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Estimating Poverty in India without Expenditure Data

A Survey-to-Survey Imputation Approach

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Abstract

This paper applies an innovative method to estimate poverty in India in the absence of recent expenditure data. The method utilizes expenditure data from 2004-05, 2009–10, and 2011–12 to impute household expenditure into a survey of durable goods expenditure conducted in 2014-15. At the $1.90 per day international poverty line, the preferred model predicts a 2014–15 head- count poverty rate of 10 percent in urban areas and 16.4 percent in rural areas, implying a poverty rate of 14.6 percent nationally. The implied poverty elasticity with respect to growth in per capita Gross Domestic Product (GDP) is within the range of past experience, and states with higher gross domestic product growth saw greater predicted poverty reductions. In validation tests, the model's predictions perform comparably to the World Bank's current adjustment method when predicting for 2011–12 but they are far more accurate when predicting for 2004–05. Three alternative specifications give moderately higher estimates of poverty. The results indicate that survey-to-survey imputation, when feasible, is a preferable alternative to the current method used to adjust survey-based poverty estimates to later years.

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A Survey-to-Survey Imputation Approach*

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I Introduction

This paper explains the methodology and results of a survey to survey imputation exercise that was used to generate headcount poverty estimates for India. India was selected as a pilot case because of its size and importance, as well as the lack of recent data on household living standards. The latest survey-based estimates of poverty are from 2011-12. The most recent nationally representative survey that could be used to impute poverty into a later year is the NSSO expenditure on services and durables survey of 2014-15. The resulting poverty estimates from the imputation informed the 2015 poverty estimates, which are the most recent that are currently available, marking the first time that the World Bank used this type of method as an input into its global and regional poverty estimates.

Understanding trends in poverty in India is not only vital to Indian policy makers to measure changes in the welfare of the poor, but also has major implications for regional and global estimates of the prevalence of poverty. In 2013, an estimate of the number of extreme poor in India, defined as those consuming less than $1.90 per day per person, numbered 250 million [1]. This means that India accounted for over a quarter of the global total of 783 million extreme poor. Although Nigeria has now likely passed India as the nation with the largest number of extremely poor persons, accurately monitoring India's progress in the fight against extreme poverty remains critical to assess progress towards the goal of reducing poverty to less than 3% by 2030.

The second motivation for undertaking a modeling exercise is that the typical method used by the World Bank to adjust poverty to a later year tends to overestimate the pace of poverty decline. When estimating global and regional poverty rates, the World Bank usually adjusts or "lines up" survey data from a variety of years to a common year, by scaling up the measured levels of household per capita consumption to account for growth in the intervening years. For example, to "line up" a survey from 2012 to 2015, each household's per capita consumption, measured in 2012, would be assumed to grow at the same rate. In most countries, this common rate of growth is assumed to be equal to the growth in household final consumption expenditure (HFCE) during the intervening period.[2] Because it is a component of the national accounts, HFCE is published annually and can therefore be used to line up the survey means to any later year.

[1] Estimate is based on the traditional line-up method explained below.

[2] In some countries, growth in per capita GDP is used instead of final household consumption expenditure.

Unfortunately, however, growth in HFCE tends to substantially exceed mean consumption growth in household surveys.[3] One study, for example, concludes that on average only about half of the growth in HFCE was reflected in growth in survey consumption.[4] This is partly because official surveys face severe challenges obtaining accurate measures of welfare for the very wealthy. Because there are few very wealthy households, they may not be included in the sample. Wealthy households are more likely than poor households to refuse to participate in the survey, and tend to underreport their income or consumption. However, there are also good reasons why national accounts data may overestimate growth in mean income or consumption, including the use of outdated 'rates and ratios' based on old survey data.[5]

Because of the systematic discrepancy between growth in national accounts data and household surveys, using HFCE to adjust survey data is prone to overstating poverty reduction for countries that lack a recent survey such as India. In fact, past analysis from India demonstrates how the typical line up adjustment procedure can greatly overestimate poverty decline, using data from 2004-05 and 2009-10.[6] Estimates were generated for 2009-10 by lining up the 2004-05 data to 2009-10, applying the HFCE growth rate during that period. These line-up estimates for 2009-10 were then compared with measurements from actual survey data from that year. The line-up procedure generated an estimated reduction in poverty from 41.6 to 13.4 percent, whereas the actual data from 2009-10 yielded a poverty rate of 32.7%.[7] In other words, the line-up method overstated the decline in poverty by 19 percentage points. However, virtually all of the discrepancy between the line-up estimate and the actual data resulted from consumption expenditure growth in the national accounts exceeding mean welfare growth in the survey. In contrast, assuming that the 2004-05 welfare distribution remained constant except for a scale factor created negligible error. In this case, assuming that the distribution of welfare changed by a common scale factor was fine; the real problem was determining what factor should be used to scale up measured welfare in the initial year.

The concern that growth in the national accounts exceeds growth in survey mean welfare motivates the use of a survey-to-survey imputation method to determine an appropriate scale factor or "pass-through rate" to apply to HFCE. The major portion of the exercise involves estimating poverty at the $1.90 line in 2014-15, using

[3] See Edward and Sumner (2013), Hillebrand (2008), Korinek, Mistiaen, and Ravallion (2006), Deaton and Kozel (2005), Ravallion (2003) and Minhas (1988).

[4] Ravallion (2003).

[5] Deaton and Kozel (2005).

[6] Jolliffe (2014) p.253.

[7] These figures are based on the older, $1.25 poverty line (in 2005 PPP).

an econometric model estimated at the household level. Urban and rural sectors are modeled separately, because they differ in fundamental ways.[8] The model draws on four rounds of past Indian National Sample Survey data, namely the 61st, 66th, 68th, and 72nd rounds, which were fielded in 2004-05, 2009-10, 2011-12, and 2014-15 respectively.[9] The 2014-15 survey, unlike the three previous rounds used in this exercise, did not collect information on aggregate household consumption and therefore cannot generate direct estimates of poverty. The 2014-15 survey, however, contains information on several household characteristics that are also present in past rounds and are reasonably well-correlated with per capita consumption.[10] These common characteristics include household age, size, caste, religion, a few labor market variables, and expenditure on three categories of services that are asked in the same way as previous rounds.

The analysis estimates a regression model that predicts household per capita consumption using these common household characteristics, plus contemporaneous rainfall shocks and a linear time trend. Most coefficients are allowed to vary over time in a linear way, slightly relaxing the usual strong assumption that the relationship between the explanatory variables and log welfare remains constant over time.[11] The model is estimated using data from the first three rounds of the survey. The coefficients from this regression model were then applied to measured values of the same common characteristics in the 2014-15 survey, as well as 2014-15 rainfall levels, to repeatedly simulate levels of welfare and poverty. The results of these simulations were aggregated to generate estimates of poverty headcount rates and their standard errors.

This exercise is similar in spirit to the adjustments for non-comparability in the consumption aggregate that led to "the great Indian poverty debate".[12] Since then, this type of nowcasting exercise has also been carried out in several other countries.[13] While this method has not yet been successfully applied to estimate changes in inequality, a significant body of evidence now exists that out of sample predictions

[8] Also, India is one of three countries for which separate poverty estimates are presented by the World Bank for urban and rural areas.

[9] Unfortunately, data between 1993 and 2004-05 were unavailable because the welfare aggregate in the 1999-2000 round was not comparable.

[10] In the pooled regression including 2004-05, 2009-10, and 2011-12 data, the R^2s are 0.57 for urban areas and 0.46 for rural areas (Table 14 (Appendix).)

[11] Nguyen and van der Weide (2018).

[12] Deaton and Dreze (2002) and Kijima and Lanjouw (2003) Deaton and Kozel (2005).

[13] See, for example, Christiaensen and Stifel (2007) in Kenya, Newhouse, Shivakumaran, Takamatsu, and Yoshida (2014) in Sri Lanka, Douidich, Ezzrari, Van der Weide, and Verme (2016) in Morocco, and Dang, Lanjouw, and Serajuddin (2017) in Jordan.

from models estimated on past data generate credible estimates, in a variety of country contexts, of poverty headcount and gaps.

The preferred model generates an estimate of 10.0% in urban areas and 16.8% in rural areas, which implies an overall poverty level of 14.6% for 2014-15 (Table 1 and Figure 1). The estimate is consistent with poverty reduction from 2004-05 to 2011-12 in rural areas and suggests a slight deceleration in poverty reduction in urban areas (Table 2). This in turn implies that the elasticity of poverty with respect to growth of per capita GDP was -2.11, which is within the range of past experience. Reassuringly, when looking at the state level, predicted poverty reduction is greater in states with higher rates of GDP growth.

We use two main tests to validate the survey-to-survey imputation models. The first estimates a model with the same specification, using data from 2004-05 and 2009-10, to predict into 2011-12. These predictions are then compared with actual measured levels of poverty from the national sample survey. In a similar, vein, the second validation test uses data from 2009-10 and 2011-12 to predict backwards to 2004-05. This is a much more challenging exercise because the data from two years apart are being used to extrapolate five years in the past.

While the traditional line-up method performs slightly better than our preferred specification in 2011-12, it gives wildly implausible estimates when projecting back to 2004-05. To be specific, the standard line-up method is off by only a percentage point in 2011-12 but exaggerates poverty by 25 percentage points when predicting back to 2004-05. Our preferred model performs much better on average, as the discrepancy is about 2 percentage points in 2011-12 and about 3 percentage points in 2004-05.

