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Poverty Dynamics in India between 2004 and 2012: Insights from Longitudinal Analysis Using Synthetic Panel Data

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I. Introduction

Poverty has steadily decreased in India over the past decade. Since India makes up a quarter of the world's poor (i.e., those living on under $1.25 a day), which is roughly half again its share of the world's population (17%), reducing poverty in this country would not only affect its own welfare but also register a significant impact on global poverty estimates.[1] What is particularly striking is the acceleration of poverty reduction that appears to be taking place. Between 2004–5 and 2009–10, poverty declined from 37.7% to 29.9%. Over the subsequent two years, poverty declined by a further 10 percentage points, to 20.0%. These achievements in poverty reduction have been widely remarked on and celebrated.[2]

We offer several contributions in this paper, on both the conceptual and empirical fronts. On the conceptual front, we analyze the dynamics of poverty transitions. We attempt to seek a better understanding of such questions as What proportion of the population remain chronically poor over time? What

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[1] We use the poverty rates and population data, respectively, from the World Bank's PovCalNet database (http://iresearch.worldbank.org/PovcalNet/index.htm) and Development Indicators database. All figures are estimated averages for the years 2011 and 2012.

[2] There have nevertheless been some concerns raised around the credibility of the most recent episode of poverty decline; we come back to more discussion in Sec. II. Unless otherwise noted, all the poverty rates are based on the national poverty lines.

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proportion of the population escape poverty or fall into poverty? And what are the characteristics that are associated with enabling these subsets of the population to participate in the processes of upward mobility or condemning them to downward mobility? Further, how do we identify and track the transitions of the vulnerable population groups that are currently nonpoor but still remain at a heightened risk of falling into poverty? To our knowledge, these questions have received some attention in the Indian context but appear to never have been studied on a national scale before—most likely because of the scarcity of nationally representative panel survey data.[3] Deeper insights into these underlying dynamics would help improve policies to sustain the recent impressive poverty decline in this country and perhaps even further accelerate its momentum.[4]

On the empirical front, the types of data that we construct and validate would be relevant to similar analyses in different contexts, particularly for developing countries where data shortage or incomparability is usually the norm rather than the exception. We specifically confront two methodological challenges that have typically held back investigations of the kind we are attempting here. First, the key difficulty is that analysis of poverty transitions and of the likelihood of escaping, or falling into, poverty depends on the availability of panel data that permit the analyst to follow households over time. Yet in India, as in many other countries, nationally representative panel data are not available. The existing data sources underpinning poverty analysis—the National Sample Surveys (NSSs)—are high-quality cross-sectional data sources that offer at best a snapshot of living conditions at specific moments of time. In order to overcome this limitation, we implement in this paper a methodology for

[3] Smaller panel surveys have been fielded for India, but none of these provide nationally representative data; see Dercon and Shapiro (2007) for a recent review. For recent studies that use these panel surveys, see, e.g., Munshi and Rosenzweig (2009), Krishna and Shariff (2011), and Dercon, Krishnan, and Krutikova (2013), respectively, for analysis of the Rural Economic Development Survey panel between 1982 and 1999, the National Council of Applied Economic Research (NCAER) panel between 1993–94 and 2004–5, and the International Crop Research Institute for the Semi-Arid Tropics panel between 1975 and 2006. While panel surveys allow more in-depth analysis of mobility, Rosenzweig (2003) discusses potential issues that can bias these surveys (which are not nationally representative), such as split-offs or attrition. A new, nationally representative panel survey (India Human Development Survey [IHDS]) fielded by the University of Maryland and NCAER promises much improvement over the previous panels (http://ihds.umd.edu). But note that, compared to the National Sample Surveys, the IHDS has less than half the sample size and collects a much reduced version of household consumption data (i.e., 47 consumption items in the latter vs. more than 400 items in the former).
[4] It is common knowledge that policies to deal with chronic poverty can be rather different from those for transient poverty. The former would often focus on longer-term interventions such as education or building infrastructure while the latter would aim at providing temporary support, including social safety net programs.

converting the NSS cross-sectional surveys into synthetic panels. The approach we follow has been recently introduced into the literature (Dang and Lanjouw 2013; Dang et al. 2014), and a number of studies that validate the method have generally yielded encouraging findings (Dang and Lanjouw 2013, 2017; Martinez et al. 2013; Dang et al. 2014; Cruces et al. 2015).[5]

Second, the methodology for constructing synthetic panels is predicated on strict comparability of the underlying cross-section surveys. It has already been noted that India's NSSs are generally regarded as high-quality data sources. We focus our attention here on the "thick" rounds that involve larger sample sizes and are designed to be representative at the rural/urban and state levels. Nonetheless, we investigate whether the 2009–10 and 2011–12 rounds are strictly comparable, since the possibility of a breakdown in comparability is prompted by the remarkable rate of poverty decline as well as evidence that there are some noticeable changes in the design of the consumption questionnaire between these two years.[6] We tackle this question with an imputation-based method recently explored in Dang, Lanjouw, and Serajuddin (2017) that builds on a number of earlier studies (Elbers, Lanjouw, and Lanjouw 2003; Tarozzi 2007).[7]

Our findings suggest that the 2009–10 and 2011–12 survey rounds do not appear to suffer from serious comparability issues. The observation of a sharply accelerated poverty decline after the 2009–10 round, from 29.9% to 20% in 2011–12, seems robust. We also appear to be on solid footing with respect to the data underpinnings for converting these three NSS rounds into synthetic panels. We show further that aggregate trends in poverty reduction mask a considerable degree of entry into—and to a larger extent, exit out of—poverty and

[5] Synthetic panels constructed with the Dang et al. (2014) and Dang and Lanjouw (2013) methods have been applied to study poverty dynamics in various settings, including multicountry analysis for Latin America (Ferreira et al. 2013; Vakis, Rigolini, and Lucchetti 2015), South Asia (Rama et al. 2015), and Europe and Central Asia (Cancho et al. 2015). Specific country case studies using synthetic panels investigate countries including the Kyrgyz Republic (Bierbaum and Gassmann 2012), Bhutan (World Bank 2014), and Senegal (Dang, Lanjouw, and Swinkels 2017). Another promising use of synthetic panels is to evaluate program impacts (Garbero 2014).

[6] Data comparability issues between different rounds of the NSS are not without precedents. For example, there had been intensive and contentious debate around the comparability of the 1999–2000 round of the NSS with earlier NSS rounds, after a certain number of changes and adjustments had been made to the questionnaire (Deaton and Kozel 2005). We return to this issue in Sec. II.

[7] Elbers, Lanjouw, and Lanjouw (2003) provide a method that imputes household consumption from a survey into a population census. Adapting this approach for survey-to-survey imputation, Christiaensen et al. (2012) impute poverty estimates by using data from several countries, including China, Kenya, Russia, and Vietnam; other studies analyze data from Morocco (Douidich et al. 2016) and Uganda (Mathiassen 2013). See also Tarozzi and Deaton (2009) and Rao (2003) for other studies on survey-to-census imputation.

vulnerability but that a substantial core of the poor have remained poor over the duration of the study period. We document some of the key household characteristics of those who have managed to escape poverty and contrast these with those who have fallen into this undesirable welfare status during this period.

We start, in Section II, with a brief discussion of poverty trends during the late 2000s and explore further the question of whether the 2009–10 and 2011–12 NSS rounds are comparable. Section III describes our efforts to assess the comparability of the 2009–10 and 2011–12 surveys. Besides offering supportive evidence for the recent poverty decline, these two sections also describe the preparatory data work required to construct synthetic panels with which to study poverty dynamics. Section IV then implements our approach to convert the three most recent NSS rounds between 2004–5 and 2011–12 into synthetic panels. We then turn in Section V to a discussion of mobility, and we produce some basic profiles of the population in different transition categories. We also discuss vulnerability dynamics as an extension of the poverty mobility analysis in this section. We end in Section VI with concluding remarks.

II. Poverty Trends and Data

Steady GDP per capita growth helped drive down poverty rates in India in the late 2000s.[8] In particular, GDP per capita increased by almost half (47%) during the period 2004–9 (World Bank 2015), and poverty decreased by 21% over the same period. The country's continued economic growth resulted in a further increase of GDP per capita over the subsequent two years, by almost one-fifth (19%) in 2011–12. While this robust growth rate should be expected to bring more poverty reduction, the contemporaneous fall in poverty rates turned out to be much larger than expected. To quite a few observers, the fall in poverty has been startling.[9]

[8] See, e.g., Datt and Ravallion (2011) and Ravallion (2011) for comprehensive discussions on economic growth and poverty in India for earlier periods.

[9] For example, Dutta and Panda (2014) observe that there is much controversy around the (arbitrariness) of the specification of the poverty line. Saxena (2013) points out a couple of inconsistencies, such as that the share of the population who need food subsidies or the slum population in major cities is much larger than the reported poverty rate and that the specified poverty lines may be too low and may potentially be distorted as a result of political motives. In addition to these last two issues, Himanshu (cited in Rao 2013) voices the concern that imputed spending values for certain social transfer programs may not be calculated correctly. See also the BBC (Limaye 2013), the *New York Times* (Gupta 2013), and the *Washington Post* (Lakshmi 2012) for related discussion on the debates on poverty in this period.

Figure 1 plots the annual growth rate of GDP per capita (left axis) and the head count poverty rate (right axis) between 2004 and 2012. Since a large share of the labor force is employed in agriculture, the figure also displays the annual growth rate of the value added per worker of the agricultural sector. The disconnect between GDP per capita growth rates and poverty reduction is brought out sharply where, despite the remarkably weaker growth of the former, the slope of the line representing the latter is much steeper in the second period than in the first period. The even weaker growth of the agricultural sector further highlights this difference.

