) to develop a time series from 1922 to the present.

As reported by Himanshu and Murgai (forthcoming), the study by Chancel and Piketty (2017) suggests that income inequality in India declined sharply between the 1950s and 1980s but increased thereafter (Figure 3). The share of income of the top 1 per cent reached a high of 21 per cent in the pre-Independence period but declined subsequently until the early 1980s to reach 6 per

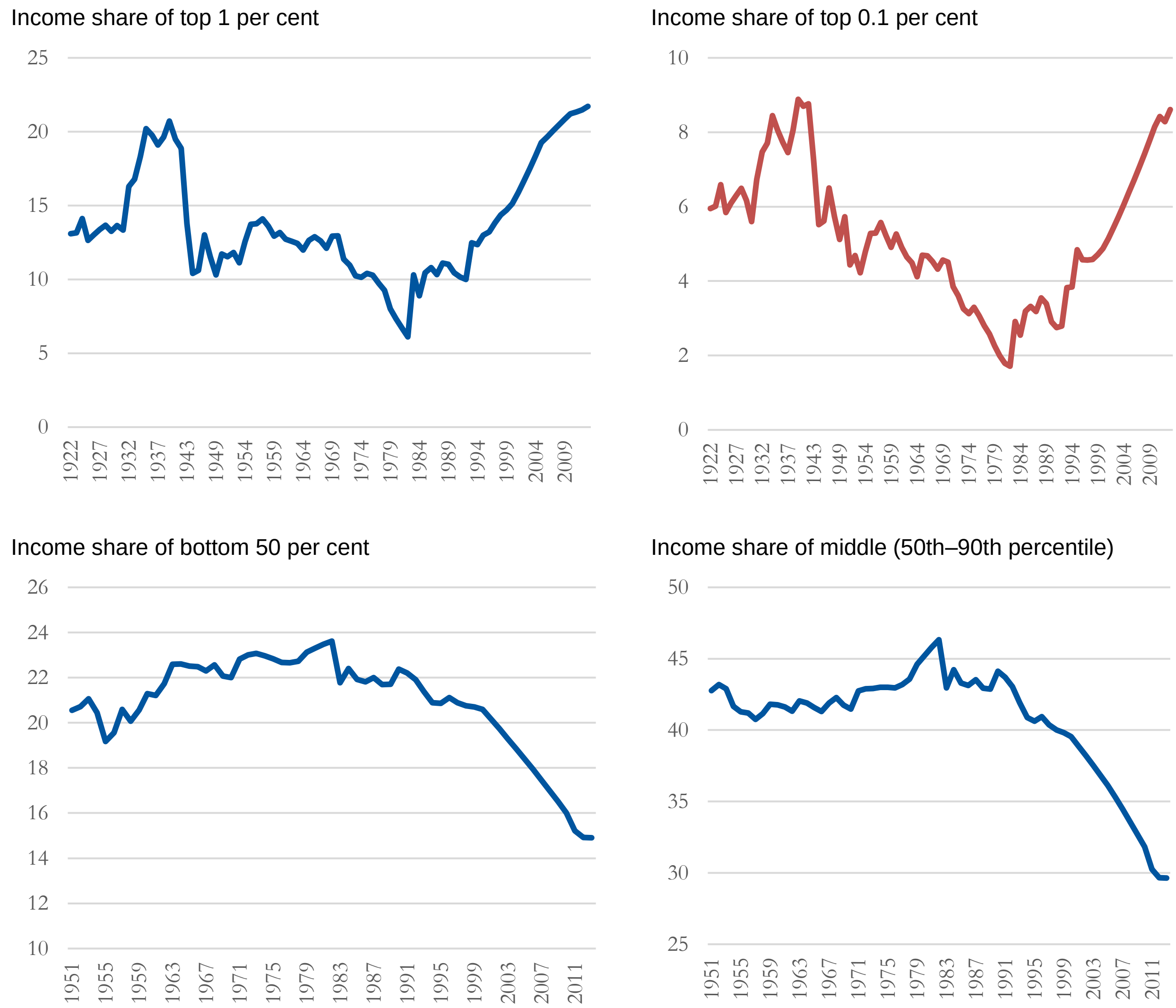
[7] See also Jayadev et al. (2007), Subramanian and Jayaraj (2006), and Vaidyanathan (1993).

[8] The ratio of NSS to NAS consumption declined from about 60 per cent in 1991 to 39 per cent in 2011/12 (Datt et. al. 2016).

cent. During the latter period, the bottom 50 per cent and top 10 per cent received nearly equal shares of income, at 28 per cent and 24 per cent, respectively. Income shares of individuals in the middle of the distribution (50th to 90th percentile) also rose.

These trends reversed in the 1980s and the income share of the top 1 per cent has since been increasing, reaching 22 per cent for the most recent year for which estimates are available. The share of the top 0.1 per cent in national incomes is now at its highest level of 9 per cent. While the bottom 50 per cent of earners experienced a growth of 97 per cent between 1980 and 2014, the top 10 per cent saw a 376 per cent increase in their incomes. During the same period, the very richest Indians—the top 0.01 per cent and top 0.001 per cent—have done extraordinarily well, with incomes rising by 1,834 per cent and 2,776 per cent, respectively .

Figure 3: Income shares of different groups



Source: Chancel and Piketty (2017) reported in Himanshu and Murgai (forthcoming).

While there has been some debate on the reliability of inequality estimates based on combining household survey and tax data, the evidence compiled by Chancel and Piketty (2017) combines to present a picture of extreme inequality in India.[9] By 2016, India was second only to the Middle Eastern countries in terms of the income share of the top 10 per cent. But it was also the country with the highest increase in the share of top incomes in the last 30 years, the share of the top 10 per cent increasing from 31 per cent in 1980 to 56 per cent in 2016 (World Inequality Lab 2018).

Rongen (2018) offers an alternative approach to gauging the impact of under-coverage of the rich from the NSS surveys. He draws on an approach introduced by van der Weide et al. (2018) that allows for the re-estimation of inequality by combining survey data with a database of house prices that can be used as predictors of income or consumption. Using the information from this second database, the distribution of top incomes can be estimated and added to the distribution inferred from the survey. Van der Weide et al. (2018) illustrate the method by applying it to Egypt, using a database of house prices to estimate the top tail of the income distribution.[10] Rongen (2018) re-estimates inequality in Mumbai by this method and finds little support for the contention that the NSS survey data under-estimate inequality in that city. Further research into the suitability of this method to empirical application with NSS data is warranted, but the results do suggest that debates about the levels and trends of monetary inequality in India are unlikely to end soon.

2.2 Non-monetary indicators: health and education

India has made substantial gains in health and education outcomes in the past few decades. Himanshu and Murgai (forthcoming) document that from 1991 to 2013, life expectancy at birth increased by more than seven years, the infant mortality rate fell by half, the share of births in health facilities more than tripled, the maternal mortality ratio fell by about 60 per cent, and the total fertility rate fell to almost replacement level. India's District Information System for Education (DISE) indicates that the education system has also expanded rapidly, leading to gross enrolment ratios of 100 and 91 in primary and upper primary grades, respectively.[11]

But the picture is not uniformly positive. While India has outpaced the world in reductions in consumption poverty, progress on nutrition outcomes has been less remarkable. Child stunting (associated with poorer socioeconomic outcomes later in life), which affected nearly half (48 per cent) of the under-five child population in 2005/06, has reduced but still afflicted 38 per cent of children in 2015/16. Under-five child wasting (weight-for-height) has shown no improvement, stagnating at one-fifth of the population. India also ranks poorly in global indices such as the Global Hunger Index and the Human Capital Index, reflecting the challenges that remain and the need for sustained progress.[12]

National averages mask disparities across social groups, states, and rural–urban areas, reflecting inequalities in opportunity to access basic services. Figure 4 shows differences in selected health and education outcomes by social groups. Although there have been improvements across all social groups, Scheduled Tribes (STs) and Scheduled Castes (SCs) persistently have worse

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[9] While the method adopted by Piketty and others is similar to what has been used in other countries where tax data have been used to estimate income distribution for the entire population, there have been concerns over the appropriateness of the method (for details see Atkinson 2007, Leigh 2007, Leigh and Posso 2009, and Sutch 2017).

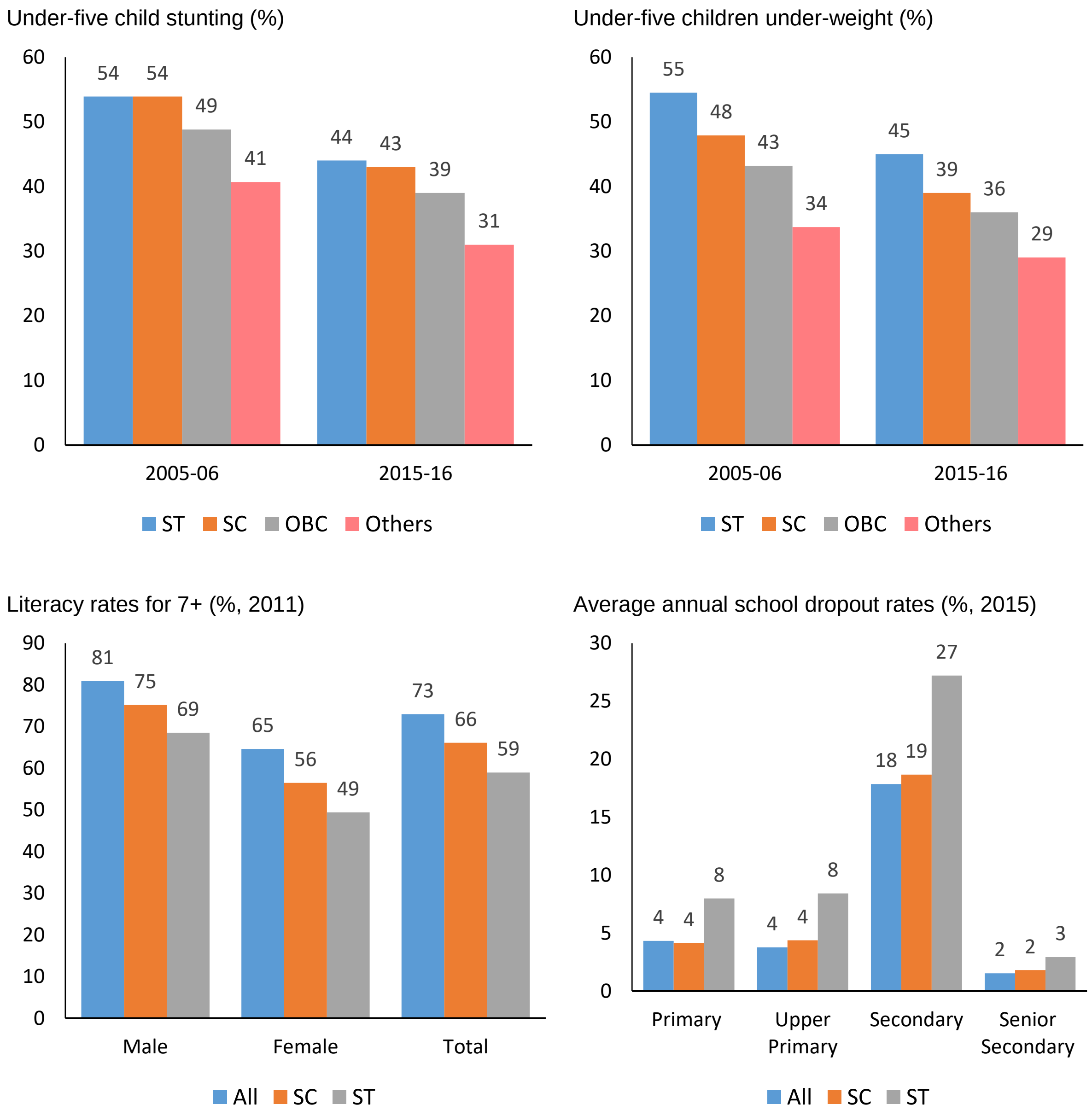
[10] Correcting for under-coverage of the rich in Egypt in this way raises the estimated Gini from 0.39 to 0.52 (van der Weide et al. 2018).

[11] National University of Educational Planning and Administration (2015).

[12] The 2017 Global Hunger Index ranks India in 100th place out of the 119 countries that were included.

outcomes.[13] In 2015/16, 44 per cent of under-five children in STs were stunted, compared with 31 per cent of children from general caste households. Even larger disparities are evident in the rates of under-weight children, and those gaps are not closing.

Figure 4: Disparities in human capital outcomes, by social group



Sources: Himanshu and Murgai (forthcoming). Nutrition outcomes from the National Family Health Surveys (2005/06 and 2015/16), literacy outcomes from the 2011 Population Census, and dropout rates from the National University of Education Planning and Administration (2015).

Gaps between social groups are also evident in education outcomes, although outcomes are better in education than in health, and gaps in enrolment rates among school-age children have been closing (Himanshu and Murgai forthcoming). Literacy rates have improved for all groups, but in

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[13] Thorat and Sabharwal (2011) provide evidence on caste-based disparities in nutrition outcomes through the 1990s and early 2000s.

