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Income mobility in the developing world: Recent approaches and evidence

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Income mobility in the developing world

Recent approaches and evidence

Himanshu¹ and Peter Lanjouw²

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Abstract: This paper examines income mobility in developing countries. We start by synthesizing findings from the available evidence on relative mobility and poverty dynamics. We then describe evidence on economic mobility obtained via synthetic panels constructed from cross-section data. We echo earlier literature in pointing to substantial movement across income classes by households over time: poverty is not inevitably a chronic condition. However, less clear are the factors driving the observed ‘churning’. In an attempt to make headway, we consider the story of economic mobility in one village in northern India over seven decades. We describe patterns of poverty dynamics and economic mobility in the village, and we highlight some of the processes that have been important in driving these patterns. While this in-depth case study does not permit inferences to broader populations, it may provide a reference point against which findings from studies elsewhere can be compared.

Key words: intra- and intergenerational mobility, welfare dynamics, developing countries, India, chronic and transitory poverty

JEL classification: C15, I32, O15

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1 Introduction

How the fruits of economic activity are distributed, and how living standards change, were central questions for classical economists such as Smith, Ricardo, and Marx. They have returned to the fore in present-day debates. The documentation and analysis of distributional outcomes in developing countries has seen great advances in recent years. However, a remaining blind spot pertains to the understanding of how living conditions evolve over time at the household level.

The analysis of such patterns of income mobility relies on longitudinal data that follow households over time. While such panel data can deliver important insights for the analysis of living standards (see for example Ashenfelter et al. 1986), the fielding of panel surveys has lagged behind the more conventional cross-section surveys that underpin standard distributional analysis. This is largely due to the relatively high cost and complexity associated with panel data collection. Recent years, however, have seen a welcome expansion of such survey efforts. For example, the World Bank's Living Standards Measurement Study Integrated Surveys on Agriculture programme has been collecting panel data in eight sub-Saharan African countries since the mid-2000s.¹

The analysis of economic mobility is typically concerned with tracking the relative position of individuals or households across the entire distribution of income or earnings. This type of enquiry is fairly common in developed countries and is also seeing increasing attention in developing countries. When there is extensive relative income mobility, then inequality of long-term income ('permanent' income) is likely to be lower than inequality measured in any given year (Fields 2010). Income mobility thus relates closely to inequality and the normative view one might take regarding the observed degree of inequality at a given moment.

An assessment of dynamics in the distribution of income as a whole is also needed when we confront questions around the emergence of a middle class (see Ferreira et al. 2013). In many developing countries, economic growth, urbanization, formalization of the economy, an expanding service sector, and closer global integration have led to increased attention to the emergence and expansion of the middle class. Crucial questions arise with respect to the flow of population into the middle class, and the possible presence of constraints that prevent the poorer segments of society from becoming part of the middle class.

In the developing country context, the panel-based analysis of welfare dynamics has often focused specifically on establishing and assessing the distinction between chronic and transient poverty. Chronic poverty occurs where the same individuals are consistently poor over time—possibly pointing to the existence of poverty traps. Efforts to combat chronic poverty may call for policies that help households overcome the structural constraints they face. In contrast, transient poverty exists where the composition of the poor changes from one period to the next—due to at least some of the currently poor exiting poverty through upwards mobility, and some of the non-poor falling back into poverty. Here, policies that are more in the nature of safety nets may be required.

Given the (current) scarcity of panel data in developing countries—particularly longitudinal data that are representative at the national level—a variety of research efforts have been directed

¹ Other well-known and highly regarded nationally representative panel surveys covering the 2000s include the Indonesian Family Life Survey, the Mexican Family Life Survey, the Indian Human Development Survey, Viet Nam's Household Living Standards Survey, Thailand's Socio-Economic Survey, Peru's National Household Survey, and Chile's National Socio-Economic Characterization Survey (see Table 1).

towards the utilization of cross-sectional surveys to extract insights about poverty dynamics. Following Deaton (1985), a large strand of research has constructed pseudo-panels based on cohorts, to track income and consumption outcomes at the cohort level over time. These approaches have the attraction that, since cross-section samples are refreshed in each wave, they are possibly less exposed to the concerns surrounding attrition and measurement error that afflict panel data sets. However, the focus on cohorts in pseudo-panels implies that relatively little can be said about poverty and mobility trajectories at the household or individual level. Recently, Dang et al. (2014) and Dang and Lanjouw (2018a) have proposed a method for constructing synthetic panels at the household level from two rounds of cross-sectional data.² The approach builds on an ‘out-of-sample’ imputation methodology described in Elbers et al. (2003) for small area estimations of poverty, to convert two or more rounds of cross-section data into a panel of individuals by predicting the income for the same households in future (or past) periods. Analysis of mobility is then possible by using actual observed incomes for households in a given year combined with their predicted incomes in the other. Validation of these methods, where synthetic panel estimates are compared with true panel estimates, has been fairly encouraging.³ Given the wide availability of cross-section data, synthetic panels promise to add significantly to the countries and time periods for which mobility analyses can be undertaken.

Mobility analysis as described above, based on quantitative panel or cross-section survey data on incomes, offers a useful entry point for understanding how, and to what extent, living standards in a population are changing. However, it has also become clear that these data are at best able to provide a partial understanding. The numerous limitations of such data (limited sample sizes, definitions of welfare, short time periods, measurement error and attrition, methodological assumptions, etc.) imply that even basic descriptions of mobility are approximate at best. More fundamentally, such analysis is at best descriptive, and moving from there to a deeper analysis of the drivers of mobility presents additional onerous challenges. As argued by Ashenfelter et al. (1986), the limitations of panel data may become particularly apparent when we move on from description to the exploration of underlying transmission mechanisms. Notably, income mobility is best understood when broader economic and social structures are also given explicit consideration. As the focus is squarely on change, and as even economic institutions are endogenous to changing economic circumstances and conditions, it seems imperative to complement the standard data on economic welfare dynamics with an understanding of life histories, and of the broader environment and its evolution. Longitudinal village studies provide a setting within which such a broader analysis may be broached—although of course these entail stepping back from making inferences to the larger populations.⁴

² Bourguignon et al. (2004) and Guell and Hu (2006) apply pseudo-panel methods to analyse poverty dynamics, but are compelled to make a number of assumptions that are difficult to verify. The former are also dependent on at least three rounds of cross-section data. Cuesta et al. (2011) report on broader income mobility in Mexico on the basis of pseudo-panel methods.

³ Dang and Lanjouw (2018a), Herault and Jenkins (2019), and Garces-Urzainqui (2017) document cases where synthetic panel estimates fall outside the confidence intervals surrounding true panel estimates. However, even in such cases the qualitative patterns of poverty transitions are generally quite similar between the panel and synthetic panel estimates. Cruces et al. (2013) warn that the synthetic panel approach may be less suited to some mobility concepts and measures than others.

⁴ Village studies are a long-standing tradition in the South Asian context, and have generated a number of insights about welfare dynamics (Jayaraman and Lanjouw 1999; Himanshu et al. 2016; Walker and Ryan 1990). Village studies per se are less common in other regions, but detailed subnational studies of dynamics are readily found (see for example Scott and Litchfield (1994) in Chile; Townsend (2013) in Thailand; Dercon and Krishnan (2000) in Ethiopia; de Weerd (2010) and Beegle et al. (2011) in Kagera, United Republic of Tanzania). Many of these look well beyond the analysis of household survey data.

