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Disaggregating Imputed Poverty Estimates by Population Groups: New Evidence from a Multi-Country Analysis

Hai-Anh H. Dang
World Bank, GLO, IZA@LISER, Indiana University and London School of Economics and Political Science

Talip Kilic
World Bank

Kseniya Abanokova
World Bank

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Disaggregating Imputed Poverty Estimates by Population Groups: New Evidence from a Multi-Country Analysis*

Abstract

Can imputed poverty estimates be reliably disaggregated by population groups, especially when the interest is monitoring poverty levels for smaller, vulnerable groups that may not be represented as well in large-scale household surveys? The study tackles this question through a comprehensive literature review and empirical analysis that leverages 18 household surveys across four different low- and middle-income countries. The results suggest that the imputation accuracy widely varies by population group, with differences being as high as 10 percentage points in pairwise comparisons of groups. The imputation accuracy for the population groups of interest increases, on average, by 1.3 percentage points in response to increasing the sample size by 1,000 observations for the target survey that is used for sourcing the predictors for the imputation model. The results are robust to extensive sensitivity analyses and also suggest that incorporating geospatial predictors into the imputation model can help increase imputation accuracy. The discussion provides useful inputs for future survey design.

JEL classification

C15, I32, O15

Keywords

consumption, poverty, survey-to-survey imputation, household surveys, Malawi, Nigeria, Tanzania, Vietnam

Corresponding author

Hai-Anh H. Dang
hdang@worldbank.org

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1. Introduction

Policy makers are often interested in disaggregating poverty estimates to smaller population groups for different reasons. First, certain population groups have more poverty and may need more support. Second, classification into these groups helps with more effective and efficient targeting, especially if the classification criteria are more amenable to policy interventions. Furthermore, to ensure cost savings with survey implementation and analysis, it is useful to know what the minimum sample sizes (or level of disaggregation) should be for these population groups.

Yet, household consumption surveys that underline official poverty estimates are often not frequently collected or are not comparable over time in many poorer countries (World Bank, 2017 and 2021). This can be due to various reasons, ranging from fewer resources devoted to data collection, weaker capacity regarding survey implementation and statistical analysis, to conflict environments. Against this background, imputation methods have become increasingly popular as an alternative approach to addressing data gaps and obtaining updated poverty estimates (Dang, Jolliffe, and Carletto, 2019; Dang and Lanjouw, 2023; Dang, Carletto, and Jolliffe, 2025).

While imputed poverty estimates at the national level can perform reasonably well, challenges arise where there is interest in disaggregating these estimates to smaller population groups. Several challenges are of particular importance. First, when imputing for poverty estimates, we need to assume that we can apply the estimated parameters (and the estimated distributions of the error terms) from the base survey to the data in the target survey.[1] For the general population, this assumption (and various variants) has been shown to work rather well for many countries at different income levels and located in different geographical regions. But it remains unclear if this key assumption applies to all the population groups of interest.

[1] This assumption (or some variant of it) is a prerequisite for imputation models to work. See Dang *et al.* (2017) for a weaker variant of this assumption.

Second, little evidence exists on sample size requirements, which provide key inputs for survey design. In particular, what is considered a minimum sample size for these smaller population groups that allow for meaningful statistical significance? Does imputation accuracy improve for larger sample sizes, and vice versa? Is there any difference between the sample size for the base survey (that is used to build imputation models) and that of the target survey (that is used to impute into)? To our knowledge, no study investigates these questions.[2]

The objective of this short paper is threefold. First, we offer a review of the stock of knowledge regarding imputed poverty estimates for population groups. Second, we examine the imputation accuracy for different population groups, using data from 18 household surveys in three Sub-Saharan African countries (Malawi, Nigeria, Tanzania) and Viet Nam over the past decade and a half. We provide meta-analysis that aims to generalize results from a large number of estimates resulting from a rich combination of sample sizes, imputation models, and country characteristics. Finally, we propose directions for future research that can shed further light on this topic.

Our review of the existing literature suggests that imputation works for both the general population and some key population groups, such as those defined by residence areas (urban/ rural and geographical regions) or household size or gender of the household head. Our findings show that the average imputation accuracy for the different population groups hovers around 77%, using our preferred imputation model.

Using a mixed-effect linear model with four levels of random effects, we find that a larger sample size of the target survey is associated with greater imputation accuracy. Specifically, an

[2] Alternatively, if the sample sizes for a specific population subgroup are large enough, we can implement imputation on this population subgroup (i.e., group-specific imputation) as we do with the general population. That is, instead of running the imputation model on the whole population and subsequently using a dummy variable to classify the imputed poverty estimates for this population subgroup, we can restrict the sample sizes to this population subgroup (in both the base and target surveys) and implement imputation for each of these sample sizes. In practice, it is typically the case that the sample size of the population subgroup of interest is small. But it would be useful to better understand how large the sample size should be for us to implement group-specific imputation for each population subgroup.

increase of 1,000 observations for the sample size of the target survey is associated with an increase of 0.013 (or 1.3 percentage points) in the probability of subgroup imputation accuracy. Imputation accuracy varies widely by population groups, with these differences in probability of imputation accuracy between population groups being as high as 10 percentage points. The results are robust to extensive sensitivity analyses and also suggests that incorporating geospatial predictors into the imputation model can help increase imputation accuracy.

This paper has six sections. We start with briefly reviewing the literature that uses various classification of population groups for poverty estimates in the next section before describing the data in Section 3. We present our analytical framework in Section 4 and discuss the estimation results in Section 5. We finally conclude in Section 6.

2. Literature review

Criteria that have been employed to classify population groups can overlap to a large extent, but they can also be strongly context-specific and vary from country to country. In fact, these classification criteria can change over time for the same country depending on progress with poverty reduction and specific development objectives in different time periods (e.g., when education achievement levels increase in a country, this country can focus on criteria other than education to better target its poverty interventions). A brief, but inexhaustive, overview of recent studies suggests that the population groups of interest in recent poverty studies include the following

- education achievement (see, e.g., Behrman (2010) for a review)
- residence location (see, e.g., Kedir and McKay (2005) for Ethiopia)
- household demographics (see, e.g., Haddad and Ahmed (2003) for Egypt)

- work sector and/ or skill levels (see, e.g., Fields *et al.* (2003) for Indonesia, South Africa, Spain and Venezuela; Himanshu *et al.* (2013) for India)
- geographical isolation/ remoteness or lack of community infrastructure (see, e.g., Bloom *et al.* (2003) and Sachs *et al.* (2004) for multi-country studies), and
- ethnicity and/ or socio-economic caste (see, e.g., Hall and Patrinos (2012) for a multi-country study)
- food insecurity (see, e.g., Bhattacharya *et al.* (2004) for the United States)
- water access (see, e.g., Sullivan (2002))
- disability status (see, e.g., Mitra *et al.* (2013) for a multi-country study)
- unexpected shocks (see, e.g., Dercon (2004) for Ethiopia), and
- migration (see, e.g., Christiaensen and Todo (2014) for a multi-country study).

These characteristics are also generally consistent with those in recent review studies on poverty mobility by Dercon and Shapiro (2007), Baulch (2011), and Iversen *et al.* (2019).

We provide a brief overview of selected poverty imputation studies (with validation) over the past 20 years in Appendix A, Table A.1. Starting with the seminal "poverty mapping" study by Elbers *et al.* (2003), which imputes from a survey into a population census, subsequent (survey-to-survey) poverty imputation studies have mostly applied or built on this method. These studies have, however, mostly considered disaggregating poverty by geographical areas. Only two studies disaggregate poverty by other criteria such as household size, household heads' age, and employment sector (Douidich *et al.*, 2015), or education, geographical regions, work sectors, and ethnic tribes and castes (Dang and Lanjouw, 2018).

Regarding the recent literature on poverty imputation (that employs the imputation method developed in Dang *et al.* (2017)), just a couple studies investigate the imputation results for population groups, and these studies offer these results only as part of their heterogeneity analysis rather than a main research question. Dang and Verme (2023) provide imputed poverty estimates for Syria refugees in Jordan, using cross-survey imputation and administrative and survey data collected by the United Nations High Commissioner for Refugees (UNHCR). The authors find that the imputed poverty estimates are not statistically significantly different from the poverty rates based on actual consumption data. As part of this exercise, the authors also impute poverty for different case (household) sizes, ranging one person to eight persons or more, and find similar results (Appendix A, Figure A.1).[3] In addition, the authors further examine imputation between two similar geographical regions (regarding their poverty and income levels) and find that imputation can also work well.

Dang *et al.* (2025) propose improvements to existing imputation models, using 14 multi-topic household surveys conducted over the past decade in Ethiopia, Malawi, Nigeria, Tanzania, and Viet Nam. They find imputation to work well for the whole country. They subsequently implement imputation separately for urban and rural areas and find that while some imputation models work for both urban and rural areas, certain imputation models (e.g., those that add utilities expenditures to a basic imputation model consisting of household demographic and employment variables) work better for urban areas or rural areas.

Sarr *et al.* (2025) impute poverty for the Venezuelan refugees in Colombia. They provide two types of heterogeneity analysis: gender of the household head and geographical regions of residence. The latter type offers relevant inputs for policy makers, given widespread interest in different levels of geographic concentration of refugee and migrant inflows. In particular, Venezuelan refugees and migrants who settle in border departments generally face more

[3] A case is a group of individuals who register at the UNHCR together with a Principal Applicant (PA) who takes responsibility for the group. This group may be a family, a household, or an extended household.

challenging conditions compared to those who settle in central departments. These include greater food insecurity, limited access to nutritional interventions, more water insufficiency and protection risks, and fewer Venezuelan children residing in border areas could enroll in the education system. The authors obtain good results for both types of heterogeneity analysis, including those who live in border regions and those who live in non-border regions (Appendix A, Figure A.2).

In summary, the limited evidence in the recent few studies suggest that imputation works for both the general population and some key population groups, such as those defined by residence areas (urban/ rural and geographical regions) or household size or household heads' gender or work sectors. But no study offers an in-depth investigation of challenges related to the sample sizes for these population groups that are discussed above.

3. Data

We harmonize and construct a database consisting of 18 multi-topic household surveys from four different countries: Malawi (5), Nigeria (3), Tanzania (6), and Viet Nam (4), with the number of survey rounds for each country being noted in parenthesis. In the three Sub-Saharan African countries (Malawi, Nigeria, and Tanzania), most of the data originate from the nationally-representative, multi-topic household surveys that have been implemented by the respective national statistical office with support from the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative. Being similar to the LSMS-type surveys supported by the World Bank, the surveys from Viet Nam are implemented biennially by the country's General Statistical Office (GSO) with technical support from the World Bank. These surveys are generally regarded as being of high quality and are regularly employed by the national governments, international organizations, and academic researchers to provide estimates on household welfare.[4]

The database includes

i. the Malawi Integrated Household Survey (IHS), 2010/11, 2016/17, and 2019/20 rounds and the Malawi Integrated Household Panel Survey (IHPS), 2010 and 2013 rounds
ii. the Nigeria General Household Survey (GHS)–Panel, 2010/11, 2012/13, and 2018/19 rounds
iii. the Tanzania National Panel Survey (TZNPS) 2008/09, 2010/11, 2012/13, 2014/15, 2019/20, and 2020/21 rounds, and
iv. the Viet Nam Household Living Standards Survey (VHLSS) 2010, 2012, 2014, and 2016 rounds.