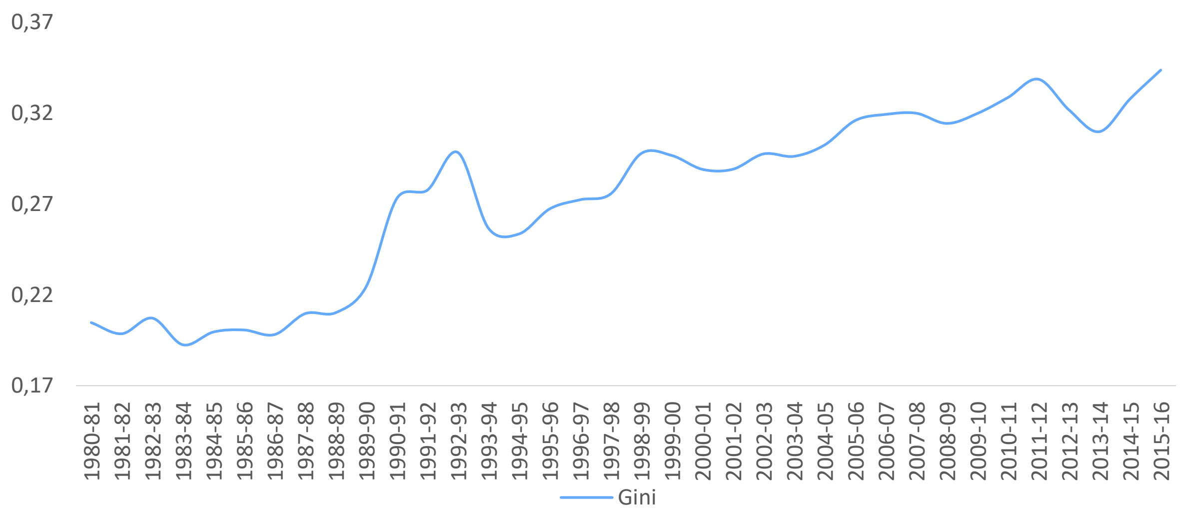
2011, literacy rates in SCs and STs were 66 per cent and 59 per cent, respectively, compared with the national average of 73 per cent. The disparity between social groups can also be seen in the average annual dropout rates at all levels of school education. Except for primary education, the dropout rates were higher than average for SC children. The rates were much higher for ST children at all levels of school education.

The intersection of gender, location, and social groups exacerbates these gaps. In 2011, more than 80 per cent of men were literate, while the rate was only 65 per cent for women. Female literacy among STs is even lower, at below 50 per cent. The literacy rate of rural women is 62 per cent, while the rate is much higher among urban women, at 81 per cent. The corresponding rates for men are 83 per cent and 91 per cent, respectively.

2.3 Structural patterns in monetary inequality

Contrary to global experience of income convergence across and within nations, India shows a growing trend of divergence across states. One way of looking at inequality across states is to estimate the inequality that arises solely as a result of differences in average per capita incomes per state (thus assuming that all individuals within each state receive the same state-level average income). Figure 5 presents the inter-state inequality using state domestic product data from the national accounts. The resulting Gini coefficient for per capita income weighted by state population confirms the trend of stable inequality in the 1980s followed by rising inequality since the 1990s.[14]

Figure 5: Per capita inter-state inequality



Source: Himanshu and Murgai (forthcoming) based on Reserve Bank of India data.

Most of the data from India's nationally representative household surveys are at best able to divide the population into broad social groups—distinguishing, for example, SCs, STs, OBCs, and a residual category of Others (which includes India's forward castes). This breakdown is far from ideal, as it does not permit any detailed assessments of differences across the many sub-groups within these broad categories.

[14] The question of spatial inequalities is pursued in Section 4.

One way to understand inequality across social and religious groups is to compare their share of income/consumption with that of the overall population. In an equal world, the share of income/consumption and the share of the population will be the same. The ratio of the share of income/consumption over a share of the population then represents the level of inequality. A share of less than 1 represents disadvantage, whereas a share greater than 1 positions a group in an advantageous position. Table 2 presents the share in consumption, income, and asset ownership over time.

Table 2: Relative shares of consumption, income, and assets, by social group

	Consumption share/Pop. share			Income share/ Pop. share		Asset Share/Pop. Share		
	1993/94	2004/05	2011/12	2004/05	2011/12	1991	2002	2012
All India								
ST	0.76	0.69	0.69	0.68	0.67	0.48	0.49	0.40
SC	0.79	0.78	0.80	0.71	0.79	0.46	0.45	0.40
OBC	--	0.92	0.93	0.89	0.92	--	0.90	0.83
Others	1.09	1.33	1.34	1.45	1.39	1.20	1.59	1.86
Rural								
ST	0.83	0.76	0.77	0.75	0.72	0.51	0.54	0.50
SC	0.85	0.85	0.88	0.75	0.83	0.49	0.49	0.50
OBC	--	1.00	1.00	0.95	0.96	--	0.98	1.01
Others	1.07	1.23	1.21	1.42	1.38	1.22	1.61	1.71
Urban								
ST	0.83	0.81	0.81	1.02	1.08	0.48	0.60	0.54
SC	0.75	0.72	0.76	0.77	0.82	0.40	0.42	0.35
OBC	--	0.83	0.85	0.84	0.87	--	0.78	0.70
Others	1.05	1.24	1.26	1.24	1.24	1.11	1.38	1.59

Notes: OBC are included in the 'Others' category in the asset survey.

Source: Estimates from Himanshu and Murgai (forthcoming) using NSS and IHDS data.

In contrast to the SC, ST, and OBC categories, the Others category has a higher share in income/consumption relative to its population share. The consumption data also report a decline in income shares for the ST group, with a corresponding increase in the share of Others. Asset ownership relative to population is particularly low for SCs and STs. The urban–rural divide is also an important factor in understanding the wealth advantage within social groups. The wealth positions of the SC and ST groups in rural areas are similar but very different from the wealth positions of the same groups in urban areas. The wealth inequality within each social group increased between 1991 and 2002.

Table 3 presents a similar analysis for groups defined by religion. Among India's religious minorities, Christians, for example, have a larger share of income/consumption than their population share, but this is not the case with Muslims, who have also seen their share in national income, relative to their population share, decline over time in both rural and urban areas.

Table 3: Share of income/consumption over share of population by religion

	Consumption share/Pop. share			Income share/Pop. share	
	1993/94	2004/05	2011/12	2004/05	2011/12
All India					
Hindu	0.99	0.99	1.00	0.98	0.99
Muslim	0.91	0.91	0.87	0.92	0.91
Christian	1.23	1.41	1.39	1.74	1.52
Others	1.12	1.28	1.29	1.22	1.21
Rural					
Hindu	0.99	0.98	0.98	0.96	0.98
Muslim	0.95	0.98	0.94	1.03	1.00
Christian	1.18	1.44	1.43	2.07	1.53
Others	0.95	0.98	1.05	1.19	1.24
Urban					
Hindu	1.02	1.03	1.04	1.03	1.03
Muslim	0.76	0.74	0.72	0.72	0.74
Christian	1.22	1.29	1.23	1.28	1.3
Others	1.15	1.33	1.18	1.29	1.33

Source: Authors' estimates using NSS and IHDS data.

Another dimension where India stands out is gender-based inequality. On the positive side, gender gaps in education and nutrition outcomes have been closing over time. While most economic dimensions are household-based and therefore mask the intra-household dimension of inequality, the disadvantaged position of women is most evident in the labour market. India continues to be among the countries with the lowest workforce participation of women; and this has seen a further decline in recent years. This can only partly be explained by the increasing female participation in education (Chandrasekhar and Ghosh 2014). The displacement of women from agricultural activities due to mechanization and increasing informalization could also be playing a role.

Inequality in the labour market also arises from the skewed distribution of workers across sectors, and the differential returns to capital and labour. A large share of the workforce is employed in agriculture (nearly 50 per cent in 2011/12) and in the unorganized sector (93 per cent). These are sectors whose share in GDP has been falling over time. Employment in the agricultural sector has been falling less rapidly than its share in income; employment in the unorganized sector has been growing, relative to the organized sector. In contrast, well paying sectors (which have grown the most rapidly), such as finance, insurance, and real estate, as well as IT-related services and telecommunications, combine to employ less than 2 per cent of the workforce. This has led to increasing divergence in per worker productivity between sectors such as agriculture or construction and the fast-growing sectors. The ratio of labour productivity in non-agricultural sectors to labour productivity in the agricultural sector has increased from 4.5 in 1993/94 to 5.5 in 2011/12 (Dev 2017).

Another feature of the labour market is vast differences in the quality of employment. Whereas a large majority of workers are employed in the informal sector with no social security or related protections, the organized sector has also seen a decline in employment quality over the years. Indeed, a striking trend in recent decades has been the rise in the percentage of informal workers in the organized sector, from only 38 per cent in 1999–2000 to 56 per cent by 2011/12 (Himanshu and Murgai forthcoming).

3 Inequality at the village level: a granular view

India's rural population resides mainly in villages—the 2011 Census reports roughly 800 million people living in more than 600,000 villages. Most of rural India's workforce (60 per cent) remains primarily involved in agriculture, but in recent decades this sector's growth has lagged behind that of other sectors in the economy. The deceleration in agricultural growth has been offset by the emergence and growth of the non-farm sector; in 2011/12 non-farm workers accounted for 40 per cent of the workforce, nearly double the ratio observed only 10 years earlier (Himanshu et al. 2018).

Elbers and Lanjouw (forthcoming) study the distributional impact of this structural transformation of the rural Indian economy at the village level. They focus on the impact of this process on income inequality and income mobility. Aggregate, national-level inequality can readily mask inequality outcomes, and trends, at the sub-national level. At the village level, inequality could be rising while national-level inequality was stable or even falling. This could occur if the underlying processes were leading to rising within-village dispersion of income accompanied by convergence across villages of average income. Evidence presented in Section 4 indicates that such a process is indeed under way in parts of rural India.

There are grounds for interest in local-level distributional outcomes. In rural areas people are likely to see the local village population as their reference group. Thinking about the magnitude and direction of change in inequality is thus likely to be influenced by village-level trends. Luttmer (2005) documents that in the United States, after controlling for income, the subjective welfare of individuals is lower in more unequal neighbourhoods. Similarly, Lentz (2007) finds that in Ghana, subjective welfare falls when neighbours become richer. Araujo et al. (2008) further document that in rural Ecuador, 'elite capture' of community-driven development projects is more likely in high-inequality communities. In general, rising inequality is likely to put pressure on village solidarity and the functioning of village-level institutions (Himanshu et al. 2018).

3.1 Inequality in Palanpur: 1957–2015

Elbers and Lanjouw (forthcoming) summarize the findings from a recent study of long-term economic development in a single village, Palanpur, in western Uttar Pradesh.[15] The village was the subject of intensive study on seven occasions between 1957/58 and 2015. In each survey year detailed quantitative and qualitative data, covering a very wide range of topics, were collected for the entire village population, with fieldwork conducted over an extended period—often a year or longer. Surveys were conducted in 1957/58, 1962/63, 1974/75, 1983/84, 1993, 2008/09, and 2015. Information is thus available for every decade since Indian independence. The village is small, with a population that grew from just over 500 in 1957/58 to roughly 1,250 in 2008/09. The population growth rate during the past 25 years was very similar to that recorded for India as a whole. Although there are eight caste groups in the village, and a few additional individual caste households, the three main castes in the village are Thakurs, Muraos, and Jatabs. Thakurs are the largest caste in the village numerically and they continue to be powerful economically. They were the first to move into the non-farm sector in a major way but have now been joined by other castes. Muraos, on the other hand, are a traditionally cultivating caste and take pride in their agricultural skills. Alongside the relative decline of agriculture in village income, Muraos have seen their economic status decline somewhat in relative terms. Jatabs, at the bottom of the village hierarchy, remained economically and socially marginalized until around 2005, but have become

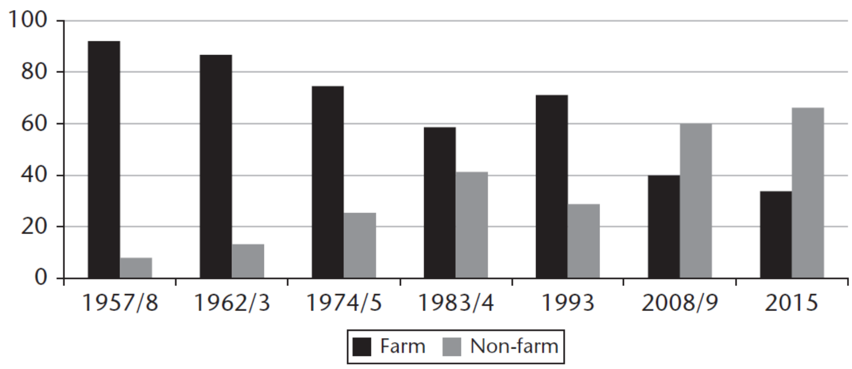
[15] These have been reported in detail in Himanshu et al. (2018).

increasingly involved in casual non-farm wage activities and are now seen as an increasingly important community within the village. They have therefore experienced significant upward mobility over the years.

Throughout the study period, Palanpur has essentially been a village of small farmers. The proportion of landless households is relatively low by Indian standards and there are no clearly outstanding large farmers. Since the late 1950s, the village has seen agricultural practices transformed in connection with the spread of irrigation, the introduction of new seed varieties, fertilizers, and pesticides, the emergence of rental markets for agricultural equipment, and the introduction of new crops. Key to the agricultural development process over the survey period has been the expansion of irrigation from around half of village land at the beginning of the survey period to 100 per cent by the 1974/75 survey, as well intensification of farm capital in the form of farm mechanization that has been both land-augmenting and labour-saving. Additional forces of agricultural change have been the shift of cropping patterns towards higher-value crops.

Over time, an increasing number of villagers have become involved in the non-farm sector. Non-farm activities represented roughly two-thirds of total primary employment by 2015 (Figure 6) and accounted for nearly 60 per cent of average household income in 2008/09 (Table 4). Better access to towns and cities via improvements in railways and communications infrastructure, particularly mobile phones, has helped villagers find jobs and has led to a growing number travelling outside Palanpur, on a commuting basis, for their employment.