Despite the various arguments for or against this swift fall in poverty, one simple but perhaps not unreasonable hypothesis is that the questionnaire design of the consumption module in the 2011–12 (sixty-eighth) round of the NSS is not comparable to that in the 2009–10 (sixty-sixth) round (and 2004–5, or sixty-first, round), which in turn leads to inconsistently constructed and incomparable consumption data. Indeed, there are several major changes to the questionnaire in the sixty-eighth round that include (1) changes in certain consumption codes, (2) aggregating some consumption items into broader groups, (3) disaggregating some consumption items into smaller groups, (4) using/providing somewhat different item names, (5) dropping some consumption items that had been included in previous rounds, and (6) adding

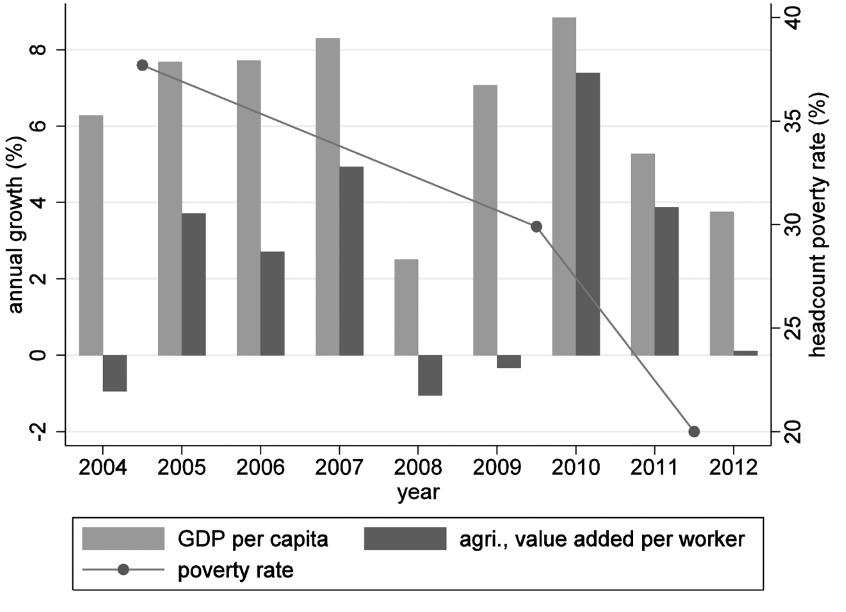

Figure 1. Annual growth of GDP per capita versus head count poverty rate, India, 2004–12; agri. = agricultural sector. A color version of this figure is available online.

new consumption items. These changes may not be harmless in affecting the comparability of the consumption data over time.[10]

To further investigate whether these changes may lead to different consumption aggregates over time, we explore the raw item-by-item consumption data at the household level and examine a variety of alternative consumption aggregations over time. The results shown in table A1 confirm that these questionnaire revisions could be a source of concern. While most consumption groupings make up rather similar shares in total household consumption, the share of the items with some change in code (grouping 2) is 2 percentage points lower, and the share of the new items added in the sixty-eighth round is 3 percentage points higher than that of the items in the sixty-sixth round that are dropped.[11] While these differences may balance out, on average, and may not result in any significant change to the total consumption aggregate, they may also point to potentially deeper comparability issues with the consumption data. Moreover, even if mean values are not much affected, these changes could affect different parts of the consumption distribution differently and could thus still have a bearing on poverty estimates.

The discussion above evokes a similar, but much larger, poverty debate that took place in India in the early 2000s. In the late 1990s, the National Sample Survey Office revised the questionnaire of the NSS in 1999–2000 (the fifty-fifth round) in an attempt to bring estimates of household consumption from the survey in line with those from national accounts. In particular, these revisions include changing the recall period for household durables and education expenses from a 30-day interval to a 365-day interval and using both the traditional 30-day recall period and a new 7-day recall period for food items. The Government of India published estimates showing that the head count poverty rate fell by 10 percentage points between 1993–94 and 1999–2000. Independent researchers, however, noted the possibility of noncomparability of the published consumption data and applied a variety of methods to adjust for this. A variety of estimates were produced, with some suggesting a rate of decline ranging from only somewhat lower than the official estimates (Deaton

[10] We use data from Schedule Type 1 for all survey rounds. An Excel file that provides a comparison and detailed tracking of the change to each consumption item for the sixty-first, sixty-sixth, and sixty-eighth rounds of the NSS is available upon request. Survey design issues that compromise the comparability of poverty estimates are found in various countries, such as China (Gibson, Huang, and Rozelle 2003), Tanzania (Beegle et al. 2012), and Vietnam (World Bank 2012). See also Deaton and Grosh (2000) and Crossley and Winter (2015) for general reviews on the influence of survey design on the quality of consumption data in developing and richer countries, respectively.

[11] Compared with the sixty-first round, the share of the new items added in the sixty-sixth round is approximately 0.1% and equals the share of the items dropped from the former. This implies greater comparability between these two survey rounds.

and Dreze 2002; Tarozzi 2007) to one estimate suggesting a mere 3 percentage point decline in poverty during the decade of the 1990s (Sen and Himanshu 2005; see also Kijima and Lanjouw 2003). As is powerfully argued in the book *The Great Indian Poverty Debate* (Deaton and Kozel 2005), concerns about comparability can greatly complicate assessments of poverty trends.

We describe in the next section a method for gauging comparability between the 2009–10 and the 2011–12 rounds of the NSS.

III. Predicted Poverty Trends Using Imputation

We provide here a brief overview of the survey-to-survey imputation method described in Dang, Lanjouw, and Serajuddin (2017) before discussing results. Further discussion on technical details and estimation procedures is available in that paper.

A. Overview of the Imputation Method

Let x_j be a vector of characteristics that are commonly observed between the two surveys, where j ($j = 1, 2$) indicates survey round.[12] These characteristics can include household variables such as the household head's age, sex, education, ethnicity, religion, language, occupation, household assets or incomes, and other community or regional variables. Household consumption (or income) data exist in one survey round but are missing in the other survey round; thus, without loss of generality, let (survey) round 1 and round 2, respectively, represent the survey round with household consumption data and the one without them, and let y_1 represent household consumption in round 1. Alternatively, we can also refer to round 1 as the base survey and round 2 as the target survey.

To further operationalize our estimation, we assume that the linear projection of household consumption on household and other characteristics (x) in both survey rounds—if such consumption data were also available in period 2—is given by a cluster random effects model,[13]

$$y_j = \beta_j' x_j + \mu_j + \varepsilon_j, \tag{1}$$

where β_j are the vector of coefficients, and the cluster random effects μ_j and the error term ε_j are assumed to be uncorrelated with each other and to follow a

[12] To make notation less cluttered, we suppress the subscript for each household in the following equations.

[13] This assumption assumes that the returns to the characteristics x_j in both periods are captured by eq. (1) and precludes the (perhaps exceptionally) rare situations where there could be no correlation between these characteristics and household consumption as a result of unexpected upheavals in the economy or calamitous disasters. Contexts where there are sudden changes to the economic structures (e.g., overnight regime change) may also introduce noise into the comparability of the estimated parameters.

normal distribution, conditional on household characteristics. Equation (1) thus provides a standard linear random effects model that can be estimated with most available statistical packages. Let z_2 be the poverty line in period 2; if y_2 existed, then the (head count) poverty rate P_2 in this period could be estimated with the following quantity:

$$P(y_2 \leq z_2), \tag{2}$$

where $P(\cdot)$ is the probability (or poverty) function that gives the percentage of the population under the poverty line z_2 in round 2.

Assume that the sampled data in round 1 and round 2 are representative of the population in each respective time period, such that estimates based on the same characteristics x in these two survey rounds are consistent and comparable over time (assumption 1). Assume further that, given the estimated consumption parameters from round 1, the changes in the distributions of the explanatory variables x between the two periods can capture the change in poverty rate in the next period (assumption 2).[14] Given these two assumptions, Dang, Lanjouw, and Serajuddin (2017) propose an approach to impute the poverty rate for round 2, where the parameter estimate $\hat{\beta}_1$ and the distributions of both the cluster random effects and the error term estimated from data in round 1 can be imposed on the data in round 2. This results in the predicted consumption y_2^1. Note that the standard errors of the imputation-based estimates can in fact be even smaller than that of the estimate directly based on the survey (the design-based or direct survey estimate) if there is a good model fit (or the sample size in the target survey is larger than that in the base survey; see, e.g., Matloff 1981).

If consumption data are available from both the base and target surveys, we can use an Oaxaca-Blinder type decomposition to formally test for assumption 2, to shed further light on model selection. In particular, the change in poverty between the survey rounds can be broken into two components, one due to the changes in the estimated coefficients (the first term in square brackets in eq. [3] below) and the other the changes in the x characteristics (the second term in square brackets in eq. [3] below). Assumption 2 would be satisfied if the poverty change is mostly explained by the latter component. This can be expressed as

$$P(y_2) - P(y_1) = [P(y_2) - P(y_2^1)] + [P(y_2^1) - P(y_1)]. \tag{3}$$

[14] While this assumption may seem counterintuitive, it may be especially relevant to economies where the returns to characteristics do not change or simply change little over time (i.e., involving survey rounds that are implemented close in time, assuming that the returns to characteristics in most economies do not normally change much within a short time interval).

Furthermore, if we make a stricter assumption about the error term in equation (1) following a standard normal distribution, that is, $\varepsilon_j | x_j \sim N(0, 1)$, we can estimate equation (1) by a random effects probit model instead of the linear random effects model,

$$P(y_j) = \Phi(\beta_j' x_j + \mu_j + \varepsilon_j). \tag{4}$$

But the standard modeling trade-off holds: if our stricter assumption is correct, estimation results are more accurate, and vice versa. For comparison purposes, we present below estimates using both the linear random effects and the random effects probit models.[15]

Following the estimation procedures in Dang, Lanjouw, and Serajuddin (2017), our empirical implementation involves a two-stage process. First, we apply the estimated parameters from the 2004–5 round on the 2009–10 data to impute poverty for the latter. Since the questionnaires remain the same over these two survey rounds, their consumption data are comparable, and we can thus validate these estimated poverty rates against those based on the actual consumption data for the 2009–10 round. Second, we produce imputation-based poverty estimates for 2011–12, using the same (model) specifications as with the first step but with the estimated parameters from the 2009–10 round on the data from the 2011–12 round.