The sample sizes hover around 3,000 to 5,000 households in each survey round for the LSMS-ISA surveys (including Nigeria and Tanzania), 9,300 households for the VHLSSs, and over 12,000 households for the Malawi IHS. The consumption data are deflated in the same survey year's prices and are comparable across survey rounds for each country.[5] The objective is to produce the imputation-based welfare estimates of interest as if we did not have consumption data and then evaluate these imputation-based estimates against those based on the actual survey data (i.e., the "true" welfare rates). For the poverty line, we use the national poverty lines for Malawi, Tanzania,

[4] For example, Baulch (2011) considers the VHLSSs as having high quality data and heavily use these surveys for poverty analysis. Other researchers analyze the LSMS-ISA surveys for various topics such as agricultural input uses (Sheahan and Barrett, 2017) or temperature shocks and household consumption (Letta, Montalbano, and Tol, 2018).
[5] In particular, for Tanzania and Viet Nam, consumption data are deflated to 2018/19 prices, 2020/21 prices, 2010 prices respectively. For the Malawi IHPSs and IHSs, consumption data are deflated to 2013 prices and 2010/11 prices respectively.

and Viet Nam and the international poverty lines of $1.90 (in 2011 Purchasing Power Parity (PPP) prices) for Nigeria.[6]

Since we want to analyze variables that are commonly available in (most of) the countries in our database, we focus on the following population groups that are defined by wealth, household size, food insecurity, access to safe drinking water, and household heads' education levels, gender, and employment status. For several population groups, we further disaggregate into population subgroups for better analysis. In total, we consider 32 population groups out of eight population groups.

Specifically, for (household heads') education, we further consider four constituent subgroups: no education, primary education and lower secondary education, upper secondary education, and higher education. For wealth, we define five wealth quintiles, ranging from the poorest quintile (quintile 1) to the richest quintile (quintile 5). For household size, we consider six groups of households: two members or fewer, three members, four members, five members, six members, seven members or more. For (household heads') age, we consider five groups: age 16-29, age 30-39, age 40-49, age 50-59, and age 60 and older.

For gender of household headship, since the definition of female-headed households matters for measuring poverty levels and dynamics (Alazzawi *et al.*, 2025), we consider two different definitions. The first definition is self-reported headship by the respondent in the household survey. The second definition is employed by USAID and is based on whether there is any working age adult member of the relevant gender in the household (i.e., no working age male adults for female

[6] For Nigeria, we employ the international poverty line for analysis since official poverty data for these countries are based on different data sources that are not available to us, such as the Nigeria Living Standards Surveys (NLSSs). However, note that Nigeria's national poverty line calculated using NLSS 2018/19 is close to the international poverty line of $1.90 per person per day in 2011 PPP (Lain and Vishwanath, 2022).

households and no working age female adults for male households).[7] For the remaining population groups (including food security, urban/rural residence, and household heads' employment status), we simply consider a dichotomous classification of whether or not the household (head) belongs to this group.

Table 1 shows that the sample sizes for these population subgroups vary from country to country. But on average, they range from 60 households (heads with higher education achievement for Tanzania in 2019/20) to more than 7,000 households (households with a male head for Viet Nam in 2016). We further provide descriptive statistics for the final estimation database in Appendix A, Table A.2. The list of the asset variables employed for constructing the wealth (index) quintiles are shown in Appendix A, Table A.3.

[7] See Alazzawi *et al.* (2025) for a more detailed discussion on different definitions of female-dominated households.

Table 1. Sample sizes in surveys by population subgroups

	Malawi					Nigeria			Tanzania							Viet Nam				Averaged over countries and periods
	2010	2013	2010/11	2016/17	2019/20	2010/11	2012/13	2018/19	2008/09	2010/11	2012/13	2014/15	2019/20	2020/21	2010	2012	2014	2016	
Head with no education	2,170	2,565	8,575	8,450	7,653	1,717	1,815	1,566	760	934	1,102	777	198	895	2,243	2,273	2,195	2,181	2,301.9
Head with primary/ lower sec education	642	863	1,253	1,317	1,284	1,213	1,106	1,230	1,927	2,256	2,865	1,905	686	2,563	2,435	2,402	2,372	2,363	1,817.8
Head with upper sec education	294	358	1,127	1,163	1,034	1,135	1,085	1,819	435	524	729	540	235	949	2,637	2,645	2,701	2,772	795.2
Head with higher educations	193	214	1,293	1,516	1,461	401	400	361	84	109	162	111	60	237	1,891	1,941	2,032	2,031	501.3
Poorest quintile	631	743	3,676	3,418	2,999	1,821	1,286	1,442	739	731	350	516	174	517	1,983	2,049	1,596	2,131	1,618.9
Wealth quintile #2	583	778	2,160	1,834	874	558	782	834	373	54	1,055	1,051	280	56	2,083	1,490	2,463	1,260	989.5
Wealth quintile #3	518	621	1,857	1,943	3,152	583	682	984	584	981	2,094	708	33	2,201	1,713	1,884	2,173	2,530	1,600.3
Wealth quintile #4	650	819	1,950	2,354	1,864	744	865	890	723	1,037	15	200	388	847	1,855	1,840	1,441	1,848	1,159.4
Richest quintile	863	1,039	2,605	2,897	2,543	760	791	826	787	1,020	1,344	858	304	1,023	1,572	1,998	1,627	1,578	1,345.9
Protected water source	2,695	3,402	10,020	10,861	9,761	2,024	2,270	944	1,277	1,666	2,099	1,431	542	2,346	N/A	N/A	N/A	N/A	3,532.2
Unprotected water source	550	598	2,166	1,548	1,243	2,379	2,136	3,644	1,925	2,122	2,729	1,902	637	2,298	N/A	N/A	N/A	N/A	1,885.7
HH size = 2 members or fewer	507	513	2,151	2,207	1,963	651	588	989	590	683	957	640	251	906	1,555	1,745	1,893	2,071	1,185.1
HH size = 3 members	570	642	2,099	2,387	2,136	429	371	561	473	514	751	558	221	749	1,835	1,753	1,841	1,809	1,099.5
HH size = 4 members	545	696	2,155	2,432	2,279	558	542	706	493	548	706	523	202	764	3,037	2,937	2,803	2,684	1,370.9
HH size = 5 members	530	640	1,992	2,123	1,894	596	550	656	462	531	640	458	157	656	1,520	1,589	1,528	1,541	997.2
HH size = 6 members	400	553	1,599	1,620	1,439	582	578	609	396	501	530	386	92	490	752	746	776	789	700.7
HH size = 7 members or more	693	956	2,252	1,677	1,721	1,650	1,777	1,455	792	1,046	1,274	768	256	1,079	507	491	459	453	1,031.7
Heads age 16-29	806	892	2,999	2,695	2,525	319	169	363	451	532	848	521	222	714	668	498	400	296	750.7
Heads age 30-39	934	1,224	3,551	3,395	3,114	920	792	1,032	856	1,018	1,205	922	309	1,157	2,030	1,881	1,706	1,587	1,487.8
Heads age 40-49	589	709	2,191	2,560	2,357	1,064	1,076	1,167	733	854	1,016	772	217	1,124	2,575	2,615	2,539	2,433	1,495.3
Heads age 50-59	373	530	1,427	1,569	1,436	908	983	1,055	514	616	791	508	186	776	2,071	2,142	2,394	2,537	1,194.1
Heads age 60 or older	539	644	2,075	2,226	1,999	1,253	1,384	1,358	652	803	998	610	245	873	1,861	2,124	2,261	2,493	1,386.0
Female household	400	421	1,700	2,100	1,884	366	366	579	428	463	611	545	178	590	N/A	N/A	N/A	N/A	773.7
Male household	161	165	659	707	674	239	188	347	171	203	303	190	81	324	N/A	N/A	N/A	N/A	318.2
Male head	2,512	3,077	9,315	8,873	7,996	3,800	3,669	3,974	2,388	2,870	3,655	2,380	888	3,386	6,953	6,988	6,950	7,009	4,747.3
Female head	733	923	2,933	3,573	3,436	666	737	1,002	818	953	1,203	953	291	1,258	2,253	2,273	2,350	2,338	1,637.7
Food security	1,817	1,611	6,563	3,641	3,883	3,593	3,487	3,393	N/A	3,115	3,098	2,104	908	3,354	N/A	N/A	N/A	N/A	2,831.0
Food insecurity	1,428	2,389	5,685	8,805	7,548	864	909	1,583	N/A	708	1,757	1,227	271	1,290	N/A	N/A	N/A	N/A	2,864.3
Rural	2,388	2,954	10,019	10,174	9,342	3,045	3,065	3,384	2,028	2,570	3,136	2,081	678	2,524	6,586	6,573	6,526	6,521	4,579.1
Urban	857	1,046	2,229	2,272	2,090	1,421	1,341	1,592	1,178	1,253	1,722	1,252	501	2,120	2,620	2,688	2,774	2,826	1,805.9
Head does not work	2,389	3,049	9,569	10,273	9,338	571	571	958	2,345	2,844	3,517	2,347	805	3,241	1,238	1,286	1,349	1,446	3,155.7
Head works	856	951	2,679	2,173	2,094	3,835	3,835	4,018	861	979	1,341	986	374	1,403	7,968	7,975	7,951	7,901	3,229.3
Total population	3245	4,000	12,248	12,446	11,432	4,466	4,406	4,976	3,206	3,823	4,858	3,333	1,179	4,644	9,206	9,261	9,300	9,347	

Notes: The wealth index is defined based on household assets and housing characteristics (Table A.2., Appendix A). The wealth quintiles are defined using the thresholds from the base year. Female households are defined as female-headed household with no adult males, male households are defined as male-headed household with no adult females. The employment status of the household head is defined differently across countries. In Malawi, it is based on whether the head earned wages, a salary, or commissions in the past 12 months. In Tanzania it reflects whether the head engaged in wage work during the last 7 days. For Viet Nam, the status depends on whether the head worked at any time during the past 12 months and for Nigeria it reflects whether the head engaged in any work during the last 7 days. The definition of food insecurity, focusing on situations where there was not enough food to feed the household, differs slightly across countries, with Malawi and Tanzania framing it within a 12-month context, while Nigeria's question is more general. Food security information is not available for Tanzania (2010/11) and Viet Nam. Water source and gendered household information is not available for Viet Nam. "N/A" represents unavailable data.

4. Analytical framework

We estimate a multi-level (linear mixed) model using four levels of nested random effects that examine the determinants of poverty imputation accuracy

$$y_{ijldct} = \beta_0 + \theta X_{ijldc} + \delta Z_{ldc} + \pi Y_c + \sum_{j=2}^{J} \beta_j \, group_j + country_c + method_d + model_l + subgroup_i + \varepsilon_{ijldct} \quad (1)$$

Specifically, y_{ijldct} is binary variable that equals 1 if the imputed poverty estimate for *population subgroup i* is not statistically significantly different from the true poverty rate in this population subgroup and equals 0 otherwise. This variable is observed for *round t* and is nested within the four random effects: *population group j* for *imputation model l* under *method d* in *country c*.

X_{ijldc} is a vector of independent variables that includes characteristics related to population subgroups, such as the sample sizes of the population subgroups in the target survey and the ratio of the sample size of the population subgroup to the target survey. Z_{ldc} include the variables for specific combinations of *country c*, *method d*, and *model l*, such as the sample sizes of the base and target surveys (measured in thousand unit) and poverty imputation accuracy for the whole population (or overall imputation accuracy).

Y_c are the country characteristics that are specific for each round, such as true poverty rate in the country. β_j are the fixed effects for population groups (e.g., education or wealth). ε_{ijldct} is the subgroup-level (i.e., observation-level) residual error. This linear mixed assumes that the random effects across the different levels and the random effects across households at the same level are uncorrelated. We estimate robust standard errors that are clustered at the country level.

Several remarks are in order for interpreting Equation (1). First, the estimated coefficients on the fixed portion associated with the observable variables (i.e., δ and θ) can be easily read off of the regression results just as with the standard OLS regression. In particular, since y_{ijldct} is a binary variable, the regression results can be interpreted similarly to those from the standard linear probability model. This particular feature of Equation (1) is useful and helps us better compare results with other model variants discussed below.