The traditional line-up method happens to do well when projecting forward into 2011-12 because growth in mean reported consumption in the survey was unusually high between 2009-10 and 2011-12 and nearly matched growth in HFCE. This is a sharp break from the pattern observed during the previous period, and in most other contexts. It remains to be seen whether this correspondence between HFCE and survey mean growth will be sustained, but there are at least two reasons to speculate it may not be. The first is that survey-based consumption may be more responsive than national account data to weather shocks. India experienced significant droughts during 2004 and 2009, followed by above-average rainfall in the 2011 season. To the extent that survey-based consumption is more sensitive than national accounts to agricultural income, favorable rainfall in 2011 would cause a larger jump in survey consumption than HFCE.[14] The second factor is the recovery from the 2008 financial crisis, which is distinctly visible in the 2009 national accounts data. Survey-based consumption, however, may have taken longer to recover. Both factors could have contributed to the unusually large increase in mean consumption observed between 2009-10 and 2011-12, which counteracted the usual tendency for HFCE growth to exceed growth in mean consumption. We know of no reason to believe, however, that growth in HFCE will accurately reflect growth in mean consumption going forward.

Turning back to the model predictions, we consider three alternative specifications that impose more restrictive assumptions. These estimate a slower poverty decline, with estimated headcount rates ranging from 17.4 to 19.1 percent. In contrast, the traditional line-up method shows a much more rapid decline in poverty, from 21.6% in 2011-12 to 10.9% in 2014-15. This shows that the choice of modeling assumptions matters, at least in this case.

The final step is to use the estimates for 2014-15 from the econometric model to generate the poverty estimate for India for 2015 used in the global estimates. This was done by estimating an appropriate fraction, or "pass-through rate", to apply to growth in HFCE, thereby assuming that only a portion of the HFCE growth is passed through to growth in mean welfare in the household survey. Pass-through rates were selected to match the $1.90 headcount poverty estimates from the survey-to-survey imputation model for 2014-15, which were 10% in urban areas and 16.8% in rural areas. These were then used to calculate estimates for 2015, based on the scaled down growth rate of HFCE.[15]

The rest of this paper is organized as follows. The next section reviews the data used for the analysis. Section III turns to the methodology. It discusses the estimation method and the process used to select the set of predictor variables, and examines the results of four alternative specifications to the model. Section IV compares the preferred model's predictions for 2014-15 to the usual method used to project poverty forward, and investigates which specific variables are accounting for the change in average welfare predicted by the model. Section V shows that the estimated poverty rate implies a reasonable elasticity of poverty reduction with respect to growth, verifies that implied poverty reduction is greater in fast-growing states, and examines the model's predictions at higher poverty lines. Section VI briefly describes how the 2014-15 estimates were used to generate poverty estimates for 2015, and Section VII concludes.

[14] According to the Economic Survey 2017-18 of the Ministry of Finance in India, agriculture employs over half of Indian workers but only contributes 17 to 18 percent of India's GDP.

[15] The 2015 estimates can be viewed at http://iresearch.worldbank.org/PovcalNet/povDuplicateWB.aspx. See http://iresearch.worldbank.org/PovcalNet/WhatIsNew.aspx for further details.

II Data

In order to obtain estimates of welfare for 2014-15, we first identify variables that are common both to the three earlier consumption surveys and the 2014-15 round. The surveys have five demographic variables in common. They are household size, age of household members, gender, religion, and caste contained in the "household characteristics" section of each survey. The three common labor market variables are the household's principal industry, principal occupation and principal means of livelihood.

The principal industry of a household is determined according to the National Industrial Classification (NIC) 2008 code for the NSSO72, NSSO68 and NSSO66 surveys and the NIC 1998 code for the NSSO61 survey.[16] Regarding the principal occupation, the NSSO72, NSSO68 and NSSO66 surveys categorize households according to the National Classification of Occupations (NCO) 2004 code and the NSS061 survey according to the NCO 1968 code. To ensure consistency, the occupation categories are harmonized across survey years. We further group households into high skill, middle skill and low skill occupation categories.[17] The household's principal means of livelihood is determined from the "household type" variable. The categories are self-employed, regular wage/salary earning, casual labor and "other".[18]

In addition, the surveys ask questions regarding expenses on miscellaneous services such as household service (domestic help, barber, beauty, laundry, priest, grinding, tailor), recreation (cinema/theater, fairs/picnics, club fees, photography, VCD/DVD on hire) and transport (conveyance related expenses). We also include a district-level rainfall variable that accounts for deviations from the mean.[19]

Second, we ensure that the wording and recall periods on the questions are comparable over time. Both different wording and/or recall periods would change the

[16] Households whose principal industry is agriculture, forestry or fishing are classified into the agricultural sector. Those that work principally in mining, manufacturing, construction or for the utilities are industrial sector households. Lastly, service sector households are those that work in wholesale or retail trade, food and accomodation, transportation and storage, information and communication, finance and insurance, real estate, professional and scientific, administrative and support, public administration and defense, education, health or arts and recreation.

[17] Legislators, senior officials, managers, professionals, technicians and associate professionals are in the high skill category. Clerks, service workers, shop and market sales workers are classified as middle skill. Workers in agriculture and fishery, craft and related trades, plant and machine operators, assemblers and those in "elementary" occupations are classified as low skill.

[18] For rural areas, each of the categories are reported as agriculture and non-agriculture sub-classifications that we group together to make them comparable to the urban areas.

[19] The rainfall data were taken from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data set on precipitation (Funk, Verdin, Michaelsen, Peterson, Pedreros, and Husak (2015)).

interpretation of the relevant variables and thus affect the predictability of our model. We find for all the variables that we include, the questions are similar across surveys. On the other hand, there are questions related to expenditure on consumer durables in both surveys that we do not include. First, there are discrepancies in relation to the wording of the questions between the NSSO72 and earlier surveys.[20] Second, the recording of possession and expenditures was different between the surveys. We observed the discrepancies in the manuals provided to the surveyors.[21]

Third, we confirm that the sampling frame is similar across all surveys. Like the earlier rounds, the NSSO72 is a multi-stage stratified survey of all states/union territories in India. To more accurately represent population density, for the 72nd round the primary sampling units (PSUs) are selected from the 2011 census list of villages in the rural sector while for the earlier rounds they are drawn from the 2001 census list of villages. Also, the number of PSUs are slightly higher, 14,088, in the 72nd round. For each of the earlier surveys, 12,784 PSUs are selected.[22] For the urban sector, in all surveys the PSUs are sampled from the Urban Frame Survey (UFS) blocks. For all surveys, the methodology to select the PSUs, the strata, sub-strata and the ultimate stage units (USUs) or households remains the same.[23]

[20]The NSSO61, NSSO66 and NSSO68 ask about "expenditure for purchase and construction (including repair and maintenance) of durable goods for domestic use" and the NSSO72 asks about "expenditure on durable goods acquired during the last *365 days* other than those used exclusively for entrepreneurial activity". Second, the NSSO61, NSSO66 and NSSO68 (type 1 survey) has questions for a 30 day and a 365 day recall period while the question on the NSSO72 only asks about expenditure for the 365 recall period. Third, the NSSO61, NSSO66 and NSSO68 asks about expenditure for "purchase and construction", while the NSSO72 asks about "acquisition" rather than explicitly about purchase. Fourth, the NSSO61, NSSO66 and NSSO68 ask about purchase for "domestic use" while the NSSO72 asks about goods "other than those used exclusively for entrepreneurial activity". This includes the total value of raw materials, services and/or labor charges and any other charges. There is no explicit mention of "construction" or "repair and maintenance" in the NSSO72, but there is a value of components column that most likely includes raw materials used in construction. Fifth, in the NSSO68, there is a separate question on whether the good was bought for "hire purchase". The surveyor is asked to make the distinction between "hire purchase" and a loan. The NSSO72 instruction manual does not mention anything about goods bought on "hire purchase".

[21]First, if an asset was bought and sold during the reference period, it is recorded in the earlier NSSO surveys but not in NSSO72. Second, in the earlier surveys if the item has been purchased but not yet in the household's possession, the expenditure is recorded by the surveyor. However, in the NSSO72 a durable good that is not in the household's possession even if full payment has been made is not included. Third, if the durable good is in possession but has not been paid for, it is not included in the earlier NSSO surveys but is included in the NSSO72 (Instructions to Field Staff, Chapter Four).

[22]The NSSO refers to PSUs as First Stage Units (FSUs). The term 'village' is Panchayat wards for Kerala.

[23]In the event that the population is greater than 1,200 in a PSU, the PSU is divided into "hamlet groups" "sub-blocks" in the rural and urban PSUs, respectively.

A Descriptive Statistics

Tables 3 and 4 report the mean values of the variables used in the model by year, for urban and rural areas. The descriptive statistics generally reflect India's rapid economic development. Average log per capita consumption, in real terms increased from 4.5 to 4.74 between 2004-05 and 2011-12. When expressed in levels, per capita consumption grew approximately 24% growth over the seven-year period, or 3.1% a year. Household size steadily fell during this time. In the decade between the first and last survey, the share of the population living in households with 4 or fewer persons rose from 39 to 47 percent in urban areas, and from 29 to 35 percent in rural areas. A byproduct of smaller households is a drop in the share of household members that are children ages 0-14, which fell by 5 percentage points in both urban and rural areas. Regular wage work became slightly more prevalent in urban areas, and the share of rural workers working in agriculture declined 3 percentage points, as industrial work became more common in rural areas.