Put differently, the key assumption for employing these estimation procedures is that the change in the characteristics, rather than in the coefficients, can well capture the change in poverty (assumption 2). While this assumption is untestable because of the missing data—which creates the need for imputation in the first place—indirect evidence to support its validity can be produced by using earlier survey rounds where they are available. Thus, the first step would offer the indirect supportive evidence that this imputation method works in the context of India as well as provide the appropriate specification to use for the imputation.

B. *Estimation Results*

Since changes in household (head's) characteristics may indicate the corresponding changes in household consumption, it can be useful to examine as a preliminary check the distributions of household characteristics across the

[15] We provide a Stata ado program named "povimp" that automates the proposed estimation process (Dang and Nguyen 2014). Type "ssc install povimp" from within Stata (StataCorp 2013) to download this program from the statistical software component archive, which is maintained by Christopher F. Baum at Boston College. Our Stata program automatically allows for complex survey designs by offering an option to specify the variables indicating the clusters and the strata.

two survey rounds in 2009–10 and 2011–12. The summary statistics provided in table A2 show that these changes appear rather negligible, with many of the differences not statistically significant. Some characteristics that are associated with higher levels of household welfare (e.g., heads with completed postgraduate education, household members with regular salary incomes, or urban residents receiving regular wages) show a statistically significant improvement over time, but others that have opposite effects (e.g., backward classes and radio ownership) also have statistically significant changes.[16] The picture provided from considering the pairwise changes in the distributions of these variables over time thus seems mixed at best.

We then proceed to impute poverty for the target survey in 2009–10, using the estimated parameters from the base survey in 2004–5. Assumption 1 on survey comparability is satisfied, since the questionnaires (and sample design) for these two survey rounds remain the same. To satisfy assumption 2, we can then consider five different household consumption model specifications, where the changes in the distributions of the explanatory variables x between the two periods can capture to varying degrees the change in poverty over time. These specifications are built on a cumulative basis for comparison purposes (and robustness checks), with later specifications sequentially adding more variables to earlier specifications.

Specification 1 is the most parsimonious specification and consists of household size, household head's age and sex, and dummy variables indicating whether the head's religion is Hinduism or Islam; whether the head belongs to a scheduled tribe, a scheduled caste, or backward classes; whether the head is literate (if he/she has less than primary education); and the head's education levels. Specification 2 adds to specification 1 household demographics such as the shares of household members in the age ranges 0–14, 15–24, and 25–59 (with the reference group being those 60 years old and older). Specification 3 adds to specification 2 employment variables, which include dummy variables indicating whether the household has any member working for a regular salary, whether the head is self-employed in the agricultural sector or the nonagricultural sector (for rural residents), and whether the head works for regular wage, is self-employed, or engaged in casual work or other type of work (for urban residents). Specification 4 adds to specification 3 a variable indicating home ownership. Finally, specification 5 adds a more detailed list of asset variables, which include the energy sources for lighting and cooking and whether the household has a radio, television set, electric fan, sewing machine, freezer,

[16] We can infer the direction of the correlation between these characteristics and household consumption from the regression results in tables A3 and A4.

air conditioner, bicycle, motorbike, and/or car. However, slightly more than 5,000 and 1,000 households are missing these assets variables in the 2004–5 and 2009–10 rounds, respectively. Full model specifications and regression results are provided in tables A3 and A4.

Estimation results using the linear random effects model shown in table 1 (method 1) indicate that all the imputation-based poverty estimates in specifications 1–4 fall within the 95% confidence interval of the poverty rate directly estimated from the actual consumption data for 2009–10. Put differently, these estimates are not statistically significantly different from the direct survey estimate of 29.9%. The exception is specification 5, where the imputation-based estimate is half a percentage point outside this confidence interval, which can be due to either model overfitting or smaller sample sizes for both the base and target surveys. Estimation results using the random effects probit model (method 2) are broadly similar, with estimates from specifications 2–4 falling within the 95% confidence interval of the direct survey estimate.

TABLE 1
PREDICTED POVERTY RATES BASED ON IMPUTATION, INDIA, 2009–10 (%)

	Estimated Rate					Direct Survey Estimate
Method	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	
1. Normal linear regression model	29.3	29.6	30.4	30.6	31.2	29.9
	(.01)	(.01)	(.01)	(.01)	(.01)	(.4)
2. Direct estimation of poverty rate using probit model	28.9	29.2	29.5	29.7	28.2	
	(.00)	(.00)	(.00)	(.00)	(.00)	
Control variables:						
Parsimonious	Y	Y	Y	Y	Y	
Demographics	N	Y	Y	Y	Y	
Employment	N	N	Y	Y	Y	
Owning home	N	N	N	Y	Y	
Household assets	N	N	N	N	Y	
Observations, base survey (2004–5)	124,543	124,543	124,374	124,340	119,292	
Observations, target survey (2009–10)	100,832	100,832	100,798	100,595	99,469	100,853

Note. Standard errors (in parentheses) are adjusted for complex survey design. All estimates are obtained with population weights. Method 1 uses the normal linear regression model with the theoretical distribution of the error terms, and method 2 uses a probit regression. Both specifications use state random effects. Imputed poverty rates for 2009–10 use the estimated parameters based on the 2004–5 data, with 1,000 simulations. The underlying regression results are provided in table A3. Direct survey estimate is the direct estimate based on survey data.

Thus, for our purpose of finding a good model specification to impute poverty in the 2009–10 round, assuming that consumption data in this round were not available, specifications 1–4 with the normal linear regression models and specifications 2–4 with the random effects probit models can all be employed. But among these specifications, our preferred specifications for interpretation are specification 2 with the normal linear regressions and specifications 3 and 4 with the random effects probit model, since these three specifications provide better estimates that are within 1 standard error of the direct survey estimate.

It is useful to note that the standard errors for the imputation-based estimates are smaller in the normal linear regression models and random effects probit models than that for the design-based poverty estimate. This is consistent with our earlier discussion, since, assuming that the specification is correct, a good model fit can help bring down the standard errors. Similarly, the random effects probit models make a stricter (modeling) assumption on the error term than the linear random effects models; their standard errors are consequently smaller.

As a further check on the model specification, we show in figure 2 the decomposition of the changes in poverty due to the changes in the household characteristics and the estimated coefficients based on equation (3). (Note that we are now working with consumption data in both surveys rather than con-

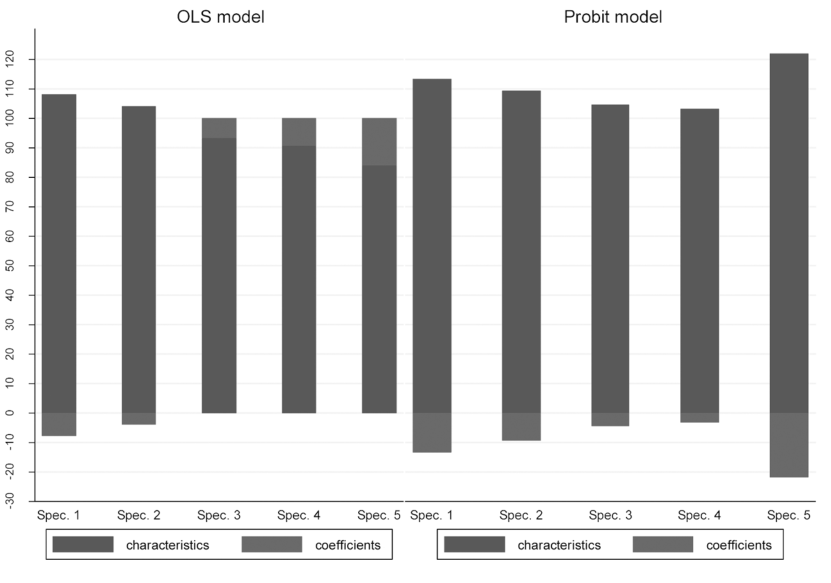

Figure 2. Decomposition of changes in poverty over time, India 2004–5 to 2009–10; OLS = ordinary least squares; spec. = specification (see text). A color version of this figure is available online.

sumption data in only the base survey, as with the estimates for table 1.) This figure confirms that, for the model specifications that provide estimates within the 95% confidence interval of the direct survey estimates, the changes captured by the characteristics are closer to 100%. For example, under specification 4 with the random effects probit regression (right-hand panel), the change due to the coefficients is the most negligible; this specification also provides a point estimate of poverty (29.7%; table 1) that is closest to the direct survey estimate.

We turn next to imputing poverty for 2011–12 with the estimated parameters from the 2009–10 survey round.[17] We have preferred specifications for analysis, but we also show estimates for all the other specifications for comparison in table 2. Our preferred specifications show that the imputation-based poverty estimates can range from 22.9% (specifications 3 and 4, the probit model) to 25% (specification 2, the linear regression model). Interestingly enough, except for specification 5, which could be excluded because of overfitting concerns, all other estimates—including even specification 5 with the probit model—fall within this range.

These imputation-based estimates are larger than the design-based estimates of 22%, and the differences are statistically significant (outside the 95% confidence interval of the latter). However, considering all specifications together, the difference between the probit estimates and the design-based estimate is between 1 and 2 percentage points, while that between the normal linear regression estimates and the design-based estimates is between 2 and 3 percentage points. Thus, according to our imputation-based estimates, while the design-based estimate may underestimate poverty in 2011–12, it appears that this underestimation may in practice be not very large.