The objective of this paper is to illustrate various entry points into the analysis of mobility, and to take stock of recently available evidence in developing countries. In doing so we adopt a three-pronged approach. First, in section 2 we briefly examine existing evidence on relative mobility and poverty dynamics. In section 3 we describe findings from the growing effort to document patterns of economic mobility via synthetic panels constructed from multiple rounds of cross-section data. In section 4 we describe in detail the story of economic mobility in the village of Palanpur, northern India, over a period of seven decades (Himanshu et al. 2018). This study allows us not just to describe the patterns of poverty dynamics and economic mobility in the village, but also to highlight some of the processes that have been important in driving these patterns. Given the important context of structural transformation within which the Palanpur story is embedded, our sense is that the broad narrative may well resonate elsewhere in the developing world. Section 5 offers some concluding remarks.

2 Evidence on income mobility and poverty dynamics from panel data

Interest in economic mobility is not new, and there exist several studies that attempt to synthesize findings from earlier panel-based analyses. A fairly comprehensive overview of findings from studies of income and earnings mobility in developing countries can be found in Fields (2011). The empirical evidence assembled in the survey reveals that current knowledge is derived to a considerable extent from Latin American countries, where there has been a longer tradition of collecting panel data. However, the survey does also present evidence on patterns of mobility in China, Ethiopia, South Africa, and the United Republic of Tanzania, and it also refers to findings from additional countries in Africa and Asia. Fields (2011) notes that much of the income mobility work has focused on earnings rather than full income, and is generally more representative of urban than rural areas. Based on his review of the evidence, Fields (2011) notes that developing countries tend to exhibit neither complete immobility nor perfect mobility. When the income trajectories of households or individuals are tracked over time, the evidence suggests that there is a general tendency for the rich to remain rich and the poor to remain poor, but there is typically also a great deal of both upwards and downwards movement in the relative income distribution.

Fields (2011) describes a fairly extensive literature investigating whether the mobility patterns of households vary according to their characteristics. An important question concerns whether changes in household earnings are related in some way to initial earnings. This has been explored unconditionally, when just baseline earnings are correlated with subsequent changes in earnings, as well as conditionally, when these patterns are examined controlling for other household characteristics such as occupation, education, demographic composition, etc. The literature has further considered this question in terms of both absolute changes in earnings and percentage changes in earnings. Overall, the literature most frequently finds evidence of ‘convergence’, suggesting that the largest increases in earnings are experienced by those who have the lowest reported incomes or earnings to begin with. Importantly, the evidence in support of convergence appears to hold when it is assessed unconditionally as well as when it is conditional on household characteristics. In some cases, convergence is observed only in terms of percentage changes rather than absolute changes in earnings, and more broadly the evidence becomes weaker when efforts are made to adjust for the possible presence of measurement error. This finding of convergence is important, as it suggests that income mobility generally acts to make the distribution of lifetime income more equal. A snapshot of income inequality, based on a single cross-section survey, could thus provide a rather misleading picture of the distribution of longer-term incomes.

As noted in the introduction, interest in welfare dynamics in developing country contexts has often been specifically focused on the dynamics of poverty. In one of the earlier syntheses of this

particular literature, Baulch and Hoddinott (2000) point out that there should be no presumption that the poor, identified as such at a given moment, are always poor. Consistent with the findings reported by Fields (2011) for the distribution of income as a whole, they suggest that the group of the ‘sometimes poor’ is strikingly large, and that there is thus a great deal of ‘churning’ that occurs across the poverty line. Some of the poor graduate out of poverty, while some of the non-poor fall back. The numbers involved are often surprisingly large.

Dercon and Shapiro (2007) build on the analysis of Baulch and Hoddinott (2000), and also examine the profiles of the transitory and chronic poor. They find that in general, individual, household, and community characteristics correlate as intuition would expect with the likelihood of escaping or falling back into poverty. They warn, however, that observing correlations is not the same as establishing causality, and they note the absence of studies that provide such causal evidence. Dercon and Shapiro (2007) further underscore the potential biases to insights that arise as a result of sample attrition, and also note that at least some of the churning observed will be driven by measurement error. They further place great emphasis on understanding the role played by risk and uncertainty in welfare dynamics.

Baulch (2011, 2013) offers the reminder that assessments of movements out of and into poverty refer to discrete jumps across a poverty line. He shows that in Viet Nam between 2002 and 2006, while the chronically poor represented a relatively small fraction of the population, the non-poor were concentrated just above the poverty line and thus remained at high risk of falling back into poverty. Indeed, Dang and Lanjouw (2016) propose designating as vulnerable that segment of the non-poor population that faces a heightened risk of falling back into poverty. Ferreira et al. (2013) offer an analogous line of reasoning in establishing a three-way division of the population into the poor, the vulnerable, and the middle class.

Table 1 presents updated evidence from a selection of countries on the incidence of chronic and transitory poverty. The table closely follows the structure of Table 1 in Baulch and Hoddinott (2000), differing essentially in that it reports evidence from the 2000s and only findings from nationally representative panel surveys. Some useful insights emerge. First, the ‘sometimes poor’ are a large share of the population in most of the countries listed. A clear outlier is South Africa, where Finn and Leibbrandt (2016) record percentages for the ‘always poor’ of between half and two thirds of the population, depending on the time interval examined. Second, when poverty dynamics are measured over a longer period, then not surprisingly there is greater scope for mobility, and the group of the ‘sometimes poor’ is larger. When mobility is measured across more than just two waves of a panel data set, as in the case of Uganda, the likelihood of being ‘always poor’ diminishes even further: there are more opportunities in the data to be observed above the poverty line. Third, notwithstanding the broad evidence of considerable mobility, Table 1 suggests that the incidence of chronic poverty in certain countries—such as Malawi, Mexico, Nicaragua, Peru, and South Africa—remains remarkably high. Finally, Table 1 also provides a window on the variability of mobility across time intervals. In Peru and the United Republic of Tanzania, mobility figures are provided across two different intervals of similar duration, and the percentages in the three classes of ‘always poor’, ‘sometimes poor’, and ‘never poor’ vary significantly. Assessments of poverty dynamics are thus liable to depend on the specific interval over which such dynamics are measured.

Table 1: Poverty dynamics in a selection of nationally representative panel studies

Source	Country	Panel interval dates	Welfare measure	Always poor	Sometimes poor	Never poor
Dang and Lanjouw (2018a)	Bosnia and Herzegovina	2001-04	Per capita consumption	10.3	23.1	66.5
Dang and Lanjouw (2018a)	Lao People's Democratic Republic	2002-07	Per capita consumption	13.8	25.2	61.0
Garces-Urzaizqui (2017)	Thailand	2006-07	Per capita income	15.3	21.6	63.1
Dang and Lanjouw (2018a)	Viet Nam	2006-08	Per capita consumption	9.9	10.8	79.3
Dang et al. (2014)	Indonesia	1997-2000	Per capita consumption	7.3	18.4	74.3
Dang and Lanjouw (2018b)	India	2004-11	Per capita consumption	12.7	32.8	54.4
Van Campenhout et al. (2016)	Uganda	2005-09-10-11-12	Per capita consumption	12.3	51.9	35.8
Ruhinduka et al. (2018)	United Republic of Tanzania	2008-10	Per capita consumption	6.6	19.9	73.5
Ruhinduka et al. (2018)	United Republic of Tanzania	2010-12	Per capita consumption	3.1	14.0	82.9
Jolliffe and Seff (2016)	Ethiopia (rural)	2011-13	Per capita consumption	14.4	30.6	55.0
World Bank (2016)	Malawi	2010-13	Per capita consumption	23	32	44
Finn and Leibbrandt (2016)	South Africa	2008-10	Per capita income	64.7	15.6	19.7
Finn and Leibbrandt (2016)	South Africa	2008-14	Per capita income	53.7	25.2	21.1
Dang and Lanjouw (2018a)	Peru	2005-06	Per capita consumption	29.9	20.5	49.7
Cruces et al. (2015)	Peru	2008-09	Per capita consumption	23.6	20.0	56.5
Cruces et al. (2015)	Nicaragua	2001-05	Per capita consumption	35.7	29.5	34.9
Cruces et al. (2015)	Chile	1996-06	Per capita income	4.6	22.6	72.8
Ramos et al. (2015)	Mexico	2002-05	Household income	26.1	45.5	28.3
Dang and Lanjouw (2018a)	United States of America	2007-09	Per capita income	6.0	8.4	85.7

Source: authors' compilation.