Figure 6: Composition of the farm and non-farm workforce



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Jobs in the non-farm sector can largely be categorized into two kinds: low-paying casual and menial activities versus regular jobs (often government-provided) and some profitable self-employment units. But even the lower-paying jobs are more remunerative than agricultural labour, and often offer additional spells of employment that can be combined with some continued involvement in agriculture. The casual non-farm sector has registered the highest growth in employment in recent decades, notably in activities related to the construction sector. Self-employment has seen the fastest income growth in Palanpur by a substantial margin. The embrace of entrepreneurship has been striking. Regular wage jobs have declined both relatively and absolutely and there has been very little growth in the number of these jobs since the early 1990s.

While full migration from Palanpur is not common and has not increased as a proportion of households, the related practice of villagers commuting from Palanpur on a daily basis, or for short periods, is now both common and increasing over time. Commuting allows villagers to continue to reside in Palanpur and maintain some involvement in cultivation while they access an ever wider range of non-farm job opportunities in the surrounding area and nearby towns and cities.

Table 4: Income shares in Palanpur over time (%)

Income source		Year				
		1957/58	1962/63	1974/75	1983/84	2008/09
Household income	Cultivation	58.5	56.7	58.4	50.2	30
	Livestock income	19.8	21.5	22	13.7	10.4
	Non-cultivation (see breakdown)	21.7	21.8	19.6	35.4	59.6
	Total income share	100	100	100	100	100
Non-cultivation income (% contribution to total income)						
Agricultural labour income	Casual labour—farm	7.3	3.5	1.8	1.5	0.9
Other non-cultivation income	Other farm income	1.2	0.6	0.1	2.7	10.7
	Rental	0	0.2	0.6	0	1.6
Non-farm income	Casual labour—non-farm	1.1	1	0	7	6.1
	Self-employment	1.3	3.5	1	3	19.8
	Regular employment	7.5	8.9	15.7	20	16.1
	Jajmani income	1.3	0.6	0.4	1	0.2
	Remittances	2	1.9	0	0.2	3.6
	Other non-farm	0	1.7	0	0.2	0.6

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The richness of data covering all households in Palanpur permits an analysis of the dynamics of poverty, inequality, and mobility at a level of detail not normally available from secondary data sources. Poverty in Palanpur was extensive in the early survey years—over 80 per cent of the population was classed as poor during the 1950s and 1960s. The growth in incomes associated with expanding irrigation in the late 1950s and the 1960s, and the green revolution technologies and methods that evolved in the late 1960s and early 1970s, led to a sharp decline in poverty, the headcount ratio falling to less than 60 per cent by 1974/75, remaining at roughly that level in 1983/84, and then falling again sharply after 1983, declining to below 40 per cent by 2008/09.

Table 5 indicates that between 1957/58 and 1962/63, inequality represented by the Gini coefficient rose from 0.336 to 0.353 and then fell back by 1974/75. The decline between 1962/63 and 1974/75 was likely linked to the expansion of irrigation and the intensification of agriculture: by 1974/75, all village land was irrigated. Between 1974/75 and 1983/84, inequality increased but remained lower than its 1957/58 and 1962/63 levels. A combination of factors helps to explain the rise. With the ongoing intensification of agriculture, the Muraos as a group experienced improved relative prosperity due to higher returns from cultivation.[16] By 1983/84 the Muraos had even surpassed the Thakurs in terms of per capita income. In addition, in 1983/84, new non-farm employment opportunities were increasingly available, and were taken up mostly by villagers from

[16] Muraos, a traditional cultivator caste, were, on average, among the earliest to take advantage of the green revolution technologies and methods.

economically better-off backgrounds. In 2008/09, the Gini index, at 0.379, was at a higher level than in any other survey year. Elbers and Lanjouw (forthcoming) report that a decomposition exercise assessing the contribution to total inequality of different income sources points to non-farm income as accounting for the bulk of inequality in the later survey years.

Table 5: Inequality of individual incomes

Measures of inequality	Survey years				
	1957/58	1962/63	1974/75	1983/84	2008/09
Gini coefficient	0.336	0.353	0.272	0.310	0.379
Coefficient of variation	0.650	0.755	0.530	0.578	0.769
Atkinson Index					
e = 1	0.173	0.191	0.137	0.170	0.229
e = 2	0.319	0.344	0.206	0.366	0.444
Theil L measure					
GE(0)	0.19	0.213	0.147	0.186	0.26
No. of observations	529	585	750	977	1,255
No. of households	100	106	112	143	233
No. of individuals (households) with missing income	0	0	5(1)	8(3)	37(12)

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The Palanpur data can be further analysed to study patterns of mobility. Over the entire survey period since the 1950s there is evidence of the increasing mobility of households across income quintiles, with a falling share of households ranked in the same quintile between survey rounds. Among the factors that seem to have contributed are the decline in per capita landholding and the expansion of non-farm employment opportunities. While access to non-farm jobs has been uneven, with the relatively affluent and socially networked being more successful in finding regular, high-paying jobs, the spread of non-farm activities to lower-ranked households in more recent years has also allowed at least some of those at the bottom to improve their fortunes.

The long time horizon covered by the Palanpur study offers an opportunity to look beyond intra-generational mobility to inter-generational mobility, and indeed to compare changes in inter-generational mobility. Elbers and Lanjouw (forthcoming) point to a father–son inter-generational income elasticity for the interval 1983/84–2008/09 that is higher than for the interval 1957/58–1983/84. This implies that inter-generational mobility has fallen: the father's income is a better predictor of his son's income in the 1983/84–2008/09 interval than in the preceding interval.

3.2 Simulating inequality change in a stylized model of a village economy

Elbers and Lanjouw (forthcoming) build a relatively simple model of a village economy that permits the study of drivers of inequality in isolation, with a view to acquiring a better understanding of the kind of inequality trends observed in a village like Palanpur. The model is calibrated on data from Palanpur and seeks to reflect some of the features observed in that village. As described above, powerful forces of change have shaped the distribution of income in the village. Technological change in agriculture, the expansion of non-farm employment opportunities, and demographic change have been influential, but largely exogenous to the village. Elbers and Lanjouw (forthcoming) scrutinize how the distribution of welfare in their village model is shaped by these forces, and examine a few counterfactual scenarios with a view to gauging how welfare might have evolved in their absence.

The model has an annual recursive structure. The unit of time is a year, which simplifies calibration of the model to the data from Palanpur. People are assumed to live for exactly 70 years. They live in single-person households, so no distinction is made between individuals and households. Between ages 15 and 51 (not included) they individually produce offspring (with constant probability per year). Those aged 15 years and over earn an income. For implementation, Elbers and Lanjouw (forthcoming) generate a population with an age distribution that is more or less in equilibrium, while at the same time producing the population growth rate observed in Palanpur between 1958 and 2009 (i.e. 2 per cent per year).[17] The model allows for three 'castes' (motivated by the three largest castes in Palanpur: Thakurs, Muraos, and Jatabs); population dynamics for all three castes are assumed to be the same.[18]

Economic dynamics are a combination of occupational and income dynamics. For income earners (adults between 15 and 70 years of age) incomes evolve according to an autoregressive process with parameters that are specific to caste and occupation. Children start earning from the age of 15, with an income that is a function of their parents' income. An individual's occupation is determined by a Markov transition process. Each caste has a set of occupations (with corresponding parameters for the income process), and transitions between occupations are determined by caste- and occupation-specific probabilities. A schematic representation of the model's structure is presented in Figure 7.

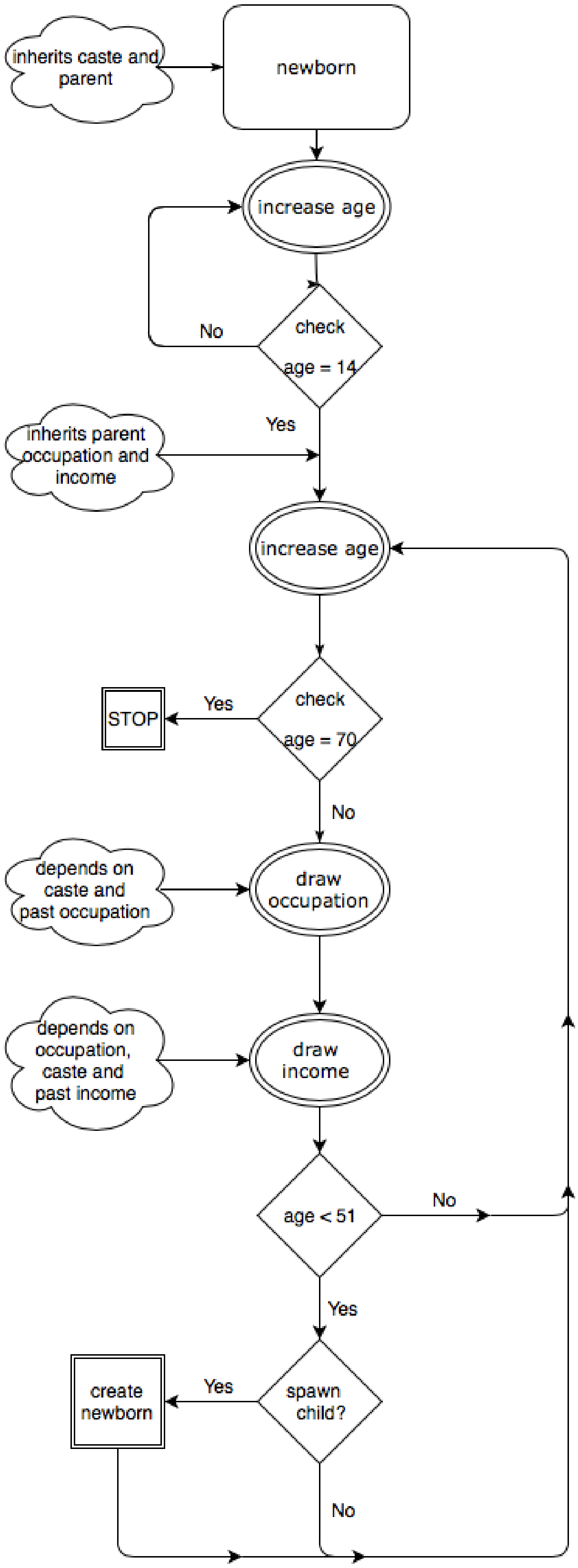
After calibration the model is run and the resulting path of inequality outcomes is examined. By repeatedly drawing new underlying random variables, the model traces out different inequality trends. The results suggest that changes in the observed Gini coefficient between 1957/58 and 1983/84 could very well reflect short-term fluctuations (such as year-to-year variations in harvest quality) rather than structural fluctuations. On the other hand, the increase in inequality between 1983/84 and 2008/09 is consistent across simulations and clearly stands out as a significant change from the period before 1983/84. A similar examination of model-based poverty outcomes over time reveals that the height of the Green Revolution period—between 1962/63 and 1974/75—was associated with a consistent and significant reduction in poverty. A further, subsequent, episode of significant poverty decline occurred between 1983/84 and 2008/09. These outcomes from the model align well with the observed distributional trends in Palanpur.

Elbers and Lanjouw (forthcoming) also consider the alternative approach of setting the parameter representing annual income autoregression to an arbitrary but reasonable-seeming value and then using the method of moments to derive the other model parameters. Figure 8 shows the path of Gini coefficients from this alternative approach. The simulated time-path of Gini coefficients for this approach also accords reasonably well with the point estimates obtained for Palanpur in the specific survey years.

[17] Given our interest in examining trends in the distribution of income, we do not incorporate data and village features from the 2015 survey.

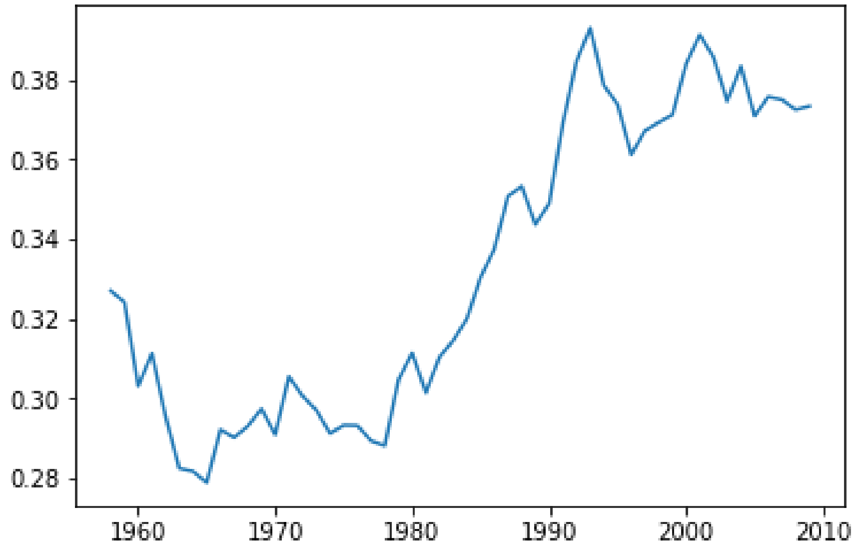
[18] Bliss et al. (1998) find little in the way of a discernible relationship between population growth and caste status in Palanpur.

Figure 7: Model summary



Source: Elbers and Lanjouw (forthcoming).

Figure 8: Alternative approach: Simulated path of Gini coefficients



Source: Elbers and Lanjouw (forthcoming).

Elbers and Lanjouw (forthcoming) undertake a counterfactual exercise with their model in which they ask how village-level inequality and poverty might have evolved if in fact the type of occupational diversification process observed in Palanpur had not taken place. To conduct this simulation they keep households in their (or their ancestors') occupation in the year 1957/58. This amounts to setting all occupations to 'agriculture', since only one of the 1957/58 households (a Thakur household) was classified as non-agricultural in that year. This scenario almost reproduces the baseline Gini values, but points to a somewhat larger increase in inequality between 1983/84 and 2008/09. The same conclusion holds for headcount rates except that in 2008/09 poverty is seen to be higher than observed with the actual data. This simulation thus suggests that moving out of agriculture has played an important role in contributing to poverty reduction, and that it has not necessarily added to village-level inequality. If anything, the counterfactual exercise implies that inequality would have been even higher if occupational diversification had not taken place. This is an important finding, as it challenges the frequent inference from inequality decomposition exercises—as described above for Palanpur—that a higher 'contribution' of non-farm income to total inequality implies that non-farm income is driving overall inequality. Such a decomposition exercise should be seen, rather, as a kind of accounting exercise and not one that 'explains' inequality in a causal sense. The analysis by Elbers and Lanjouw (forthcoming) indicates that the common perception of rural non-farm diversification resulting in higher inequality may require nuancing.