IV. Constructing Synthetic Panels[18]

Our findings in the previous section suggest that the sharp decrease in poverty rate between 2009–10 and 2011–12 is reasonably captured by the sixty-sixth and sixty-eighth rounds of the NSS. Put differently, these two survey rounds provide comparable consumption data for most practical poverty measure-

[17] We use estimated parameters from the 2009–10 round, rather than the 2004–5 round, to impute poverty in the 2011–12 round, since these parameters may change over time. Indeed, the null hypothesis of the equality of the estimated parameters in these two survey rounds is rejected with significantly large value from a Wald test (results available upon request). More generally, survey rounds that are closer in time are more appropriate for imputation.

[18] We provide an overview of the methods that construct synthetic panels and vulnerability lines developed by Dang et al. (2014) and Dang and Lanjouw (2013, 2017) in this section. For more details, interested readers are encouraged to read the original papers.

TABLE 2
PREDICTED POVERTY RATES BASED ON IMPUTATION, INDIA, 2011–12 (%)

Method	Estimated Rate: Specification 1	Specification 2	Specification 3	Specification 4	Specification 5	Direct Survey Estimate
1. Normal linear regression model	24.4	25.0	24.3	24.5	27.1	22.0
	(.01)	(.01)	(.01)	(.01)	(.01)	(.3)
2. Direct estimation of poverty rate using probit model	23.7	24.3	22.8	22.9	24.1	
	(.00)	(.00)	(.00)	(.00)	(.00)	
Control variables:						
Parsimonious	Y	Y	Y	Y	Y	
Demographics	N	Y	Y	Y	Y	
Employment	N	N	Y	Y	Y	
Owning home	N	N	N	Y	Y	
Household assets	N	N	N	N	Y	
Observations, base survey (2009–10)	100,832	100,832	100,798	100,595	99,469	
Observations, target survey (2011–12)	101,639	101,639	101,603	101,596	101,525	101,662

Note. Standard errors (in parentheses) are adjusted for complex survey design. All estimates are obtained with population weights. Method 1 uses the normal linear regression model with the theoretical distribution of the error terms, and method 2 uses a probit regression. Both models use state random effects. Imputed poverty rates for 2011–12 use the estimated model parameters based on the 2009–10 data, with 1,000 simulations. The underlying regression results are provided in table A4. Direct survey estimate is the direct estimate based on survey data.

ment purposes, which is a prerequisite for constructing synthetic panel data. We next provide a brief overview of the methods used.

Let x_{ij} be a vector of household characteristics observed in survey round j ($j = 1, 2$) that are also observed in the other survey round for household i ($i = 1, \ldots, N$). 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: (1) time-invariant variables, such as ethnicity, religion, place of birth, or parental education;[19] (2) 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); and (3) time-varying household characteristics,

[19] We use the term "ethnicity" in a broad sense that can include other time-invariant characteristics, such as ancestry or scheduled castes.

if retrospective questions about the values of such characteristics in the first survey round are asked in the second round.

To reduce spurious changes due to changes in household composition over time, we follow the literature on pseudopanel analysis and usually restrict the estimation samples to household heads aged, say, 25–55 in the first cross section and adjust this age range accordingly in the second cross section. This restriction also helps ensure that certain variables, such as head's education attainment, remain relatively stable over time (assuming that most heads are finished with their schooling). This age range is usually used in traditional pseudopanel analysis but can vary, depending on the cultural and economic factors in each specific setting. Population weights are then used to provide estimates that represent the whole population.

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

$$y_{ij} = \beta_j' x_{ij} + \varepsilon_{ij}. \tag{5}$$

Let z_j be the poverty line in period j. We are interested in knowing such quantities as

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2), \tag{6a}$$

which represents the percentage of households that are poor in the first survey round (year) but nonpoor in the second survey round, or

$$P(y_{i2} > z_2 | y_{i1} < z_1), \tag{6b}$$

which represents the percentage of poor households in the first round that escape poverty in the second round. In other words, for the average household, quantity (6a) provides the joint (unconditional) probabilities of household poverty status in both years and quantity (6b) the conditional probabilities of household poverty status in the second year, given their poverty status in the first year. For convenience, we also refer to (6a)-type quantities and (6b)-type quantities, respectively, as the unconditional measure and the conditional measure.

Some straightforward decompositions are useful for interpretation of results. Note that the following equality holds for the unconditional probabilities:

$$P(y_{i1} < z_1 \text{ and } y_{i2} < z_2) + P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) = P(y_{i1} < z_1), \tag{7a}$$

where the first and second terms on the left-hand side, respectively, represent chronic poverty (i.e., the percentage of households that are poor in both years) and upward-mobility poverty (i.e., the percentage of households that are poor in the first year but escape poverty in the second year). Thus, for the same poverty rate, equality (7a) implies an inverse relationship between chronic poverty and upward mobility. A similar result applies for the corresponding equality for the conditional probabilities,

$$P(y_{i2} < z_2 | y_{i1} < z_1) + P(y_{i2} > z_2 | y_{i1} < z_1) = 1. \tag{7b}$$

Rewriting equalities (7a) and (7b) to switch the less-than sign (<) to the greater-than sign (>) for y_{i1} and z_1, a similar inverse relationship holds for downward mobility (i.e., the percentage of households that are nonpoor in the first year but fall into poverty in the second year) and nonpoverty.

If true panel data are available, we can straightforwardly estimate the quantities (6a) and (6b), but in the absence of such data, we can use synthetic panels to study mobility. To operationalize the framework, we make two standard assumptions. First, we assume that the underlying populations being sampled in survey rounds 1 and 2 are identical, such that their time-invariant characteristics remain the same over time. More specifically, coupled with equation (5), 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). Second, we assume that ε_{i1} and ε_{i2} have a bivariate normal distribution with positive correlation coefficient ρ and standard deviations σ_{ε_1} and σ_{ε_2}, respectively. Quantity (6a) can be estimated by

$$P(y_{i1} < z_1 \text{ and } y_{i2} > z_2) = \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, -\rho\right), \tag{8}$$

where $\Phi_2(\cdot)$ stands for the bivariate normal cumulative distribution function (cdf) and $\phi_2(\cdot)$ stands for the bivariate normal probability density function. In equality (8), the parameters β_j and σ_{ε_j} are estimated from equation (5), and ρ can be estimated with an approximation of the correlation of the cohort-aggregated household consumption between the two surveys. In particular, given an approximation of the simple correlation coefficient $\rho_{y_{c1}y_{c2}}$, where c indexes the cohorts constructed from the household survey data, the partial correlation coefficient ρ can be estimated by

$$\rho = \frac{\rho_{y_{i1}y_{i2}}\sqrt{\text{var}(y_{i1})\text{var}(y_{i2})} - \beta_1' \text{var}(x_i)\beta_2}{\sigma_{\varepsilon_1}\sigma_{\varepsilon_2}}. \tag{9}$$

Dang and Lanjouw (2013) show that estimates of ρ using equation (9) are reasonably close to those based on the actual panels for several countries located in different regions and at different income levels, such as Bosnia-Herzegovina, the Lao People's Democratic Republic (PDR), Peru, Vietnam, and the United States. More importantly, once ρ is estimated, it can be used to provide estimates for poverty mobility—the final quantities of interest—and our validation exercises show these estimates to closely track those based on the actual panel data. Further asymptotic results and formulas for the standard errors of the partial correlation coefficient and other quantities are provided in this paper. Note that we assume homogeneity of ρ and estimate it for the whole population in equation (9); a potentially useful extension is to assume some heterogeneity for this parameter (e.g., for rich households vs. poor households). Implementing the latter may, however, require further assumptions on the estimate of the simple correlation coefficient and is beyond the scope of this paper; thus, we leave this extension for future research.[20]

Note that in equality (8), 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 that we can use data from the first survey round as the base year as well. It is then straightforward to estimate quantity (6b) by dividing quantity (6a) by $\Phi[(z_1 - \beta_1' x_{i2})/\sigma_{\varepsilon_1}]$, where $\Phi(\cdot)$ stands for the univariate normal cdf.

Using the given poverty lines z_j, quantities (6a) and (6b) classify the population into two groups: poor and nonpoor. But we can obtain richer analysis by further disaggregating the nonpoor group into two additional groups: the vulnerable (those who are nonpoor but still face a significant risk of falling into poverty) and the middle class (the remaining group, with higher consumption levels). A common, but rather ad hoc, approach is to arbitrarily scale up the poverty line by a certain factor to obtain the vulnerability line. In particular, vulnerability has been defined as simply occurring within a fixed income range between 1.25 times and twice the national poverty line in India (NCEUS 2007). Other countries similarly define the vulnerability line as twice (Pakistan; Lopez-Calix et al. 2014) or 30% above (Vietnam; World Bank 2012) the national poverty line. This approach has the advantage of being simple and easy to understand, but it appears to be based on no underlying welfare theoretical framework.

[20] Also note that we have limited degrees of freedom in constructing the cohort-aggregated household consumption between the two surveys (e.g., restricting household head age to between 25 and 55 in the first survey implies that we have only 31 data points for the cohort-aggregated household consumption for both surveys). As a result, the simple correlation coefficient is approximated with a much simpler model for household consumption between the two periods, rather than the linear projection of consumption on other household characteristics as in eq. (5). See Dang and Lanjouw (2013) for more details.