Average spending on transport declined in 2014-15 after a consistent rise between 2004-05 and 2011-12. In contrast, expenditure on household miscellaneous services and recreational spending showed a continual strong increase from 2004-05 to 2014-15. The drop in transport expenditures may in part result from differences in the components of transport expenditure in 2014-15.[24] To the extent this is causing the drop in reported transport expenditure, the model may underestimate poverty reduction. We therefore also consider a model that only includes whether households reported any consumption on these three items in the past month, rather than including the amounts, as a robustness check to see how much including expenditure amounts matters.

The final rows of Tables 3 and 4 report the population-weighted mean rainfall, across districts, in terms of deviation from historical district means. Monsoons in India typically occur between June and October, making the third quarter rainfall important for agricultural production. Table 4 indicates that in rural areas, rainfall was below average in the second half of 2004, the third quarter of 2009 and the first two

[24] While the recall periods are the same and most of the categories of transportation expenditure are similar across surveys, in the NSSO72 the surveyors were asked to exclude expenditure on fuel for one's own transport. The consumption expenditure surveys do include expenditure on petrol and diesel for vehicles. Also, in the NSSO72 survey questions regarding transportation expenditure were asked separately for overnight and non-overnight journeys. We include the expenses for both types of journeys as well as expenditure on services incidental to transport to make it comparable to the consumption expenditures surveys where the questions do not make any distinction on the type of journey and also include expenditures on services incidental to transport.

quarters of 2010. On the other hand, rainfall was substantially above average in the third quarter of 2011, and close to exactly average in the third quarter of 2014. As mentioned above, favorable rainfall may have contributed to the strong growth in survey consumption between 2009-10 and 2011-12, but did not continue in the summer of 2014.

III Empirical Methodology

A Econometric Model

The specification of the model is based on the small area estimation (SAE) methodology originally proposed by Elbers, Lanjouw, and Lanjouw (2003). This methodology generates a joint distribution of economic welfare and independent variables in the target data set, where a welfare measure is not available. The process consists of two steps. The first involves estimating the relationship between economic welfare and explanatory variables in the source data set, in which a welfare measure is available. The parameters are then used to simulate economic welfare into the target data set.

The first step in this analysis is to estimate the relationship between household per capita consumption expenditure (the measure of economic welfare) and other explanatory variables, in the three available source data sets with consumption data. The explanatory variables are those that are available in both the source and target data sets. The regression is a log linear specification relating per capita consumption expenditure to household and regional variables using the 2004-05, 2009-10 and 2011-12 surveys (equation 1).[25] The welfare measure is y_{cht}, which is household per capita expenditure for a household in cluster c and household h, interviewed in survey round t. A cluster is a primary sampling unit (PSU) as defined in the NSSO surveys. For all surveys, y_{cht} is measured in 2011 rupees using separate CPI indices for urban and rural areas.[26]

The X^h vector in equation (1) consists of an intercept plus household level demographic variables, labor market variables and expenses on miscellaneous services. Expenses on miscellaneous services for all survey years are measured in 2011 rupees.[27] The vector Z^h is a subset of the X^h variables whose coefficients are allowed to vary linearly over time. In order to avoid introducing severe multicollinearity into

[25] NSSO61, NSSO66 AND NSSO68. The coefficients in this semi-log model are interpreted as a relative change in welfare as a result of an absolute change in the explanatory variables.

[26] For rural areas, we use the CPI for Agricultural and Rural Laborers and for urban areas the CPI for Industrial workers. Source: CEIC (from Labor Bureau Government of India).

[27] The CPI indices are the same as those used for the welfare measure, y_{cht}.

the model, only a subset of the X^h variables are interacted with a linear time trend (Nguyen and van der Weide (2018)). The X^d vector consists of district level variables calculated as means of household variables for each district. This vector also includes a measure of rainfall shocks, which is the district's deviation from mean historical rainfall. District level characteristics are included both to improve the accuracy of model predictions, and to generate more accurate estimates.[28] Area means are calculated at the district rather than the PSU level due to measurement error arising from insufficient numbers of observations per PSU. As with household characteristics, a subset of district characteristics are interacted with time trends ($Z^d t$).

$$ln(y_{cht}) = X^h_{cht}\gamma_1 + Z^h_{cht}t\gamma_2 + X^d_{ct}\gamma_3 + Z^d_{ct}t\gamma_4 + \gamma_5 t + u_{cht} \tag{1}$$

The regressions are weighted using population weights.[29] In addition, because of important differences in consumption patterns in urban versus rural areas, and because poverty rates are reported separately for urban and rural India, separate models are estimated for each sector.

Taking X as the vector of all variables and β as the vector of coefficients, equation (1) can be rewritten as:

$$ln(y_{cht}) = X'\beta + u_{cht} \tag{2}$$

An initial estimate of β is obtained using weighted Ordinary Least Squares (OLS) (equation 2). The consumption spending of households within a cluster are assumed to be correlated. To allow for this within-cluster correlation, the random disturbance term u_{ch} has a cluster, η_c, and a household component ϵ_{ch}. Therefore, the random disturbance term can be written as,

$$u_{ch} = \eta_c + \epsilon_{ch} \tag{3}$$

The variables η_c and ϵ_{ch} are assumed to be independent of each other and uncorrelated with the explanatory variables. We do not allow for heteroskedasticity in the cluster component of u_{ch}, due to the small number of clusters.[30] However, the household error term, ϵ_{ch}, is assumed to be heteroskedastic reflecting unequal variances in the error terms across households.

Because of heteroskedasticity in the error term and spatial correlation from the introduction of η_c, we re-estimate equation (2) using Generalized Least Squares (GLS).

[28] Elbers, Lanjouw, and Leite (2008).

[29] Household weights are multiplied by household size to calculate population weights.

[30] Elbers, Lanjouw, and Lanjouw (2003).

The weights for the GLS specification are the predicted variances of the error terms from the OLS regression. We estimate the variance of the error term parametrically as specified in Elbers, Lanjouw, and Lanjouw (2003) and Nguyen, Corral, Azevedo, and Zhao (2017). The variance model has a logistic form with (ϵ^2_{ch}) as the dependent variable (equation 4). In equation 5, the dependent variable is the estimated variance, derived from the residuals of the first OLS regression. The explanatory variables of the variance model are chosen using the Least Absolute Shrinkage and Selection Operator (LASSO) method (Tibshirani (1996)).[31] The estimates from the LASSO regression and the residuals are then used to predict the variance of (ϵ_{ch}) (equation 6).

$$E[\epsilon^2{}_{ch}] = \sigma^2{}_{\epsilon_{ch}} = \left[\frac{Ae^{Z'\alpha} + B}{1 + e^{Z'\alpha}}\right] \tag{4}$$

$$ln\left[\frac{\epsilon^2_{ch}}{A - \epsilon^2_{ch}}\right] = Z'_{ch}\alpha + r_{ch} \tag{5}$$

$$\hat{\sigma}^2_{\varepsilon_{ch}} \approx \left[\frac{Ae^{Z'\alpha}}{1 + e^{Z'\alpha}}\right] + \frac{1}{2}\widehat{Var}(r)\left[\frac{Ae^{Z'\alpha}(1 - e^{Z'\alpha})}{(1 + e^{Z'\alpha})^3}\right] \tag{6}$$

The predicted variances are used to re-estimate equation (2) using GLS (equation (7)).

$$ln(y_{cht}) = X'\beta_{GLS} + u_{cht} \tag{7}$$

Next, we estimate predicted welfare using estimates from the analysis in the first step. Since we would like to generate a joint distribution of welfare, and not solely the expected value, we use Monte-Carlo simulations to generate 100 simulated distributions of welfare. In equation (8), $\tilde{\beta}$, $\tilde{\eta}_c$ and $\tilde{\epsilon}_{ch}$ are vectors from the simulations.

$$\tilde{y}_{cht} = X'\tilde{\beta} + \tilde{\eta}_{ct} + \tilde{\epsilon}_{cht} \tag{8}$$

Following the literature on small area estimation, we make the following assumptions for the simulations. The vector $\tilde{\beta}$ is drawn from a normal distribution with mean $\hat{\beta}_{GLS}$ and variance Var($\hat{\beta}_{GLS}$).

$$\tilde{\beta} \sim N(\hat{\beta}_{GLS}, Var(\hat{\beta}_{GLS}))$$

[31]In this method all district and household characteristics used in step 1 are included on the right- hand side. The resulting estimates include zero coefficients for several variables, thereby selecting the remaining variables with non-zero coefficients for the variance model.

The cluster component of the error term, η_c, is drawn from a normal distribution with mean 0 and variance, $\hat{\sigma}^2_\eta$. The data generating process of the variance term is assumed to follow a gamma distribution.

$$\tilde{\eta}_c \sim N(0, \hat{\sigma}^2_\eta)$$

$$\hat{\sigma}^2_\eta \sim Gamma(\bar{\sigma}^2_\eta, Var(\hat{\sigma}^2_\eta))$$

The household component of the error term, ϵ_{ch}, is drawn from a normal distribution with mean 0 and the variance predicted by equation (6). The variance term is calculated by applying the parameters from the source data (equation 5) to the 2014-15 data (equation 6).

$$\tilde{\epsilon}_{ch} \sim N(0, \hat{\sigma}^2_{\epsilon_{ch}})$$

The 100 simulated values, $\tilde{\beta}$, α, $\tilde{\eta}_c$ and $\tilde{\epsilon}_{ch}$ are used to obtain a vector of 100 simulated welfare estimates, $\tilde{y}_{ch}$. The mean of the 100 simulations gives the point estimate of household expenditure. The standard error of the poverty estimate is calculated using Rubin's rules (Rubin (2004)) which takes into account the variation both within and across simulations. We use the STATA package SAE developed by (Nguyen, Corral, Azevedo, and Zhao (2017)) to carry out the estimation and the Monte Carlo simulations.