3 Insights from synthetic panels

As noted in the introduction, there have been efforts in recent years to develop methods to extract insights about economic mobility and poverty dynamics from cross-section data. The goal is to find a way to draw on the far more abundant cross-sectional household surveys in order to start filling in the knowledge gaps on the international experience of mobility. We outline below a synthetic panel method proposed by Dang et al. (2014) and Dang and Lanjouw (2018a), and we report findings concerning poverty dynamics in a number of countries based on this approach. It should be emphasized, however, that while synthetic panels show promise, a great deal of additional work is needed to establish their ultimate reliability. The brief description below of

findings from several attempts to obtain synthetic panel-based estimates should thus be treated with circumspection.

3.1 Overview of synthetic panel and vulnerability analysis methods

We start with a brief description of the method proposed by Dang et al. (2014) and extended further by Dang and Lanjouw (2018a) for constructing synthetic panels.

Let x_{ij} be a vector of household characteristics observed in survey round j ($j = 1$ or 2) that are also observed in the other survey round for household i ($i = 1, \dots, N$). These household characteristics include variables that may be collected in only one survey round, but whose values can be inferred for the other round. These variables may be roughly categorized into three types:

- i. time-invariant variables such as ethnicity, religion, place of birth, or parental education;
- ii. deterministic variables such as age (which, given the value in one survey round, can then be determined given the time interval between the two survey rounds)⁵;
- iii. time-varying household characteristics, if retrospective questions about the values of such characteristics in the first survey round are asked in the second round.

Let y_{ij} then represent household consumption or income in survey round j ($j = 1$ or 2). The linear projection of household consumption (or income) on household characteristics for each survey round is given by

$$y_{ij} = \beta_j' x_{ij} + \varepsilon_{ij} \quad [1]$$

Let z_j be the poverty line in period j ($j = 1$ or 2). When the interest is in poverty dynamics, we will wish to know quantities such as

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) \quad [2]$$

which represents the percentage of households that are poor in the first period but non-poor in the second period (considered together for two periods), or

$$P(y_{i2} > z_2 \mid y_{i1} < z_1) \quad [3]$$

which represents the percentage of poor households in the first period that escape poverty in the second period. In other words, for the average household, quantity 2 provides the joint probabilities of household poverty status in both periods, and quantity 3 the conditional probabilities of household poverty status in the second period given its poverty status in the first period.

When true panel data are available, the quantities in equations 2 and 3 can be straightforwardly calculated; but in the absence of such data, synthetic panels can be drawn on. This framework is predicated on two fairly standard assumptions. First, the underlying population being sampled in survey rounds 1 and 2 is assumed to be identical, such that time-invariant population characteristics

⁵ To reduce spurious changes due to changes in household composition over time, attention is often restricted to household heads aged, say, 25 to 55 in the first cross-section, with a corresponding adjustment in the second cross-section. This age range is usually used in traditional pseudo-panel analysis, but can vary depending on the cultural and economic factors in each specific setting.

remain the same over time. More specifically, this implies that the conditional distribution of expenditure in a given period is identical whether it is conditional on the given household characteristics in period 1 or period 2 (i.e. $x_{i1} = x_{i2}$ implies that $y_{i1}|x_{i1}$ and $y_{i1}|x_{i2}$ have identical distributions).⁶ Second, ε_{i1} and ε_{i2} are assumed to have a bivariate normal distribution with correlation coefficient ρ and standard deviations σ_{ε_1} and σ_{ε_2} respectively. Equation 2 can be estimated by

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) = \Phi_2\left(\frac{z_1 - \beta_1'x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2 - \beta_2'x_{i2}}{\sigma_{\varepsilon_2}}, -\rho\right) \quad [4]$$

where $\Phi_2(\cdot)$ stands for the bivariate normal cumulative distribution function, and $\phi_2(\cdot)$ stands for the bivariate normal probability density function. In equation 4, the parameters β_j and σ_{ε_j} are obtained from equation 1, and ρ from the following formula:

$$\rho = \frac{\rho_{y_1y_2} \sqrt{\text{var}(y_1) \text{var}(y_2)} - \beta_1' \text{var}(x) \beta_2}{\sigma_{\varepsilon_1} \sigma_{\varepsilon_2}} \quad [5]$$

where the simple correlation coefficient $\rho_{y_1y_2}$ is approximated from the birth-cohort-aggregated household consumption between the two surveys. Note that in equation 4, the estimated parameters obtained from data in both survey rounds are applied to data from the second survey round (x_2) (or the base year) for prediction, but one can also use data from the first survey round as the base year as well. It is then straightforward to estimate quantity 3, by dividing quantity 2 by

$$\Phi\left(\frac{z_1 - \beta_1'x_{i2}}{\sigma_{\varepsilon_1}}\right), \text{ where } \Phi(\cdot) \text{ stands for the univariate normal cumulative distribution function.}^7$$

3.2 Evidence from synthetic panels

Ferreira et al. (2013) undertake a systematic analysis of household survey data from 18 Latin American countries to assess patterns of mobility—both out of poverty and into the middle class—over the interval from around the mid-1990s to around 2010. They draw on the Dang et al. (2014) methodology of producing synthetic panels, and in particular they adapt the method in such a way as to err on the side of understating mobility. At the aggregate level, obtained by pooling together the data from all the countries, Ferreira et al. (2013) estimate that around 22.5 per cent of the population in these countries remained below a poverty line of US\$4 per person per day in 2005 purchasing power standards (PPPs) over the period circa 1995 to circa 2010. Similarly, 22 per cent of the population were ‘sometimes poor’, while about 55.5 per cent were non-poor throughout. Taking a cut-off point of PPP US\$10 per person per day to demark the entry into the

⁶ In other words, this assumption implies that households in period 2 that have similar characteristics to households in period 1 would have achieved the same consumption levels in period 1, or vice versa.

⁷ Further asymptotic results and formulae for the standard errors are provided in Dang and Lanjouw (2013, 2018b). These studies also provide validation results for the synthetic panels against the actual panel data for several countries, including Bosnia and Herzegovina, Lao People’s Democratic Republic, Peru, the United States of American, and Viet Nam. Other studies that offer further validation and extension include Cruces et al. (2015).

middle class, Ferreira et al. (2013) report that only about 20 per cent of the population were counted among the middle class over the whole period.