The recent approach proposed in Dang and Lanjouw (2017) instead derives the vulnerability line from a specified vulnerability index in the spirit of vulnerability to poverty.[21] While sharing a similar conceptual approach and motivation with existing studies on vulnerability (e.g., Pritchett, Suryahadi, and Sumarto 2000; Chaudhuri 2003; Christiaensen and Subbarao 2005), this approach is notably different in several respects. In particular, it explicitly provides a framework to estimate the vulnerability line that—to our knowledge—appears not to have been discussed in previous studies. This vulnerability line is associated with a vulnerability index that can be derived in various and more flexible ways, including budgetary planning, (ideal or desirable) social welfare objectives, or relative concepts of well-being. In addition, the target population consists of the currently nonpoor households rather than all households; and this approach employs simpler nonparametric estimation methods to estimate vulnerability as a function of consumption alone and can work with either actual panel data or synthetic panel data that can be constructed from cross sections. We employ a vulnerability index of 15% and the associated vulnerability line for our welfare analysis in the next section.[22]

Given a vulnerability line v_j, we can extend expression (6a) to analyze the dynamics for these three categories: poor, vulnerable, and middle class. For example, the percentage of poor households in the first period that escape poverty but still remain vulnerable in the second period (joint probability) is

$$P(y_{i1} < z_1 \text{ and } z_2 < y_{i2} < v_2) = \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, \frac{v_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right) - \Phi_2\left(\frac{z_1 - \beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, \frac{z_2 - \beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right). \tag{10}$$

V. Welfare Dynamics Analysis

We have discussed the changes in poverty over time in the previous section and thus will focus on discussing the other dynamics with vulnerability in this section. We start with showing the poverty transitions for all the population

[21] See, e.g., table 8 in Dang and Lanjouw (2017) for a comparison of this approach with some existing studies. See also Hoddinott and Quisumbing (2010) for a recent review of approaches to measuring vulnerability.

[22] All numbers are converted to 2004 prices for all rural India. We provide more detailed estimation results for India for the period 2004–9 in this paper than in our other paper (Dang and Lanjouw 2017). Our estimates are also different from those in the latter, which deflate all numbers to a population-weighted monthly national poverty line instead.

before delving further into population groups and offering further analysis with vulnerability.[23]

It is useful to briefly note the estimation of ρ before discussing estimation results. We form cohorts by interacting household heads' age with a dummy variable indicating whether they belong to scheduled castes. The partial correlation coefficient ρ is estimated to be 0.63, 0.52, and 0.56 for the periods 2004–9, 2009–11, and 2004–11, respectively, which are strongly statistically significantly different from 0.

A. All Population

Estimation results on poverty dynamics are provided in table 3, where panels A and B, respectively, show the transition dynamics in the first and second periods in India. The dynamic patterns reveal a positive picture on the composition of the changes in poverty reduction, which is not seen from the net changes in poverty based on the cross sections. Using the unconditional measure, 23% of the population were chronically poor (remained in poverty) in the period 2004–9 (panel A), but this figure decreased to 15% in the period 2009–11 (panel B). This change is even more noticeable for the conditional probabilities, where, conditional on being poor in the first year, the percentage of the population that remained in poverty in the second year is 63% (23.2/37) for the first period but fell to 50% in the second period.

Using the decomposition shown in equalities (7a) and (7b), we can also analyze the opposite patterns with upward mobility instead of chronic poverty. For example, while 37% ($1 - 0.63$) of the population escaped poverty in the first period (table 3, panel A), the corresponding figure for the second period climbed to 50% (panel B). Downward mobility is, however, rather similar for both periods. Around 9% of the population fell into poverty in both periods for the unconditional measure, and around 13% (8.8/69.8) of the population fell into poverty for the conditional measure.

These estimates for India in the period 2004–9 fall well within a range of estimates experienced by other countries in a similar time interval. In partic-

[23] As noted earlier, we restrict the data to households whose head's age is between 25 and 55 in the first survey round and adjust accordingly for the second survey round (e.g., age ranges 25–55 for 2004–5 and 30–60 for 2009–10 in the period 2004–9) to keep household units stable. This results in some slight differences with poverty rates based on these data, compared to the full data. For example, the poverty rates (with the same restriction on head's age as with the synthetic panels) are, respectively, 31% and 22.4% for 2009–10 and 2011–12, which are close to the corresponding estimates of 32.1% and 23.7% (table 3). Also note that the row and total columns in tables 3, 4, and 6 are also estimated with the synthetic panels.

TABLE 3
POVERTY TRANSITION DYNAMICS BASED ON SYNTHETIC PANEL DATA OVER TWO PERIODS, INDIA, 2004–5 TO 2011–12 (%)

	Poor	Nonpoor	Total
	A. First Period (2004–9)		
2004:			
Poor	23.2	13.8	37.0
	(.1)	(.0)	(.1)
Nonpoor	8.9	54.1	63.0
	(.0)	(.1)	(.1)
Total	32.1	67.9	100
	(.0)	(.1)	(.1)
	B. Second Period (2009–11)		
2009:			
Poor	15.0	15.2	30.2
	(.0)	(.0)	(.1)
Nonpoor	8.8	61.1	69.8
	(.0)	(.1)	(.1)
Total	23.7	76.3	100
	(.0)	(.1)	(.1)

Note. All consumption and poverty numbers are in 2004 prices for all rural India. The all-rural-India poverty line is 446.68 rupees per capita per month for 2004–5. 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 of the base year are 91,751 and 73,681 households for the first and second periods, respectively.

ular, the percentage of the poor population in these countries that escaped poverty is estimated to be 24% for Egypt (2004–9), 45% for Senegal (2006–11), 50% for the Lao PDR (2002–3 to 2007–8), and 56% for Bhutan (2007–12; Dang and Lanjouw 2013; World Bank 2014; Dang, Lanjouw, and Swinkels 2017; Dang and Ianchovichina, forthcoming). Among these countries, estimates for the Lao PDR are also validated against those based on the actual panel data.

Besides looking at the two shorter periods 2004–9 and 2009–11, we can also study the longer period 2004–11 for a richer picture of poverty dynamics. Estimates shown in table 4 point to qualitatively similar results and suggest that, for the unconditional measure, 18% of the population remained chronically poor in this period. This figure, however, climbed to almost three times as high, 49%, for the conditional measure. For the unconditional measure, upward mobility was 19%, which is also around three times the downward mobility (7%). The difference is, again, sharper for the conditional measure, where upward mobility is 51%, almost five times as high as downward mobility.

TABLE 4
POVERTY TRANSITION DYNAMICS BASED ON SYNTHETIC PANEL DATA, INDIA, 2004–5 TO 2011–12 (%)

	2011		
	Poor	Nonpoor	Total
2004:			
Poor	18.3	18.7	37.0
	(.0)	(.0)	(.1)
Nonpoor	6.8	56.3	63.0
	(.0)	(.1)	(.1)
Total	25.0	75.0	100
	(.0)	(.1)	(.1)

Note. All consumption and poverty numbers are in 2004 prices for all rural India. The all-rural-India poverty line is 446.68 rupees per capita per month for 2004–5. 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 size of the base year is 91,751 households.

B. *Profiling of Population Groups*

Figure 3 plots the percentage of the poor in the first year that escaped poverty in the second year in the two periods 2004–9 and 2009–11.[24] The transitions are disaggregated by education levels (i.e., less than primary education, primary education, middle education, secondary education, and college), occupation (which is further broken down into two categories of residence: [1] rural areas: self-employment in nonagriculture, agricultural labor, other labor categories, self-employment in agriculture, remaining categories; and [2] urban areas: self-employment, wage workers, and remaining categories), and socioethnic groups (i.e., scheduled tribes, scheduled castes, other backward groups, and remaining groups).[25] To further help with interpretation, we also calculate the differences between upward (and downward) mobility for these groups relative to the national average and provide them in table 5.

Several remarks are in order for figure 3 and table 5. First, more education achievement, urban residence, wage work, and belonging to social groups other

[24] We show the conditional, rather than the joint, probabilities for figs. 3–6, since this provides larger numbers that help bring out more clearly the transition patterns for the different population groups. For example, a small percentage of the population with secondary or higher education are usually found in poverty or vulnerability in the first period to start with; consequently, their unconditional probabilities in higher income categories in the second period are even smaller. For brevity, we show only the profiles for upward mobility and downward mobility, since the opposite results, respectively, hold for chronic poverty and the never-poor, as discussed with equalities (7a) and (7b).

[25] An additional assumption required for producing these graphs is that mobility for each population group/profile should generally follow that for the whole population.

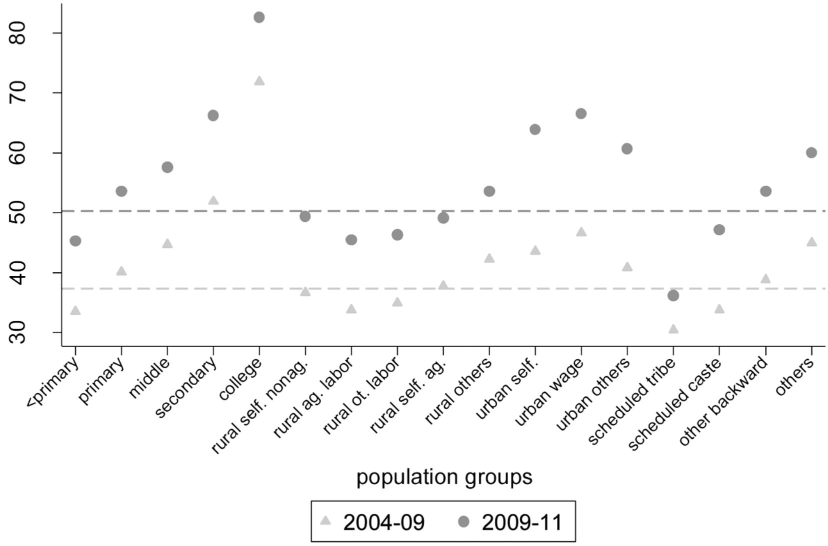

Figure 3. Profile of the population that escaped poverty in the second year, India, 2004–5 to 2011–12. Dashed lines represent the national average for each period (i.e., 37.3% for 2004–9 and 50.3% for 2009–11); ag. = agricultural; ot. = other; self. = self-employed. A color version of this figure is available online.

than the scheduled or backward groups were positively associated with higher-than-average chances of upward mobility. For example, these results are shown for the period 2009–11, with the circles representing these probabilities lying above the (upper) dashed line that represents the national average. Second, the period 2004–9 shows mobility that is qualitatively similar to, albeit weaker than, that for the period 2009–11. For example, ceteris paribus, having a middle education was associated with having a 45% chance for upward mobility in the first period but with a much higher 58% chance for upward mobility in the second period (fig. 3). Furthermore, mobility gradients were also somewhat steeper for the latter period, particularly for the different occupation groups in urban areas. Upward mobility for these groups relative to the national average in the latter period ranged from around twice (wage workers) to three times as high as in the first period (remaining categories; table 5, cols. 1, 3). This generally concurs with our earlier findings that the period 2009–11 exhibits more mobility than the period 2004–9.