B Variable Selection

The process described above requires a set of right-hand side variables to estimate equation (1). We elected for a model selection process that emphasizes transparency and simplicity, while addressing concerns that excessive multi-collinearity could jeopardize the model's out-of-sample predictive accuracy. Multicollinearity, which occurs when one or more right-hand side variables are highly correlated with the remaining right-hand side variables, leads to imprecise coefficient estimates. Coefficient estimates that are imprecise, especially for important drivers of predicted welfare change such as the coefficient on the linear time trend, will reduce the accuracy of the predictions. In addition, models with greater multicollinearity among the regressors are fragile to minor changes in the model's specification such as removing particular variables.

We start with the set of candidate variables listed in Tables 3 and 4, which are common to both surveys. For each variable, we also take district means, in order to improve the accuracy of the prediction and their standard errors. Finally, a subset of household and district mean variables are interacted with the year of the survey, allowing the coefficients to vary linearly over time. This reflects the fact that the association between certain characteristics and welfare changes over time. We restrict the model to interactions with a linear time trend because of the importance of maintaining a consistent model for both the estimation and the validation exercise. For the validation exercise, only two rounds of data are available to estimate the model, leaving insufficient degrees of freedom to estimate polynomial time trend interactions.

To alleviate concerns about multicollinearity, we sequentially calculate variance inflation factors (VIF) for all variables. The VIF for a coefficient is equal to the reciprocal of one minus the R^2 from regressing that variable on the full set of other right-hand side variables. Therefore, the greater the variation in a variable that can be explained by the other independent variables, the greater the VIF. We follow the informal rule of thumb most prevalent in past studies, which recommends concern about the model if any VIFs exceed 10.[32] We therefore sequentially remove the variable with the largest VIF if that variable exceeds 10, with the exception of the time trend variable. This variable was deemed critical to the model because it accounts for most of the change in predicted mean consumption per capita between 2011-12 and 2014-15. This process was carried out separately for urban and rural areas, and eliminated 23 variables in urban areas and 21 in rural areas. Selecting the optimal set of variables for prediction is an active area of research and no clear consensus has emerged regarding the most appropriate method to use. The procedure described above successfully reduces multi-collinearity while remaining simple to apply and explain.

C Model Selection

Besides the primary model that was ultimately used for the estimation, we consider three alternative specifications. In one we interact each district level variable with a linear time trend. We refer to this model as the "District dummies*Time Trend" model. The district dummies subsume the district mean characteristics, which are dropped from this specification. The inclusion of district time trends in the model has the advantage of accounting for unobserved characteristics of the district whose effects vary over time in a linear way. The potential downside of the district time

[32] See Kennedy (1992), Chatterjee and Hadi (2012), Menard (1995), and others quoted in O'Brien (2007). As noted by O'Brien, removing variables changes the interpretation of the coefficients; however, since the objective of this model is prediction, this is less of a concern than if the focus were on the regression coefficients.

trends model is that it extrapolates past trends to predict district mean welfare in 2014-15 rather than using actual data on district characteristics in 2014-15. While this is more likely to give a rate of poverty reduction in line with past trends, it will ignore the signal from district level indicators in characteristics.

The second alternative model tested includes dummy variables for the three types of expenditure instead of the actual expenditure amounts. The dummy variables are equal to one if the household incurred any expenditure for the particular item. We refer to this model as "Expenditures at the Extensive Margin". This has the advantage of potentially being more robust to outliers in consumption, as well as changes in the way that the question was asked. However, it potentially ignores valuable information on the level of expenditures.

Lastly, we use only the 2011-12 data to predict into 2014-15. Because only one round of data is used to estimate the model, no variables are interacted with a time trend. We refer to this as the "Constant Coefficient" model, which has been utilized in past studies of survey to survey imputation.

We report predicted poverty rates of the four models in Table 5. We choose the primary model as our preferred specification because it utilizes all the available data, including levels of expenditure, imposes the least restrictive modeling assumptions on the data and has the most accurate predictions. We validate each model's predictive quality by conducting two tests. First, for each specification we use data from 2004-05 and 2009-10 to predict poverty in 2011-12. We refer to this as forward projection. In the second analysis, we reverse project poverty in 2004-05 using the 2009-10 and 2011-12 data (see e.g., Deaton and Dreze (2002)). In the forward and reverse projections, we compare the actual versus predicted headcount of poverty, in 2011-12 and 2004-5 respectively.[33] Our final choice of model is based on which yields the most accurate estimates of poverty, on average, in both tests.

C.1 Forward projection into 2011-12

Table 6 compares actual poverty in 2011-12 with the predictions of the four models. For urban areas, the projection of model 1 (14.6%) is closest to the actual poverty number (13.4%). Model 3, the extensive margin model, gives predictions that are closet to the actual poverty number for rural areas (24.8%), followed by model 1 (27.4%). Therefore, models 1 or 3 could be possibilities for the final choice based on the forward projection test.

[33] Using the \$1.90 per day threshold.

C.2 Reverse projection into 2004-05

Table 7 compares model predictions with measured poverty in 2004-05. For urban areas, predictions of models 1 and 2, (approx. 34%) are closest to the actual poverty number (25%). For rural areas, model 1 outperforms all other models. The predicted poverty rate of 44% is less than 1 percent different from the actual rate of 43.4%. Therefore, according to reverse projection, model 1 is the most accurate overall specification.

The model finally selected is that which has the closest overall prediction. Based on the forward projection, we could pick model 1 or 3. However, for the 2004-05 projection, model 3 fares worse than model 1 and is far off the mark, by almost 30 percentage points, in rural areas. Therefore, we select model 1 as the primary specification because of its relatively accurate performance on both the forward and reverse projections.

IV Predicted Poverty Rates in 2014-15

A Comparison to the Line-Up Method

Table 8 compares the predictions for headcount poverty from the preferred model to that of the typical line-up method with no pass-through. The model gives an estimated 10% poverty rate in urban India, which represents a fall of 3.4 percentage points from 2011-12. The 95 percent confidence interval for urban areas ranges from 8.5 to 11.6 percent. The predicted headcount rate for rural areas is 16.8, with a 95 percent confidence interval ranging from 15.2 to 18.3 percent. This represents an 8 percentage point reduction from 2011-12. The national estimate is obtained by taking a weighted average of the urban and rural estimates, weighting by the proportion of population in 2011-12. This gives an estimated headcount rate of 14.6 percent, a 6.6 percentage point reduction from 2011-12, with a 95 percent confidence interval of 13.0 to 16.1 percent.

The typical line-up method, with no pass-through, gives much lower predictions for headcount poverty, namely 7.1% in urban areas and 12.9% in rural areas. This translates to a national poverty rate of 10.9%, which would have implied that India nearly halved the 21.2% poverty rate reported in 2011-12. A comparison of implied elasticities with respect to growth suggests that the typical line up method, based on growth in HFCE, would have overestimated poverty reduction in India (Table 10).

B Which Variables Account for Growth in Mean Welfare?

Which variables in the model account for the bulk of the change in poverty? While this question is difficult to answer directly, indirect evidence is available by decomposing the growth in log per capita consumption predicted by the model. A natural framework for better understanding the contribution of individual variables is the classic Oaxaca-Blinder decomposition (Oaxaca (1973), Blinder (1973)). This technique decomposes the mean difference across two groups into a portion explained by differences in endowments and a portion due to differences in returns. In this case, the two groups are the households in the 2011-12 survey and the households in the 2014-15 survey. We decompose the difference between the model's mean predicted per capita consumption in 2014-15 and 2011-12. Because the means from each year are generated by predictions from the same model, none of the difference is attributable to changes in the coefficients (returns), and all of the change is due to the mean of the predictor variables (endowments). These changes can easily be decomposed into the portion due to each individual predictor variable, which helps to identify the variables that account for the largest changes in the model.

Table 9 displays the results. Each cell represents the percentage of the total change in mean log per capita consumption attributable to each variable. The time trend alone, for example, explains 83 percent of the increase in urban areas and 80 percent in rural areas. Notably, transport expenditure declined in real terms during this period. This slowed the predicted increase in per capita consumption, particularly in urban areas. The rainfall variables contributed to a relatively large share of the increase in urban areas. However, the total increase in welfare was much smaller in urban areas, meaning that in absolute terms rainfall's contribution was similar in urban and rural areas. As might be expected, changes in the means of livelihood categories contribute a significant amount in urban areas, but much less in rural areas. The results overall indicate that the time trend is a key driver of predicted change in the model. However, transport expenditure plays a significant role, as does the increase in service expenditure in rural areas. Finally, rainfall contributes a significant amount in urban areas, as do changes in the types of jobs held by workers.