4 Dynamics of spatial and local inequality

Section 2 above indicated that inequality in India—in a variety of dimensions—is both high and increasing over time. Section 3 went on to show that in a small village in Uttar Pradesh a process of rising inequality within the village can be observed and can be linked to the ongoing process of structural transformation that is under way in India. A stripped-down, stylized model of village-level income dynamics can readily replicate the patterns observed in Palanpur, suggesting that in villages which are in some respects similar to Palanpur, inequality might similarly be rising. Systematic evidence on the evolution of inequality in spatial units smaller than districts and states remains scarce, however. This evidence gap has largely been due to a lack of representative income or consumption data for individual cities, blocks, and villages. Mukhopadhyay and Garcés Urzainqui (2018) confront this measurement challenge by implementing imputation techniques that draw upon census and satellite data for all urban sub-districts and all villages of India. They chronicle the evolution of inequality in India over the period 2004 to 2011, in the process providing estimates of the importance of inequalities that exist within and between such disaggregate spatial units.

Delving into the spatial distribution of inequality is of interest given the widely shared perception that gains from growth in India have been spatially uneven. As noted by Mukhopadhyay and Garcés Urzainqui (2018), there is a sense that a 'biased' growth process is making India 'look more and more like islands of California in a sea of Sub-Saharan Africa' (Sen and Drèze 2013). Indian cities have been singled out by their contrasting landscape of flourishing well-off residential areas and deprived slums. In line with these anecdotal observations, a strand of the academic literature has investigated the extent of segregation of Indian cities (Sidhwani 2015). It is therefore natural to wonder whether the national trend of increasing urban inequality is reproduced at small scale—within urban blocks. Concerning rural areas, existing research sends mixed signals on what kind of patterns could be expected. On the one hand, there is evidence that points towards widening differences between rural areas: echoing the discussion in Section 2 concerning the growing divergence between states, Narayan and Murgai (2016) show that rural poverty is becoming increasingly concentrated in poor states. On the other hand, Li and Rama (2015) find substantial spill-overs from proximity to 'top locations' in rural areas, suggesting the existence of localized patterns of rural development, with some villages catching up and others lagging behind. The Palanpur study, examined in Section 3, and other village studies suggest that inequality within villages has been rising (Himanshu et al. 2016). It is thus a priori not obvious which of these phenomena will predominate when we aggregate up to the national level. These considerations underline the importance of tracking the evolution of inequality at the finest spatial level possible.

In contrast to most other studies of spatial inequality in India, the analysis by Mukhopadhyay and Garcés Urzainqui (2018) defines spatial units at the lowest Indian administrative level: blocks (sub-districts) in urban areas and villages in rural areas. They estimate a regression model of district-level real consumption expenditure per capita on a host of district-level characteristics for which information is available, as well as for lower levels of aggregation, such as their geography, demography, structure of employment, and night-time luminosity. The analysis is based on consumption expenditure data from NSS surveys for 2004/05 and 2011/12 and thus enables temporal comparisons. Their prediction model is specified on the basis of stepwise selection procedures and out-of-sample forecast evaluations, and is subsequently used to impute per capita consumption expenditure for all rural villages and urban blocks of India. After successfully validating the predictions of the model against NSS data at levels where such comparisons are feasible, Mukhopadhyay and Garcés Urzainqui (2018) compute inequality measures for the country, as well as for its states, based on imputed consumption at the village and urban block level. This is tantamount to asking how much inequality would exist in India as a whole, and in each state, if one were to assume that there was no inequality within villages or within urban blocks such that overall inequality arose only because of differences in average consumption *between* villages and blocks. Invoking the additive decomposability property of the Theil index, Mukhopadhyay and Garcés Urzainqui then deduct this calculation of spatial inequality from their direct measure of total inequality, to arrive at an estimate of the share of total inequality, at the level of the country or the state, that can be attributed to within-village (or within-block) consumption differences. Implementation of this procedure to derive inequality within villages and urban blocks by combining a national survey and imputed data, and the reporting of the results, is a major contribution of the study by Mukhopadhyay and Garcés Urzainqui (2018).

Table 6 presents total inequality of India (rural and urban separately), and its decomposition into within and between spatial units. In rural India, 75 per cent of overall inequality is accounted for by within-village inequality. Although income inequality has increased slightly in rural areas, the within-village proportion has stayed more or less the same over time. Mukhopadhyay and Garcés Urzainqui (2018) indicate that the absence of a rise in inequality between villages contrasts with the observation of rapidly rising inequality *between districts*. It seems that while districts may be diverging from one another, the villages within the districts have not seen a similar divergence. For urban India, Table 6 reveals that the within component accounts for an even larger share—88 per cent—of total inequality. In urban areas, this share has also been stable but has accompanied a significant increase in overall inequality. Again, in urban India, Mukhopadhyay and Garcés Urzainqui (2018) find clear evidence of divergence across districts, but little divergence across blocks within them. What clearly emerges from these calculations is that national-level inequality can be viewed as a kind of aggregation of local-level inequalities. Understanding inequality trends at the national level requires understanding of what is occurring at the local level.

Table 6: Decomposing inequality in India

	2004	2011
All India (NSS)	0.188 (100 per cent)	0.210 (100 per cent)
Imputation-based Inequality (between spatial units)	0.050 (27 per cent)	0.055 (26 per cent)
Residual: within spatial unit	0.138 (73 per cent)	0.155 (74 per cent)
Rural India (NSS)	0.140 (100 per cent)	0.143 (100 per cent)
Rural Inequality based on village-level imputation (between)	0.035 (25 per cent)	0.037 (25 per cent)
Residual: within village	0.105 (75 per cent)	0.106 (75 per cent)
Urban India (NSS)	*0.234 (100 per cent)*	*0.264 (100 per cent)*
Urban inequality based on urban blocks (between)	0.028 (12 per cent)	0.033 (13 per cent)
Residual: within urban block	0.206 (88 per cent)	0.231 (87 per cent)

Source: Mukhopadhyay and Garcés Urzainqui (2018).

Of course, as discussed in Section 2, and seen also in Table 6, consumption inequality at the national level did not increase markedly between 2004/05 and 2011/12. One might conclude that, the importance of local inequality as a share of total inequality notwithstanding, this period was not associated with significant movements in inequality domain. This conclusion is resoundingly rejected once the analysis by Mukhopadhyay and Garcés Urzainqui (2018) is taken to the state level. Their analysis unveils vast heterogeneity in the evolution of inequality at the local level. Thus, the relative stillness in overall inequality hides a diverse landscape of changing inequalities. In particular, states show very different trends, with spatial and local inequalities often moving in different directions (Tables 7–9). By way of example, Kerala and Bihar show rising local inequality but falling spatial inequality (Table 7). Overall inequality in Bihar remained stable (and low) between 2004/05 and 2011/12 but the share deriving from local inequality increased from just over half to nearly three-quarters. In Kerala overall inequality increased from a Theil index of 0.258 to 0.310, the share attributed to local inequality rising from an already very high 95 per cent to as much as 97 per cent. This heterogeneity becomes even more evident in Tables 8 and 9, where separate within and between indices are calculated for rural and urban strata.[19]

Table 7: State-wise: Rural + Urban

State Name	NSS 2004	Imputed 2004	Within 2004	NSS 2011	Imputed 2011	Within 2011
Jammu & Kashmir	0.096	0.058	0.038	0.143	0.037	0.106
Himachal Pradesh	0.173	0.030	0.143	0.169	0.025	0.144
Punjab	0.179	0.024	0.155	0.174	0.019	0.155
Chandigarh	0.225	0.006	0.218	0.268	0.002	0.265
Uttaranchal	0.139	0.046	0.093	0.169	0.032	0.138
Haryana	0.223	0.018	0.205	0.207	0.022	0.185
Delhi	0.191	0.009	0.183	0.260	0.002	0.257
Rajasthan	0.125	0.036	0.089	0.133	0.028	0.105
Uttar Pradesh	0.158	0.034	0.124	0.194	0.033	0.161
Bihar	0.082	0.036	0.045	0.082	0.022	0.060
Sikkim	0.129	0.040	0.089	0.097	0.041	0.056
Arunachal Pradesh	0.118	0.037	0.081	0.202	0.038	0.164
Nagaland	0.089	0.037	0.052	0.074	0.027	0.047
Manipur	0.046	0.030	0.016	0.076	0.021	0.054
Mizoram	0.076	0.035	0.041	0.129	0.042	0.087
Tripura	0.116	0.026	0.090	0.104	0.022	0.082
Meghalaya	0.068	0.056	0.012	0.085	0.050	0.036
Assam	0.086	0.047	0.039	0.128	0.039	0.089
West Bengal	0.190	0.044	0.146	0.212	0.040	0.171
Jharkhand	0.144	0.075	0.069	0.143	0.058	0.085
Orissa	0.155	0.067	0.088	0.145	0.045	0.100
Chhattisgarh	0.193	0.040	0.153	0.175	0.037	0.138
Madhya Pradesh	0.173	0.042	0.131	0.190	0.036	0.154
Gujarat	0.167	0.028	0.139	0.148	0.039	0.109
Daman & Diu	0.153	0.037	0.116	0.068	0.007	0.061
Dadra and Nagar Haveli	0.225	0.063	0.161	0.219	0.066	0.153
Maharashtra	0.225	0.050	0.174	0.251	0.050	0.200
Andhra Pradesh	0.183	0.022	0.161	0.147	0.024	0.123
Karnataka	0.194	0.034	0.159	0.264	0.044	0.221
Goa	0.182	0.011	0.171	0.165	0.005	0.160
Lakshadweep	0.122	0.004	0.118	0.140	0.003	0.137
Kerala	0.258	0.012	0.246	0.310	0.009	0.301
Tamil Nadu	0.216	0.024	0.192	0.190	0.024	0.166
Pondicherry	0.202	0.004	0.198	0.133	0.008	0.124
Andaman & Nicobar Islands	0.240	0.027	0.213	0.203	0.028	0.174

Source: Mukhopadhyay and Urzainqui (2018).

[19] Mukhopadhyay and Garcés Urzainqui (2018) acknowledge that assessments of inequality change based on these estimates should take account of the statistical imprecision associated with both sampling and imputation error. Calculating and reporting standard errors on their findings is subject to ongoing research.

Table 8: State-wise: Rural

State Name	NSS 2004	Imputed 2004	Within 2004	NSS 2011	Imputed 2011	Within 2011
Jammu & Kashmir	0.084	0.041	0.043	0.126	0.034	0.092
Himachal Pradesh	0.169	0.023	0.147	0.150	0.022	0.129
Punjab	0.150	0.012	0.138	0.144	0.012	0.131
Chandigarh	0.117	0.003	0.114	0.123	0.003	0.120
Uttaranchal	0.109	0.037	0.073	0.128	0.029	0.099
Haryana	0.228	0.008	0.219	0.119	0.007	0.111
Delhi	0.157	0.004	0.153	0.119	0.004	0.116
Rajasthan	0.090	0.021	0.069	0.098	0.016	0.082
Uttar Pradesh	0.121	0.020	0.102	0.124	0.021	0.103
Bihar	0.063	0.018	0.045	0.074	0.019	0.056
Sikkim	0.118	0.027	0.091	0.069	0.018	0.051
Arunachal Pradesh	0.121	0.037	0.084	0.197	0.034	0.163
Nagaland	0.081	0.037	0.044	0.064	0.033	0.031
Manipur	0.044	0.029	0.015	0.070	0.025	0.045
Mizoram	0.061	0.023	0.038	0.107	0.013	0.094
Tripura	0.081	0.023	0.058	0.081	0.014	0.067
Meghalaya	0.040	0.042	-0.002	0.054	0.027	0.027
Assam	0.062	0.034	0.028	0.085	0.025	0.060
West Bengal	0.128	0.021	0.107	0.104	0.020	0.084
Jharkhand	0.077	0.036	0.041	0.091	0.034	0.057
Orissa	0.128	0.039	0.089	0.102	0.033	0.069
Chhattisgarh	0.143	0.024	0.119	0.110	0.021	0.089
Madhya Pradesh	0.117	0.019	0.098	0.135	0.023	0.112
Gujarat	0.131	0.018	0.113	0.122	0.015	0.107
Daman & Diu	0.142	0.043	0.100	0.041	0.022	0.019
Dadra and Nagar Haveli	0.198	0.053	0.145	0.183	0.035	0.147
Maharashtra	0.153	0.019	0.134	0.139	0.016	0.123
Andhra Pradesh	0.133	0.017	0.116	0.112	0.013	0.099
Karnataka	0.131	0.015	0.116	0.146	0.018	0.128
Goa	0.149	0.007	0.142	0.146	0.006	0.139
Lakshadweep	0.128	0.002	0.127	0.110	0.002	0.107
Kerala	0.239	0.007	0.231	0.307	0.004	0.303
Tamil Nadu	0.152	0.013	0.139	0.149	0.011	0.137
Pondicherry	0.212	0.006	0.206	0.120	0.006	0.115
Andaman & Nicobar Islands	0.213	0.026	0.187	0.154	0.020	0.134

Source: Mukhopadhyay and Garcés Urzainqui (2018).