It is instructive to compare the mobility rates estimated in Ferreira et al. (2013) with those reported in Table 1 for the four Latin American countries for which true panel estimates are provided.⁸ Table 2 reveals that—as foreshadowed by Ferreira et al. (2013)—the synthetic panel estimates of mobility point to a higher degree of chronic poverty than was observed in Table 1. However, it is interesting to note that in Chile—where the true panel estimates corresponded to the 10-year interval between 1996 and 2010, and the welfare indicator was also income—chronic poverty was 4.6 per cent, relative to 11.6 per cent in Table 2. Additionally, the Ferreira et al. (2013) study suggests that roughly 27 per cent of the population was ‘sometimes poor’ between 1992 and 2009. This compares with an estimate of 22.6 in Table 2, based on true panel data between 1996 and 2006. These findings suggest that biases in the Ferreira et al. (2013) study may not be egregious everywhere.

Table 2: Poverty dynamics in Latin America—synthetic panel estimates

Country	Panel interval dates	Always poor	Sometimes poor	Never poor
Nicaragua	1998-2005	54.3	16.0	29.7
Peru	1999-2009	31.0	25.7	43.3
Chile	1992-2009	11.6	27.3	61.1
Mexico	2000-08	24.9	12.0	63.1

Source: authors’ compilation adapted from Ferreira et al. (2013).

A recent study by Dang and Dabalen (2018) undertakes a similar effort to produce estimates of poverty dynamics for 21 sub-Saharan African countries, accounting for roughly two thirds of the entire sub-Saharan population. Although the precise interval over which the dynamics are assessed varies, the comparisons span six years on average during the 2000s. Whereas Ferreira et al. (2013) reported lower-bound estimates of mobility, Dang and Dabalen (2018) attempt to estimate point estimates of mobility, based on a refinement of the methodology described in Dang and Lanjouw (2018a). When pooling the data for all 21 countries, Dang and Dabalen (2018) report that just under 36 per cent of the population remained under the poverty line of US\$1.90 per person per day, in 2011 PPP terms, across the intervals compared. Transitory poverty accounted for 13.4 per cent, and the ‘never poor’ accounted for 50.7 per cent of the population.

Dang and Dabalen (2018) point to great variation in the levels of chronic poverty across African countries. Worryingly, but perhaps not surprisingly, the incidence of chronic poverty is particularly high in countries such as the Democratic Republic of the Congo (DRC), Madagascar, and Malawi, with also very high overall poverty rates. For example, the overall poverty rate in DRC was nearly 80 per cent in 2012 (although down from 92 per cent in 2004), and the chronically poor represented nearly three quarters of this group. More generally, Table 3 confirms that transitory poverty is consistently high in sub-Saharan Africa, and it points to several countries where the category of the ‘never poor’ is vanishingly small (DRC, Madagascar, Malawi, and Mozambique).

⁸ However, strict comparisons are not valid, due to the different time periods under consideration and the facts that the welfare levels in the Ferreira et al. (2013) study are uniformly income, and the poverty lines under consideration are country-specific in Table 1 and common across countries in the Ferreira et al. (2013) study.

Table 3: Poverty dynamics in sub-Saharan Africa—synthetic panel estimates

Country	Panel interval dates	Always poor	Sometimes poor	Never poor
Mauritania	2004-08	6.5	12.1	81.4
Botswana	2002-09	8.9	24.9	66.2
Nigeria	2011-13	11.7	17.9	70.4
Ghana	1998-2005	20.4	18.4	61.2
Cote D'Ivoire	2002-08	17.3	11.2	71.5
Cameroon	2001-07	13.9	23.3	62.8
Ethiopia	2004-10	28.6	18.8	52.6
Senegal	2005-11	29.5	17.2	53.3
Chad	2003-11	24.8	55.3	19.9
Eswatini (formerly Swaziland)	2000-09	18.0	51.2	30.8
Uganda	2005-09	32.4	33.1	34.5
United Republic of Tanzania	2007-11	27.6	47.7	24.7
Togo	2006-11	41.1	25.5	33.4
Sierra Leone	2003-11	37.8	36.3	25.9
Burkina Faso	2003-09	47.6	16.3	36.1
Rwanda	2005-10	50.8	29.3	19.9
Zambia	2006-10	45.1	32.0	22.9
Mozambique	2002-08	51.1	48.5	0.4
Malawi	2004-10	54.1	37.8	8.1
DRC	2004-12	72.8	24.1	3.1
Madagascar	2005-10	59.9	36.8	3.3

Source: authors' compilation adapted from Dang and Dabalen (2018).

Table 4: Poverty dynamics in the Arab world—synthetic panel estimates

Country/territory	Panel interval dates	Always poor	Sometimes poor	Never poor
Palestinian territories	2005-09	0.1	1.9	98.0
Syrian Arab Republic	1997-2004	7.3	34.3	58.4
Jordan	2006-08	2.4	4.7	92.9
Yemen	1998-2006	28.3	31.5	40.2
Egypt	2004-09	13.3	22.8	63.9
Tunisia	2005-10	1.2	11.9	86.9

Source: authors' compilation adapted from Dang and Ianchovichina (2018).

A third application of synthetic panel-based mobility analysis across a set of countries can be found in Dang and Ianchovichina (2018), assessing patterns of mobility in Arab countries. Dang and Ianchovichina (2018) construct synthetic panels from cross-section data in six Arab countries/territories: Egypt, Jordan, Palestinian territories, the Syrian Arab Republic, Tunisia, and Yemen. The panels span different time periods—mid- to late 2000s in Egypt, Jordan, Palestinian territories, and Tunisia, and late 1990s to mid-2000s in the Syrian Arab Republic and Yemen. End-year poverty rates, based on a uniform poverty line of US\$2 per person per day in 2005 PPPs, varied sharply across these countries, with a low of less than one per cent in the Palestinian territories, and a high of 56 per cent in Yemen (Table 4). Poverty dynamics, assessed on the basis of the US\$2 poverty line, were negligible in the Palestinian territories and Jordan—where the 'never poor' represented more than 90 per cent of the population. In the other four countries, chronic and transitory poverty were rather higher, with the 'sometimes poor' accounting for the bulk of the poor in each country. Given the degree of churning that can be observed, it becomes apparent that simply comparing aggregate poverty rates over time might not capture the extent to which the population was exposed—at one point or another—to acute deprivation. Since in several countries the intervals examined spanned the social upheaval of the 'Arab spring', this helps

us to understand why disaffection was so widespread, even though poverty (and inequality) rates were rather low and stable.

4 Income mobility at the village level: a case study

4.1 Village studies as a tool for studying mobility

The preceding discussion has highlighted the challenge of describing and measuring mobility in the developing world. Better techniques, improvements in data quality, and accessibility of unit data have allowed researchers to use panels or synthetic panels to expand assessments of mobility in a growing number of countries. However, even where such data are available, they rarely cover sufficiently long periods to enable the study of long-term processes, such as mobility across two or three generations. The problems apply not just to finding sufficiently long panel data, but also to getting accurate measures of the variables required for such analysis for all the time periods.

In addition, large-scale sample surveys have the advantage of representativeness but are constrained by the nature of the (typically quantitative) questions they ask. Mobility is not just an isolated event. Rather, it is crucially linked to the social, political, and institutional context in which the individual operates. Large-scale representative surveys are not well placed to capture such contextual evidence. Village surveys, on the other hand, typically use multiple survey instruments, including qualitative surveys that aim to capture different aspects of the social, political, and institutional context. Such surveys may not be suited for studying trends and patterns of mobility for a country as whole, because of their small size and limited domain of reference. But these limitations may be compensated for in part by the depth of analysis that these studies occasionally permit.