V Robustness Checks

We conduct three checks to assess the robustness of our model. First, we calculate elasticities and semi-elasticities to see what the models' predictions imply about the change in extreme poverty with respect to real GDP growth. Second, we examine predicted headcount rates at the state level to test whether the model generates plausible predictions. Lastly, we examine estimated poverty rates at higher poverty lines to ensure that they are reasonable. Ultimately, only the estimated urban and rural poverty rates at the $1.90 line were used to determine the official poverty estimates, by calculating an appropriate pass-through rate to apply to consumption growth in the national accounts.

A Elasticities and Semi-Elasticities

Table 10 shows the elasticity and semi-elasticity of the predictions, compared with the typical lining up procedure and past experience. As mentioned above, India experienced a rapid fall in poverty despite moderate growth between 2009-10 and 2011-12. This is reflected in a large swing in the poverty-growth elasticity, from about -0.6 between 2004-05 and 2009-10, to about -3 between 2009-10 and 2011-12. This swing is also reflected in the semi-elasticity, which jumped in magnitude from about -21 to -85. The model predictions for 2014-15 imply an elasticity and semi-elasticity of -2.1 and -40. Both are within the range of the two previous measurements, with the predicted elasticity closer to the measure from 2009-10 to 2010-11, and the semi-elasticity closer to the 2004-05 to 2009-10 period.

As a point of comparison, the typical method used by the World Bank would scale up the 2011-12 survey welfare measure by the growth rate in Household Final Consumption Expenditure (HFCE). That method would predict a poverty rate of 11.0% in 2014-15, which would imply an elasticity of -3.5 and a semi-elasticity of -60. The implied elasticity is substantially greater in magnitude than even the large values observed from 2009-10 to 2011-12, which were boosted by the post-drought recovery. In short, the implied elasticities and semi-elasticities from the model predictions are much more plausible, in light of past experience, than those generated by the typical line-up approach.

B Implied State Level Results

One would expect that states with greater GDP growth would see larger reductions in extreme poverty. State per capita GDP growth does not enter into the model, and the model includes only one global time trend rather than state-specific time trends. Comparing state GDP growth with predicted poverty reductions therefore reveals the extent to which differences in state level per capita GDP growth are reflected in the predictors included in the model.

Figure 2 displays, for each state, change in headcount poverty between 2011-12 and 2014-15, as predicted by the model, on the y axis. The x axis represents the real annual state GDP growth during that period. Goa, which suffered a sharp decline during this period, is a clear outlier. Whether Goa is included or excluded, there is a clear negative correlation between state GDP growth and poverty reduction, as would be expected. Figure 3 shows a comparable plot for the period from 2004-05 to 2011-2. With all states included, the relationship between state GDP growth and poverty reduction between 2011-12 and 2014-15 is remarkably similar to the actual relationship between state GDP growth and poverty reduction between 2004-05 and 2011-12. In particular, both show that a growth rate of 5% per year is associated with about a one percentage point per year reduction in poverty, while a growth rate of 10% is associated with a reduction of about two percentage points per year. Excluding Goa from the more recent period makes the relationship between state GDP growth and poverty reduction somewhat stronger, underscoring the point that, as would be expected, the model predicts more rapid reductions in faster-growing states.

C Higher Poverty Lines

Tables 11 and 12 and Figures 4 and 5 report the predicted poverty rates at the lower middle- income line of $3.20 per day per person, and the upper middle- income line of $5.50 per day per person. The predicted 2014-15 poverty rates for the $3.20 line are 60.3% in rural areas, 39% in urban areas, and 53.4% nationally. This is a moderate reduction from the 2011-12 estimate of nearly 7 percentage point, or 12% at the $3.20 line. The predicted poverty rates at the $5.50 line suggest a more modest decline, from 89.7% in 2011-12 to a predicted rate of 85.6% in 2014-15 (Table 12). This reflects the skewed nature of the welfare distribution, with larger numbers of people near the $3.20 line being pushed out of poverty as the economy improves. Finally, the predicted distribution can also be used to obtain an estimate of "shared prosperity", defined as the growth rate of mean consumption of the bottom 40%. When averaging across the 100 simulations, the growth rate of consumption of the bottom 40% amounts to 5.1% per year between 2009-10 and 2014-15, which is well within the range exhibited by other countries(World Bank Group (2018)). Overall, these predicted values for higher poverty lines appear to be consistent with past trends.

VI Estimating the Pass-Through Factor to Generate Estimates for 2015

The previous sections describe in detail the methodology used to generate urban and rural estimates of extreme poverty for 2014-15, as well as a battery of validation and robustness checks designed to build confidence in the method and results. This section considers the final portion of the exercise, which is the process of determining the appropriate pass-through factors to apply to Household Final Consumption Growth that replicate these poverty rates. This portion has two main steps. The first is to calculate a growth rate, that when applied uniformly to the 2011-12 welfare distribution, generates the predicted 2014-15 poverty rate of 10.0% for urban areas and 16.8% for rural areas. The appropriate growth rates are 9.6% in urban areas and 12.6% in rural areas. The second step is to calculate these growth rates as a fraction of HFCE growth during that period, which was 17.2%. Dividing 9.6 by 17.2 gives an estimated pass-through rate of 55.9% for urban areas. Similarly, dividing 12.6 by 17.2 gives the 73.3% pass-through rate for rural areas. These pass-through rates were then applied to the 2011-12 distribution in order to project out to 2015. The final $1.90 poverty rate for 2015 is 9.5% in urban areas, 15.3% in rural areas, and 13.4% nationally.[34]

VII Conclusion

This analysis was motivated by concerns that the standard method of applying growth in HFCE to the most recent survey measurement of per capita consumption would overstate poverty reduction in India, and therefore the world. These concerns were heightened by the age of the most recent available poverty data from India, which was collected three and a half years before the 2015 target estimate. This paper describes an alternative method for estimating poverty, which utilized a more recent nationally representative survey from 2014-15 containing some of the same demographic and socioeconomic characteristics collected in previous expenditure surveys. These previous surveys were used to estimate a model, which was then used to predict expenditure and poverty into the 2014-15 survey. This type of statistical method has generated plausible headcount poverty estimates in other countries and appears to work well in India as well, based on two validation exercises and a variety of robustness checks. The model's predictions imply an elasticity with respect to growth that is in line with past experience, in contrast to the traditional

[34]Information on other lines can be obtained on the Povcalnet website.

line-up method, which gives elasticities that are significantly higher in magnitude than previously observed. The model estimates plausible poverty rates at higher poverty lines, and predicts greater poverty reduction in faster growing states. The validation exercises show that in 2011-12, the imputation model fared slightly worse than the typical method of applying HFCE growth to older survey data. When predicting back to 2004-05, however, the imputation model performed dramatically better. This evidence, though limited, suggests that a survey to survey approach generates more reliable estimates than the current line-up method.

The 2015 poverty rates reported for urban and rural India were calculated by applying a fractional "pass-through rate" to growth in Household Final Consumption Expenditure, with pass-through rates selected separately for urban and rural areas to match the model's estimated \$1.90 poverty rates. Therefore, the 2015 poverty rate was calculated by scaling up the 2011-12 survey data in a distributionally neutral way, rather than treating the predicted welfare distribution as if it were a new survey. Three considerations influenced this decision. First, using a pass-through rate to line up the estimates more clearly signals that the 2014-15 estimates are model-based predictions rather than actual survey data on welfare. The alternative of lining up the predicted 2014-15 welfare distribution to 2015 could create confusion by blurring the line between predicted and actual data. Second, applying a partial pass-through builds on and improves the existing practice of assuming a full pass-through to line up the estimates. Finally, no study to our knowledge has convincingly shown that survey to survey imputation methods can accurately predict welfare at the very top of the welfare distribution. As a result, it is not clear that this methodology can be used to accurately predict mean welfare and inequality, which unlike poverty are sensitive to the accuracy of the predictions for the richest households. Maintaining a distributionally neutral adjustment provides a way to use a survey to survey imputation for poverty without entering the uncharted territory of using imputed values to estimate mean welfare and inequality. Better understanding whether and how imputation methods can be used to accurately predict changes in mean welfare and inequality is an important topic for future research.

Table 1: International Poverty Rates: 2004-05 to 2014-15

	2004-05	**2009-10**	**2011-12**	**2014-15**
National				
Poverty rate	38.9	31.7	21.6	14.6
Standard Error	0.4	0.4	0.4	0.8
Urban				
Poverty rate	25.4	19.8	13.4	10.0
Standard Error	0.6	0.5	0.4	0.8
Rural				
Poverty rate	43.4	36.1	24.8	16.8
Standard Error	0.4	0.5	0.5	0.8

Sources: India National Sample Survey Office (NSSO) Surveys and staff estimates.

Figure 1: Historical Poverty Rates: 2004-05 to 2014-15

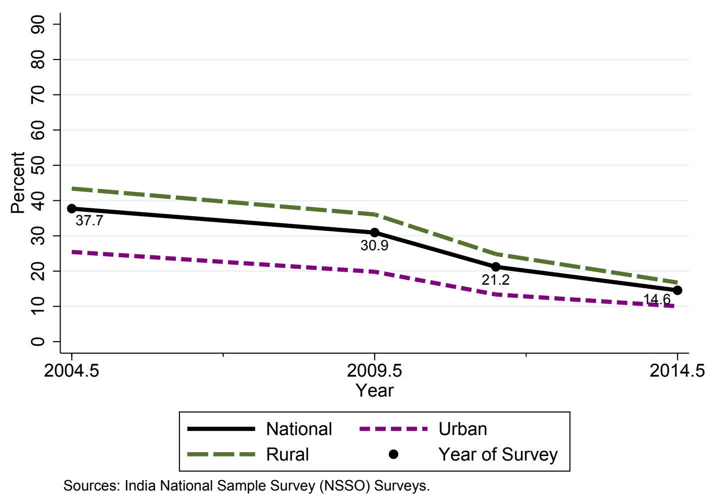


Table 2: Average Annual Change in Poverty Rates

	2004-05 to 2011-12	**2011-12 to 2014-15**
National	-2.4	-2.2
Urban	-1.7	-1.1
Rural	-2.7	-2.7

Changes in percentage points.