Table 9: State-wise: Urban

State Name	NSS 2004	Imputed 2004	Within 2004	NSS 2011	Imputed 2011	Within 2011
Jammu & Kashmir	0.114	0.078	0.036	0.160	0.021	0.139
Himachal Pradesh	0.141	0.011	0.130	0.215	0.003	0.212
Punjab	0.215	0.015	0.200	0.209	0.009	0.199
Chandigarh	0.214	0.000	0.214	0.277	0.000	0.277
Uttaranchal	0.178	0.015	0.163	0.238	0.010	0.228
Haryana	0.208	0.012	0.196	0.273	0.010	0.263
Delhi	0.191	0.008	0.183	0.269	0.002	0.267
Rajasthan	0.187	0.025	0.163	0.182	0.018	0.164
Uttar Pradesh	0.242	0.033	0.209	0.344	0.034	0.310
Bihar	0.177	0.036	0.141	0.143	0.019	0.124
Sikkim	0.106	0.008	0.098	0.068	0.001	0.068
Arunachal Pradesh	0.094	0.027	0.067	0.182	0.018	0.164
Nagaland	0.093	0.034	0.059	0.085	0.009	0.076
Manipur	0.046	0.023	0.023	0.072	0.006	0.066
Mizoram	0.086	0.017	0.069	0.103	0.013	0.090
Tripura	0.177	0.008	0.169	0.141	0.006	0.135
Meghalaya	0.119	0.004	0.115	0.088	0.006	0.082
Assam	0.161	0.021	0.140	0.223	0.016	0.207
West Bengal	0.250	0.017	0.233	0.297	0.025	0.272
Jharkhand	0.195	0.014	0.181	0.216	0.016	0.200
Orissa	0.200	0.026	0.174	0.221	0.015	0.206
Chhattisgarh	0.252	0.010	0.241	0.301	0.012	0.290
Madhya Pradesh	0.245	0.022	0.224	0.268	0.018	0.250
Gujarat	0.179	0.031	0.148	0.154	0.028	0.126
Daman & Diu	0.134	0.000	0.133	0.107	0.001	0.106
Dadra and Nagar Haveli	0.166	0.000	0.166	0.164	0.000	0.164
Maharashtra	0.242	0.026	0.216	0.263	0.028	0.235
Andhra Pradesh	0.250	0.022	0.229	0.180	0.022	0.158
Karnataka	0.242	0.036	0.206	0.334	0.037	0.297
Goa	0.239	0.002	0.237	0.184	0.002	0.182
Lakshadweep	0.115	0.003	0.112	0.169	0.002	0.167
Kerala	0.299	0.013	0.286	0.299	0.005	0.294
Tamil Nadu	0.238	0.019	0.219	0.208	0.024	0.184
Pondicherry	0.191	0.003	0.188	0.135	0.009	0.126
Andaman & Nicobar Islands	0.255	0.004	0.251	0.221	0.002	0.219

Source: Mukhopadhyay and Garcés Urzainqui (2018).

Having pointed to the heterogeneity of results at the state level, Mukhopadhyay and Garcés Urzainqui (2018) move to the district level and explore how changes in inequality relate to baseline real consumption expenditure and its growth. They group districts in terms of per capita consumption expenditure (top and bottom 10 per cent, top and bottom quarter) and find that the inequality increase in the bottom decile is larger than at the top, driven by an even larger increase in local inequality (particularly pronounced for rural India) and attenuated by a decrease in between-inequality. Their findings suggest that higher growth is strongly associated with increases in overall inequality, and low growth with reductions in such inequality, both within and between spatial units.

To better understand how changes in various socioeconomic indicators correlate with changes in inequality, Mukhopadyay and Garcés Urzainqui (2018) then move on to regress changes in total, within, and between inequalities at the district level on changes in covariates over time. Their results show that increased urbanization is correlated with a fall in spatial inequalities between villages. However, it has a positive correlation with the rise of overall inequality in rural areas, and with rising local as well as spatial inequalities in urban regions. Similarly, employment—particularly regular employment—is correlated with a fall in inequality between spatial units (especially in the rural sector) but is associated with increased within-inequality. Increases in literacy rates are unambiguously associated with a slower inequality growth: improvements in literacy are correlated with slower growth in total inequality and, especially, within-inequality, both in rural areas and overall. The expansion of access to banking services is robustly associated with slower growth in inequality. In rural areas and for the district as whole, the associated decrease takes place through spatial inequality, while it is local inequalities that are most affected in urban areas. Similarly, access to sanitation (arguably a strong proxy for pro-poor intervention) is associated with more sluggish growth in spatial inequalities. In general, the correlation exercise reveals that structural factors are often associated with countervailing developments in spatial and local inequalities. They may lower the one while simultaneously increasing the other. These opposing forces often lead to a false impression that there is no dynamism in inequality in India.

5 Poverty, vulnerability, and mobility in India

While there has been much progress in the production of inequality statistics around the world, offering expanding opportunities to track trends over time and to make comparisons across countries, the underlying processes that characterize changes in inequality merit further and continued investigation. Notably, the patterns of relative income mobility that underpin changes in inequality are rarely documented, let alone well understood, particularly for developing countries. Yet, mobility patterns interact closely with inequality levels. As noted by Paul Krugman (1992), 'if income mobility were very high, the degree of inequality in any given year would be unimportant, because the distribution of lifetime income would be very even'.

Assessing the degree of income mobility requires analysis of panel data, as only such data permit the tracking of households over time. Collecting panel data, however, can be very costly and can also pose logistical and capacity-related challenges, particularly in developing countries. The scarcity of panel data has thus rendered the analysis of welfare dynamics difficult, if not impossible, in many developing country settings. Dang and Lanjouw (2018) overcome this data challenge by employing recently developed statistical techniques that allow them to construct synthetic panels from repeated cross-sections of the NSS surveys (Dang and Lanjouw 2013, 2018a, 2018b; Dang et al. 2014). While these synthetic panel techniques have been validated against actual panel data (and applied) in other contexts, they have not been validated using actual panel data for India.[20] Therefore, before offering new analysis, Dang and Lanjouw (2018) validate the synthetic panel

[20] See Dang et al. (2017) for a recent review of synthetic panel techniques and other related poverty imputation methods.

approach with the Indian Human Development Surveys (IHDS) data—the one nationally representative panel dataset that has been collected in India in recent years.[21]

5.1 Validating the synthetic panel method

Despite some limitations with the IHDS data themselves, Dang and Lanjouw (2018) consider this data source as the 'benchmark' to validate the synthetic panels.[22] Finding that the method appears to work well, they then appeal to the common timing of the IHDS data with the NSS data for 2004/05 and 2011/12, and the representative sampling design of both data sources, to suggest that the method is also likely to work well for mobility comparisons based on the NSS rounds.

Since the IHDS are panel surveys, Dang and Lanjouw (2018) split the IHDS panels into two randomly drawn sub-samples (each representing half of the total sample): sub-samples A and B. They then use sub-sample A in the first round and sub-sample B in the second round as two repeated cross-sections to which they apply their method. They compare the mobility results obtained from using sub-sample A to impute round 1 values for sub-sample B with the results they would get using the genuine panel for sub-sample B. And they use panels with the same household heads only for the genuine panels. As is common in pseudo-panel-based analysis, they restrict their attention to households whose head, in 2004/05, was in the 25–55 years age range.

Table 10 compares point estimates of IHDS consumption dynamics in the IHDS true panel and the synthetic panel. Dang and Lanjouw (2018) use data from the 2011/12 second survey round as the base for predictions. They calculate bootstrap standard errors, adjusting also for the complex survey design of the IHDS (including stratification, cluster sample, and population weights). Table 10 reveals that of the 15 possible cells, the synthetic panel method produces estimates that fall within the 95 per cent confidence interval of the true panel estimates in 10 cases (and in half of those the estimates fall within one standard error). Even in those cases where the estimates fall outside the 95 per cent confidence interval, scrutiny of the estimates reveals that they are actually quite close. For example, while 21 per cent of the population in the actual panel was estimated to be vulnerable in both 2004/05 and 2011/12, the corresponding estimate in the synthetic panel was 19.3 per cent.[23] Similarly, 18.6 per cent of the population in the actual panel comprised those who had been poor in 2004/05 but were non-poor but vulnerable in 2011/12. This compares with an estimate of 16.7 per cent in the synthetic panel. Overall, the impression one is left with is that the synthetic panels do a reasonably good job in reproducing the true-panel estimates. Certainly, broad-brush, qualitative conclusions derived from the synthetic panels would seem to be rather robust. These validation results are taken to provide justification for use of the synthetic panel method to obtain estimates of consumption dynamics over the 1987–2012 period using NSS data.

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[21] As also discussed in Section 2, the IHDS covers the period 2004/05–2011/12 and yields a fairly credible measure of household income. The consumption data in the IHDS are rather abbreviated and rarely used as a result. Dang and Lanjouw (2018) focus on analysing mobility with NSS-based synthetic panels because these are far larger samples and also offer a longer period over which to explore such dynamics. NSS consumption data also underpin official estimates of poverty and inequality in India.

[22] As noted above, the IHDS data have far fewer consumption items than the NSS, which can result in concerns about a less comprehensive consumption aggregate. The IHDS is also affected by an attrition rate of around 17 per cent between 2004/05 and 2011/12 (https://ihds.umd.edu/faq/can-i-link-ihds-ii-households-and-individuals-ihds-i-files). Clearly, these issues can affect the validity of the IHDS as the benchmark data source for validation.

[23] In Table 10 we apply a vulnerability line that is twice the poverty line of Rs 486. As our focus was on probing the validity of the synthetic panel method, we chose not to also apply the method for estimating a vulnerability line from the data, as described in Section 3. Mobility patterns associated with our estimated poverty line are examined when we turn to our description of mobility patterns based on the NSS-based synthetic panels.

Table 10: Validation against the IHDS, India 2004/05–2011/12 (%)

Panel A: Vulnerability line equals twice poverty line, IHDS actual panels		2011			
		Poor	Vulnerable	Secure	Total
2004	Poor	12.7	18.6	6.1	37.4
		(0.5)	(0.5)	(0.3)	(0.8)
	Vulnerable	6.9	21.0	15.1	43.0
		(0.4)	(0.5)	(0.5)	(0.7)
	Secure	1.2	6.2	12.1	19.6
		(0.1)	(0.3)	(0.4)	(0.6)
	Total	20.8	45.8	33.4	100
		(0.7)	(0.7)	(0.7)	

Panel B: Vulnerability line equals twice poverty line, IHDS synthetic panels		2011			
		Poor	Vulnerable	Secure	Total
2004	Poor	15.1	16.7	**5.9***	**37.7***
		(0.2)	(0.2)	(0.1)	(0.4)
	Vulnerable	**7.1***	19.3	**15.9**	**42.3**
		(0.0)	(0.1)	(0.1)	(0.2)
	Secure	**1.1**	**6.1***	**12.9**	**20.0***
		(0.0)	(0.1)	(0.2)	(0.3)
	Total	23.3	42.1	**34.6**	100
		(0.2)	(0.1)	(0.3)	

Note: Bold font indicates that the estimate falls within the 95 per cent CI of the actual estimate; a star ('*') indicates that the estimate falls within one standard error of the actual estimate. Standard errors in parentheses are estimated with 500 bootstraps for the synthetic panels, and with adjustment for the complex survey design for both the actual and synthetic panels.

Source: Dang and Lanjouw (2018).

5.2 Mobility levels and trends

Dang and Lanjouw (2018) employ two different approaches to setting the vulnerability line. The first arbitrarily sets a vulnerability line equal to twice the national poverty line, which corresponds to the maximum vulnerability that has been proposed in India (NCEUS 2007). The second estimates a vulnerability line associated with an average risk of falling into poverty by the 'vulnerable' of no less than 20 per cent, using a framework proposed by Dang and Lanjouw (2017). These two approaches provide rather similar results. Estimates for poverty and vulnerability mobility are then reported, based on the synthetic panels that are constructed using five 'thick' (large-sample) rounds of the NSS for 1987/88, 1993/94, 2004/05, 2009/10, and 2011/12.[24]

Using the synthetic panels, Dang and Lanjouw (2018) estimate that between the 1987/88 and 1993/94 survey years, about 30 per cent of the population experienced some consumption mobility. Of those that moved, only a very small percentage of the population was associated with

[24] Dang and Lanjouw (2018) extends an earlier study by the same authors (2018a) in three important dimensions. First, its time period is 1987–2012, three times longer than that studied in the latter. In fact, Dang and Lanjouw (2018) represents the longest-term analysis of mobility for the country to date. Second, this study offers richer analysis of mobility patterns for three income groups: the poor, the vulnerable, and the secure. Finally, it provides a more disaggregated state-level analysis than is available in existing studies. Other studies that examine income mobility for rural India and for shorter periods using the IHDS data include Azam (2016), Ranganathan et al. (2016), and Seetahul (2018).

jumps of more than one cell. For example, only 0.2 per cent of the population was secure in 1993/94 having been poor in 1987/88, and only 0.3 per cent of the population was poor in 1993/94 having been secure in 1987/88. In terms of conditional mobility (i.e. the estimate of mobility conditional on initial position), about 75 per cent of the poor in 1987/88 remained poor in 1993/94, and 64 per cent of the vulnerable remained vulnerable over this period. Interestingly, nearly half (45 per cent) of the secure transitioned downward into the vulnerable group between 1987/88 and 1993/94.

In the years following 1993/94, poverty decline started to accelerate and welfare transitions also increased. Between 1993/94 and 2004/05, about 60 per cent of the population remained on the diagonal of the transition matrix, indicating that mobility rose from 30 per cent to about 40 per cent of the population. Of course, the interval in this case is somewhat longer than was considered in the previous period, and one might expect more mobility over longer periods. However, the rising average consumption levels occurring over this period would suggest, a priori, an increased likelihood of the population crossing the fixed standard of living captured by an absolute poverty line (and its associated vulnerability lines). So, the rise in mobility captured in this way is likely real.

