Data Gaps, Data Incomparability, and Data Imputation: A Review of Poverty Measurement Methods for Data-Scarce Environments

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Data Gaps, Data Incomparability, and Data Imputation:
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Abstract

Questions that often come up in contexts where household consumption data are unavailable or missing include: what are the best existing methods to obtain poverty estimates at a single snapshot in time? and over time? and what are the best available methods to study poverty dynamics? A variety of different techniques have been developed to tackle these questions, but unfortunately, they are presented in different forms and lack unified terminology. We offer a review of poverty imputation methods that address contexts ranging from completely missing and partially missing consumption data in cross sectional household surveys, to missing panel household data. We present the various existing methods under a common framework, with pedagogical discussion on their intuition. Empirical illustrations are provided using several rounds of household survey data from Vietnam. Furthermore, we also offer a practical guide with detailed instructions on computer programs that can be used to implement the reviewed techniques.

Key words: poverty, mobility, imputation, consumption, wealth index, synthetic panels, household survey

JEL: C15, I32, O15

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I. Introduction

Poverty reduction consistently ranks among the most prioritized tasks of developing countries as well as the international community. For example, the Sustainable Development Goals (SDGs) recently adopted by the United Nations General Assembly call for eliminating poverty by 2030 in its very first goal.[1] But effective and efficient poverty eradication entails the prerequisite of accurate poverty measurement, since it would be hardly possible to claim progress with decreasing poverty—or perhaps good performance with diminishing just about almost all other undesirable phenomena—if we cannot measure it well. Yet, this seemingly simple task is hindered in practice since household consumption data are often either unavailable, or infrequently collected, particularly for low-income countries.[2]

For a motivating example, we plot in Figure 1 the number of data points of poverty estimates against a country's income level (as measured by its consumption level in the household survey), using the World Bank's PovCalNet database that covers the period 1981-2014. For better presentation, we also graph the fitted line for the regression of the former outcome on the latter outcome. The estimated slope of this regression line is positive and strongly statistically significant, suggesting that countries with higher incomes more frequently implement household surveys. Indeed, a 10 percent increase in a country's household consumption is associated with almost one-third (i.e., 0.3) more surveys. Figure 1 thus helps highlight the—perhaps paradoxical—fact that poorer countries with a stronger need for poverty reduction also face a more demanding challenge of poverty measurement given their smaller numbers of surveys. This is unsurprisingly consistent with a prevailing perception among some development practitioners that collecting survey data may not be the top priority for many developing countries (see, for example, Devarajan (2013)).[3]

Research questions that come up in contexts where (household) consumption data are either inadequate or missing often include the following.

(i) What are the best existing methods to obtain poverty estimates at one point in time? or for different points over time? And what are the advantages and limitations of these methods?

(ii) What are the best available methods to study the dynamics of poverty in the absence of panel data? Similarly, what are the advantages and limitations of these methods?

Put differently, the first set of questions concern the measurement of poverty in the absence of consumption data. They also concern how best to track the trends of poverty over time, or measuring the net change in poverty, when consumption data are partially available. The second set of questions, on the other hand, relate to the composition of poverty transitions over time, or measuring the gross change in poverty, in the absence of panel data. Specifically, they can further include such detailed questions as: what is the proportion of the poor in one period that remain poor or escape poverty in the next period? Or what is the proportion of the non-poor that fall into poverty in the next period? In terms of data requirement, (adequate) cross-sectional consumption data are important for the first question, while the ideal data setting for the second question is having (good-quality) panel data. However, as suggested in Figure 1, the paucity of consumption data is common place, particularly in low-income countries. The availability of good quality panel data is even more constrained.

We attempt to offer in this paper a systematization of knowledge on the measurement of poverty when there is a lack of adequate data, or missing data. We make several contributions on both the conceptual front and the empirical front. On the conceptual front, we offer a review of methods that have been employed to provide estimates of welfare in the absence of consumption data, with a particular focus on comparing trends of poverty outcomes over time. Since the existing studies are presented in a variety of formats and technical approaches, we attempt to consistently present these various methods, some new and some more established, under a common framework. For this purpose, we provide some rather simple, yet new, theoretical results to guide our empirical results and also to highlight the nuanced differences between the methods that appears to have received scant, if any, attention in previous studies. For example, most development practitioners would likely implement a full-fledged household consumption survey—if given this choice—to produce poverty estimates, rather than attempt to do so using household assets alone. But to our knowledge, there has been no formal discussion to provide insights into this choice, and possibly other similar choices as well. Our paper attempts to fill in this gap in the literature by offering a review on poverty imputation methods that has not been available before.

Furthermore, we focus on providing the intuition behind each estimation method in an effort to make these techniques accessible to a larger audience. For this objective, we refer to the most important theoretical results in the text, and offer a more detailed technical discussion of these results in Appendix 1. In addition, we mostly review the economics literature, while also referring to the statistics literature where relevant.