Interestingly, while developing countries suffer from a relative scarcity of large-scale panel surveys, detailed longitudinal village surveys are not so unusual—particularly in South and East Asia. Many of these village studies examine welfare dynamics, including aspects of social mobility as revealed by non-income indicators. In India, the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) village studies are particularly well known, and have been intensively studied to explore the role of agricultural productivity growth, non-farm diversification, weather shocks, and migration as means to manage risk and as pathways to upwards mobility (Dercon et al. 2013; Walker and Ryan 1990).⁹

Among longitudinal village surveys, Palanpur, a small village in western Uttar Pradesh in India, is particularly well placed for a more detailed study of mobility and poverty dynamics. Palanpur is uniquely endowed with data, having been intensively surveyed on seven occasions spanning the interval from 1957–58 to 2015. There is a comprehensive survey available for every decade since the 1950s. These surveys cover the entire village population, and over time the themes of research have become increasingly rich and ambitious. The data allow researchers to track the economic, social, and political status of all village households and individuals across the seven decades. Himanshu et al. (2018) provide a detailed account of economic development in Palanpur and how lives have changed in the face this process. In what follows we present a brief description of the most salient aspects of mobility and its drivers.

⁹ Village studies are particularly common in South Asia. Some of these, along with methodological issues related to longitudinal village surveys, are examined in Himanshu et al. (2016).

A unique feature of the Palanpur data arises from the fact that the surveys cover the entire village population, as opposed to a sample of households or individuals (as in the ICRISAT surveys). This is useful for the detailed analysis of inequality and relative mobility. In addition, although some of the Palanpur surveys were conducted more than 50 years ago, the ready availability of the raw questionnaires has allowed incomes to be re-estimated in light of newer concepts and methodologies. The Palanpur data also allow the use of caste as an occupational classification category. Occupational transitions can provide important insights into welfare dynamics. In any analysis spanning seven decades, occupational classifications are always difficult to define consistently. One way of dealing with such problems is to use caste as a category of classification.¹⁰ While they are not synonymous with occupational classifications, the fact that caste hierarchies are generally stable over time offers a window onto aspects of mobility that go beyond the standard income metrics.

4.2 Palanpur: a brief description

In the most recent detailed survey, conducted in 2008–10, Palanpur had a population of 1,255 persons in 233 households.¹¹ Table 5 presents basic population indicators since the 1950s. The three main castes among Hindus that accounted for about two thirds of the village population were Thakurs (23 per cent), Muraos (24 per cent), and Jatabs (16 per cent). Muslims, at around 15 per cent, were divided into two main groups, Telis and Dhobis.

Highest in the village social hierarchy are the Thakurs, who have traditionally had the largest landholdings in the village. However, declining land endowments and rising real wages have gradually compelled most of them to take up employment opportunities outside the village. In economic terms, the Muraos are placed similarly to the Thakurs, and occasionally rank even higher in per capita income terms. Muraos are traditional cultivators and have generally been successful in taking advantage of technological changes in agriculture. They have tended to eschew involvement in the growing non-agricultural sector. At the bottom end of the hierarchy are the Jatabs, who comprise the bulk of the Scheduled Caste population in the village. The Jatabs are historically the most deprived caste in Palanpur in social and economic terms. They own little land, and until very recently lived in a cluster of shabby mud dwellings, earning most of their income from casual labour and subsistence farming. The Jatabs also remain at the bottom in terms of human development outcomes, with particularly high levels of illiteracy throughout the survey period. Before 1993, few Jatabs had ever succeeded in obtaining regular employment outside the village.¹² Muslims are not part of the traditional caste hierarchy but were generally also among the poorest households until 2008, when the Telis saw significant improvement in their economic fortunes.

¹⁰ Hindu society is divided into various caste and subcastes, which are hereditary. The caste of an individual is generally also associated with the status of the individual/household, based on the position of the caste in the social hierarchy. For a detailed description of caste and social status in Palanpur, see Lanjouw and Stern (1998).

¹¹ The population of the village increased marginally to 1,299 residents in the latest survey in 2015. Since the 2015 data do not include income estimates, we avoid reference to the 2015 survey in this paper. For income estimates, we also exclude the 1993 survey, which did not collect detailed income data.

¹² Lanjouw and Stern (1998) indicate that in the period up to 1983–84, even after controls for wealth position and education levels, Jatabs were unlikely to find regular employment in the non-farm sector.

Table 5: Basic population indicators of Palanpur

	1957-58	1962-63	1974-75	1983-4	1993	2008
Population	528	585	790	960	1,133	1,255
No. of households	100	106	117	143	193	233
Average household size	5.3	5.5	6.8	6.7	5.9	5.4
Female-male ratio	0.87	0.87	0.85	0.93	0.85	0.98
Annual growth rate of population	-	2.2	2.5	2.2	1.7	0.74
Migration-adjusted growth rate		2.3	2.7	1.9	2.2	1.9
Proportions of population in different caste groups (%)						
Thakur	19.7	21.4	22.0	22.6	25.0	22.9
Murao	22.2	22.7	22.5	22.6	25.9	24.2
Muslim	10.0	10.1	11.8	12.4	12.4	15.1
Jatab	13.4	12.1	12.3	12.3	11.7	16.2
Other	34.7	33.7	31.4	30.1	25.0	21.7

Source: primary survey data.

Between 1957–58 and 2008–09, total village income increased more than fivefold.¹³ As a result of population growth, however, real per capita income growth was slower, increasing 2.4 times.¹⁴ During the seven decades of the survey period, not only did the village see uneven growth, but the fortunes of its residents also evolved differently. In particular, growth was not shared equally by all caste groups. While the relative ranking of different caste groups changed little, what did appear to affect the economic fortunes of households/individuals was the changing nature of economic growth in the village.

Lanjouw and Stern (1998) identify technological change, non-farm jobs, and population growth as the primary drivers of growth during the first three decades. These three forces also remained relevant during the most recent three decades, but the degree to which they played a role changed. Agricultural intensification ushered in by the Green Revolution played an important role during the 1960s, 1970s, and early 1980s. Non-farm diversification played only a modest role in that period. The processes of change launched by the Green Revolution—expansion of irrigation, intensification of cultivation, changing cropping patterns, farm mechanization, marketization of factors of production, and improvements in formal credit supply—continued throughout the survey period, and combined over time to result in the release of labour from agriculture. This was increasingly absorbed by a growing non-farm sector. Mirroring trends also observable at the all-India level, over time this non-farm sector saw a qualitative shift away from regular jobs to casual manual jobs. The availability of casual manual jobs and self-employment opportunities in the form of small ‘petty’ businesses such as general shops, milk businesses, tailoring, etc. resulted in a larger pool of villagers employed in the non-farm sector. One feature of this in recent decades has been a significant increase in access to non-farm jobs among hitherto disadvantaged groups such as Jatabs and Telis. The non-farm sector has emerged as a major driver not just of economic outcomes but also of changing income distribution and mobility.

¹³ This growth was not even, with village income increasing at 3.83 per cent per year during 1958 to 1983, but slowing down to three per cent over the next 25 years (1983 to 2008).

¹⁴ Back-of-the-envelope calculations show that the average income in Palanpur in the period 2008 to 2009 was around the World Bank International Poverty Line, indicating that in this sense it is a poor village by international standards.