Alongside the rise in unconditional mobility, there was an increase in conditional mobility. Just under two-thirds of the poor in 1993/94 remained poor in 2004/05 (compared with three-quarters in the preceding interval), and between 51 and 61 per cent of the vulnerable (depending on choice of vulnerability line) remained vulnerable (down from 64 per cent). Downward mobility amongst the secure also declined, from about 45 per cent in the 1987/88–1993/94 interval to less than a third in 1993/94–2004/05.

Mobility rose further in the 2004/05–2011/12 interval to around 45 per cent of the population. More than half of the poor in 2004/05 (about 54 per cent) were no longer poor in 2011/12. Interestingly, however, although (conditional) mobility by the poor into the category of the secure did increase in comparison with the earlier intervals, it remained a rather rare event: regardless of the choice of vulnerability line, less than 10 per cent of the poor were able to make this transition across two welfare classes between 2004/05 and 2010/11. The picture of poverty decline emerging from this assessment is that, although the poor did see improvements in living standards during the 2000s, they generally continued to face a heightened risk of falling back into poverty.

Tables 11 and 12 consider consumption mobility over the longer intervals of 1993/94–2011/12, and 1987/88–2011/12, in an effort to enquire into longer-term welfare transitions. A striking observation from these tables is that, although poverty declined markedly over this entire period, a very significant percentage did not experience mobility out of poverty. About 43 per cent of the poor in 1993/94 were still poor in 2011/12 (Table 11, panels A and B). Reading down the first column of this table reveals that of the 25.5 per cent of the population that was poor in 2011/12, a remarkable three-quarters (76 per cent) had been poor in 1993/94. The corresponding figures for the 1987/88–2011/12 interval (Table 12) are very similar.

Table 11: Welfare transition dynamics based on synthetic panel data, India 1993/94–2011/12 (%)

Panel A: Vulnerability line equals twice poverty line		2011			
		Poor	Vulnerable	Secure	Total
1993	Poor	19.3	22.1	3.5	44.9
		(0.1)	(0.0)	(0.0)	(0.1)
	Vulnerable	6.0	24.3	13.6	43.8
		(0.0)	(0.0)	(0.0)	(0.0)
	Secure	0.2	3.0	8.0	11.3
		(0.0)	(0.0)	(0.1)	(0.1)
	Total	25.5	49.4	25.1	100
		(0.1)	(0.0)	(0.1)	
Panel B: Vulnerability line corresponding to V-index= 0.2		**2011**			
		Poor	Vulnerable	Secure	Total
1993	Poor	19.3	19.2	6.4	44.9
		(0.1)	(0.0)	(0.0)	(0.1)
	Vulnerable	5.6	16.7	15.3	37.6
		(0.0)	(0.0)	(0.0)	(0.0)
	Secure	0.5	3.8	13.1	17.4
		(0.0)	(0.0)	(0.1)	(0.1)
	Total	25.5	39.8	34.7	100
		(0.1)	(0.0)	(0.1)	

Notes: The vulnerability line is defined as twice the poverty line (i.e. 893.4 rupees) in Panel A and that corresponding to a vulnerability index of 0.2 in 2004/05–2011/12 (i.e. 770 rupees) in Panel B. All numbers are in 2004 prices for all rural India. The all-rural-India poverty line is 446.68 rupees for 2004/05. All numbers are estimated with synthetic panel data and weighted with population weights, where the first survey round in each period is used as the base year. Bootstrap standard errors in parentheses are estimated with 1,000 bootstraps adjusting for the complex survey design. Household head's age range is restricted to between 25 and 55 for the first survey and adjusted accordingly for the second survey in each period. Estimation sample sizes are 85,385 and 55,757 for the first and second period, respectively.

Source: Dang and Lanjouw (2018).

Table 12: Welfare transition dynamics based on synthetic panel data, India 1987/88–2011/12 (%)

Panel A: Vulnerability line equals twice poverty line		2011			
		Poor	Vulnerable	Secure	Total
1987	Poor	18.4	23.0	4.9	46.4
		(0.1)	(0.0)	(0.0)	(0.1)
	Vulnerable	6.0	22.4	13.7	42.1
		(0.0)	(0.0)	(0.0)	(0.0)
	Secure	0.3	3.5	7.7	11.5
		(0.0)	(0.0)	(0.1)	(0.1)
	Total	24.7	48.9	26.3	100
		(0.1)	(0.0)	(0.1)	
Panel B: Vulnerability line corresponding to V-index= 0.2		**2011**			
		Poor	Vulnerable	Secure	Total
1987	Poor	18.4	19.7	8.2	46.4
		(0.1)	(0.0)	(0.0)	(0.1)
	Vulnerable	5.6	15.3	15.2	36.1
		(0.0)	(0.0)	(0.0)	(0.0)
	Secure	0.7	4.2	12.6	17.6
		(0.0)	(0.0)	(0.1)	(0.1)
	Total	24.7	39.2	36.1	100
		(0.1)	(0.0)	(0.1)	

Notes: The vulnerability index is defined as twice the poverty line (i.e. 893.4 rupees) in Panel A and that corresponding to a vulnerability index of 0.2 in 2004/05–2011/12 (i.e. 770 rupees) in Panel B. All numbers are in 2004 prices for all rural India. The all-rural-India poverty line is 446.68 rupees for 2004/05. All numbers are estimated with synthetic panel data and weighted with population weights, where the first survey round in each period is used as the base year. Bootstrap standard errors in parentheses are estimated with 1,000 bootstraps adjusting for the complex survey design. Household head's age range is restricted to between 25 and 55 for the first survey and adjusted accordingly for the second survey in each period. Estimation sample sizes are 95,391 and 55,757 for the first and second period, respectively.

Source: Dang and Lanjouw (2018).

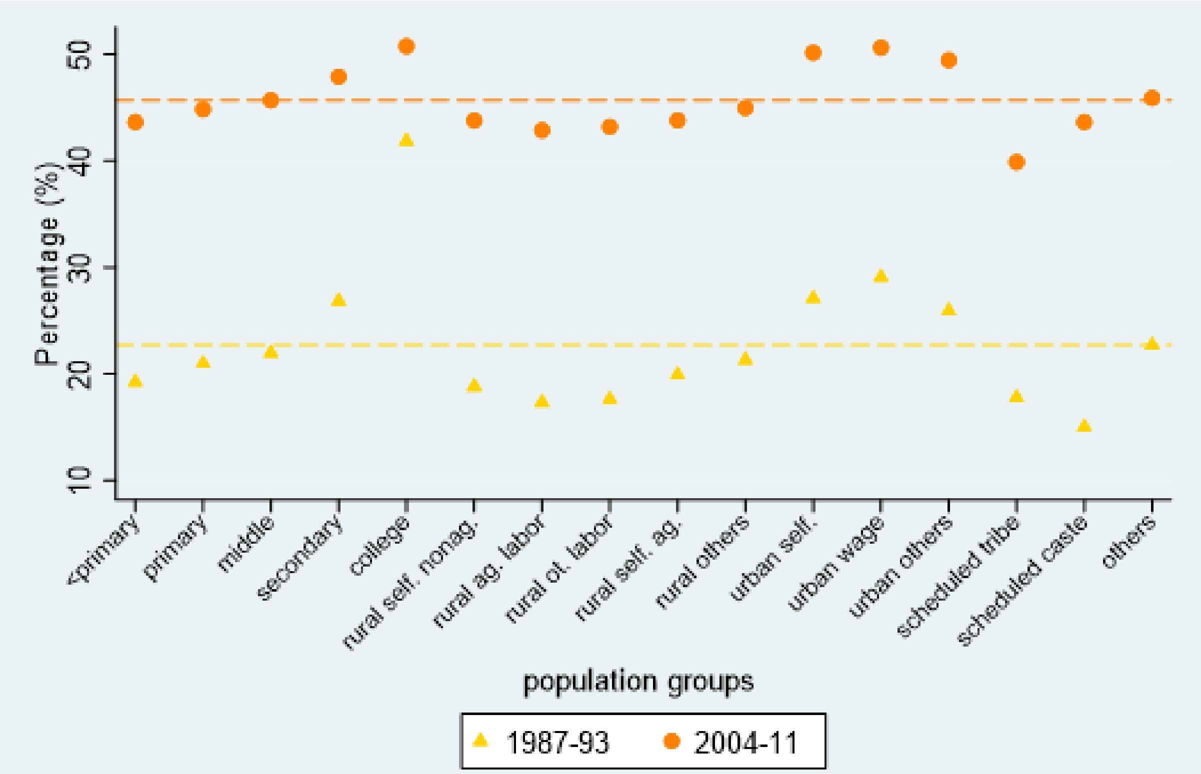
Thus, while mobility has risen in India, with growing numbers of the poor transitioning upward into the category of the vulnerable (and even some graduating to secure status), those who were poor in 2011/12 largely comprised the long-term, or chronically, poor. This picture accords with a narrative of poverty decline accompanying accelerating economic growth in India, but with the poor increasingly comprising the structural, long-term, poor, who have been non-participants in the growth process. It is important to note that, although intuitive, this picture is far from inevitable: one could also have imagined a growth process involving a great deal of 'churning' in which households escape and fall back into their respective consumption classes, and the poor in any one year largely consist of previously vulnerable and secure households. A potential concern emerging from the patterns we observe is that poverty reduction will become increasingly difficult to achieve through a general growth process that fails to address the structural factors that prevent the chronically poor from escaping poverty.

5.3 Mobility profiles by population groups and states

Dang and Lanjouw (2018) turn next to an examination of the population characteristics associated with upward and downward mobility. They also ask how these have changed over time, and focus their attention on two intervals of roughly similar duration (5–6 years): 1987/88–1993/94 and 2004/05–2011/12. As was seen above, these two intervals are clearly distinguishable in that the former was marked by modest rates of economic growth and little overall reduction in poverty, while the latter was associated with rapid per capita income growth and a dramatic fall in poverty. They ask whether these two very different economic settings were associated with different 'profiles' of the mobile.

Figure 9 examines cases of upward mobility, and considers the population shares of different groups that moved up one or two consumption categories. Groups are defined in terms of the reported schooling completion level of the household head, the sector and occupation category of the household head, and the social group composition of the household (Scheduled Tribe, Scheduled Caste, or Other). On average, between 1987/88 and 1993/94, 22.7 per cent of the population moved up one or two consumption categories. This compares with a rate of 45.7 per cent of the population between 2004/05 and 2011/12. The general profiles of the upwardly mobile remained rather similar across these two intervals: upward mobility is more likely than average amongst those with middle schooling or higher levels of education; and amongst those residing in urban areas engaged in self-employment and wage-earning activities. The uneducated, the rural population, and Scheduled Tribes and Scheduled Castes are markedly less likely to experience upward mobility. Across the two intervals, there is a suggestion that the advantage conferred by secondary schooling and, more strongly, college education has attenuated somewhat over time. This is perhaps not surprising given the general expansion of education in India over this quarter century. The disadvantage conferred by Scheduled Caste status appears also to have diminished over time, although not to the extent that it has disappeared. Overall, there seems to be clear advantage to residing in urban areas and a pronounced disadvantage to belonging to the Scheduled Tribes.

Figure 9: Profiling of the population that moved up one or two consumption categories, India 1987/88–2011/12

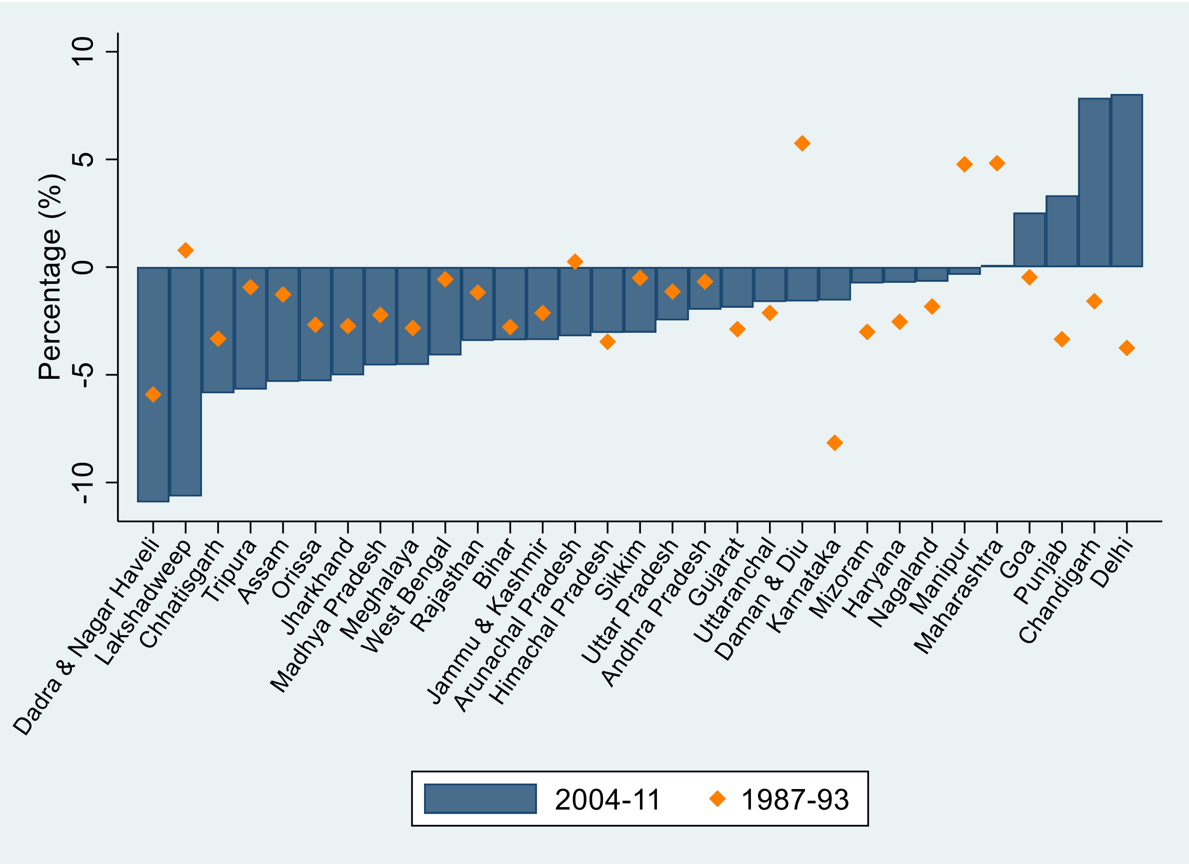


Note: Dashed lines represent the national average for each period (i.e. 22.7% for 1987–93 and 45.7% for 2004–11).