Source: India National Sample Survey Office (NSSO) Surveys.

Table 3: Descriptive Statistics: Urban model

	2004/05	**2009/10**	**2011/12**	**2014/15**
Log HH per capita expenditure				
Mean	4.50	4.61	4.74	.
HH size				
1 or 2	0.07	0.08	0.08	0.09
3	0.10	0.11	0.12	0.13
4	0.22	0.24	0.24	0.25
5	0.21	0.20	0.20	0.20
District HH size				
Share 1 or 2	0.06	0.07	0.08	0.08
Share 3	0.09	0.10	0.11	0.12
Share 4	0.20	0.23	0.23	0.24
Share 5	0.20	0.21	0.21	0.20
HH age structure				
Share 0-14	0.31	0.29	0.27	0.26
Share 15-24	0.19	0.18	0.18	0.18
Share 25-34	0.17	0.17	0.17	0.17
Share 35-49	0.20	0.20	0.21	0.22
Share 50-64	0.10	0.11	0.11	0.12
District avg HH age structure				
Share 0-14	0.33	0.30	0.29	0.28
Share 15-24	0.17	0.17	0.17	0.17
Share 25-34	0.16	0.17	0.17	0.17
Share 35-49	0.19	0.20	0.20	0.21
Share 50-64	0.10	0.11	0.11	0.12
Religion and social group				
Hindu	0.78	0.78	0.77	0.76
Share Hindu in district	0.81	0.81	0.81	0.79
Share sched caste in district	0.63	0.65	0.67	0.68
Household type				
Self-employed	0.43	0.42	0.41	0.37
Share self-employed in district	0.48	0.45	0.46	0.44
Casual laborer	0.12	0.14	0.13	0.15
Share casual labor in district	0.04	0.06	0.05	0.06
Regular wage worker	0.39	0.37	0.40	0.41
Share reg wage worker in distric	0.20	0.19	0.21	0.23
Principal industry				
Agriculture	0.06	0.06	0.06	0.06
Industry	0.31	0.31	0.31	0.31
Share industry in district	0.24	0.25	0.26	0.26
HH expenditure				
Avg misc services in district	2265	2430	2904	4015
Misc services	2629	2903	3427	4840
Avg rec services in district	247	232	345	591
Recreational services	328	317	433	710
Avg transport expenses in distri	5419	6048	8058	5905
Transport expenses	6817	7408	9647	6553
Avg transport expenses no fuel i	3007.01	2921.62	3905.65	5566.62
Transport expenses no fuel	3389.36	3280.83	4299.62	6137.85
Avg transport expenses no fuel a	1101.70	1092.88	1640.71	1964.33
Transport expenses no fuel and b	1457.71	1378.05	1967.59	2316.02
District rainfall shock				
July-September	-0.20	-0.04	0.50	0.02
July-September (squared)	0.34	0.17	0.44	0.28
October-December	-0.26	0.32	-0.51	-0.07
October-December (squared)	0.21	0.55	0.42	0.17
January-March	0.13	-0.25	-0.33	0.62
January-March (squared)	0.29	0.18	0.37	1.14
April-June	-0.04	-0.07	-0.18	0.42
April-June (squared)	0.28	0.35	0.19	0.40

Table 4: Descriptive Statistics: Rural model

	2004/05	2009/10	2011/12	2014/15
Log HH per capita expenditure				
Mean	4.18	4.25	4.40	.
HH size				
1 or 2	0.05	0.06	0.06	0.06
3	0.08	0.09	0.09	0.09
4	0.16	0.19	0.19	0.20
5	0.19	0.20	0.21	0.21
District HH size				
Share 1 or 2	0.05	0.06	0.06	0.06
Share 3	0.08	0.09	0.10	0.10
Share 4	0.17	0.19	0.20	0.21
Share 5	0.20	0.20	0.21	0.21
HH age structure				
Share 0-14	0.38	0.35	0.34	0.33
Share 15-24	0.16	0.16	0.16	0.16
Share 25-34	0.15	0.15	0.15	0.15
Share 35-49	0.17	0.19	0.19	0.20
Share 50-64	0.10	0.11	0.11	0.11
District avg HH age structure				
Share 15-24	0.16	0.17	0.17	0.17
Share 25-34	0.15	0.15	0.15	0.16
Share 35-49	0.18	0.19	0.19	0.20
Share 50-64	0.10	0.11	0.11	0.11
Religion and social group				
Hindu	0.84	0.84	0.83	0.83
Share Hindu in district	0.82	0.82	0.82	0.81
Share sched caste in district	0.71	0.73	0.74	0.76
Household type				
Self-employed	0.56	0.52	0.55	0.58
Share self-employed in district	0.54	0.51	0.53	0.55
Share casual labor in district	0.03	0.03	0.03	0.04
Share reg wage worker in distric	0.07	0.07	0.07	0.08
Principal industry				
Agriculture	0.65	0.62	0.58	0.62
Industry	0.15	0.18	0.20	0.19
Share industry in district	0.17	0.20	0.22	0.21
HH expenditure				
Avg misc services in district	1587	1536	1828	2602
Misc services	1464	1361	1619	2256
Avg rec services in district	168	147	187	326
Recreational services	141	116	152	276
Avg transport expenses in distri	3020	3320	4414	3309
Transport expenses	2546	2816	3779	3039
Avg transport expenses no fuel i	1859.51	1765.98	2221.08	3110.80
Transport expenses no fuel	1729.88	1632.93	2063.66	2872.47
Avg transport expenses no fuel a	530.47	584.66	742.01	958.93
Transport expenses no fuel and b	409.70	478.95	611.28	811.38
District rainfall shock				
July-September	-0.22	-0.10	0.42	0.02
July-September (squared)	0.27	0.21	0.38	0.22
October-December	-0.30	0.26	-0.62	-0.07
October-December (squared)	0.23	0.43	0.51	0.26
January-March	0.30	-0.30	-0.22	0.63
January-March (squared)	0.43	0.22	0.29	1.15
April-June	-0.21	-0.14	-0.15	0.34
April-June (squared)	0.35	0.43	0.17	0.34

Table 5: Predicted Poverty Rates ($1.90 per Day) from Different Models

	Model 1	Model 2	Model 3	Model 4
National	14.6	19.1	18.0	17.4
Urban	10.0	11.3	12.1	12.5
Rural	16.8	22.8	20.9	19.8

Sources: India National Sample Survey Office (NSSO) Surveys.

Table 6: Comparison of Actual Poverty in 2011-12 with Forward Prediction of Models

	Actual	Model 1	Model 2	Model 3	Model 4
National	21.1	23.2	25.9	23.1	19.1
Urban	13.4	14.6	16.0	16.3	16.7
Rural	24.8	27.4	30.7	26.5	20.2

Table 7: Comparison of Actual Poverty in 2004-05 with Reverse Projection of Models

	Actual	Model 1	Model 2	Model 3	Model 4
National	37.5	41.0	48.7	61.0	26.6
Urban	25.4	34.6	34.2	38.7	14.9
Rural	43.4	44.1	55.8	71.9	32.4

Sources: India National Sample Survey Office (NSSO) Surveys.

Model 1: Final Model

Model 2: District dummies*Time Trend

Model 3: Expenditures at the Extensive Margin

Model 4: Constant Coefficient Model

Table 8: Preferred Model vs. Typical Line-Up Method Predictions for 2014-15

	Model	Line-up
National	14.6	11.0
Urban	10.0	7.1
Rural	16.8	12.9

Source: India National Sample Surveys (NSSO) Surveys.

Table 9: Understanding the Drivers of Changes in Log Welfare

	Urban	Rural
HH Size (Dist)	0.2	0.0
HH Size	0.0	0.8
Age Category (Dist)	-0.2	-0.0
Age Category	1.3	-3.0
Hindu (Dist)	0.2	0.1
Hindu	0.1	-0.4
Low Caste	-0.0	0.8
HH Type (Dist)	1.9	0.2
HH Type	1.0	-1.0
Occupation (Dist)	-0.2	-1.3
Occupation	0.7	-0.2
Sector (Dist)	-0.1	-0.2
Sector	0.4	-0.3
Expd on Services (Dist)	0.1	4.5
Expd on Services	-0.0	3.0
Expd on Recreation (Dist)	-0.7	1.3
Expd on Recreation	0.4	-0.3
Expd on Transportation (Dist)	-4.7	-3.1
Expd on Transportation	-2.3	-1.5
Rainfall	2.7	2.8
Time Trend	3.6	8.7
overall		
Difference	4.4	10.9
Mean Log Welfare (2011-12)*100	473.4	439.2
Mean Pred Log Welfare (2014-15)*100	477.7	450.1

Sources: India National Sample Survey Office (NSSO) Surveys.