Second, the linear mixed model is a generalized version of the commonly used random effects model in econometrics, which is typically a model with one level of random effects. For example, if there are only one level of unobserved factors in this model at the country level, Equation (1) would be equivalent to the standard country random effects panel data model commonly used in econometrics.[8] But with four level of random effects, Equation (1) is more flexible and allows for different variables to contribute both as fixed effects and random effects such as the variable(s) at the country level. We can provide formal tests for these random effects.

Finally, for robustness checks, we also estimate other variants of Equation (1). These include a two-level nested random effects model (with the first level being the country and the second level being a subgroup created from a unique combination of *population subgroup* i, *population group* j, *imputation model* l, and *method* d) and a one-level random effects model (at the subgroup level described above). These variant models are discussed in more detail in Appendix B. Since both are also linear mixed models, we can compare the estimated coefficients for the fixed portion in Equation (1) (i.e., θ, δ, π, and β_j), particularly for the sample size variables.

[8] See, for example, Skrondal and Rabe-Hesketh (2004) for a comprehensive treatment of multilevel modeling and Dang and Glewwe (2018) for a recent application of this model to study factors that contribute to education achievement in Vietnam.

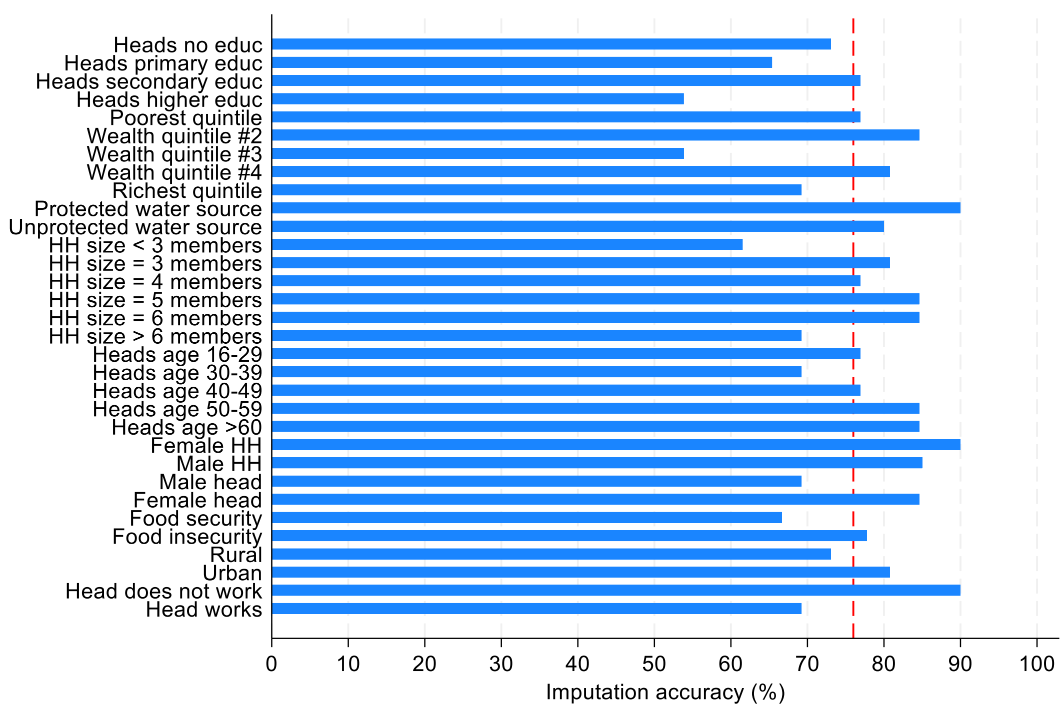
5. Estimation results

5.1. Overall imputation accuracy

We implement nine imputation models similar to the core Models 1 to 9 in Dang *et al.* (2025) on seven commonly used population groups. These groups are defined by household heads' education levels, household wealth, safe drinking water, food security, household size, household gender composition and gender of the household head.

Given the various results that we tested for different population subgroups, using 18 surveys from the four countries and survey years, it is useful to summarize the results through simple unconditional meta-analysis. Figure 1 plots for each population subgroup the imputation accuracy, which is defined as the share of the estimates that is not statistically significantly different from the "true" poverty rate (based on actual consumption data) for each population subgroup.

Figure 1. Imputation accuracy over all imputation models



Notes: Imputation accuracy is the share of the estimates that are statistically insignificantly different from the true poverty rates for all countries, models, and groups. Red dashed line indicates mean accuracy. The estimation results are shown using imputation Model 3 in Dang *et al.* (2025).

Figure 1 shows that overall, the imputation accuracy for the different population subgroups is 77%, using the well-performing Model 3 in Dang et al. (2025) (which adds food expenditure to a basic imputation model). The imputation accuracy is especially higher for certain groups, such as those with completed secondary education, or those with average wealth (wealth quintiles 2 or 4), or those with protected water sources, or those with larger family sizes (with five or six family members), or those who are older (age 50 or higher), or female-headed households, or households where heads do not work.

We provide a similar figure that summarizes imputation accuracy for all the nine imputation models and for each imputation model respectively in Appendix A, Figures A.3 and A.4. Notably, Figure A.3 shows that the imputation accuracy averaged over all the imputation models is unsurprisingly lower at 55% since not all imputation models work in all contexts. Figure A.4 shows that except for Model 3, Models 8 and Model 9 offer better-performance than the other models with average imputation accuracy hovering around 60% for all population subgroups. These are qualitatively similar with the results for imputation accuracy for the whole population (as discussed in Dang *et al.* (2025)).[9]

5.2. Meta-analysis results

The unconditional meta-analysis shown in Figure 1 is obtained by simply averaging the poverty estimates for population subgroups across the countries, the years, the imputation models, and the estimation methods. To further take into account the potential contributions from these model characteristics, we conduct conditional meta-analysis using Equation (1) and the results are reported in Table 2.

[9] These findings are consistent with recent studies including Dang *et al.* (2026) for Tanzania and Dang *et al.* (forthcoming) for more countries.

Table 2. Meta-analysis for subgroup imputation accuracy, mixed-effects linear regressions

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.004	0.002	-0.003	-0.003
	(0.01)	(0.01)	(0.02)	(0.02)
Ratio of sample size of subgroup over that of target survey		-0.062		
		(0.24)		
Sample size of target survey			-0.005	0.013**
			(0.02)	(0.01)
Imputation accuracy for all population's poverty				0.419***
				(0.02)
Sample size of base survey	-0.001	-0.003	0.003	-0.008
	(0.02)	(0.01)	(0.02)	(0.01)
Interval length between base survey and target survey	-0.046	-0.045	-0.048	0.020
	(0.05)	(0.05)	(0.05)	(0.02)
R squared	0.282***	0.287***	0.266*	0.363***
	(0.11)	(0.11)	(0.14)	(0.05)
Actual poverty rate in target survey	-0.015	-0.015	-0.015	-0.011**
	(0.01)	(0.02)	(0.01)	(0.01)
Population groups				
Household wealth	-0.144**	-0.146*	-0.144**	-0.144**
	(0.07)	(0.08)	(0.07)	(0.07)
Water	-0.020	-0.012	-0.021	-0.018
	(0.07)	(0.08)	(0.08)	(0.08)
Household size	0.009	0.006	0.009	0.009
	(0.08)	(0.09)	(0.08)	(0.08)
Heads' age	0.067	0.065	0.067	0.066
	(0.08)	(0.08)	(0.08)	(0.08)
Gendered households	0.147	0.143	0.148	0.151
	(0.10)	(0.12)	(0.11)	(0.11)
Female-headed households	-0.047	-0.040	-0.048	-0.046
	(0.06)	(0.08)	(0.07)	(0.07)
Food security	-0.168***	-0.161***	-0.170***	-0.179***
	(0.04)	(0.05)	(0.04)	(0.05)
Urban/rural	-0.032	-0.025	-0.033	-0.030
	(0.07)	(0.04)	(0.06)	(0.06)
Heads' employment status	-0.062	-0.055	-0.063	-0.061
	(0.04)	(0.05)	(0.05)	(0.05)
Constant	0.960***	0.969***	0.982***	0.362**
	(0.33)	(0.35)	(0.34)	(0.18)
$ln\sigma_c$	-1.352***	-1.354***	-1.346***	-1.848***
	(0.42)	(0.42)	(0.43)	(0.32)
$ln\sigma_d$	-18.081	-14.670	-18.055	-14.938
	(235.30)	(239.65)	(229.92)	(337.32)
$ln\sigma_l$	-2.224***	-2.229***	-2.219***	-3.191***
	(0.28)	(0.28)	(0.28)	(0.77)
$ln\sigma_i$	-3.887	-3.704	-3.899	-3.343***
	(3.19)	(2.42)	(3.25)	(1.05)
$ln\sigma_{it}$	-0.800***	-0.800***	-0.800***	-0.870***
	(0.03)	(0.03)	(0.03)	(0.04)
Number of countries	4	4	4	4
Number of methods	8	8	8	8
Number of models	72	72	72	72
Number of subgroups	504	504	504	504
Number of observations	7128	7128	7128	7128
Log likelihood	-4493.74	-4493.20	-4493.32	-3965.43

Notes: Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).

Table 2 shows the estimation results for four different model specifications that cumulatively build on each other. For Specification 1, we first add the sample sizes of the population subgroups in the target survey to a basic model consisting of the following variables: actual poverty rate in the target survey, the sample size of the base survey, the interval length between the base survey and the target survey, the R^2 of the imputation model (goodness-of-fit statistics), and the dummy variables indicating the population groups. For Specification 2, we add to Specification 1 the ratio of the sample size of the population subgroup to the target survey. The two variables that we add to the base model to form Specifications 1 and 2 form the X_{ijldc} variables as discussed earlier in Section 4.

We add the sample size of the target survey to the base model to form Specification 3, and we further add to Specification 3 a dummy variable indicating whether the imputed poverty estimate for the whole population is accurate to form Specification 4. The two variables that we add to the base model to form Specifications 3 and 4 form the Z_{ldc} variables as discussed earlier in Section 4. Specification 4 is our preferred specification for interpretation.

Table 2, Specification 4 indicates that three random effects at the country, model and subgroup levels are strongly statistically significant at the 1 percent level, providing support for the inclusion of these random effects in this model specification.