4.3 Mobility across survey years

The conventional analysis of mobility, based on income and consumption, is central to an understanding of distributional outcomes. However, quantitative measures of income or consumption provide only a partial perspective on patterns.¹⁵ The Palanpur surveys have also looked at qualitative measures of well-being, especially measures that reflect the resident investigators' perspectives on living standards and capture the relative socio-economic status of households from the villagers' own standpoint.¹⁶ For most of the mobility analysis that follows, we combine these quantitative and qualitative measures. While they broadly agree with each other for rankings at the two ends of the welfare distribution, there are differences in the middle. The differences in various ranking methodologies highlight the role and relative importance of different aspects of well-being, thereby providing a multidimensional view of poverty and the circumstances of poor people, a view that is broader than that available from a single dimension.

As in any village, Palanpur villagers live in a close-knit community where individuals know a great deal about each other. With the investigators' long residence in the village, much of this local knowledge is absorbed and can be considered together with direct observation and quantitative measures. This knowledge has been used by the resident investigators to develop an 'observed means' classification. As considered here, 'means' should be understood as the ability to command resources. Drawing on personal observations and consultation with the villagers, the investigators constructed a ranking of overall prosperity for every household during the survey years 1983–84 and 2008–09.¹⁷

4.4 Intragenerational mobility

We use both quantitative and qualitative rankings to compare the relative positions of households in survey years, and to compare their position in one period with their position in the second period. We start with an examination of the interval between 1983–84 and 2008–09, as this allows us to consider both income and the observed means categorization. While the analysis based on observed means is limited to the interval between 1983–84 and 2008–09, it is arguably less prey to idiosyncratic fluctuations in incomes, and may therefore be more robust for tracking the movements of individuals and their households across survey rounds. Since income data are available from 1957–58 onwards, we use the income classification to examine below how intergenerational mobility has evolved.

¹⁵ Apart from the difficulty of imputation and coverage of income/consumption, the quantitative measures are affected by the choice of survey years. For example, a comparison between a drought year and a normal year may lead to a different understanding of mobility, given that such external shocks do not affect all households in the same manner or to the same extent.

¹⁶ It is important to acknowledge, of course, that qualitative surveys and qualitative rankings may introduce their own subjective biases.

¹⁷ In the 1983–84 round of the survey, the classification exercise was undertaken by Jean Drèze and Naresh Sharma. They first classified households into seven groups and categorized them as follows: 'very poor', 'poor', 'modest', 'secure', 'prosperous', 'rich', and 'very rich' (see Drèze et al. 1998; Lanjouw and Stern 1991, 1998). In the final stage of classification, the rankings were combined into five quintiles of roughly equal sizes, designated as follows: 'very poor', 'poor', 'secure', 'prosperous', and 'rich'. This ranking procedure was repeated during the 2008–09 survey round. This time, four investigators independently categorized households into the same five groups, without insistence that the households be evenly distributed across groups. Again, the independent rankings of the investigators were remarkably consistent.

Table 6 displays the movement of individuals and their households according to the observed means classification in 1983–84 and 2008–09. Similarly to the income classification,¹⁸ the transition matrix by observed means reveals that a relatively high percentage of the better-off were able to maintain their rankings between 1983–84 and 2008–09 (28 per cent of the rich, and 26 per cent of the prosperous group; see cells on the diagonal of the transition matrix in Table 6). At the bottom, the percentage of the very poor and poor in 1983 who remained very poor and poor was only 13 per cent in both categories (see the diagonal in Table 6). As with income quintiles, this suggests greater mobility by those at the bottom of the rankings than by the top two categories.

Table 6: Cross-tabulation of households by observed means (investigator rankings) between 1983–84 and 2008–10

		Observed means household rankings in 2008-10						Households in 1983-84
		Very poor	Poor	Secure	Prosperous	Rich	Matched households	
Observed means household rankings in 1983-84	Very poor	0.13	0.42	0.39	0.06	0.00	31	20
	Poor	0.17	0.13	0.57	0.03	0.10	30	19
	Secure	0.10	0.31	0.27	0.19	0.13	52	24
	Prosperous	0.05	0.19	0.40	0.26	0.10	42	22
	Rich	0.02	0.11	0.34	0.25	0.28	61	22
Households in 2008-10		17	48	81	39	31	216	107

Note: the total number of households (216) matched between the two survey rounds is less than the actual number of households (233) in 2008–09.

Source: primary survey data.

The detailed information on income along with observed means also allows us to throw light on the patterns of mobility by caste. Table 7 gives the distribution of households by observed means by caste. The dominance of Thakurs and Muraos among the relatively well-off is once again seen from the fact that no Thakur or Murao household was ranked as very poor in 1983–84. On the other hand, there was no Jatab household which was classified as prosperous or rich. The situation changed in 2008–09, with at least some Thakur and Murao households then appearing as very poor. While there were no poor households in 1983–84 among the Muraos, a little over one fifth of Murao households were classified as poor in 2008–09. As against this, with no Jatab households classified as prosperous or rich in 1983, eight per cent were classified as prosperous in 2008–09. But what is remarkable is that only eight per cent of Jatab households were classified as very poor in 2008–09, as against three quarters classified as very poor in 1983. The rise of Jatabs in the rankings is a reflection of fundamental changes in Palanpur's economic and social structures.

The evidence for Palanpur thus points to a significant improvement in the relative position of what has historically been a particularly vulnerable and disadvantaged group of households. These households are also, for the first time, actively engaged in the non-farm sector, earning roughly as much from non-farm sources (as a percentage of total income) as the other castes. The picture is one of an expanding non-farm sector generating returns that appear to exceed those from

¹⁸ We do not present the income transition matrices for the sake of brevity. Interested readers can refer to Himanshu et al. (2018) for details.

agriculture, slowly becoming less exclusively the preserve of the well-off, and therefore representing an increasingly important engine of rural poverty reduction.

Table 7: Observed means classification of Palanpur households by caste

Panel A: 1983-84

	Very poor	Poor	Secure	Prosperous	Rich	% (no. of households)
Thakur	0.0	0.267	0.233	0.267	0.233	1.00 (30)
Murao	0.0	0	0.222	0.370	0.407	1.00 (27)
Dhimar	0.154	0.462	0.308	0.077	0.0	1.00 (13)
Gadariya	0.0	0.250	0.25	0.167	0.333	1.00 (12)
Dhobi	0.250	0.250	0.250	0.0	0.250	1.00 (4)
Teli	0.375	0.313	0.188	0.063	0.063	1.00 (16)
Passi	0.400	0.067	0.133	0.200	0.200	1.00 (14)
Jatab	0.737	0.158	0.105	0.0	0.0	1.00 (19)
Other	0.286	0.143	0.0	0.429	0.143	1.00 (8)
% of households	22%	19%	20%	19%	20%	100% (143)

Panel B: 2008-09

	Very poor	Poor	Secure	Prosperous	Rich	% (no. of households)
Thakur	0.052	0.121	0.345	0.259	0.224	1.00 (56)
Murao	0.036	0.200	0.400	0.182	0.182	1.00 (58)
Dhimar	0.136	0.364	0.273	0.091	0.136	1.00 (18)
Gadariya	0.0	0.133	0.533	0.267	0.067	1.00 (16)
Dhobi	0.250	0.250	0.250	0.250	0.00	1.00 (8)
Teli	0.273	0.182	0.273	0.136	0.136	1.00 (21)
Passi	0.0	0.167	0.667	0.0	0.167	1.00 (6)
Jatab	0.077	0.436	0.410	0.077	0.0	1.00 (38)
Other	0.182	0.182	0.182	0.455	0.0	1.00 (9)
% of households	8%	23%	37%	19%	13%	100% (230)

Source: primary survey data.