On the empirical front, we provide illustrations using real household survey data from Vietnam. While we mostly design these illustrations on a pedagogical basis, they can also be regarded as stand-alone examples of method applications in the context of Vietnam (if the actual benchmark data for this country are pretended to be non-existent) and other settings. For this purpose, we also offer a practical guide in an appendix offering detailed instructions on computer programs (mostly in Stata) that can be used to implement the reviewed techniques.[4] In order to make these methods more accessible, and where there is not yet an established literature, we also provide more specific—and somewhat prescriptive—discussion of best-practices methods. Given our focus on data-scarce environments, we emphasize methods which are operationally feasible and that can be practiced at scale.

We discuss a typology of data scarcity situations, including their commonly associated imputation methods in the next section. This is subsequently followed by the analytical framework in Section III. After a short presentation of the general setup (Section III.1), we discuss in this section key data shortage situations ranging from the cross-sectional consumption data being completely missing (Section III.2) to being partially missing (Section III.3), and missing panel data (Section III.4). We then discuss the data sources and provide the empirical analysis in Section IV. To facilitate cross-reference between our discussion of the theory and the empirics, we provide in this section several illustrative examples that offer estimation results under the same headings that correspond to the theory discussed in Section III. We offer further discussion and conclude in Section V.

II. Typology of Data Scarcity Situations and Imputation Methods

II.1. Overview of Data-Scarce Environments

Given the conceptually broad meaning of household welfare, it is useful to lay out in the beginning the practical strategy that we will employ in this paper. More precisely speaking, we sidestep the theoretical debates about the various approaches to measuring household welfare, and focus on the most common practice with measuring household welfare, namely a money-metric measure that can be obtained from household consumption expenditure (or income) data, as widely collected in household surveys. In particular, our central premise is that household consumption (or income) data provide the benchmark measure of household welfare.[5] This key assumption helps operationalize and better focus the measurement of household welfare, whereby a household's position in the welfare space can be quantitatively identified by their consumption level. For example, households can be identified as poor if their consumption levels are below a specified threshold (i.e., the poverty line). As another example, since we can rank different households' welfare against each other on a common scale according to their consumption, we can obtain the relative distribution of household welfare, or measures of inequality.

Contexts where consumption data are unavailable in one way or another are more widespread than one might think. It can be useful to provide an overview of these contexts. For example, Serajuddin *et al.* (2015) find that, over the period 2002- 2011, more than one-third (i.e., 57) of the 155 countries for which the World Bank monitors poverty data using the WDI database have only one poverty data point or no data at all. While the availability of household consumption surveys is essential for tracking poverty, the quality of these surveys is no less important. In particular, where household consumption data are available, it should not be taken for granted that these data are comparable over time. Indeed, a recent survey by Beegle *et al.* (2016) points out that just more than half (i.e., 27) of the 48 countries in Sub-Saharan Africa had two or more comparable household surveys for the period between 1990 and 2012. Even countries with a respectable and long-running household survey such as India from time to time run into issues with survey comparability (Deaton and Kozel, 2005; Dang and Lanjouw, in press).[6]

A less rosy picture emerges with panel survey data, where far fewer developing countries can afford to collect such data. Tracking the same household (or individual) over time is a costly undertaking for various reasons. For example, households can grow larger with new members (through birth or marriage) or smaller (with previous members dying or migrating) over time, or the whole household can migrate, making it more difficult for interviewers to follow them. Consequently, even where panel data exist, the estimates of poverty mobility based on these panel data are often found to be affected by various data quality issues such as national representativeness or cross-country comparability.[7]

Still, financial constraints aside, it is common knowledge that a certain level of technical and logistical capacity is required to implement a high-quality consumption survey. For example, fielding an LSMS-type (Living Standards Measurement Study) household survey is a demanding task that often involves a number of months of preparation, which consists of a variety of steps ranging from pre-survey stages (e.g., questionnaire design, sample selection, enumerator training, survey firm selection) to post-survey stages (e.g., data entry, data cleaning and checking, post-survey weighting or stratification).[8] Put differently, available resources may provide the necessary condition, but it is technical/logistical capacity that forms the sufficient condition for producing high-quality survey data. The latter issue is perhaps a common challenge for which most national statistical agencies are keen on finding a solution.

Furthermore, development practitioners working on smaller-scale projects have been more and more interested in measuring poverty, say, for project evaluation purposes. Such projects more often than not lack the financial and technical resources, nor the intention, to implement an LSMS-type regular household consumption survey. But properly evaluating the poverty impact of such projects would clearly rely on good-quality consumption data which may not be feasible in those contexts. As such, data gaps and the need to come up with innovative measurement methods—particularly those that can be implemented at scale—to fill in these gaps are increasingly receiving more attention.

We next propose a typology of data situations and an overview of imputation methods before discussing an illustrative example of these data situations.