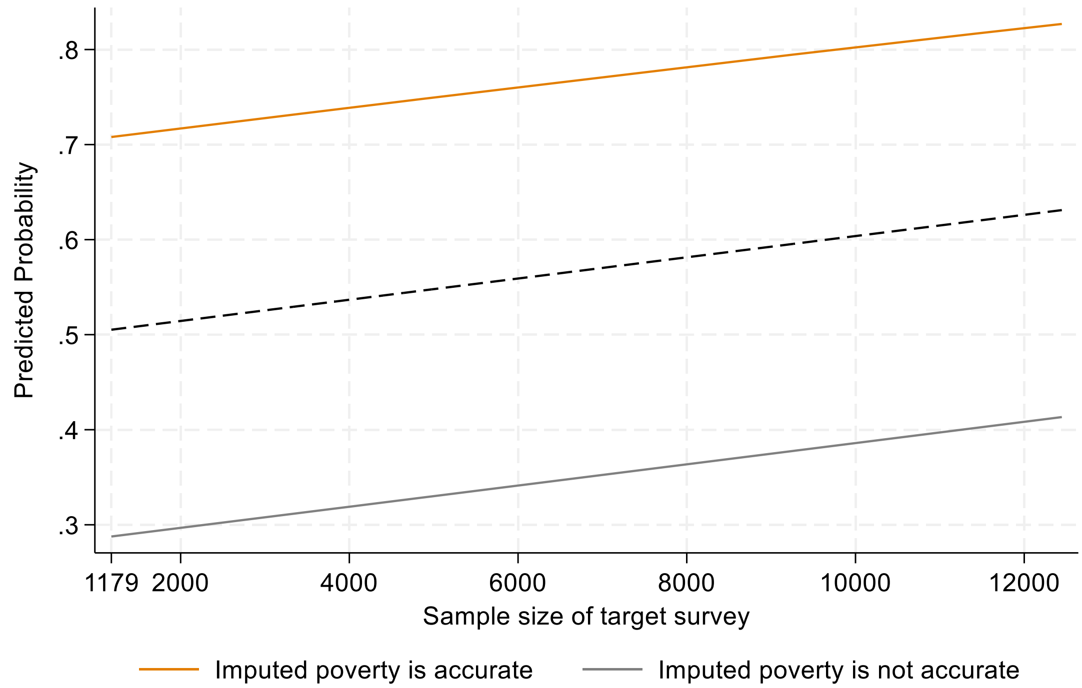
Several interesting findings stand out from Table 2. First, the sample sizes of the population subgroups in the target survey and the ratio of the sample size of the population subgroup to the target survey are both not statistically significant (Specifications 1 and 2). Second, while the sample size of the target survey is not statistically significant on its own, this variable becomes statistically significant when we further control for overall imputation accuracy. This result is reasonable, since it would certainly appear harder to achieve imputation accuracy for the population subgroups when the imputation is not accurate for the overall population.

Specification 4 shows that an increase of an additional 1,000 observations for the sample size of the target survey is associated with an increase of 0.013 (or 1.3 percentage points) in the probability of subgroup imputation accuracy. Notably, Specification 4 also shows that once imputation accuracy for the overall population is achieved, this is associated with a 41.9 percentage points increase in the probability of subgroup imputation accuracy. Certain population groups have lower imputation accuracy such as wealth and food security.[10]

Figure 2 provides a visual illustration of the predicted probabilities of subgroup imputation accuracy for different sample sizes of the target survey, using the estimated results from Table 2, Specification 4. We generate this figure using the actual (empirical) values for the sample sizes of the target survey (i.e., using in-sample predictions). Figure 2 shows that, for a target survey sample size of 1,179 (i.e., the smallest sample size in our data), the predicted probability of subgroup imputation accuracy when overall imputation accuracy is achieved is slightly more than 0.70 (orange line). This probability increases to around 0.72 for sample size of 2,000, 0.74 for sample size of 4,000, 0.76 for a sample size of 6,000, and 0.80 for a sample size of 10,000. This probability decreases by around 40 percentage points when overall imputation accuracy is not achieved (gray solid line) as also seen with the results in Table 2.

[10] Different from the results in Dang et al. (2025), a higher value of R^2 is strongly statistically significant and has good correlation with subgroup imputation accuracy. Specifically, Specification 4 shows that a 10% increase in R^2 is associated with a 3.6 percentage points increase in subgroup imputation accuracy.

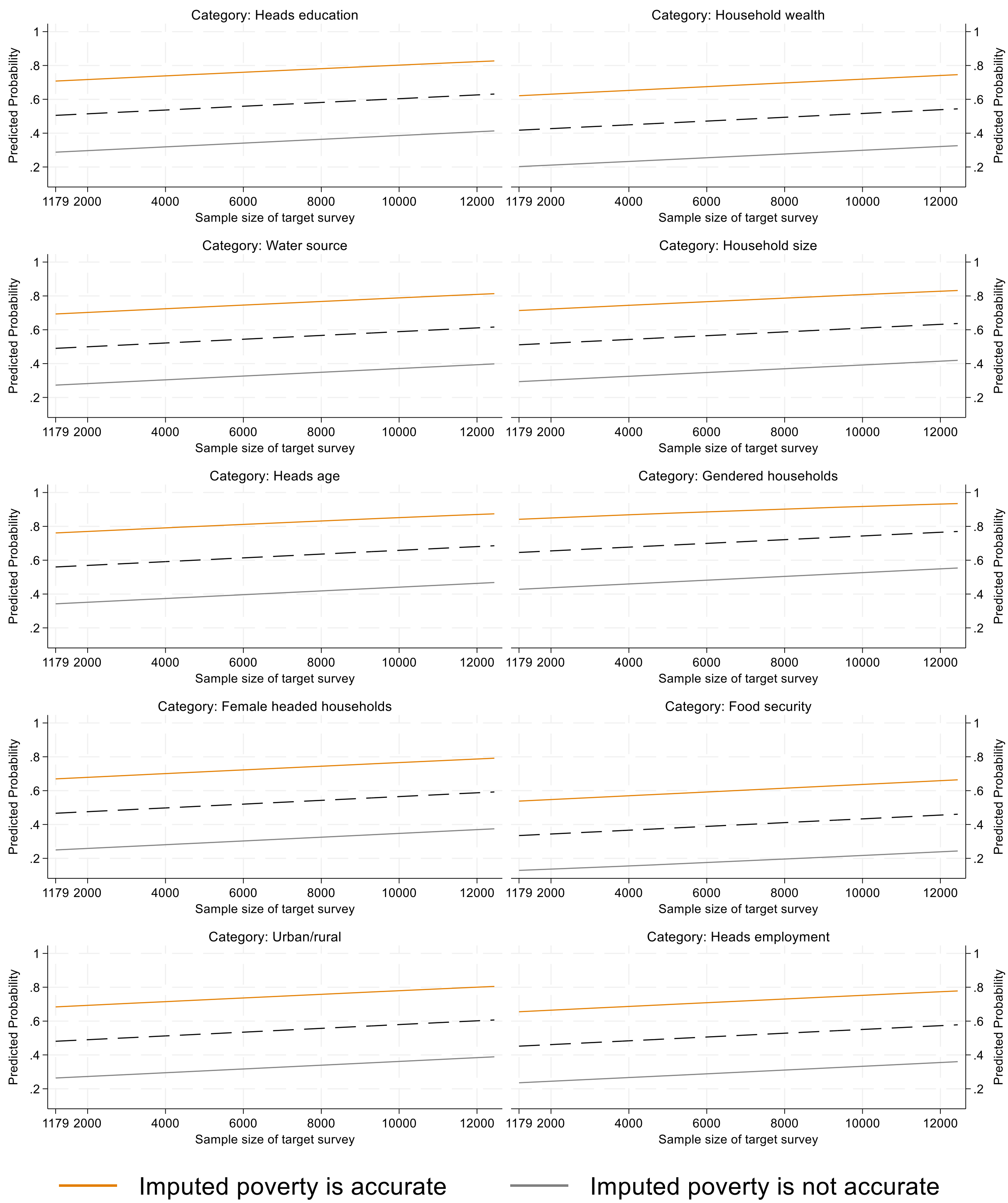
Figure 2. Predicted probability of imputation accuracy in subgroups by sample size of target survey



Notes: This figure is based on the estimates provided in Table 2, Specification 4. Dashed line represents the predicted probability of imputation accuracy for subgroups, keeping other variables fixed at the means.

Figure 3 further illustrates for the different population groups. Using the minimum sample size of 1,179 observations in our data, the predicted probabilities of subgroup imputation accuracy range from around 0.6 for population group defined by food security or wealth or employment status to 0.7 for population groups defined by education, water sources, and urban/ rural residence to 0.8 for population groups defined by age, household female composition. (For a mid-sized target survey of 6,000 observations, we should add about 0.065 to these probabilities). Put differently, given an imputation accuracy increase of 1.3 percentage points for each additional 1,000 observations to the sample size of the target survey, these differences in probabilities between the different population groups translate into an increase in the sample size of roughly 10,000 observations.

Figure 3. Predicted probability of imputation accuracy in subgroups for each population group by sample size of target survey



Notes: This figure is based on the estimates provided in Table 2, Specification 4. Dashed line represents the predicted probability of imputation accuracy for subgroups, keeping other variables fixed at the means.

5.3. Robustness checks

We offer several robustness checks on the analytical framework. First, instead of nesting models under methods as with Equation (1), we switch this order and nest methods under models. The estimation results, shown in Appendix A, Table A.4, remain very similar.

Second, instead of a four-level random effects model, we consider a simpler two-level random effects model where we combine all the levels of random effects under the country level into one level of random effects. In other words, we consider methods, models, and subgroups as not nested but at an equal level to each other. The full estimating equation is shown in Appendix B, Equation (B.1). The estimation results are very similar (Appendix B, Table B.1). We also estimate the alternative mixed-effects logit model (instead of the linear regression model) and the results are also qualitatively similar (Appendix B, Table B.2).

Finally, instead of the more general mixed-effects model, we estimate a one-level random effects model. This is equivalent to the subgroup random effects model that is typically estimated in econometrics. The estimating equation is shown in Appendix B, Equation (B.2). Both the linear and logit versions of this model show similar results (Appendix B, Tables B.3 and B.4).

5.4. Further extensions

Dang *et al.* (2025) find that adding GIS variables to the imputation model can help improve imputation accuracy. Adding GIS variables, however, requires more data work. For now, we can add GIS information to 15 surveys. These include data from Malawi HIS 2010/11, 2016/17, 2019/20 rounds and IHPS 2010 and 2013 rounds, Nigeria GHS 2010/11, 2012/13, and 2018/19 rounds, Tanzania TZNPS 2008/09, 2010/11 and 2012/13, and Vietnam VHLSS 2010, 2012, 2014, and 2016 rounds.

Preliminary analysis, shown in Appendix A, Figure A.5, suggests that adding GIS information, particularly soil index quality, could slightly increase imputation accuracy.

6. Conclusion

Our review of the existing literature suggests that imputation works for the general population and can perform reasonably well for some key population subgroups, such as those defined by residence areas (urban/ rural and geographical regions) or household size or work sectors. Further analysis using 18 household surveys from Malawi, Nigeria and Tanzania shows that a larger sample size of the target survey is positively associated with imputation accuracy. While an increase of 1,000 observations is associated with an increase of 1.3 percentage points in the probability of subgroup imputation accuracy, imputation accuracy strongly varies by population groups. Preliminary analysis suggests that including geospatial predictors in the imputation model can help slightly improve imputation accuracy.

Further research could examine the differences in performance between implementing imputation for the whole population versus implementing group-specific imputation or add more geospatial data or other variables that are highly correlated with poverty and available in both surveys.