Figure 4 presents a similar graph, in which upward mobility is disaggregated at the state level, where, for better presentation purposes, states are represented by dots proportional to their population and states' mobility in the period 2009–11 is ranked in an ascending order. While this figure indicates that certain states maintained a similar level of performance in both periods (e.g., Chandigarh and Delhi were strong performers, but Lakshadweep and Dadra

TABLE 5

HOUSEHOLD (HEADS') CHARACTERISTICS ASSOCIATED WITH POVERTY MOBILITY RELATIVE TO THE MEAN OVER TWO PERIODS, INDIA (%)

	2004–5 to 2009–10		2009–10 to 2011–12	
Characteristics	Upward Mobility: Poor in 2004–5, Escaped Poverty in 2009–10 (1)	Downward Mobility: Nonpoor in 2004–5, Fell into Poverty in 2009–10 (2)	Upward Mobility: Poor in 2009–10, Escaped Poverty in 2011–12 (3)	Downward Mobility: Nonpoor in 2009–10, Fell into Poverty in 2011–12 (4)
1. Ethnicity:				
Scheduled tribe	−6.9	7.5	−14.1	11.8
Scheduled caste	−3.5	5.1	−3.2	4.5
Other backward groups	1.4	1.1	3.3	.0
Others	7.7	−4.9	9.7	−5.2
2. Educational levels:				
Less than primary education	−3.8	6.3	−5.0	6.6
Primary education	2.8	2.1	3.2	1.7
Middle education	7.4	−1.1	7.3	−.9
Secondary education	14.6	−5.7	15.9	−5.6
College	34.5	−12.8	32.3	−11.4
3. Residence area and work sector:				
Rural area:				
Self-employed in nonagriculture	−.6	1.8	−.9	1.9
Agricultural labor	−3.6	6.0	−4.9	6.3
Other labor categories	−2.4	4.3	−4.0	5.2
Self-employed in agriculture	.4	1.2	−1.2	1.9
Remaining categories	4.9	−3.8	3.3	−2.7
Urban area:				
Self-employed	6.2	−4.3	13.6	−6.4
Wage worker	9.3	−6.9	16.2	−8.2
Remaining categories	3.5	−.6	10.4	−3.4
National average	37.3	14.2	50.3	12.5

Note. Estimates show the difference between the probability of falling into each category and the national average (conditional probabilities) and are based on the same estimation results shown in figures 3–6.

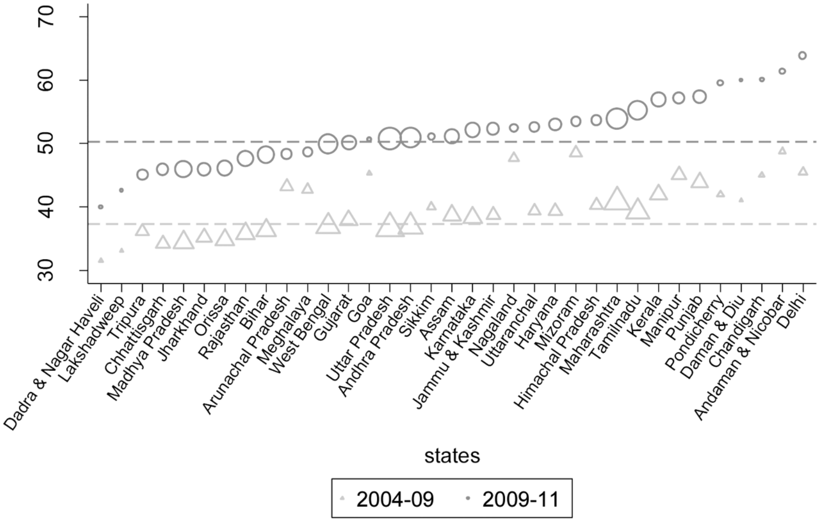

Figure 4. Profile of the population that escaped poverty in the second year by state, India, 2004–5 to 2011–12. Dashed lines represent the national average for each period (i.e., 37.3% for 2004–9 and 50.3% for 2009–11). A color version of this figure is available online.

and Nagar Haveli were weak performers), this may change over time. For example, such states as Meghalaya and Arunachal Pradesh were strong performers in the first period but became weak performers in the second period. The differences relative to the national average for the states are provided in table A5.[26]

Factors that were positively correlated with upward mobility are in general related to those associated with escaping downward mobility, but this may not always hold (see, e.g., Dang, Lanjouw, and Swinkels 2017, for an analysis of mobility in Senegal). We thus produce two figures for downward mobility for the same population groups (figs. 5, 6). Interestingly, for India it is generally true that the same factors can be associated with both increasing upward mobility and decreasing downward mobility. For example, out of all occupational categories, wage workers living in urban areas had the largest and smallest chance of upward mobility and downward mobility, respectively. Relative to the national average, being a wage worker in the second period was associated with having 16 percentage points higher upward mobility—which is slightly higher than that for having a secondary education—and 8 percentage points less of downward mobility (table 5, cols. 3, 4).

[26] But also note that the ranking of states in terms of mobility changes slightly between the two periods. For example, Chandigarh and Andaman and Nicobar switch places from fig. 4 (upward mobility) to fig. 6 (downward mobility).

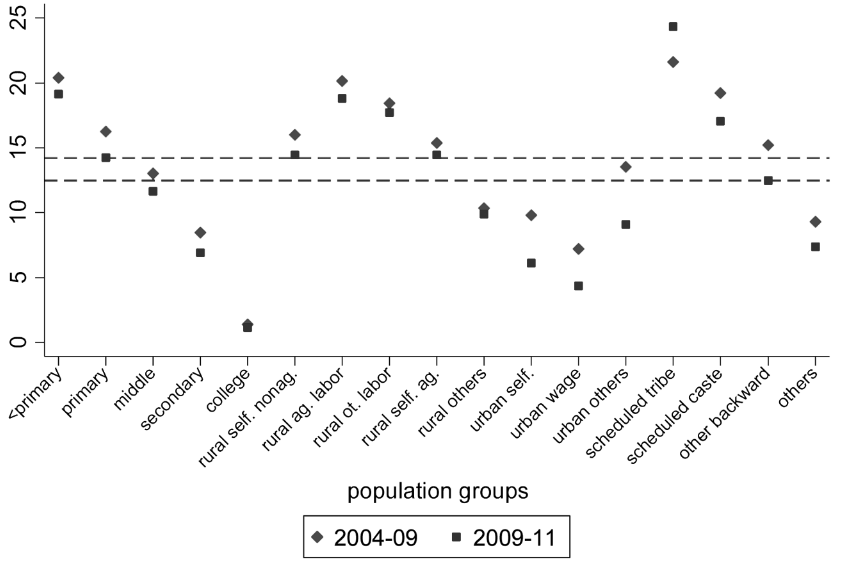

Figure 5. Profile of the population that fell into poverty in the second year, India, 2004–5 to 2011–12. Dashed lines represent the national average for each period (i.e., 14.2% for 2004–9 and 12.5% for 2009–11); ag. = agricultural; ot. = other; self. = self-employed. A color version of this figure is available online.

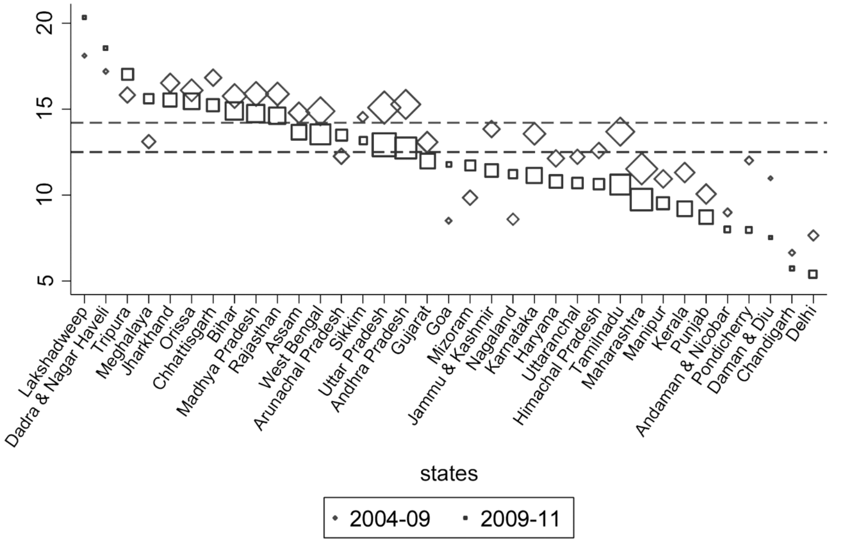

Figure 6. Profile of the population that fell into poverty in the second year by state, India, 2004–5 to 2011–12. Dashed lines represent the national average for each period (i.e., 14.2% for 2004–9 and 12.5% for 2009–11). A color version of this figure is available online.

C. Vulnerability Analysis

The welfare transition matrixes for the three consumption groups for the two periods 2004–9 and 2009–11 are shown in panels A and B, respectively, in table 6. Since vulnerability may change over time, for better comparison we fix the vulnerability index at 15% in the first period but use its associated vulnerability line of 1,115 rupees per month as the vulnerability line in the second period. Put differently, once the vulnerability index is given in the first period, we hold constant the vulnerability line in both periods.

Table 6 shows that, together with the decrease in poverty, there is an expansion of the vulnerable and the middle class (categories) in the period 2004–9.