Source: Dang and Lanjouw (2018).

Dang and Lanjouw (2018) then ask whether the different states exhibit the same mobility patterns as seen at the all-India level. To study this question, they examine each state's performance relative to the national averages in the two periods 1987/88–1993/94 and 2004/05–2011/12. Since some states split (or merged) over time, Figure 10 displays upward mobility patterns for 31 states (or Union Territories) that remained the same over these periods. For better comparison, states' performance is shown relative to the all-India level.

Figure 10: Profiling of the population that moved up one or two consumption categories by state, India 1987/88–2011/12



Source: Dang and Lanjouw (2018).

Several observations are in order for Figure 10. First, this shows that states that perform worse than the national average in terms of upward mobility in the first period tend to display a similar performance in the second period. Indeed, in both periods more than two-thirds (22 out of 31 of all states and Union Territories) have worse-than-average performance, and only one state (Maharashtra) performs above the average in both periods. Four states improve in the second period (Goa, Punjab, Delhi, and Chandigarh), while four other states deteriorate (Lakshadweep, Arunachal Pradesh, Daman & Diu, and Manipur). Second, some states stand out with their change over time. For example, Lakshadweep performs better than the national average in first period, but becomes the next-to-last performer in the second period, while the opposite happens with Delhi, which turns into the best performer in the second period despite being among the worst performers in the first period.[25]

6 Inequality of opportunity and economic growth

In a recent global study, Narayan et al. (2018) identify India as a country with some of the lowest rates of inter-generational mobility in the world. Prompted by this finding, van der Weide and Vigh (2018) provide an in-depth study of inter-generational mobility for India. In particular, they

[25] Downward mobility patterns are mostly a mirror image of upward mobility patterns, so we do not show these results here for reasons of space. More details are provided in Dang and Lanjouw (2018c).

pose several questions. Given the size of the country, it is conceivable that economic mobility exhibits considerable within-country variation: so where are the most and least economically mobile municipalities located? And what municipalities have made the most, or least, progress over time? Does the lack of human capital accumulation in part stem from low levels of socioeconomic mobility in India? If so, how does this impact on the income growth prospects for lower-, middle-, and upper-income households?

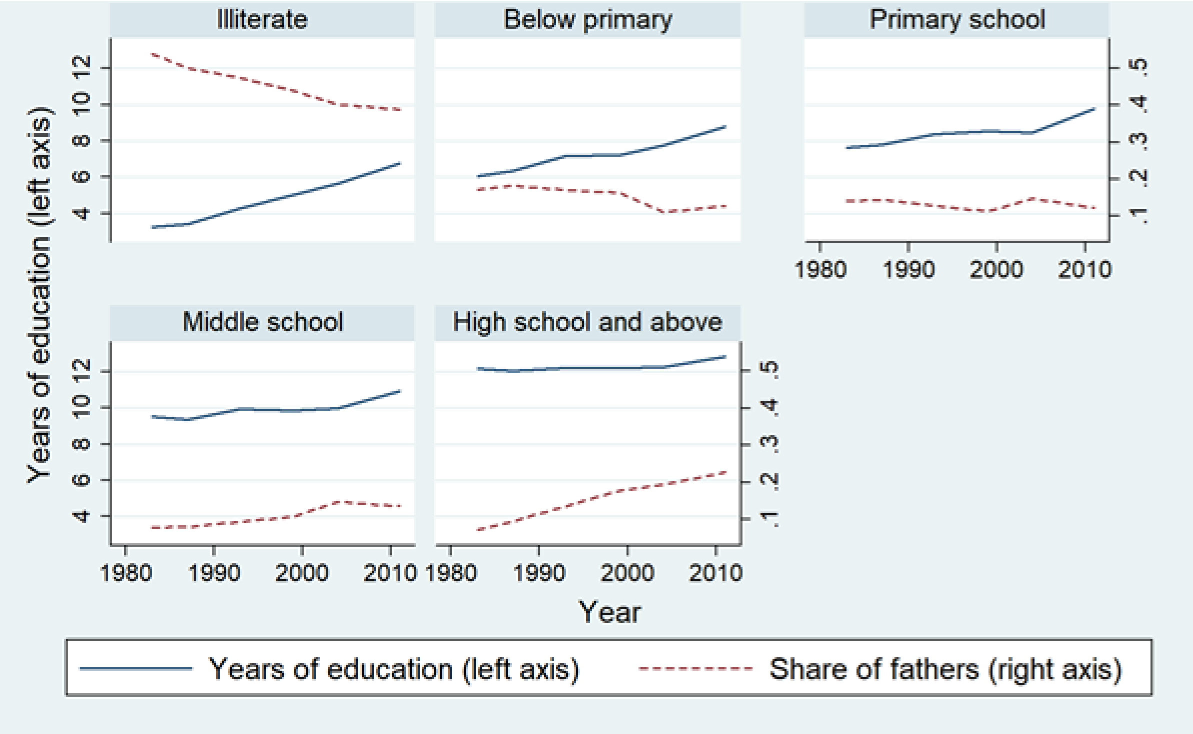
To study these questions, van der Weide and Vigh (2018) build a database at the state-region level for India that tracks socioeconomic mobility and human capital accumulation at the subnational (NSS region) level over the last 30 years. This database is built using various rounds of the NSS (1983, 1987, 1993, 1999, 2004, and 2011) and is modelled after an earlier NSS regional-level database constructed by Lanjouw and Murgai (2009), which accounts for merging and splitting of the subnational units over this extended period. This database includes a large range of variables, including (a) household expenditure growth for the low-, middle-, and upper-income classes, (b) inequality in household expenditure per capita, (c) demographics, (d) employment variables, (e) domestic infrastructure connectivity (capturing domestic market integration), (f) financial inclusion, and (g) selected political variables (i.e. voter turnout and political competition).

Van der Weide and Vigh (2018) examine three different measures of mobility: (1) the expected rank of a child (in the child education distribution) whose parents are in the bottom 50 per cent of the parental education rank distribution; (2) the statistical correlation between years of schooling of parents and years of schooling of their children; and (3) the share of inequality in years of schooling that is due to differences in parental education background (i.e. the share of 'between inequality' over total inequality). The first of these three measures is their preferred measure, and is referred to as 'upward mobility'.

6.1 Inter-generational mobility in education

Van der Weide and Vigh (2018) show the average years of education of boys conditional on their father's education (solid line) in Figure 11, which suggests a positive correlation between the father's and son's education level. The dashed line also reveals the change in the share of fathers in each education category. Particularly, the share of illiterate and higher-educated fathers changed significantly over time. It can be calculated from Figure 11 that gains in human capital accumulation at all education levels of fathers were highest in the late 1980s and 2000s. In the 1990s, gains in education attainment were mostly achieved by the least privileged groups with illiterate fathers.

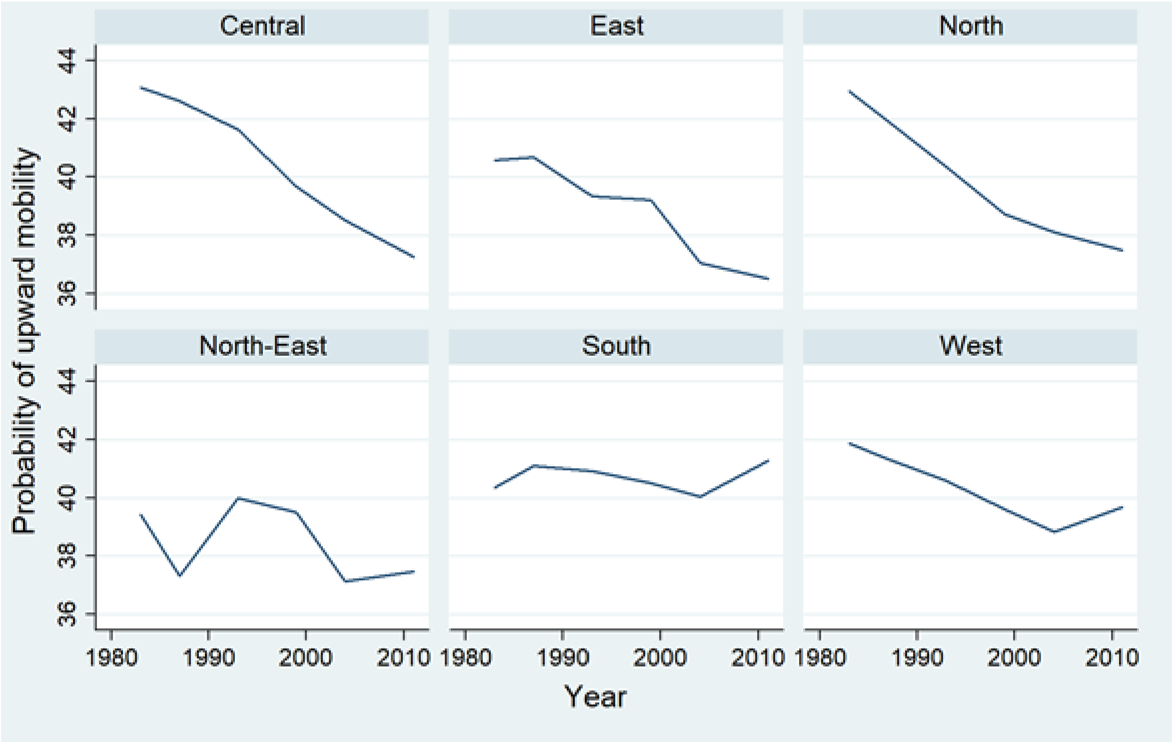
Figure 11: Years of education for men aged 20–25 (by father's education)



Source: Van der Weide and Vigh (2018).

Van der Weide and Vigh (2018) indicate that the period with the highest illiteracy rate but also large improvements in literacy exhibits the highest levels of upward mobility. Upward mobility in 1993 has a negative correlation (-0.38) with that in 1983. As the level of education increased in the population, this negative correlation became weaker and changed sign. In 2011, the correlation between the two indicators was 0.22. Figure 12 indicates that the zones with the highest education level (North-Eastern and Southern) display the most stable upward mobility pattern over the study period, while we observe a reduction in upward mobility in the other zones.

Figure 12: Upward mobility in education for men aged 20–25 (by zone)

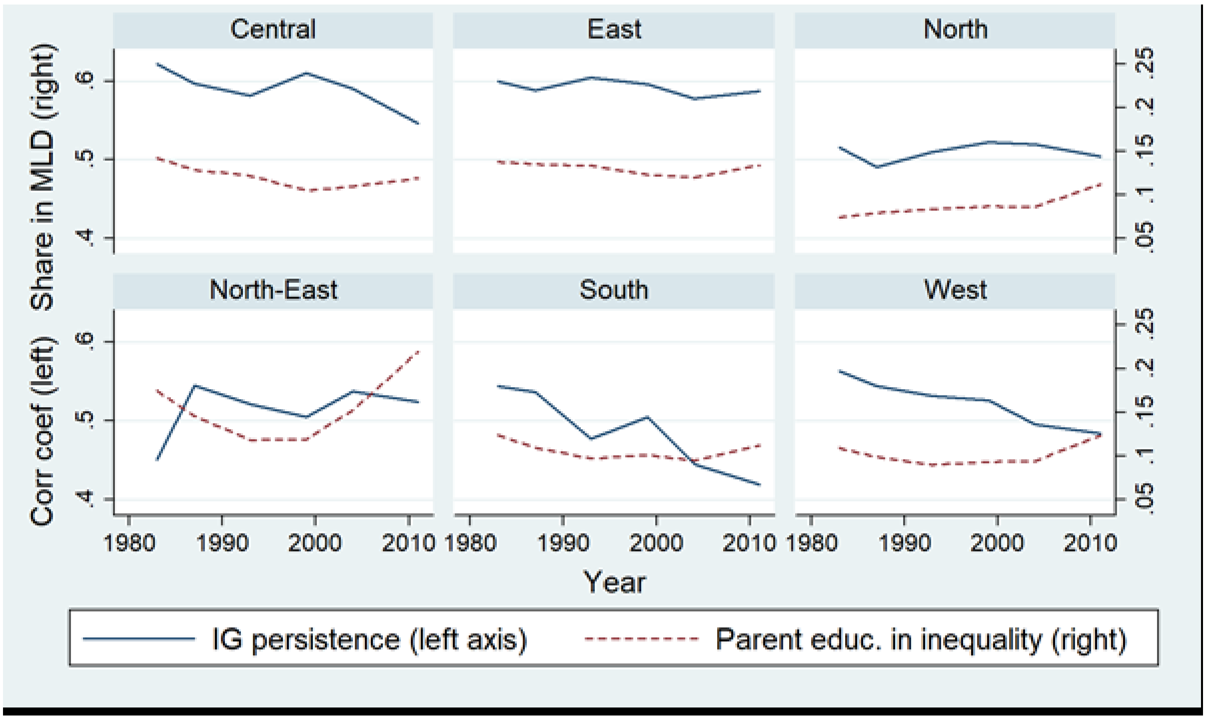


Source: Van der Weide and Vigh (2018).