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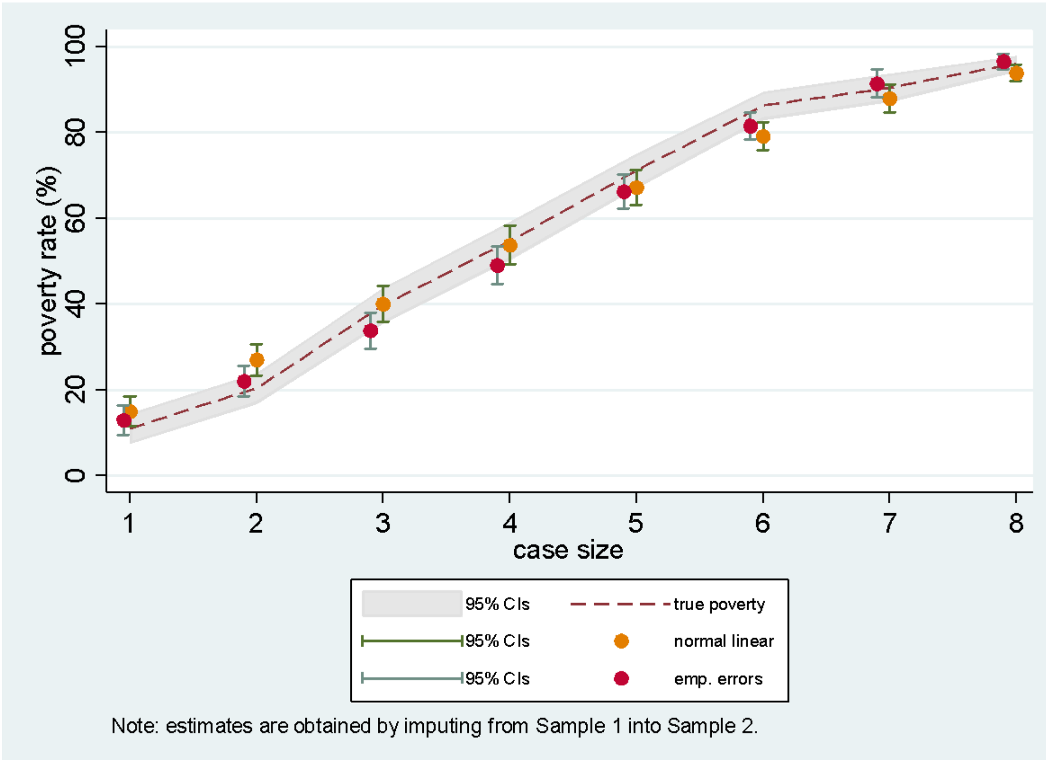
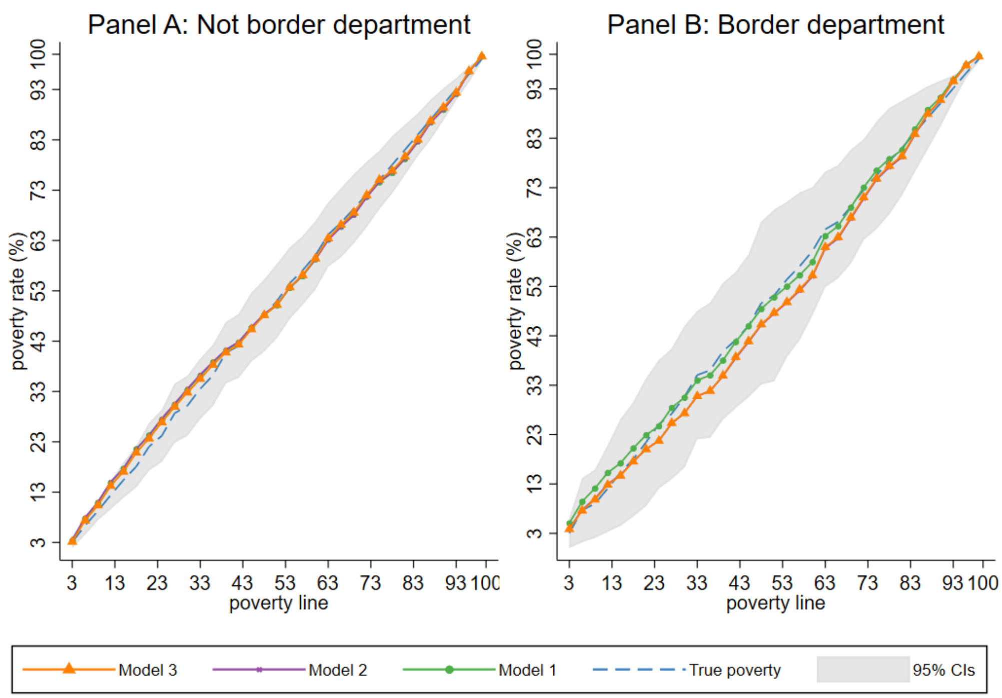
Appendix A: Additional tables and figures

Figure A.1. Imputed poverty rates by household size



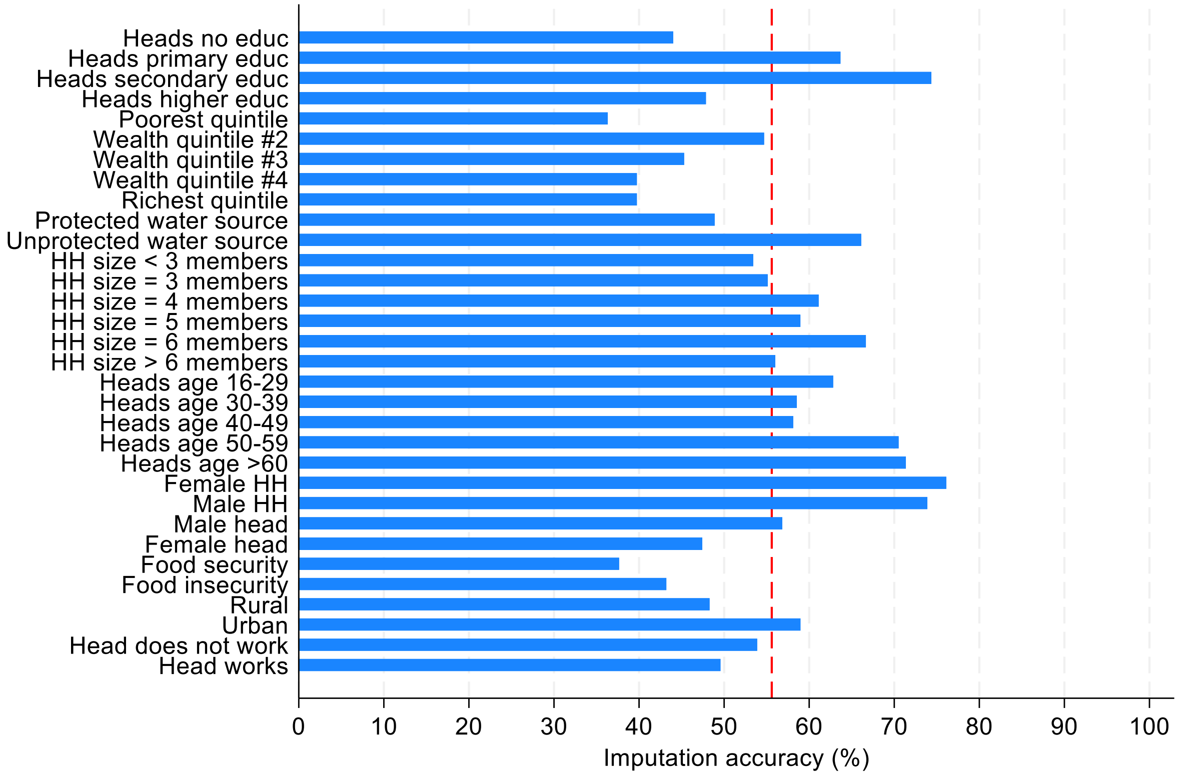
Source: Dang and Verme (2023).

Figure A.2. Imputed poverty rates for refugees in border departments vs. non-border departments



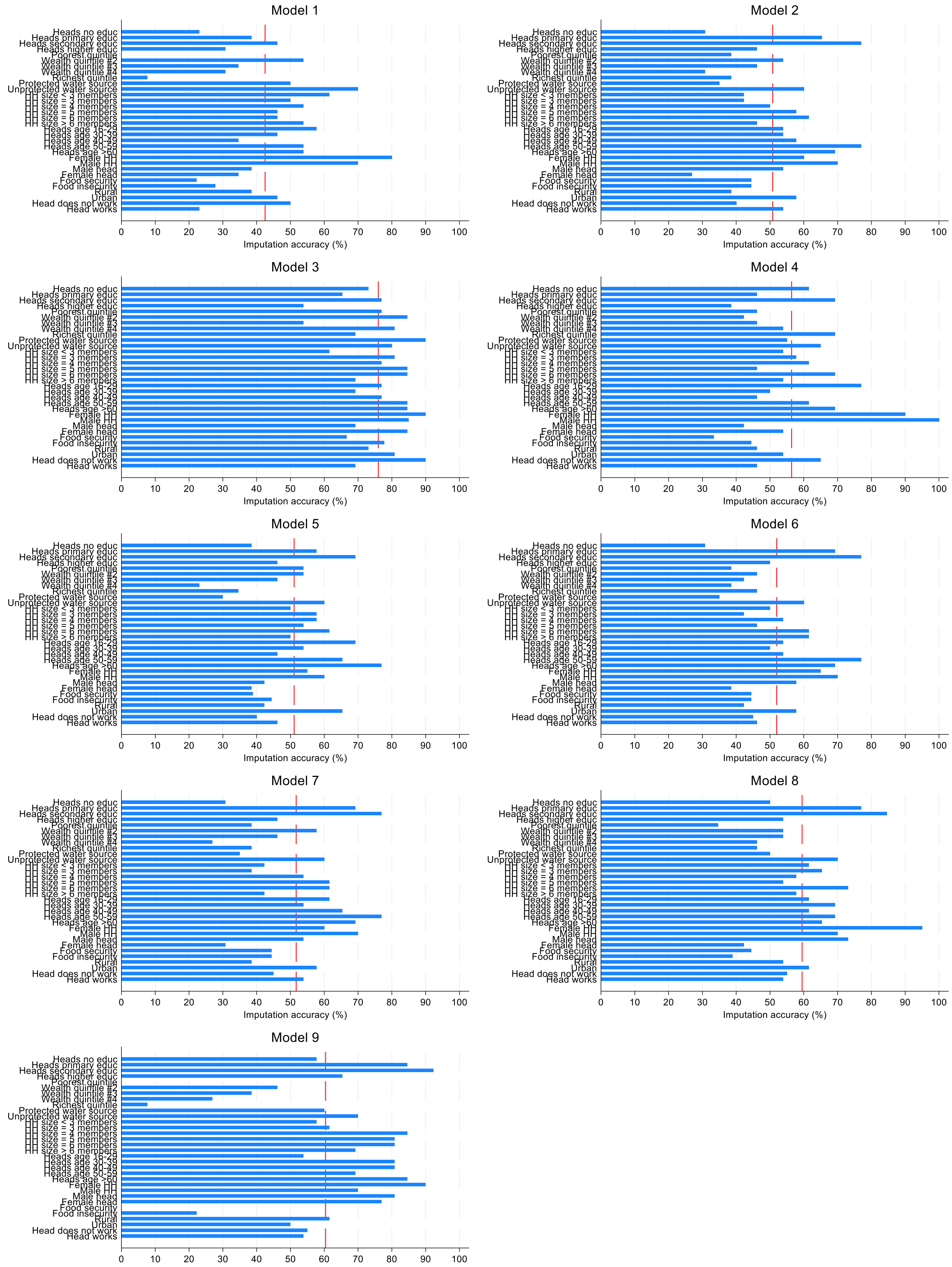
Source: Sarr *et al.* (2025).