Table 10: Elasticity of Poverty to Growth by Model

	Elasticity	Semi-Elasticity
2004-05 to 2011-12	-0.6	-21.4
2009-10 to 2011-12	-3.0	-85.4
2011-12 to 2014-15 (Predicted)	.	.
Model 1	-2.1	-39.5
District dummies*Time Trend	-0.6	-12.8
Expd at the Extensive Margin	-0.9	-18.8
Constant Coefficient Model	-1.1	-22.4
Typical line-up method	-3.5	-60.6

Sources: India National Sample Survey Office (NSSO) Surveys.
Using 2009-10 and 2011-12 to predict in 2004-05.

Figure 2: Changes in Poverty Across States: 2011 to 2014

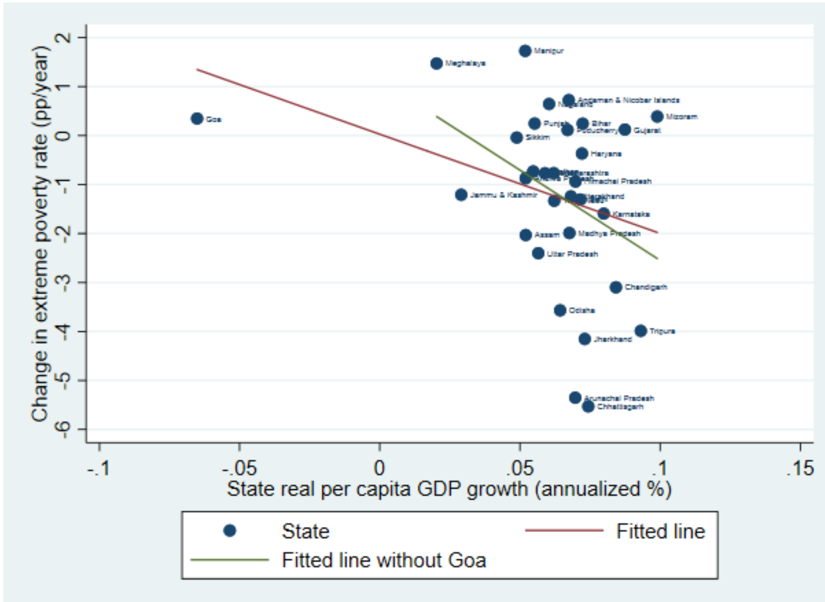


Figure 3: Changes in Poverty Across States: 2004 to 2011

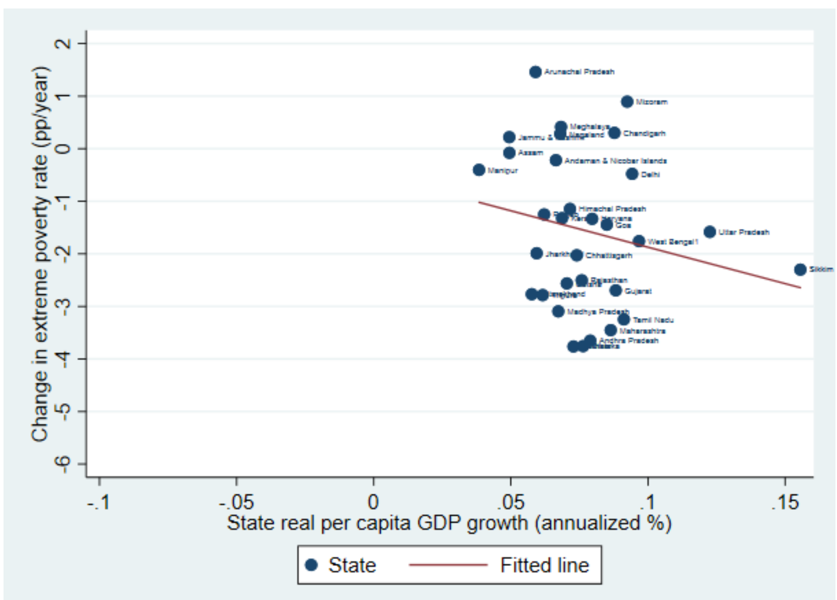


Table 11: Actual and Predicted Poverty Rates at $3.20 Per Day

	2004-05	2009-10	2011-12	2014-15*
National	74.6	69.7	60.4	53.4
Urban	58.4	51.5	43.3	39.0
Rural	82.1	78.1	68.3	60.3

At $1.90 per day (2011 PPP) poverty line

Sources: India National Sample Survey Office (NSSO) Surveys.

*Preferred Model predictions

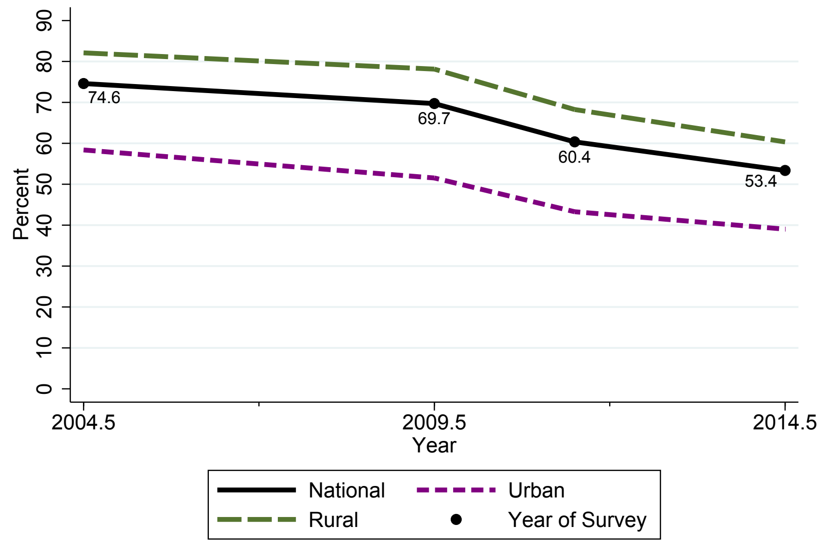
Table 12: Actual and Predicted Poverty Rates at $5.50 Per Day

	2004-05	**2009-10**	**2011-12**	**2014-15***
National	95.7	94.3	89.7	85.6
Urban	95.4	92.1	84.5	74.9
Rural	95.8	95.4	92.1	90.8

Sources: India National Sample Survey Office (NSSO) Surveys.

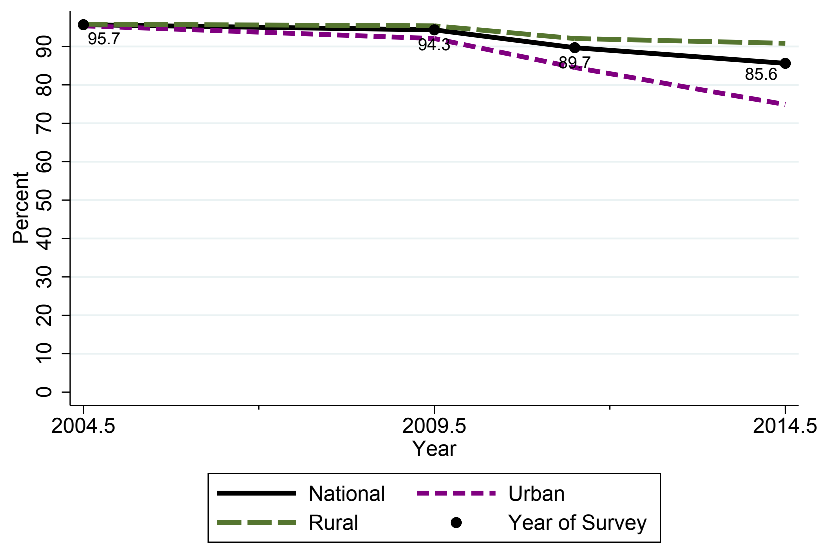
*Preferred model predictions at $1.90 per day line

Figure 4: Poverty Rates: $3.20 Per Day



Sources: India National Sample Survey (NSSO) Surveys.

Figure 5: Poverty Rates: $5.50 Per Day



Sources: India National Sample Survey (NSSO) Surveys.

VIII Appendix

Table 13: Descriptive Statistics

	Mean	Min	Max	SD	N
HH size					
1 or 2 (Dist)	0.06	0.0	0.8	0.04	410,761
3 (Dist)	0.10	0.0	0.4	0.05	410,761
4 (Dist)	0.20	0.0	0.8	0.09	410,761
5 (Dist)	0.20	0.0	0.6	0.07	410,761
6+ (Dist)	0.44	0.0	0.9	0.17	410,761
1 or 2	0.06	0.0	1.0	0.24	410,761
3	0.10	0.0	1.0	0.29	410,761
4	0.20	0.0	1.0	0.40	410,761
5	0.20	0.0	1.0	0.40	410,761
6+	0.44	0.0	1.0	0.50	410,761
Prop HH					
0-15 yrs (Dist)	0.33	0.1	0.9	0.07	410,761
16-24 yrs (Dist)	0.17	0.0	0.4	0.03	410,761
25-34 yrs (Dist)	0.16	0.0	0.5	0.03	410,761
35-49 yrs (Dist)	0.19	0.0	0.5	0.04	410,761
50-64 yrs (Dist)	0.11	0.0	0.2	0.03	410,761
65+ yrs (Dist)	0.05	0.0	0.2	0.02	410,761
0-15 yrs	0.33	0.0	1.0	0.22	410,758
16-24 yrs	0.17	0.0	1.0	0.20	410,758
25-34 yrs	0.16	0.0	1.0	0.18	410,758
35-49 yrs	0.19	0.0	1.0	0.19	410,758
50-64 yrs	0.11	0.0	1.0	0.17	410,758
-					
Hindu (Dist)	0.05	0.0	1.0	0.12	410,758
Hindu	0.82	0.0	1.0	0.18	410,761
Low Caste (Dist)	0.82	0.0	1.0	0.39	410,761
Lowcaste	0.72	0.0	1.0	0.20	410,761
Lowcaste	0.72	0.0	1.0	0.45	410,761