TABLE 6
WELFARE TRANSITION DYNAMICS BASED ON SYNTHETIC PANEL DATA AT SIMILAR VULNERABILITY LINE, INDIA, 2004–5 TO 2011–12 (%)

	Poor	Vulnerable	Middle Class	Total
	A. Vulnerability Line Corresponding to Vulnerability Index of .15			
	2009			
2004:				
Poor	23.2	13.7	.1	37.0
	(.1)	(.0)	(.0)	(.1)
Vulnerable	8.9	41.5	4.9	55.2
	(.0)	(.0)	(.0)	(.1)
Middle class	.0	3.0	4.7	7.8
	(.0)	(.0)	(.0)	(.1)
Total	32.1	58.2	9.7	100
	(.1)	(.0)	(.1)	
	B. Same Vulnerability Line in Both Periods			
	2011			
2009:				
Poor	15.0	14.8	.4	30.2
	(.0)	(.0)	(.0)	(.1)
Vulnerable	8.7	42.6	8.0	59.3
	(.0)	(.0)	(.0)	(.0)
Middle class	.1	4.2	6.3	10.5
	(.0)	(.0)	(.1)	(.1)
Total	23.7	61.6	14.6	100
	(.1)	(.1)	(.1)	

Note. The vulnerability index is defined as $P(y_1 < z_1 | z_0 < y_0 < v_0) = 0.15$ in the first period, yielding a monthly vulnerability line of 1,115 rupees per capita. We use this same vulnerability line for the second period. The all-rural-India poverty line for 2004–5 is 446.68 rupees per capita per month. All consumption and poverty numbers are in 2004 prices for all rural India. Estimates are obtained 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 is restricted to between 25 and 55 for the first survey and adjusted accordingly for the second survey in each period. Estimation sample sizes of the base year are 91,751 and 73,681 households for the first and second periods, respectively.

This trend continues in the second period, 2009–11, but with a faster shrinkage of the poor and growth of the middle class and a small increase in the vulnerable. Specifically, the fall in poverty rises from 13% (i.e., $1 - (32.1/37)$) during the first period to 22% during the second period, while the middle class growth increases from 24% to 39% over the same time interval. In terms of absolute numbers, the vulnerable category increases by roughly 4 percentage points and makes up almost two-thirds of the population in 2009–11; the middle class is half again as large in the latter as in the former (e.g., 14.6% vs. 9.7%).

Another useful way to gauge welfare mobility in the two periods is to look at the percentage of the population who change their welfare status over time. In 2004–9, 19% of the population move up one or two welfare categories (i.e., the sum of the upper off-diagonal cells), while 12% move down one or two welfare categories (i.e., the sum of the lower off-diagonal cells). The corresponding figures in 2009–11 are larger, respectively 23% and 13%, suggesting that the population as a whole are both better off and more mobile in this period.

VI. Conclusion

We investigate in this paper the poverty dynamics in India between 2004–5 and 2011–12, using three rounds of the NSSs. In the absence of actual panel data, we construct synthetic panels, using statistical methods that were recently developed by Dang et al. (2014) and Dang and Lanjouw (2013). Estimation results point to faster poverty reduction and more upward mobility in the period 2009–11 than in the period 2004–9. Further analysis using vulnerability lines that correspond to a vulnerability index of 15% and are also close to twice the national poverty line offers a qualitatively similar result.

In particular, with the unconditional measure, 23% of the population were chronically poor in the period 2004–9, but this figure decreased to 15% in the period 2009–11. Upward and downward mobility hover around 15% and 9%, respectively, for both periods. The conditional measure, however, points to sharper differences between the two periods. For example, 37% of the poor population escaped poverty in the first period, and as many as 50% of the poor population could do so in the second period; the corresponding figures for downward mobility are around 13% in both periods. This pattern of stronger upward mobility is qualitatively similar when considered over the longer period 2004–11. Factors including more educational achievement, urban residence, wage work, and belonging to socioethnic groups other than the scheduled or backward groups are positively associated with higher-than-average chances of upward mobility and lower-than-average chances of downward mobility.

Our paper also presents a two-step analysis procedure where careful checks should be done in the first step to ensure data comparability across survey rounds before synthetic panels can be constructed in the second step. This procedure may be relevant to quite a few other contexts, since situations where data are not comparable across survey rounds—leading to, for example, the recent debate on poverty decline in 2011–12 in India—appear to occur more frequently than one might think. We discuss a statistical method (Dang, Lanjouw, and Serajuddin 2017) that can be employed for this checking purpose. Estimation results show that the poverty decline between 2009–10 and 2011–12 is not severely overestimated (or equivalently, that the design-based poverty estimate using the 2011–12 survey round is practically comparable to those from previous rounds). However, as discussed above, this statistical method relies on the key assumption that the change in the characteristics, rather than in the coefficients, can capture the change in poverty, which is supported with our estimates using the earlier survey data in 2004–5 and 2009–10, where household consumption data are comparable. Thus, seen from a modeling viewpoint, this assumption is an integral part of this statistical method and can be validated for previous survey rounds where data are available. Still, we acknowledge that it is an untestable assumption, and caution should be taken to ensure that this assumption is valid for a similar application in another contexts.

Our methods are promising for more-detailed analyses of welfare dynamics that can further exploit the richness of the NSS data. For example, future research can provide more-disaggregated analysis within each state and analyze either more survey rounds to study transition trajectories between more than two periods or survey rounds that are farther apart to investigate longer-term transitions. Another direction is to make better use of the “thin” rounds, in addition to the “thick” rounds, to build a more comprehensive picture of these dynamics over time.

Appendix
Additional Tables

TABLE A1

DISAGGREGATION OF TOTAL MONTHLY HOUSEHOLD CONSUMPTION BY ITEM, INDIA, 2009–10 TO 2011–12

	2009–10		2011–12	
Total Expenditure Category	Mean Expenditure (Rupees)	Share of Expenditure (%)	Mean Expenditure (Rupees)	Share of Expenditure (%)
Same item code in 2009 and 2011	3,275.8	63.2	4,335.1	63.0
Same item but different code in 2009 and 2011	1,605.1	31.0	1,981.0	28.8
Item more disaggregated in 2009	19.8	.4	26.7	.4
Item more disaggregated in 2011	75.4	1.5	76.5	1.1
Item partly different between 2009 and 2011	80.2	1.5	114.2	1.7
Item found in 2009 only	128.1	2.5	NA	NA
Item found in 2011 only	NA	NA	346.5	5.0
Other household expenditure	.0	.0	.0	.0
Total household expenditure	5,184.4	100	6,880.0	100

Note. All expenditure data are adjusted for state and sector deflators and obtained with household weight. NA = not applicable.

TABLE A2

SUMMARY STATISTICS, INDIA, 2009–10 AND 2011–12

	2009–10	2011–12	Difference
Household size	5.67	5.53	−.13***
	(2.65)	(2.54)	(.03)
Age (years)	46.59	46.69	.10
	(13.05)	(13.04)	(.13)
Female head	.08	.09	.01***
	(.27)	(.28)	(.00)
Hindu	.82	.81	−.01
	(.38)	(.39)	(.00)
Muslim	.13	.14	.01**
	(.33)	(.34)	(.00)
Scheduled tribes	.09	.09	.00
	(.28)	(.29)	(.00)
Scheduled castes	.20	.19	−.01***
	(.40)	(.39)	(.00)
Other backward classes	.42	.44	.02***
	(.49)	(.50)	(.01)
Literate (for those with less than primary education)	.11	.12	.01***
	(.32)	(.33)	(.00)
Completed primary education	.14	.13	−.01***
	(.34)	(.33)	(.00)
Completed middle education	.15	.15	.00
	(.35)	(.36)	(.00)
Completed secondary education	.11	.12	.00
	(.32)	(.32)	(.00)
Completed senior secondary education	.06	.06	.00
	(.24)	(.24)	(.00)
Have a diploma/certificate	.01	.01	−.00
	(.09)	(.09)	(.00)
Completed graduate education	.05	.06	.00**
	(.22)	(.23)	(.00)
Completed postgraduate education	.02	.02	.00***
	(.13)	(.15)	(.00)
Share of household members aged 0–14	.31	.30	−.01***
	(.22)	(.22)	(.00)
Share of household members aged 15–24	.19	.19	−.00
	(.21)	(.21)	(.00)
Share of household members aged 25–59	.42	.43	.01***
	(.19)	(.19)	(.00)
Any household member has regular salary income	.18	.21	.03***
	(.38)	(.41)	(.00)
Rural, self-employed in nonagriculture	.12	.12	.00
	(.32)	(.33)	(.00)
Rural, self-employed in agriculture	.26	.27	.01***
	(.44)	(.44)	(.01)
Urban, self-employed	.11	.12	.00
	(.32)	(.32)	(.00)
Urban, regular wage/salary earning	.10	.11	.01***
	(.30)	(.32)	(.00)
Urban, casual labor	.04	.04	.00
	(.19)	(.19)	(.00)
Urban, other work	.02	.02	.00
	(.13)	(.13)	(.00)

TABLE A2 (*Continued*)

	2009–10	2011–12	Difference
Own home	.89	.89	−.00
	(.32)	(.32)	(.00)
Main lighting source is electricity	.73	.78	.06***
	(.45)	(.41)	(.01)
Mainly use firewood for cooking	.62	.53	−.09***
	(.49)	(.50)	(.01)
Mainly use LPG for cooking	.27	.30	.03***
	(.44)	(.46)	(.00)
Own a radio	.27	.20	−.07***
	(.44)	(.40)	(.00)
Own a television	.53	.61	.08***
	(.50)	(.49)	(.01)
Own an electric fan	.65	.72	.07***
	(.48)	(.45)	(.01)
Own a sewing machine	.16	.19	.03***
	(.37)	(.40)	(.00)
Own a freezer	.17	.21	.04***
	(.38)	(.41)	(.00)
Own an air conditioner	.11	.13	.02***
	(.31)	(.33)	(.00)
Own a bike	.57	.58	.01**
	(.49)	(.49)	(.01)
Own a motorbike	.22	.27	.05***
	(.42)	(.45)	(.00)
Own a car	.03	.04	.01***
	(.18)	(.21)	(.00)
Observations	99,469	101,525	

Note. Except as noted, data are reported as share of the population; standard deviations (first two columns) and standard errors (last column) are in parentheses. Differences are estimated with *t*-tests that take into account complex survey design with cluster sampling and stratification. All estimates are obtained with population weights. LPG = liquefied petroleum gas.
** $p < .05$.
*** $p < .01$.