Figure A.3. Imputation accuracy over all imputation models



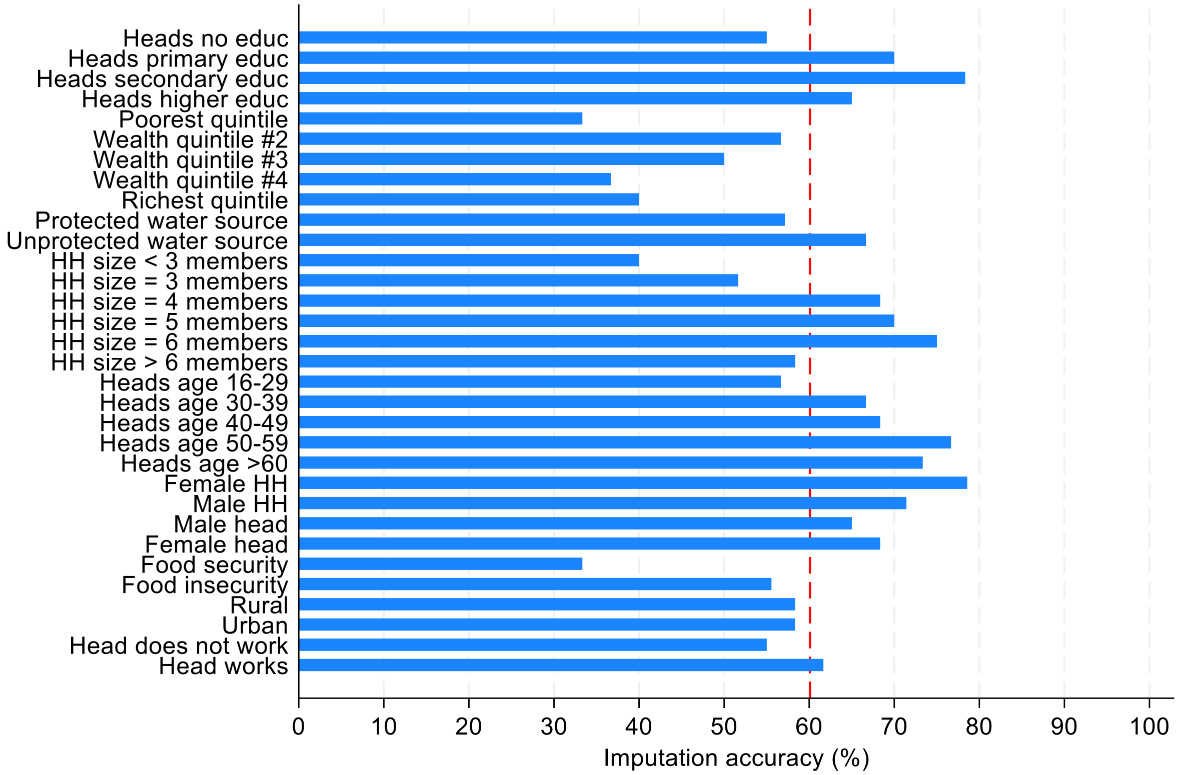
Note: Imputation accuracy is the share of the estimates that are statistically insignificantly different from the true poverty rates for all countries, models and groups. Red dashed line indicates mean accuracy.

Figure A.4. Imputation accuracy for different imputation models



Note: Imputation accuracy is the share of the estimates that are statistically insignificantly different from the true poverty rates for all countries in Model. Red dashed line indicates mean accuracy.

Figure A.5. Imputation accuracy across models with GIS variables



Note: The dataset includes data from Malawi HIS 2010/11, 2016/17, 2019/20 rounds and IHPS 2010 and 2013 rounds, Nigeria GHS 2010/11, 2012/13, and 2018/19 rounds, Tanzania TZNPS 2008/09, 2010/11 and 2012/13, and Vietnam VHLSS 2010, 2012, 2014, and 2016 rounds. The estimation results are shown using imputation models with soil index.

Table A.1. Overview of selected poverty imputation studies (with validation) since the 2000s

No	Authors	Country	Data	Estimation method	Main variables in the imputation model	Main findings
1	Elbers et al.'s (2003)	Ecuador	Ecuadorian Encuesta Sobre Las Condiciones de Vida in 1994 and Ecuadorian census in 1990	Small area estimation method	Household-level variables that are common in household survey and census with location means and information about household access to sewage infrastructure	Applying imputation rule from a household survey to census data accurately predicts poverty estimates for small geographic areas.
2	Stifel and Christiaensen (2007)	Kenya	Welfare Monitoring Survey (WMS) in 1997 and Demographic and Health Survey (DHS) in 1993, 1998, 2003	Elbers *et al.*'s (2003) method	Housing characteristics (quality of floor, roof, drinking water sources), house durables (ownership of radio, television, refrigerator, bike), cluster characteristics (cluster averages of households with low-quality floors and with access to piped water), and district characteristics (district averages of household with access to electricity, early onset of rainfall, malaria prevalence, household under-five height-for-age z scores).	Changes in poverty headcount are estimated for urban areas, rural areas, and Nairobi, with trends in predicted poverty gap and poverty severity indices across rural, other urban, and Nairobi populations aligning with the headcount estimates.
3	Christiaensen *et al.* (2012)	Vietnam, Russia, China, Kenya	Vietnam Living Standards Survey (VLSS) in 1992/93 and 1997/98; Russian Longitudinal Monitoring Survey (RLMS) in 1993, 1998, 2003; Gansu and Inner Mongolia survey in 2000/04; Welfare Monitoring Survey (WMS) in 1997 and KIHBS in 2005/06	Elbers *et al.*'s (2003) method	Demographic characteristics, geographics, education/ profession, location, housing quality, consumer durables, food expenditure (rice and non-rice expenditure), nonfood expenditure (30 day and annual recalls)	Poverty estimates are calculated by urban, rural, and provincial levels, with predicted poverty rates showing no statistically significant difference from observed poverty estimates in Vietnam and Kenya.
4	Mathiassen (2013)	Uganda	Monitoring Survey (MS) 1-4, Uganda National Household Survey (UNHS) 1-3	Elbers *et al.*'s (2003) method with refinements for estimating variance of error temr	Demographic characteristics, education, employment characteristics, occupation, housing, consumption of food, non-durable and semi-durable expenditures, welfare indicators, and regional dummies.	The prediction model is estimated for both urban and rural areas, with predicted poverty trends for urban areas aligning more closely with actual poverty trends than those for rural areas.
5	Daniels and Minot (2016)	Uganda	National Household Survey in 2005/06, Demographic and Household Surveys (DHS) in 1995, 2000, 2001, 2006 and 2009	Elbers *et al.*'s (2003) method	Demographic characteristics, ownership of assets (ownership of motorbike, bicycle, tv or radio) and housing characteristics (type of floor, source of water, type of toilet, electricity).	The estimates of headcount poverty from the UNPS align with those from the DHSs, showing a decline in poverty incidence nationally, across urban and rural areas, and within each of the eight strata, with the highest poverty in the northern rural region and the

						lowest in the central urban region.
6	Douidich et al. (2015)	Morocco	National Survey on Consumption and Expenditure (NSCE) in 2000/01 and National Living Standards Survey (NLSS) in 2006/07, LFS from 2000 to 2009	Elbers *et al.*'s (2003) method	Demographic characteristics, education, employment characteristics, household assets and durables (kitchen, douche, tv, parabole), house characteristics (number of rooms, electricity, sewage, drinking water, flush toilet), interactions of urban/rural variable with employment or with house characteristics.	Disaggregating poverty estimates into urban and rural trends shows a divide in standards of living over time but follows actual poverty estimates. Poverty trends disaggregated by household size, head's age, and employment sector show a decline in poverty, with larger households, those with older heads, and those in agriculture and construction experiencing above-average reductions; however, all trends align with actual survey estimates for 2001 and 2007.
7	Dang and Lanjouw (2018)	India	National Sample Surveys (NSSs) in 2009/10 and 2011/12	Dang *et al.*'s (2017) method	Demographic characteristics, religion, social classes, education, employment status and work sector, assets, house durables and home ownership, urban/rural location	Mobility trends were estimated by population subgroups: upward mobility favored those with middle or higher education, urban residents, and individuals in self-employment or wage work, while the uneducated, rural populations, and scheduled tribes and castes experienced less mobility.
8	Mathiassen and Wold (2021)	Malawi	Integrated Household Survey IHS2 in 2010/11 and IHS3 in 2014/15, Welfare and Monitoring surveys (WMS) from 2005 to 2009 and in 2014, Integrated Household Panel Survey (IHPS) in 2013	Elbers *et al.*'s (2003) method with refinements for accounting for seasonal variations in consumption and explanatory variables	Demographic characteristics and characteristics of head of household, education, housing characteristics, assets ownership, food consumption (yes/no for specific food items), non-food consumption (yes/no for specific non-food items), and subjective assessment of head of household's welfare. In addition, controls for districts and seasons are included.	Systematic exclusion of explanatory variable groups in each geographic stratum affects poverty prediction accuracy; models including all variables align closely with actual poverty rates, while excluding demographic variables produces the largest discrepancies.

Table A.2. Descriptive Statistics

	Malawi	Nigeria	Tanzania	Vietnam	All
Sample size of subgroup in target survey	2.67	1.34	1.01	2.50	1.76
	(2.60)	(1.03)	(0.84)	(1.81)	(1.82)
Ratio of sample size of subgroup over that of target survey	0.29	0.28	0.28	0.27	0.28
	(0.23)	(0.22)	(0.20)	(0.19)	(0.21)
Sample size of target survey	9.29	4.69	3.56	9.30	6.27
	(3.77)	(0.29)	(1.32)	(0.04)	(3.39)
Sample size of base survey	9.31	4.44	3.28	9.26	6.11
	(4.29)	(0.03)	(1.21)	(0.04)	(3.62)
Normal method	0.50	0.50	0.50	0.50	0.50
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Interval length between base survey and target survey	4.00	2.00	2.41	2.00	2.65
	(1.41)	(0.00)	(1.36)	(0.00)	(1.36)
R squared	0.69	0.60	0.60	0.70	0.64
	(0.13)	(0.14)	(0.14)	(0.13)	(0.14)
Actual poverty rate in target survey	46.82	37.52	18.23	13.12	27.27
	(6.35)	(8.84)	(7.17)	(2.89)	(15.04)
Population groups					
Household wealth	0.16	0.16	0.16	0.19	0.16
	(0.36)	(0.36)	(0.37)	(0.39)	(0.37)
Water	0.06	0.06	0.06		0.05
	(0.24)	(0.24)	(0.24)		(0.22)
Household size	0.19	0.19	0.19	0.23	0.20
	(0.39)	(0.39)	(0.39)	(0.42)	(0.40)
Heads age	0.16	0.16	0.16	0.19	0.16
	(0.36)	(0.36)	(0.37)	(0.39)	(0.37)
Gendered households	0.06	0.06	0.06		0.05
	(0.24)	(0.24)	(0.24)		(0.22)
Female-headed households	0.06	0.06	0.06	0.08	0.07
	(0.24)	(0.24)	(0.24)	(0.27)	(0.25)
Food security	0.06	0.06	0.05		0.05
	(0.24)	(0.24)	(0.22)		(0.21)
Urban/rural	0.06	0.06	0.06	0.08	0.07
	(0.24)	(0.24)	(0.24)	(0.27)	(0.25)
Heads labor status	0.06	0.06	0.06	0.08	0.07
	(0.24)	(0.24)	(0.24)	(0.27)	(0.25)
Imputation Model 2	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 3	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 4	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 5	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 6	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 7	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 8	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation Model 9	0.11	0.11	0.11	0.11	0.11
	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Imputation accuracy for all population's poverty (%)	61.11	38.89	55.70	42.59	51.71
	(48.76)	(48.77)	(49.68)	(49.47)	(49.97)
Imputation accuracy for subgroup poverty (%)	55.38	52.86	61.53	46.15	55.61
	(49.72)	(49.94)	(48.66)	(49.87)	(49.69)
Number of observations	1,728	1,152	2,844	1,404	7,128

Note: Standard deviations are in parentheses. The sample size variables are rescaled by dividing the original sample size by 1,000.