Descriptive Statistics (contd)

	Mean	**Min**	**Max**	**SD**	**N**
HH type					
Self Employed (Dist)	0.51	0.0	1.0	0.15	410,761
Self Employed	0.51	0.0	1.0	0.50	410,761
Casual Urban (Dist)	0.04	0.0	0.5	0.04	410,761
Casual Urban	0.04	0.0	1.0	0.19	410,761
Regular Wage Worker (Dist)	0.11	0.0	1.0	0.13	410,761
Regular Wage Worker	0.11	0.0	1.0	0.31	410,761
-					
Middle Skill Occupation(Dist)	0.11	0.0	0.7	0.07	410,761
Middle Skill Occupation	0.11	0.0	1.0	0.31	410,761
High Skill Occupation (Dist)	0.13	0.0	1.0	0.10	410,761
High Skill Occupation	0.13	0.0	1.0	0.34	410,761
Princip Ind					
Agri (Dist)	0.46	0.0	1.0	0.20	410,761
Agri	0.46	0.0	1.0	0.50	410,761
Industry (Dist)	0.22	0.0	0.7	0.11	410,761
Industry	0.22	0.0	1.0	0.41	410,761
-					
HH services expenses (Dist)	2192.54	0.0	15555.8	1,500.28	410,761
HH services expenses	2192.70	0.0	359904.6	4,706.94	410,348
Rec services expenses (Dist)	251.86	0.0	4264.4	324.15	410,761
Rec services expenses	251.83	0.0	376508.5	1,477.84	410,348
Transp services expenses (Dist)	4328.45	0.0	40845.0	3,495.47	410,761
Transp services expenses	4329.40	0.0	2600945.8	11,789.84	410,348
Rainfall Q3	0.05	-1.3	1.9	0.53	406,829
Rainfall Q4	-0.17	-1.5	2.3	0.57	406,829
Rainfall Q1	0.08	-1.1	2.3	0.72	406,829
Rainfall Q2	-0.02	-1.3	2.1	0.56	406,829
Rainfall $Q1^2$	0.52	0.0	5.2	0.83	406,829
Rainfall $Q2^2$	0.32	0.0	4.6	0.43	406,829
Rainfall $Q3^2$	0.28	0.0	3.5	0.37	406,829
Rainfall $Q4^2$	0.36	0.0	5.3	0.50	406,829

Table 14: Model 1

	Urban	**Rural**
HH size 1 or 2	0.66***	0.39***
	(0.01)	(0.01)
HH size 1 or 2*t	0.00	0.01***
	(0.00)	(0.00)
HH size 3	0.46***	0.29***
	(0.01)	(0.00)
HH size 3*t	0.00	0.01***
	(0.00)	(0.00)
HH size 4	0.33***	0.22***
	(0.01)	(0.00)
HH size 4*t	-0.00	0.00***
	(0.00)	(0.00)
HH size 5	0.21***	0.14***
	(0.01)	(0.00)
HH size 5*t	-0.00**	0.00
	(0.00)	(0.00)
Prop HH 0-15 yrs	-0.12***	-0.18***
	(0.02)	(0.01)
Prop HH 16-24 yrs	0.08***	0.07***
	(0.02)	(0.01)
Prop HH 16-24 yrs*t	0.00	-0.01***
	(0.00)	(0.00)
Prop HH 25-34 yrs	0.14***	0.15***
	(0.02)	(0.01)
Prop HH 25-34 yrs*t	0.01***	-0.01***
	(0.00)	(0.00)
Prop HH 35-49	0.28***	0.28***
	(0.02)	(0.01)
Prop HH 35-49 yrs*t		-0.02***
		(0.00)
Prop HH 50-64 yrs	0.14***	0.16***
	(0.02)	(0.01)
Prop HH 50-64 yrs*t	-0.00	-0.01***
	(0.00)	(0.00)
R^2	0.57	0.46
N	128252	197303
F-Stat	2468	2542

Table 14: Model 1 (contd.)

	Urban	**Rural**
Hindu	0.03***	0.02***
	(0.01)	(0.01)
Hindu*t	0.00	-0.00**
	(0.00)	(0.00)
Low caste	-0.09***	-0.11***
	(0.01)	(0.00)
Low caste*t	-0.00	0.00***
	(0.00)	(0.00)
HH type: Self Employed	-0.18***	0.15***
	(0.01)	(0.00)
HH type: Self Employed*t		-0.01***
		(0.00)
HH type: Casual Laborer	-0.35***	
	(0.01)	
HH type: Casual Laborer*t	0.01***	
	(0.00)	
HH type: Regular Wage Worker	-0.10***	
	(0.01)	
HH type: Regular Wage Worker*t	0.00*	
	(0.00)	
Princip Ind: Agri	0.01	-0.07***
	(0.01)	(0.00)
Princip Ind: Agri*t	0.00*	
	(0.00)	
Princip Ind: Industry	-0.02***	-0.07***
	(0.01)	(0.00)
Princip Ind: Industry*t	0.00***	0.00
	(0.00)	(0.00)
High Skill Occupation	0.17***	0.11***
	(0.01)	(0.01)
High Skill Occupation*t	0.00	-0.01***
	(0.00)	(0.00)
Middle Skill Occupation	0.04***	-0.01**
	(0.01)	(0.01)
Middle Skill Occupation*t	0.01***	0.01***
	(0.00)	(0.00)
Transport services expenses	0.00***	0.00***
	(0.00)	(0.00)
Transport services expenses*t	-0.00***	-0.00***
	(0.00)	(0.00)
R^2	0.57	0.46
N	128252	197303
F-Stat	2468	2542

Table 14: Model 1 (contd.)

	Urban	**Rural**
Recreation services expenses	0.00***	0.00***
	(0.00)	(0.00)
Recreation services expenses*t	0.00	-0.00***
	(0.00)	(0.00)
Household services expenses	0.00***	0.00***
	(0.00)	(0.00)
Household services expenses*t	-0.00***	0.00
	(0.00)	(0.00)
HH type: Self Employed (Dist)	0.02	0.06**
	(0.03)	(0.02)
HH type: Casual Laborer (Dist)	-0.65***	-0.26*
	(0.18)	(0.15)
HH type: Casual Laborer (Dist)*t	0.09***	0.05*
	(0.03)	(0.03)
HH type: Regular Wage Worker (Dist)	0.14***	-0.54***
	(0.05)	(0.07)
HH type: Regular Wage Worker (Dist)*t		-0.01
		(0.01)
Hindu (Dist)	-0.10***	-0.14***
	(0.02)	(0.01)
Princip Ind: Industry (Dist)	0.27***	0.16***
	(0.03)	(0.03)
High Skill Occupation (Dist)	-0.05	0.15***
	(0.05)	(0.05)
Middle Skill Occupation(Dist)	0.02	0.50***
	(0.08)	(0.07)
Middle Skill Occupation(Dist)*t	-0.00	-0.06***
	(0.02)	(0.02)
Transport services expenses (Dist)	0.00***	0.00***
	(0.00)	(0.00)
Recreation services expenses (Dist)	0.00	0.00
	(0.00)	(0.00)
Recreation services expenses (Dist)*t	-0.00	0.00
	(0.00)	(0.00)
Household services expenses (Dist)	0.00	0.00***
	(0.00)	(0.00)
R^2	0.57	0.46
N	128252	197303
F-Stat	2468	2542

Table 14: Model 1 (contd.)

	Urban	**Rural**
HH size 1 or 2 (Dist)	-0.11	0.35***
	(0.11)	(0.08)
HH size 3 (Dist)	0.13	0.25***
	(0.09)	(0.07)
HH size 4 (Dist)	0.18***	0.12**
	(0.06)	(0.05)
HH size 5 (Dist)	0.14**	-0.00
	(0.06)	(0.04)
Prop HH 16-24 yrs (Dist)	0.04	0.34***
	(0.12)	(0.08)
Prop HH 25-34 yrs (Dist)	0.24	-0.04
	(0.17)	(0.12)
Prop HH 35-49 (Dist)	-0.14	-0.09
	(0.15)	(0.11)
Prop HH 50-64 yrs (Dist)	0.28*	0.18
	(0.16)	(0.11)
Rainfall Q1	-0.01*	-0.01
	(0.01)	(0.01)
Rainfall $Q1^2$	0.04***	0.02***
	(0.01)	(0.01)
Rainfall Q2	0.01	0.01**
	(0.01)	(0.01)
Rainfall $Q2^2$	0.00	0.01**
	(0.01)	(0.01)
Rainfall Q3	-0.01	-0.03***
	(0.01)	(0.01)
Rainfall $Q3^2$	0.04***	0.06***
	(0.01)	(0.01)
Rainfall Q4	0.01	-0.02***
	(0.01)	(0.00)
Rainfall $Q4^2$	-0.01**	-0.02***
	(0.01)	(0.01)
Time trend	0.01***	0.03***
	(0.00)	(0.00)
R^2	0.57	0.46
N	128252	197303
F-Stat	2468	2542

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