4.5 Intergenerational income mobility

A further unique feature of the Palanpur study is its ability to offer a window onto mobility patterns across generations. Given that we have data for all the individuals and households over seven decades, the Palanpur study allows us to look at the change in the occupational patterns as well as income rankings of households over generations. There are three main aspects that determine the economic outcomes achieved during an individual's lifetime: first, the circumstances into which he or she is born, such as caste, gender, or wealth of the family; second, people's efforts or talents in terms of the initiative and work that they put into sustaining a livelihood; third, good or bad fortune, including health and outcomes of risky activities in agriculture or elsewhere, and the extent to which behaviour (such as gambling) involves exposure to risk. Inequalities of outcome attributed to effort or talent are sometimes regarded differently from those associated with family background or ill health.

Recent years have seen a growing literature assessing 'intergenerational elasticity in earnings', which captures the strength of the association of income earnings across generations. For example, an intergenerational elasticity in earnings of 0.6 means that a one per cent increase in the father's income is associated with a 0.6 per cent higher income for the son. In other words, a higher elasticity means a stronger correspondence between a father's income and that of his son, therefore implying less mobility in this sense. In cross-country comparisons, estimates of these elasticities sometimes attempt to control for other phenomena in a multivariable analysis. Such analyses

commonly use father-son (rather than, say, mother-daughter) comparisons, as the data tend to reflect gender structures in the society.

Corak (2013) focuses on the father-son relationship and evaluates the elasticity of a son's lifetime earnings with respect to his father's lifetime earnings. He introduces the idea of the Great Gatsby curve, which plots the relationship across countries between the intergenerational elasticity in income and a cross-sectional measure of income inequality, the Gini coefficient. The Great Gatsby curve shows a positive relationship across countries, suggesting that higher inequality in a given country at a given point in time is associated with lower intergenerational mobility (a higher intergenerational elasticity in earnings) in that country. This is an intriguing finding, pointing to the possibility that rising inequality might unleash forces that act to reduce economic mobility.

Using the very long time span of our data, we enquire into mobility across generations in Palanpur. The long period of the surveys, covering income data for 1957–58 to 2008–09, allows us not only to look at father-son intergenerational income elasticity over one generation, but also to track and assess changes in this elasticity over two generations. We calculate the intergenerational elasticity in income for two periods of at least 25 years: 1957–58 to 1983–84, and 1983–84 to 2008–09. For each period we identify father-son pairs where sons in the latter period belong to the 25-to-35 age group. The per capita income of the household in the initial period is assumed to be the father's income. In other words, if the son falls into the working-age group mentioned and is part of the household in 2008–09, then the per capita income of the household in 1983–84 is considered to be his father's income. Table 8 reports the estimated elasticities.

Table 8: Intergenerational elasticity in earnings and inequality, 1958–2009

	1958-84	1984-2009	1958-74 (1984)	1974 (1983)- 2009
	(1)	(2)	(3)	(4)
No. of observations (in the age group 25-35 years)	58	100	58	100
Gini coefficient in terminal year	0.336	0.379	0.235	0.379
Intergenerational elasticity	0.328	0.396	0.294	0.441

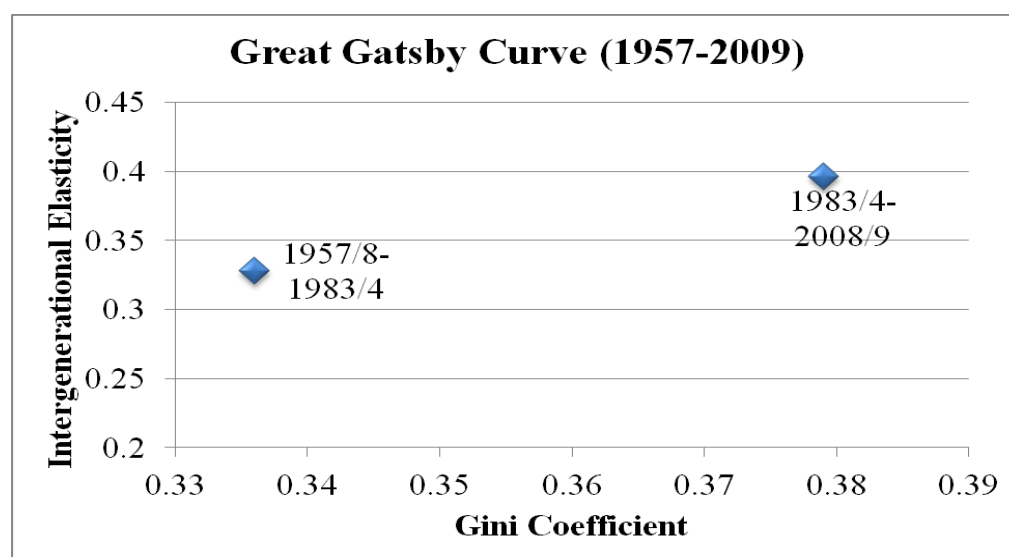
Note: columns 3 and 4 represent the elasticity by replacing the income for 1983–84 with an average of 1974–75 and 1983–84, because 1974–75 was a good agricultural year and 1983–84 was a bad year.

Source: primary survey data.

The picture in Palanpur is consistent with Corak's (2006) observation of higher income inequality in the later period being associated with a higher intergenerational income elasticity (and thus lower mobility). We observe an increase in the intergenerational elasticity over time, along with a rise in overall inequality as measured by the Gini coefficient. Because 1983–84 was a bad year in terms of agricultural production, we probe the robustness of this result by recalculating the elasticities by taking the average of incomes for 1974–75 and 1983–84. The increase in intergenerational elasticity is even more pronounced in this case. Figure 1 plots the Gini coefficients of the terminal year and the value of intergenerational elasticity—the figure known as the Great Gatsby curve.

Interestingly, the estimates of intergenerational elasticity of 0.396 and 0.441 for the period 1983–84 to 2008–09 are broadly in line with the findings from Atkinson et al. (1983), who report an earnings elasticity of 0.436 between sons and fathers in the British town of York over the period 1950 to 1975–78. As an indication that 0.4 is quite a high elasticity, representing rather low mobility, Atkinson et al. (1983) note that it is similar to the typical elasticity of a son's height with respect to his father's.

Figure 1: Great Gatsby Curve for Palanpur



Source: authors' illustration based on primary survey data.

While the persistence of income rankings is presumably strongly influenced by inheritance passed on to successive generations—notably land in the case of an agrarian economy such as Palanpur—the emergence of the non-farm sector as an alternative source of income can also be seen to have generated the opportunity for some households to break the rigidities in income and wealth transmission. As noted earlier, not only has the nature of non-farm diversification varied across caste and income strata, but there has also been an evolution in the extent to which households from different groups have been able to take advantage of non-farm occupations, as well in the nature of the non-farm jobs that have become available. Jatabs and households in the lower-end income strata have now gained access to some non-farm activities. However, these are mostly of a casual nature. It is important to recognize, moreover, that although non-farm employment has become accessible to a wider population, the importance of networks and assets has not diminished and may well have increased. In particular, access to regular, well-paying non-farm jobs remains concentrated among Thakurs and other advantaged households, who have better access to networks and can finance 'entrance fees' or bribes where these are necessary. In addition, in a few cases where educational qualifications have been important, these have been concentrated among the relatively advantaged. The story emerging from our examination of intergenerational mobility, and finding evidence of some decline, is thus not inconsistent with increased intragenerational mobility among Jatabs and other caste groups. Broadly speaking, the new non-farm opportunities do open up possibilities for upwards mobility, and within any group some move to take up these opportunities more quickly than others. At the same time, income and social status increase the likelihood of obtaining these non-farm jobs, and this effect becomes more important in overall structures as the number of non-farm opportunities rises.