Table A.3. List of variables that are used in wealth index, by country

Viet Nam	Tanzania	Malawi	Nigeria
Household owns car	Household owns cars and other vehicles	Household owns car	Household owns cars and other vehicles
Household owns motorbike	Household owns motorcycle	Household owns motorcycle	Household owns motorcycle
Household owns bicycle	Household owns bicycle	Household owns bicycle	Household owns bicycle
Household owns desc phone	Household owns desc phone		
Household owns cell phone	Household owns cell phone	Household owns cell phone	Household owns cell phone
Household owns DVD player	Household owns video/DVD player	Household owns CD/DVD player	Household owns DVD player
Household owns TV	Household owns TV	Household owns TV	Household owns TV
Household owns computer	Household owns computer	Household owns computer	Household owns computer
Household owns refrigerator	Household owns refrigerator/freezer	Household owns refrigerator	Household owns refrigerator
Household owns air conditioner	Household owns air conditioner/fan	Household owns air conditioner	Household owns air conditioner
Household owns washing machine		Household owns washing machine	Household owns washing machine
Household owns electric fan		Household owns electric fan	Household owns electric fan
	Household owns radio		
			Household owns satellite
	Household owns mosquito nets	Household owns mosquito nets	
		Log of residential area	Log of residential area
		House wall materials	House wall materials
		House floor materials	
		House roof materials	House roof materials
		Source of drinking water	Source of drinking water
		Type of toilet	Type of toilet

Table A.4. Meta-analysis for subgroup imputation accuracy, mixed-effects linear regressions (with methods nested under imputation model)

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.006	-0.005	-0.005	-0.005
	(0.01)	(0.01)	(0.02)	(0.02)
Ratio of sample size of subgroup over that of target survey		-0.017		
		(0.23)		
Sample size of target survey			-0.009	0.011**
			(0.02)	(0.00)
Imputation accuracy for all population's poverty				0.408***
				(0.02)
Sample size of base survey	0.003	0.003	0.010	-0.002
	(0.02)	(0.01)	(0.02)	(0.01)
Interval length between base survey and target survey	-0.054	-0.054	-0.059	0.011
	(0.05)	(0.05)	(0.05)	(0.02)
R squared	0.215**	0.274**	0.294**	0.350***
	(0.11)	(0.14)	(0.15)	(0.05)
Actual poverty rate in target survey	-0.015	-0.015	-0.015	-0.011*
	(0.02)	(0.02)	(0.02)	(0.01)
Population groups				
Household wealth	-0.132*	-0.132*	-0.112	-0.114
	(0.08)	(0.08)	(0.08)	(0.08)
Water	-0.020	-0.018	-0.022	-0.018
	(0.07)	(0.08)	(0.08)	(0.08)
Household size	0.007	0.007	0.008	0.008
	(0.08)	(0.09)	(0.08)	(0.08)
Heads' age	0.066	0.066	0.066	0.066
	(0.08)	(0.08)	(0.08)	(0.08)
Gendered households	0.141	0.140	0.142	0.147
	(0.11)	(0.12)	(0.11)	(0.11)
Female-headed households	-0.043	-0.041	-0.046	-0.043
	(0.06)	(0.08)	(0.07)	(0.07)
Food security	-0.169***	-0.168***	-0.172***	-0.180***
	(0.04)	(0.05)	(0.04)	(0.05)
Urban/rural	-0.028	-0.026	-0.031	-0.027
	(0.06)	(0.04)	(0.06)	(0.06)
Heads' employment status	-0.058	-0.056	-0.061	-0.058
	(0.04)	(0.05)	(0.05)	(0.05)
Constant	1.093***	1.094***	1.187***	0.350*
	(0.33)	(0.34)	(0.39)	(0.18)
$ln\sigma_c$	-1.350***	-1.351***	-1.343***	-1.821***
	(0.42)	(0.42)	(0.44)	(0.28)
$ln\sigma_l$	-2.049***	-2.051***	-1.989**	-3.014***
	(0.67)	(0.66)	(0.94)	(0.51)
$ln\sigma_d$	-17.559	-11.679	-18.319	-13.184
	(175.35)	(200.15)	(190.25)	(178.02)
$ln\sigma_i$	-9.760	-9.102	-11.613	-3.428***
	(49.47)	(122.63)	(180.30)	(1.04)
$ln\sigma_{it}$	-0.799***	-0.799***	-0.799***	-0.869***
	(0.03)	(0.03)	(0.03)	(0.04)
Number of countries	4	4	4	4
Number of models	36	36	36	36
Number of methods	72	72	72	72
Number of subgroups	504	504	504	504
Number of observations	7128	7128	7128	7128
Log likelihood	-4465.48	-4465.44	-4464.06	-3957.51

Note. Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).

Appendix B: Alternative estimation equations

For the multi-country analysis, we estimate the following nested mixed model for all the countries:

$$y_{ijldct} = \beta_0 + \theta X_{ijldct} + \delta Z_{ldct} + \pi Y_c + \sum_{j=2}^{J} \beta_j \, type_j + \beta_d normal_d + \sum_{l=2}^{L} \beta_l \, model_l + country_c + subgroup_i + \varepsilon_{ijldct} \qquad \text{(B.1)}$$

- y_{ijldct} is binary variable that equals 1 if the poverty estimates in *subgroup i* is not statistically significantly different from the true poverty rate in *subgroup i* (or 0 otherwise) within *type j* for *model l* under *method d* in *country c* observed for *round t*.
- X_{ijldc} is a vector of independent variables that includes characteristics related to population subgroups, such as the sample sizes of the population subgroups in the target survey and the ratio of the sample size of the population subgroup to the target survey;
- Z_{ldc} are the variables for specific combinations of *country c*, *method l*, and *model d*, such as the sample sizes of the base and target survey and population imputation accuracy;
- Y_c are the country characteristics that are specific for each round, such as true poverty rate in the country;
- β_j are fixed effects for group type or category (e.g., education, wealth quintile), with the first type as a reference category;
- β_l are fixed effects for model with the first model as a reference category;

ε_{ijldct} is an observation-level residual error, representing unexplained variability.

For the multi-country analysis, we estimate a multi-level linear model using the following model for all the countries:

$$y_{ijldct} = \beta_0 + \theta X_{ijldc} + \delta Z_{ldc} + \pi Y_c + \sum_{j=2}^{J} \beta_j \, type_j + \sum_{c=2}^{C} \beta_c \, country_c + \beta_d normal_d + \sum_{l=2}^{L} \beta_l \, model_l + subgroup_i + \varepsilon_{ijldct} \qquad \text{(B.2)}$$

- y_{ijldct} is binary variable that equals 1 if the poverty estimates in *subgroup i* is not statistically significantly different from the true poverty rate in *subgroup i* (or 0 otherwise) within *type j* for *model l* under *method d* in *country c* observed for *round t*.
- X_{ijldc} is a vector of independent variables that includes characteristics related to population subgroups, such as the sample sizes of the population subgroups in the target survey and the ratio of the sample size of the population subgroup to the target survey;
- Z_{ldc} are the variables for specific combinations of *country c*, *method d*, and *model l*, such as the sample sizes of the base and target survey and population imputation accuracy;
- Y_c are the country characteristics that are specific for each round, such as true poverty rate in the country;
- β_j are fixed effects for group type or category (e.g., education, wealth quintile), with the first type as a reference category;
- β_l are fixed effects for model with the first model as a reference category;
- β_c are fixed effects for country with Malawi as a reference category;
- ε_{ijldct} is an observation-level residual error, representing unexplained variability.

Table B.1. Meta-analysis for subgroup imputation accuracy, mixed-effects linear regressions

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.007	-0.001	-0.006	-0.006
	(0.01)	(0.01)	(0.02)	(0.02)
Ratio of sample size of subgroup over that of target survey		-0.061		
		(0.21)		
Sample size of target survey			-0.005	0.012**
			(0.02)	(0.01)
Imputation accuracy for all population's poverty				0.425***
				(0.02)
Sample size of base survey	0.004	0.003	0.008	-0.002
	(0.02)	(0.01)	(0.02)	(0.01)
Normal method	0.015**	0.015**	0.015**	0.000
	(0.01)	(0.01)	(0.01)	(0.01)
Interval length between base survey and target survey	-0.054	-0.053	-0.056	0.012
	(0.05)	(0.05)	(0.05)	(0.02)
R squared	0.432	0.444	0.387	0.357
	(0.30)	(0.33)	(0.44)	(0.28)
Actual poverty rate in target survey	-0.015	-0.015	-0.015	-0.010*
	(0.02)	(0.02)	(0.02)	(0.01)
Population groups				
Household wealth	-0.105	-0.107	-0.105	-0.109
	(0.08)	(0.08)	(0.08)	(0.08)
Water	-0.022	-0.015	-0.023	-0.024
	(0.08)	(0.08)	(0.08)	(0.08)
Household size	0.001	-0.001	0.001	-0.001
	(0.08)	(0.08)	(0.08)	(0.08)
Heads' age	0.059	0.058	0.059	0.056
	(0.08)	(0.08)	(0.08)	(0.08)
Gendered households	0.137	0.133	0.138	0.137
	(0.11)	(0.12)	(0.11)	(0.11)
Female-headed households	-0.041	-0.034	-0.042	-0.041
	(0.06)	(0.08)	(0.07)	(0.07)
Food security	-0.172***	-0.164***	-0.173***	-0.185***
	(0.04)	(0.05)	(0.04)	(0.04)
Urban/rural	-0.035	-0.028	-0.036	-0.039
	(0.06)	(0.05)	(0.06)	(0.06)
Heads' employment status	-0.060	-0.054	-0.062	-0.063
	(0.04)	(0.05)	(0.05)	(0.05)
Imputation Model 2	0.033	0.031	0.040	-0.057
	(0.07)	(0.06)	(0.07)	(0.06)
Imputation Model 3	0.130	0.124	0.150	-0.003
	(0.16)	(0.17)	(0.22)	(0.16)
Imputation Model 4	0.004	0.000	0.019	-0.011
	(0.07)	(0.08)	(0.10)	(0.10)
Imputation Model 5	0.033	0.031	0.041	0.011
	(0.09)	(0.09)	(0.09)	(0.09)
Imputation Model 6	0.042	0.040	0.050	-0.032
	(0.05)	(0.05)	(0.06)	(0.06)
Imputation Model 7	0.042	0.040	0.049	-0.047
	(0.07)	(0.06)	(0.07)	(0.05)
Imputation Model 8	0.103**	0.101***	0.111**	0.013
	(0.04)	(0.04)	(0.05)	(0.08)
Imputation Model 9	0.162*	0.161*	0.164*	-0.012
	(0.09)	(0.09)	(0.09)	(0.07)
_cons	0.769**	0.776**	0.804*	0.356**
	(0.39)	(0.39)	(0.45)	(0.16)
$ln\sigma_c$	-1.323***	-1.325***	-1.319***	-1.824***
	(0.26)	(0.26)	(0.26)	(0.27)
$ln\sigma_i$	-2.191***	-2.184***	-2.188***	-2.058***
	(0.37)	(0.37)	(0.37)	(0.23)
$ln\sigma_{it}$	-0.810***	-0.810***	-0.810***	-0.911***
	(0.03)	(0.03)	(0.03)	(0.03)
Number of countries	4	4	4	4
Number of subgroups	2,196	2,196	2,196	2,196
Number of observations	7128	7128	7128	7128
Log likelihood	-4544.35	-4543.85	-4543.82	-3928.66

Note. Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The results are obtained using Equation (B.1). The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).