Van der Weide and Vigh (2018)'s observation that increases in average educational attainment are driven primarily by increases among the sons of less-educated fathers is consistent with other studies. For example, Azam and Bhatt (2015) finds that educational persistence measured by the regression coefficient of father's education as a predictor of son's education also declined over time.

Van der Weide and Vigh (2018) subsequently run the same regression specification as in Azam and Bhatt (2015). The solid line in Figure 13 shows the correlation coefficient between the years of education of sons and fathers based on these regressions. Like Azam and Bhatt (2015) they do not find the same declining trend for the correlation coefficient as for upward mobility, which indicates that while persistence declined at the lower end of the father's educational distribution, it increased at the top end, as high school graduation is becoming more common in India. They capture a different aspect of inter-generational education persistence using the share of education inequality that is explained by the father's education level. The dashed line in Figure 13 suggests that the relative importance of parental education in education inequality has not changed much in recent decades. It has remained at about 10 per cent in most zones despite the declining overall inequality in education. Based on these three indicators of mobility, the overall assessment of van der Weide and Vigh (2018) is that there is no conclusive evidence of inter-generational socioeconomic mobility in India improving over time.

Figure 13: Measures of inter-generational education persistence for men aged 20–25 (by zone)



Source: Van der Weide and Vigh (2018).

6.2 Impacts of inter-generational mobility on consumption growth

Van der Weide and Vigh (2018) examine next the impacts of inter-generational mobility on per capita consumption growth. In particular, using state-regions as the unit of analysis, they attempt to identify the causal effect of inter-generational mobility on growth of household expenditure per capita at different percentiles of the consumption distribution.

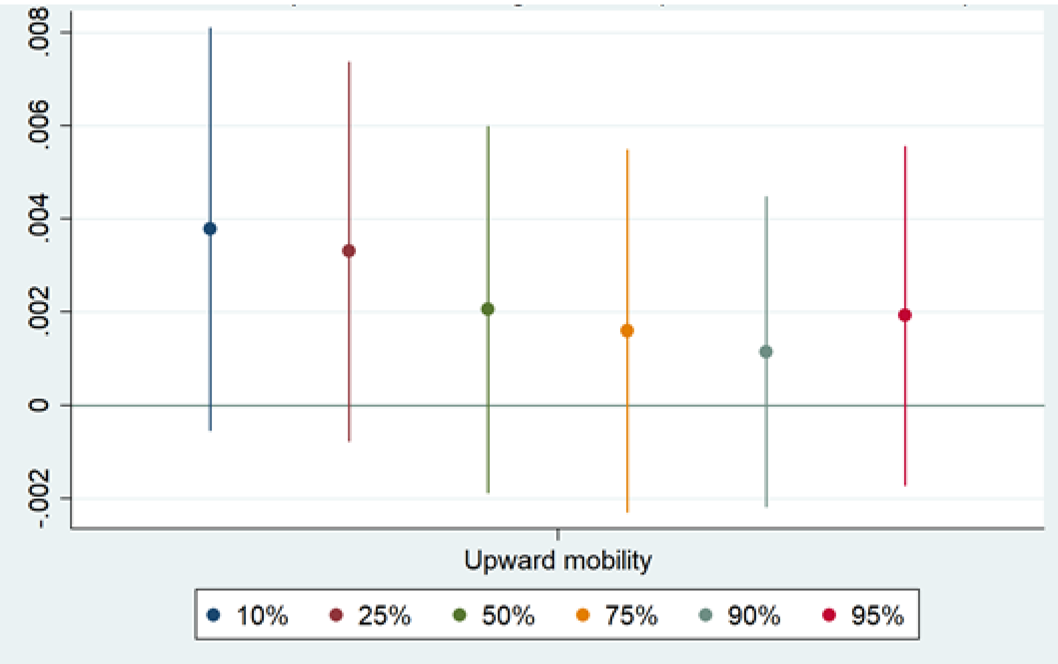
Van der Weide and Vigh (2018) run a regression of the change in log per capita household expenditure on a measure of relative inter-generational mobility, controlling for a number of other variables such as the first lag of log per capita household expenditure, other time-varying state-region characteristics, zone fixed effects, and year fixed effects. The zone fixed effects control for local features that are time-invariant such as local climate, geographic conditions, and local culture. The year effects control for time-varying conditions at the India level, including global food and commodity prices, terms of trade, and public policy. To account for time-varying features at the state-region level that could affect both socioeconomic mobility and household expenditure growth, they also control for total inequality in household expenditure per capita, the share of working-age individuals (between the ages of 16 and 65), average years of education among working-age individuals, the sectoral composition of the labour market (share working in manufacturing and share working in services), the share of households with access to electricity, financial inclusion (log of number of banks per capita), share of urban population, and share of Christians. All controls are lagged by one period.

Even so, a simple OLS estimation is subject to several potential sources of bias, such as omitted variables bias, and reverse causality bias. Van der Weide and Vigh (2018) thus propose an IV estimation model where the instrument for inter-generational mobility consists of the local share of the Brahmin caste in 1931 and the local share of Scheduled Tribes in 1961, both interacted with national trends in inter-generational mobility. Specifically, they regress inter-generational mobility on the local shares of Brahman and Scheduled Tribes interacted with the six time-period dummy variables to allow for non-linear time trends, and use the predicted values from this regression as their instrument.

The Brahmin caste were among the first to take up Western education and arguably played an important role in spreading such education in India. In contrast, the Scheduled Tribes rank among the most disadvantaged in India, with historically very limited access to education. On the basis of this one would expect socioeconomic mobility to be positively correlated with the share of Brahman and negatively correlated with the share of Scheduled Tribes.

The regression coefficients corresponding to inter-generational mobility are plotted in Figure 14. Several observations from this stand out. First, inter-generational mobility is found to have a positive effect on growth for all percentiles, although the effects are not statistically significant. Second, the effect is visibly larger (and almost significant) at lower percentiles. This is consistent with the hypothesis that higher inter-generational mobility is good for growth, particularly for inclusive growth, as those held back by an uneven playing field tend to be concentrated toward the bottom of the income distribution. This finding also predicts a negative relationship between inter-generational mobility and inequality: higher mobility is associated with inclusive growth, which in turn is associated with lower inequality.

Figure 14: Impacts of upward mobility on consumption growth (at different percentiles: IV regression 1 (90% confidence bound)

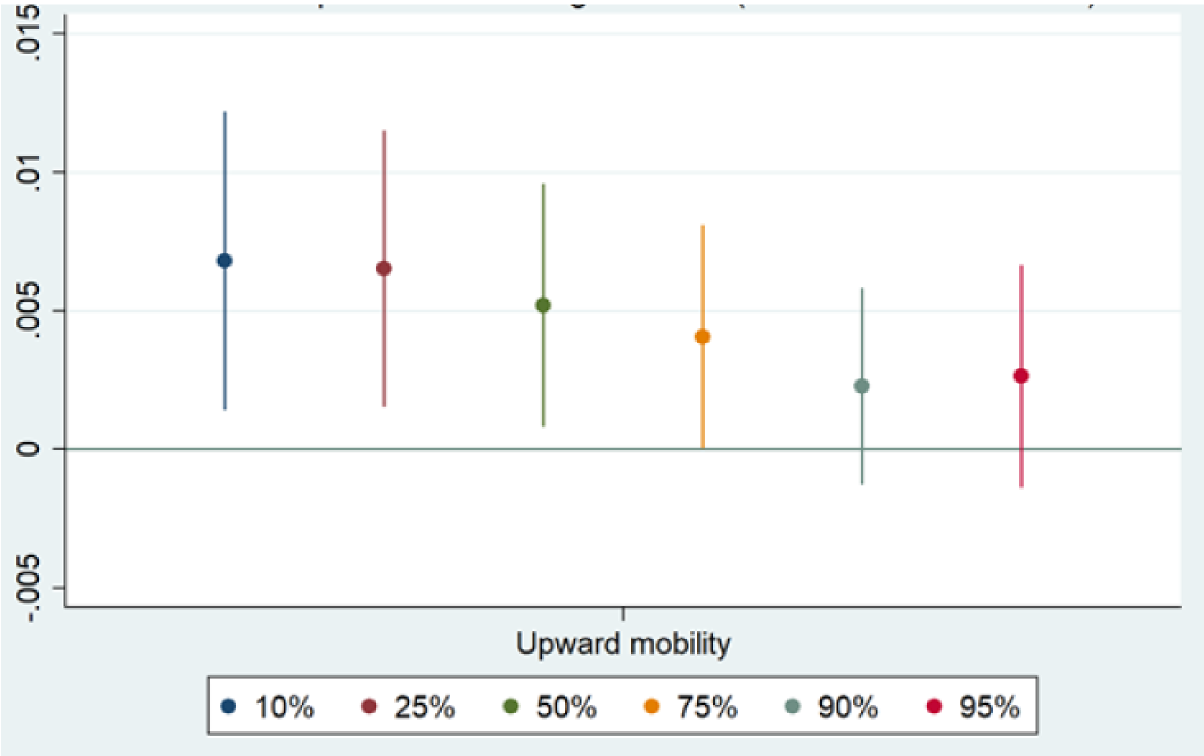


Source: Van der Weide and Vigh (2018).

To further address concerns of omitted variables bias, van der Weide and Vigh (2018) expand the set of control variables. This results in a somewhat smaller number of observations, as the additional controls are not available for the regions of small states. The added controls comprise: (a) log of market access, which captures the extent of domestic market integration; (b) public expenditures as a share of local GDP; (c) voter turnout in the most recent state election; and (d) political competition, measured by the share of votes going to the second-largest political party minus the share going the largest party.

Figure 15 below plots the coefficients corresponding to inter-generational mobility. While the relationship between inter-generational mobility and growth at the different percentiles is similar to the one obtained using the smaller set of controls, the significance of this relationship becomes notably stronger when the expanded set of controls is used. The effect of mobility is now positive and strongly significant for growth at low percentiles, while it is small and insignificant at higher percentiles. This confirms that higher socioeconomic mobility is good for growth, particularly for inclusive growth.

Figure 15: Effects of upward mobility on consumption expenditure growth (at different percentiles: IV regression 2 (90% confidence bound)), with expanded list of control variables



Source: Van der Weide and Vigh (2018).

Van der Weide and Vigh (2018) further hypothesize that human capital accumulation denotes an important channel via which inter-generational mobility impacts on growth and on the degree of 'inclusivity' of growth. To explore the plausibility of this conjecture, they consider changes in years of schooling for individuals with different parental education backgrounds as dependent variable. These estimates confirm that mobility has a positive and significant effect on human capital accumulation of individuals with less than highly educated parents—while the effect is insignificant for individuals with highly educated parents (for whom it matters less whether the playing field is level or not). This result is robust to the choice of controls.

7 Conclusion

Following the economic reforms of the early 1990s, India today is achieving per capita growth rates that are historically unprecedented. Poverty reduction has also accelerated, and is justly celebrated. There is great concern, however, that this growth is being accompanied by rising inequality. This paper reports on a recently completed research project that seeks to inform the debate on inequality in India by offering a 'bird's-eye' view of inequality trends and dynamics at the all-India level over three decades up to 2011/12 and contrasting this with similar evidence at the level of the Indian village or urban block. The study further unpacks inequality to explore dynamics in attempting not just to report 'snapshots' of inequality at different periods, but also to trace the movement of people within the income distribution over time. This analysis of income mobility is motivated by the sense that normative views about changes in inequality are likely to vary according to whether a rise in inequality is, for example, characterized by a simple stretching-out of the income distribution—leaving individuals in the same relative position but just further apart in absolute income—or associated with significant 'leap-frogging' upwards and downwards in relative position within the income distribution. Again, the assessment of mobility is informed both by evidence at the very local level and by aggregate, national-level, trends. Close attention is paid to the circumstances and fortunes of population groups defined in terms of characteristics that should not, ideally, be associated with differing outcomes. The study attempts to encapsulate these horizontal inequalities into a measure of inequality of opportunity as captured by inter-generational mobility in education outcomes.

Our estimation results point to rising inequality between 1983/84 and 2011/12, but to differing degrees depending on the dimension being considered and the measurement method employed. This national trend is consistent with village-level trends in the North Indian village of Palanpur over a period of six decades. The Palanpur study also provides a window on patterns of income mobility, both within and across generations, and points to important changes over time. We then show that local-level inequality (within-village, in rural areas; within-block in urban) accounts for the bulk of overall inequality in India. Understanding what occurs at the local level is thus important for understanding overall inequality.

Our estimates for the dynamics based on synthetic panel data constructed at the household level reveal rising intra-generational income mobility over time. This is consistent with the idea that inequality of lifetime income may be lower than is observed in a given year. However, the evidence also suggests that while poverty has fallen, most of the poor who have escaped poverty continue to face a high risk of falling back into poverty. Moreover, those who remain poor are increasingly chronically poor, and may be particularly difficult to reach via the introduction or expansion of safety nets.

These results are consistent with our finding of a negative relationship between inter-generational mobility and inequality: higher mobility is associated with inclusive growth, which in turn is associated with lower inequality. Furthermore, inter-generational mobility is found to have a positive effect on growth for all percentiles, and specifically stronger effects at lower percentiles. Furthermore, mobility has a positive and significant effect on human capital accumulation of individuals with less than highly educated parents.

Our project offers a comprehensive analysis of poverty and inequality trends in India over the last three decades. Our analysis presents several innovative contributions that have not been available in previous studies. First, we examine trends both across and within the all-India level, the state level, and the microscopic village level. Second, we study both intra-generational mobility and inter-generational mobility. To accomplish these objectives, we both analyse the existing data and create new datasets such as synthetic panels at the state-region and household levels. Our methods of analysis may be applicable not only to India but also to other developing countries in a similar context.

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