TABLE A3

MODEL SPECIFICATIONS OF HOUSEHOLD CONSUMPTION, INDIA, 2004–5

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Household size	−.064***	−.041***	−.045***	−.044***	−.055***
Age	.015***	.001	.000	.002***	−.002***
Age^2	−.000***	.000***	.000***	.000***	.000***
Female head	.014***	.046***	.046***	.047***	.030***
Hindu	−.104***	−.108***	−.098***	−.100***	−.054***
Muslim	−.171***	−.158***	−.135***	−.136***	−.021***
Scheduled tribes	−.229***	−.217***	−.216***	−.212***	−.111***
Scheduled castes	−.224***	−.208***	−.178***	−.175***	−.086***
Other backward classes	−.108***	−.099***	−.092***	−.091***	−.046***
Literate (for those with less than primary education)	.105***	.097***	.084***	.083***	.042***
Completed primary education	.164***	.152***	.132***	.132***	.069***
Completed middle education	.274***	.259***	.226***	.227***	.113***
Completed secondary education	.423***	.400***	.356***	.356***	.157***
Completed senior secondary education	.548***	.519***	.469***	.468***	.237***
Have a diploma/ certificate	.724***	.696***	.634***	.630***	.312***
Completed graduate education	.785***	.752***	.697***	.697***	.348***
Completed post graduate education	.928***	.895***	.835***	.836***	.421***
Share of household members aged 0–14		−.341***	−.334***	−.340***	−.349***
Share of household members aged 15–24		.100***	.088***	.079***	.020**
Share of household members aged 25–59		.281***	.266***	.257***	.158***
Any household member has regular salary income			.139***	.134***	.079***
Rural, self-employed in nonagriculture			.120***	.122***	.068***
Rural, self-employed in agriculture			.164***	.166***	.143***
Urban, self-employed			.066***	.052***	−.147***
Urban, regular wage/ salary earning			.009*	−.016***	−.160***
Urban, casual labor			−.168***	−.187***	−.221***
Urban, other work			.166***	.147***	.005
Own home				−.079***	−.129***
Main lighting source is electricity					.043***
Mainly use firewood for cooking					−.076***

TABLE A3 (*Continued*)

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Mainly use LPG for cooking					.088***
Own a radio					.080***
Own a television					.090***
Own an electric fan					.081***
Own a sewing machine					.023***
Own a freezer					.202***
Own an air conditioner					.041***
Own a bike					.003
Own a motorbike					.208***
Own a car					.340***
Constant	6.272***	6.489***	6.448***	6.476***	6.615***
σ_u	.10	.10	.10	.11	.00
σ_e	.43	.42	.41	.41	.37
R^2 (overall)	.05	.05	.06	.07	0
Observations	124,543	124,543	124,374	124,340	119,292

Note. Standard errors are not shown for lack of space. All model specifications use normal linear regression with state random effect. The square roots of the state random effects and the error term are, respectively, σ_u and σ_e. LPG = liquefied petroleum gas.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

TABLE A4
MODEL SPECIFICATIONS OF HOUSEHOLD CONSUMPTION, INDIA, 2009–10

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Household size	−.074***	−.054***	−.057***	−.055***	−.070***
Age	.006***	−.007***	−.008***	−.005***	−.010***
Age^2	−.000	.000***	.000***	.000***	.000***
Female head	.019***	.045***	.041***	.044***	.039***
Hindu	−.114***	−.117***	−.107***	−.110***	−.043***
Muslim	−.164***	−.155***	−.130***	−.131***	−.019***
Scheduled tribes	−.197***	−.190***	−.195***	−.191***	−.113***
Scheduled castes	−.208***	−.197***	−.168***	−.164***	−.086***
Other backward classes	−.104***	−.098***	−.092***	−.090***	−.054***
Literate (for those with less than primary education)	.104***	.094***	.080***	.081***	.053***
Completed primary education	.152***	.141***	.119***	.121***	.065***
Completed middle education	.259***	.245***	.212***	.214***	.109***
Completed secondary education	.401***	.384***	.334***	.337***	.147***
Completed senior secondary education	.538***	.516***	.455***	.456***	.209***
Have a diploma/ certificate	.723***	.705***	.624***	.621***	.307***
Completed graduate education	.729***	.708***	.640***	.642***	.294***

TABLE A4 (*Continued*)

	Specification 1	Specification 2	Specification 3	Specification 4	Specification 5
Completed postgraduate education	.876***	.852***	.776***	.777***	.377***
Share of household members aged 0–14		−.264***	−.253***	−.263***	−.295***
Share of household members aged 15–24		.148***	.139***	.122***	.061***
Share of household members aged 25–59		.277***	.266***	.253***	.161***
Any household member has regular salary income			.150***	.143***	.077***
Rural, self-employed in nonagriculture			.106***	.105***	.036***
Rural, self-employed in agriculture			.188***	.190***	.124***
Urban, self-employed			.049***	.031***	−.175***
Urban, regular wage/ salary earning			.003	−.029***	−.160***
Urban, casual labor			−.214***	−.236***	−.268***
Urban, other work			.149***	.122***	−.006
Own home				−.112***	−.177***
Main lighting source is electricity					.038***
Mainly use firewood for cooking					−.086***
Mainly use LPG for cooking					.028***
Own a radio					.035***
Own a television					.098***
Own an electric fan					.069***
Own a sewing machine					.040***
Own a freezer					.206***
Own an air conditioner					.064***
Own a bike					−.029***
Own a motorbike					.185***
Own a car					.335***
Constant	7.028***	7.194***	7.161***	7.190***	7.407***
σ_u	.12	.10	.08	.05	.00
σ_e	.44	.43	.42	.42	.37
R^2 (overall)	.07	.05	.04	.01	.00
Observations	100,832	100,832	100,798	100,595	99,469

Note. Standard errors are not shown for lack of space. All model specifications use normal linear regression with state random effect. The square roots of the state random effects and the error term are, respectively, σ_u and σ_e. LPG = liquefied petroleum gas.
*** $p < .01$.

TABLE A5

POVERTY MOBILITY RELATIVE TO THE MEAN BY STATE OVER TWO PERIODS, INDIA (%)

	2004–5 to 2009–10		2009–10 to 2011–12	
State	Upward Mobility: Poor in 2004–5, Escaped Poverty in 2009–10 (1)	Downward Mobility: Nonpoor in 2004–5, Fell into Poverty in 2009–10 (2)	Upward Mobility: Poor in 2009–10, Escaped Poverty in 2011–12 (3)	Downward Mobility: Nonpoor in 2009–10, Fell into Poverty in 2011–12 (4)
Andaman and Nicobar	11.5	−5.2	11.1	−4.5
Andhra Pradesh	−.4	1.1	.6	.2
Arunachal Pradesh	5.9	−1.9	−2.0	.9
Assam	1.4	.6	.8	1.1
Bihar	−1.0	1.6	−2.0	2.4
Chandigarh	7.7	−7.5	9.8	−6.8
Chhattisgarh	−3.1	2.7	−4.4	2.7
Dadra and Nagar Haveli	−5.8	3.0	−10.3	6.0
Daman and Diu	3.7	−3.2	9.7	−5.0
Delhi	8.2	−6.5	13.6	−7.1
Goa	8.0	−5.7	.4	−.7
Gujarat	.6	−1.1	−.2	−.6
Haryana	2.0	−2.0	2.7	−1.7
Himachal Pradesh	2.9	−1.6	3.5	−1.9
Jammu and Kashmir	1.4	−.3	2.1	−1.1
Jharkhand	−2.1	2.4	−4.3	3.0
Karnataka	1.0	−.6	1.8	−1.4
Kerala	4.6	−2.8	6.7	−3.3
Lakshadweep	−4.2	3.9	−7.6	7.8
Madhya Pradesh	−2.9	1.7	−4.4	2.2
Maharashtra	3.5	−2.6	3.6	−2.8
Manipur	7.8	−3.2	6.8	−3.0
Meghalaya	5.4	−1.1	−1.6	3.1
Mizoram	11.2	−4.3	3.3	−.8
Nagaland	10.3	−5.6	2.2	−1.3
Orissa	−2.5	1.9	−4.2	2.9

TABLE A5 (*Continued*)

	2004–5 to 2009–10		2009–10 to 2011–12	
State	Upward Mobility: Poor in 2004–5, Escaped Poverty in 2009–10 (1)	Downward Mobility: Nonpoor in 2004–5, Fell into Poverty in 2009–10 (2)	Upward Mobility: Poor in 2009–10, Escaped Poverty in 2011–12 (3)	Downward Mobility: Nonpoor in 2009–10, Fell into Poverty in 2011–12 (4)
Pondicherry	4.6	−2.2	9.3	−4.6
Punjab	6.6	−4.1	7.1	−3.8
Rajasthan	−1.5	1.7	−2.7	2.1
Sikkim	2.7	.4	.8	.6
Tamilnadu	1.9	−.5	4.9	−1.9
Tripura	−1.2	1.6	−5.2	4.5
Uttar Pradesh	−.7	.9	.5	.4
Uttaranchal	2.1	−1.9	2.3	−1.8
West Bengal	−.4	.7	−.3	1.0
National average	37.3	14.2	50.3	12.5

Note. Estimates show the difference between the probability of falling into each category and the national average (conditional probabilities) and are based on the same estimation results shown in figures 3–6.

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