Table B.2. Meta-analysis for subgroup imputation accuracy, mixed-effects logit regressions

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.027	0.013	-0.024	-0.031
	(0.07)	(0.05)	(0.07)	(0.09)
Ratio of sample size of subgroup over that of target survey		-0.442		
		(1.07)		
Sample size of target survey			-0.016	0.083***
			(0.09)	(0.03)
Imputation accuracy for all population's poverty				2.277***
				(0.14)
Sample size of base survey	0.019	0.009	0.030	-0.014
	(0.09)	(0.07)	(0.11)	(0.07)
Normal method	0.073**	0.073**	0.073**	0.001
	(0.03)	(0.03)	(0.03)	(0.03)
Interval length between base survey and target survey	-0.254	-0.249	-0.261	0.103
	(0.25)	(0.26)	(0.25)	(0.12)
R squared	2.911***	3.013***	2.773*	3.453**
	(0.98)	(1.17)	(1.64)	(1.69)
Actual poverty rate in target survey	-0.073	-0.074	-0.073	-0.066*
	(0.08)	(0.08)	(0.08)	(0.04)
Population groups				
Household wealth	-0.512	-0.521	-0.511	-0.651
	(0.38)	(0.39)	(0.38)	(0.48)
Water	-0.115	-0.064	-0.119	-0.141
	(0.37)	(0.41)	(0.39)	(0.49)
Household size	0.015	-0.000	0.016	0.009
	(0.38)	(0.41)	(0.38)	(0.48)
Heads' age	0.310	0.302	0.311	0.365
	(0.41)	(0.42)	(0.41)	(0.50)
Gendered households	0.792	0.760	0.794	0.967
	(0.68)	(0.73)	(0.69)	(0.83)
Female-headed households	-0.204	-0.161	-0.209	-0.250
	(0.30)	(0.38)	(0.32)	(0.40)
Food security	-0.863***	-0.813***	-0.868***	-1.155***
	(0.20)	(0.25)	(0.21)	(0.29)
Urban/rural	-0.178	-0.135	-0.184	-0.240
	(0.31)	(0.22)	(0.29)	(0.37)
Heads' employment status	-0.299	-0.256	-0.304	-0.377
	(0.20)	(0.25)	(0.22)	(0.29)
Imputation Model 2	0.041	0.027	0.063	-0.566*
	(0.29)	(0.27)	(0.30)	(0.33)
Imputation Model 3	0.416	0.373	0.478	-0.401
	(0.70)	(0.79)	(0.99)	(0.96)
Imputation Model 4	-0.240	-0.274	-0.192	-0.531
	(0.39)	(0.41)	(0.41)	(0.64)
Imputation Model 5	0.018	0.001	0.043	-0.177
	(0.39)	(0.37)	(0.40)	(0.55)
Imputation Model 6	0.074	0.058	0.098	-0.435
	(0.23)	(0.20)	(0.23)	(0.36)
Imputation Model 7	0.085	0.070	0.106	-0.512
	(0.29)	(0.27)	(0.29)	(0.32)
Imputation Model 8	0.380**	0.364***	0.404**	-0.137
	(0.15)	(0.13)	(0.18)	(0.45)
Imputation Model 9	0.766*	0.762*	0.773*	-0.155
	(0.44)	(0.44)	(0.44)	(0.41)
_cons	0.945	0.993	1.051	-1.379
	(1.76)	(1.79)	(2.05)	(0.88)
var(_cons[country])	1.745	1.746	1.750	1.116
	(2.26)	(2.29)	(2.25)	(1.25)
var(_cons[country>id])	0.331	0.338	0.331	0.623**
	(0.21)	(0.21)	(0.21)	(0.28)
Number of countries	4	4	4	4
Number of subgroups	2,196	2,196	2,196	2,196
Number of observations	7128	7128	7128	7128
Log likelihood	-4314.28	-4313.29	-4314.10	-3761.28

Note. Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The results are obtained using Equation (B.1). The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).

Table B.3. Meta-analysis for subgroup imputation accuracy, mixed-effects linear regressions

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.007	-0.001	-0.006	-0.006
	(0.01)	(0.01)	(0.02)	(0.02)
Ratio of sample size of subgroup over that of target survey		-0.060		
		(0.21)		
Sample size of target survey			-0.006	0.012**
			(0.02)	(0.00)
Imputation accuracy for all population's poverty				0.424***
				(0.02)
Sample size of base survey	-0.427	-0.423	-0.439	-0.150
	(0.30)	(0.29)	(0.31)	(0.10)
Normal method	-0.737*	-0.735*	-0.741*	-0.382**
	(0.43)	(0.42)	(0.43)	(0.16)
Interval length between base survey and target survey	-0.015	-0.015	-0.015	-0.011*
	(0.02)	(0.02)	(0.02)	(0.01)
R squared	0.004	0.003	0.009	-0.002
	(0.02)	(0.01)	(0.02)	(0.01)
Actual poverty rate in target survey	-0.244***	-0.240***	-0.257**	0.041
	(0.06)	(0.06)	(0.10)	(0.03)
Population groups				
Household wealth	-0.106	-0.107	-0.105	-0.109
	(0.08)	(0.08)	(0.08)	(0.08)
Water	-0.022	-0.015	-0.024	-0.025
	(0.08)	(0.08)	(0.08)	(0.08)
Household size	0.001	-0.001	0.001	-0.001
	(0.08)	(0.08)	(0.08)	(0.08)
Heads' age	0.059	0.058	0.059	0.056
	(0.08)	(0.08)	(0.08)	(0.08)
Gendered households	0.137	0.132	0.138	0.137
	(0.11)	(0.12)	(0.11)	(0.11)
Female-headed households	-0.041	-0.034	-0.042	-0.041
	(0.06)	(0.08)	(0.07)	(0.07)
Food security	-0.172***	-0.165***	-0.173***	-0.186***
	(0.04)	(0.05)	(0.04)	(0.04)
Urban/rural	-0.034	-0.028	-0.036	-0.039
	(0.06)	(0.05)	(0.06)	(0.06)
Heads' employment status	-0.060	-0.054	-0.062	-0.063
	(0.04)	(0.05)	(0.05)	(0.05)
Imputation Model 2	0.032	0.030	0.039	-0.060
	(0.06)	(0.06)	(0.07)	(0.06)
Imputation Model 3	0.127	0.121	0.148	-0.011
	(0.16)	(0.17)	(0.22)	(0.16)
Imputation Model 4	0.002	-0.002	0.018	-0.018
	(0.07)	(0.08)	(0.10)	(0.10)
Imputation Model 5	0.032	0.029	0.040	0.007
	(0.09)	(0.08)	(0.09)	(0.09)
Imputation Model 6	0.041	0.039	0.049	-0.035
	(0.05)	(0.04)	(0.06)	(0.06)
Imputation Model 7	0.041	0.039	0.048	-0.050
	(0.06)	(0.06)	(0.07)	(0.05)
Imputation Model 8	0.102***	0.100***	0.110**	0.010
	(0.04)	(0.04)	(0.05)	(0.08)
Imputation Model 9	0.162*	0.161*	0.164*	-0.013
	(0.09)	(0.09)	(0.09)	(0.07)
Nigeria	0.015**	0.015**	0.015**	0.000
	(0.01)	(0.01)	(0.01)	(0.01)
Tanzania	-0.053	-0.052	-0.056	0.013
	(0.05)	(0.05)	(0.05)	(0.02)
Viet Nam	0.438	0.450	0.392	0.377
	(0.30)	(0.34)	(0.44)	(0.28)
_cons	1.121**	1.125**	1.164**	0.473**
	(0.50)	(0.50)	(0.59)	(0.20)
$ln\sigma_i$	-2.196***	-2.189***	-2.193***	-2.061***
	(0.37)	(0.38)	(0.37)	(0.23)
$ln\sigma_{it}$	-0.810***	-0.810***	-0.810***	-0.911***
	(0.03)	(0.03)	(0.03)	(0.03)
Number of subgroups	2,196	2,196	2,196	2,196
Number of observations	7128	7128	7128	7128
Log likelihood	-4529.90	-4529.41	-4529.35	-3915.96

Note. Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The reference group is Education for categories, Model 1 for Models and Malawi for countries. The results are obtained using Equation (B.2). The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).

Table B.4. Meta-analysis for subgroup imputation accuracy, mixed-effects logit regressions

	Spec.1	Spec.2	Spec.3	Spec.4
Sample size of subgroup in target survey	-0.027	0.013	-0.024	-0.031
	(0.07)	(0.05)	(0.07)	(0.09)
Ratio of sample size of subgroup over that of target survey		-0.440		
		(1.07)		
Sample size of target survey			-0.016	0.084***
			(0.09)	(0.02)
Imputation accuracy for all population's poverty				2.275***
				(0.15)
Sample size of base survey	0.020	0.011	0.032	-0.012
	(0.09)	(0.07)	(0.11)	(0.07)
Normal method	0.073**	0.073**	0.073**	0.001
	(0.03)	(0.03)	(0.03)	(0.03)
Interval length between base survey and target survey	-0.253	-0.247	-0.260	0.106
	(0.25)	(0.25)	(0.25)	(0.12)
R squared	2.951***	3.055***	2.810*	3.612**
	(0.98)	(1.17)	(1.64)	(1.68)
Actual poverty rate in target survey	-0.074	-0.075	-0.074	-0.068*
	(0.08)	(0.08)	(0.08)	(0.04)
Population groups				
Household wealth	-0.512	-0.521	-0.511	-0.651
	(0.38)	(0.39)	(0.38)	(0.48)
Water	-0.116	-0.066	-0.120	-0.144
	(0.37)	(0.42)	(0.39)	(0.49)
Household size	0.015	0.000	0.016	0.010
	(0.38)	(0.41)	(0.38)	(0.48)
Heads' age	0.311	0.302	0.311	0.365
	(0.41)	(0.42)	(0.41)	(0.50)
Gendered households	0.791	0.759	0.793	0.965
	(0.68)	(0.73)	(0.69)	(0.83)
Female-headed households	-0.204	-0.162	-0.209	-0.250
	(0.30)	(0.38)	(0.32)	(0.40)
Food security	-0.864***	-0.814***	-0.869***	-1.157***
	(0.20)	(0.25)	(0.21)	(0.29)
Urban/rural	-0.178	-0.135	-0.183	-0.240
	(0.31)	(0.22)	(0.29)	(0.37)
Heads' employment status	-0.299	-0.256	-0.304	-0.377
	(0.20)	(0.25)	(0.22)	(0.29)
Imputation Model 2	0.035	0.020	0.057	-0.589*
	(0.28)	(0.26)	(0.29)	(0.33)
Imputation Model 3	0.398	0.355	0.462	-0.468
	(0.70)	(0.79)	(0.99)	(0.96)
Imputation Model 4	-0.253	-0.288	-0.205	-0.585
	(0.41)	(0.43)	(0.43)	(0.63)
Imputation Model 5	0.010	-0.007	0.036	-0.205
	(0.38)	(0.36)	(0.39)	(0.54)
Imputation Model 6	0.067	0.051	0.092	-0.461
	(0.23)	(0.19)	(0.22)	(0.35)
Imputation Model 7	0.078	0.063	0.100	-0.536*
	(0.29)	(0.26)	(0.28)	(0.32)
Imputation Model 8	0.373***	0.357***	0.397**	-0.162
	(0.14)	(0.12)	(0.17)	(0.45)
Imputation Model 9	0.764*	0.760*	0.771*	-0.161
	(0.44)	(0.44)	(0.43)	(0.41)
Nigeria	-1.124***	-1.098***	-1.164**	0.510**
	(0.29)	(0.33)	(0.49)	(0.22)
Tanzania	-2.034	-2.011	-2.074	-0.723
	(1.37)	(1.36)	(1.46)	(0.60)
Viet Nam	-3.645*	-3.643*	-3.655*	-2.363**
	(2.03)	(2.04)	(2.03)	(1.00)
_cons	2.642	2.676	2.772	-0.791
	(2.18)	(2.22)	(2.65)	(1.20)
var(_cons[id])	0.328	0.335	0.328	0.619**
	(0.21)	(0.21)	(0.21)	(0.27)
Number of subgroups	2,196	2,196	2,196	2,196
Number of observations	7128	7128	7128	7128
Log likelihood	-4299.91	-4298.93	-4299.73	-3748.40

Note. Standard errors are in parentheses and clustered at the country level (4 countries). The sample size variables are rescaled by dividing the original sample size by 1,000. The reference group is Education for categories, Model 1 for Models and Malawi for countries. The results are obtained using Equation (B.2). The dependent variable is a binary variable indicating whether the poverty estimate for the subgroup is correct (equals 1) or not (equals 0).