We can further examine the changing nature and structure of non-farm opportunities by looking at the transition matrix of occupations between fathers and sons. Table 9 presents the occupational transition matrix for two generations. We match fathers' occupations in 1957–58 with sons' occupations in 1983, and fathers' occupations in 1983 with sons' occupations in 2008–09. The various occupations are classified into the following broad categories: not working, student, cultivation, agricultural labour, casual labour (non-farm), regular employment, and self-employment. One of the striking results from this analysis is the concentration of casual labour jobs in 2008–09 compared with 1983–84. Only 40 per cent of casual non-farm labourers in 1983–84 had a father who also worked as a casual non-farm labourer in 1957–58, but 54 per cent of casual non-farm labourers in 2008–09 were in households where the father was also a casual non-

farm labourer in 1983–84. On the other hand, if we compare the bottom and top panels, we see that overall, the transmission of parental occupation was weaker in 2008–09 compared with 1983–84 for cultivators and regular non-farm workers.

Table 9: Transition matrix of fathers' and sons' occupational categories, 1983–84 and 2008–09

		Sons (2008-09)					
Occupation		Student	Cultivation	Agricultural labour	Casual labour	Regular employment	Self-employment
Fathers (1983-84)	Not working	0.08	0.38	0	0.08	0.23	0.23
	Cultivation	0.21	0.40	0.05	0.16	0.10	0.10
	Agricultural labour	0	0	0	0	0	0
	Casual labour	0.15	0.08	0.15	0.54	0.08	0
	Regular employment	0.39	0.19	0	0.17	0.17	0.08
	Self-employment	0.25	0.25	0	0.25	0.06	0.19
		Sons (1983-84)					
Occupation		Student	Cultivation	Agricultural labour	Casual labour	Regular employment	Self-employment
Fathers (1957-58)	Not working	0	0.33	0	0.17	0.17	0.33
	Cultivation	0.05	0.58	0	0.06	0.31	0
	Agricultural labour	0	0	0	0	1.00	0
	Casual labour	0.20	0	0	0.40	0.20	0.20
	Regular employment	0.18	0.09	0.18	0.18	0.36	0
	Self-employment	0	0	0.33	0	0.67	0

Note: entries in the table are fractions moving from the status in the row to the status in the column. For the first block of the table, the sons' occupation class (present and surveyed in 2008–09) in the age group 15–50 is matched with fathers' (heads of household) occupation in 1983–84. For the second block of the table, the sons' occupation class (present and surveyed in 1983–84) in the age group 15–50 is matched with fathers' (heads of household) occupation in 1957–58. Total number of sons matched with their fathers in 2008–09: 141. Total number of sons matched with their fathers in 1983–84: 104. Sons falling under the category of 'not working' were students.

Source: primary survey data.

4.6 Discussion

The analysis above clearly brings out the rise in per capita incomes in Palanpur and the consequent fall in poverty in recent years. Consistent with all-India trends, the rise in incomes is also accompanied by increasing inequality in the later decades of the study period. Also consistent with the all-India experience, there is an accelerating trend towards non-farm employment diversification. This has been accompanied by a change in the composition of the non-farm sector since 1983–84, with a rise in the share of casual labour and self-employment activities and a fall in regular employment. The expansion of non-farm activities has led to some increase in the participation of disadvantaged castes in these activities. This has not only increased the overall incomes of disadvantaged castes, notably the Jatabs, but has also contributed to narrowing the gap between the Jatabs as a group and the rest of the village. The Telis, a much smaller group, have moved up even more sharply. This has been in large measure through self-employment and entrepreneurship—driven by the remarkable progress of one particularly enterprising household.

Although the greater dispersion of non-farm jobs across caste groups has been an important driver of the mobility of households, particularly for those at the bottom of economic ladder, these jobs are still governed to an important extent by access to networks, as well as by the acquisition of assets for some self-employment activities. The village elites have been particularly well placed to take advantage of their more extensive networks and relative wealth. The story of mobility in Palanpur has thus seen both an increase in intragenerational mobility—benefitting to a large extent

the weaker segments of the village population—and a decline in intergenerational mobility over the seven decades covered by the village surveys.

5 Concluding remarks

This paper aimed to present an overview of the available evidence on income mobility and poverty dynamics in developing countries. We briefly summarized the key messages from an earlier literature on the subject of income mobility and poverty dynamics. Next, we supplemented this evidence base with emerging findings derived from the growing effort to document patterns of economic mobility via synthetic panels constructed from multiple rounds of cross-section data. While these synthetic panels appear to provide useful additional evidence, we would also emphasize that ongoing work to establish the reliability of the methods and resulting estimates remains essential.

At the global level, it is difficult to draw general conclusions regarding income mobility in the developing world. Context-specific circumstances, the durations of the intervals under consideration, and numerous other factors combine to prevent broad generalizations. One robust finding from the available national-level studies, and from the earlier literature on the topic, is that there is substantial movement by households across income classes, or the poverty line, from one year to the next. Poverty dynamics, and indeed dynamics across all classes of the income distribution, are more frequent than is often believed. Poverty in developing countries is not universally a chronic condition. It is understood that some of this observed churning may be driven by data issues—notably measurement error. But much of this mobility is likely to be real, and there are important remaining gaps in our understanding of the factors, such as migration, that are likely to play an important role.

One way to get deeper insights into the underlying processes at work is to look at detailed case studies. In section 4 we attempted to look more closely at the processes that drive mobility, and at the welfare interpretation of those processes, by describing in detail the story of economic mobility in the village of Palanpur, northern India, over a period of seven decades. The Palanpur data are unique because of the quality of the data collected and the long time span that they cover. The richness of the data, covering all households in the village for a span of many decades, has allowed us to track changes in poverty, inequality, and mobility at a level of detail not normally available from secondary data sources. The close attention to detail and the long time spent in the village have also given us an opportunity to highlight individual examples, and to set observed changes in a broader social context. For example, we have employed a multidimensional observed means indicator of economic status, as assessed by research investigators resident in the village, to classify households, and to analyse household and individual mobility across groups over time. The key finding from the Palanpur story is that against a background of structural transformation out of agriculture towards a more diversified rural economy, income mobility has increased. There is clear evidence of a greater ability of the more disadvantaged segments of rural society to lift themselves out of poverty and to rise in relative income rankings. At the same time, the Palanpur story points to rising inequality accompanying the diversification process, and this in turn appears to be associated with an attenuation of intergenerational mobility. This is a sobering message about the possible longer-term impacts of this kind of development process.

While a longitudinal study of a village such as Palanpur offers opportunities for the in-depth analysis of dynamics, it obviously comes at the cost of constraining our ability to make inferences to broader populations. Nonetheless, we suggest that the story of mobility in Palanpur may not be so unusual in the Indian context.

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