II.2. Typology of Data Situations and Associated Imputation Methods

For presentation purposes, we group all situations of missing data into three broad categories as follows (Table 1):

A. the cross-sectional household consumption data are *completely* missing

B. the cross-sectional household consumption data are *partially* missing, and

C. although the cross-sectional consumption data are available, the panel household consumption data are (completely or partially) missing

These categories can also be thought of as being ranked, in a roughly decreasing order, according to their severity of data scarcity. Put differently, we assume that the ideal data scenario is one where we have (high-quality) panel consumption data, the second-best scenario is one where we have cross sectional consumption data (but no panel data), and the least desirable scenario is one where we have no cross-sectional consumption data.

Group A thus represents the most data-scarce situation, where no (cross-sectional) data are collected on household consumption, although some data may be collected on other household characteristics.[9] Clearly, a typical example of the surveys that belong to Group A is non-consumption surveys where no consumption data are collected by design. Group A remarkably covers quite a few surveys that are commonly implemented. For example, these surveys include the popular Demographic and Health Surveys (DHS), (most) Labor Force Surveys (LFS), and other surveys such as school-based surveys. In fact, implementing a household consumption module requires considerable resources and logistic arrangement, thus almost all small-scale surveys that are conducted on an *ad hoc* basis would normally fall into this category.

Group B represents data situations that are less data-scarce but, on the other hand, covers a large number of cases. Consequently, it is useful to break this group into the following three smaller sub-cases i) the (cross-sectional) consumption data not comparable across survey rounds, ii) the (cross-sectional) consumption data unavailable in the current survey but available in another related survey, and iii) the (cross-sectional) consumption data unavailable at more disaggregated administrative levels than those in the current survey. Sub-case (i) thus concerns the data situations with several Sub-Saharan African countries and India as discussed earlier. Sub-case (ii) is relevant to all situations where we do not have consumption data in the survey under consideration, but have consumption data in other similar surveys that somehow can be linked to the former. An example of this sub-case is where we have a more recent LFS that has no consumption data but has a similar design to an older household consumption survey.[10]

Given the significantly higher costs of implementing panel surveys, Group C represents situations with least data availability. This is especially true for developing countries. For example, two major household consumption surveys that are commonly employed to provide poverty estimates in China and India—the China Household Income Project (CHIP) survey and the National Sample Survey (NSS)—are both cross-sectional surveys.[11] For countries where panel surveys exist, few such surveys are likely to be representative of the population over a long period of time without a great deal of efforts. One major reason is that the surveyed household unit can change (e.g., household members can die, split off to form a new household, or simply migrate to another place) and it is very costly to track all household members over time. For example, due to attrition, the percentage of households that remain in the panel Russia Longitudinal Monitoring Survey (RLMS) in the first 10 years after it was fielded is around 60 percent; this figure further decreases by half to 29 percent after another 10 years (Kozyreva, Kosolapov, and Popkin, 2016). But as global living standards are rising, this data situation can be improved as more resources may be invested in fielding panel surveys.

We briefly show in Table 1 (last column) the imputation methods that can be used to provide poverty estimates in the absence of consumption data. These imputation techniques vary depending on whether the consumption data needed are cross-sectional or panel. For data situations in Group A, the most commonly used method is to generate a wealth index from household assets and the physical characteristics of the house (e.g., the material of the floor or the wall, or which type of toilet is available). For data situations in Group B, techniques have been developed to offer survey-to-survey imputation (i.e., imputation from one survey to another) for sub-cases (i) and (ii), and survey-to-census imputation (i.e., imputation from a survey into a census) for sub-case (iii). Finally, data situations in Group C can be addressed with recently developed methods that construct synthetic panel data from cross-sectional data, which can substitute for actual panel data to some extent.

We offer next an illustrative example for the different data situations that are described in Table 1.

Illustrative Example 1

We show in Table 2 some recent household surveys in four countries with a low-income level— Ethiopia—and a middle-income level—China, India, and Indonesia—that can be classified under the data situations in Table 1. While the selected countries (and surveys) are a subjective choice, it is useful to note that these countries together account for approximately half of the world population, and more than two-thirds of the global poor.[12] Similarly, these surveys are widely used for welfare analysis by the international community and academic researchers. We use the same notation in Table 1 for consistency, and add a new notation "P" that represents panel data.

A couple remarks stand out from this table. First, the classification in Table 1 does not apply to all the surveys in a country, but is survey-specific. Consequently, as an example, while the China Household Income Project (CHIP) survey is a cross-sectional survey and belongs to Category C, China has two other panel surveys—the China Health and Nutrition Survey (CHNS) and the

Chinese Family Panel Studies (CFPS) (that belong to the new Category P). Second, all the selected four countries collect some panel consumption data either on their own or in collaboration with other organizations, which is better than the average data situation in Sub-Saharan Africa discussed earlier. Yet, it should not be taken for granted that these panel surveys are nationally representative. Both the CHNS and the Indonesia Indonesian Family Life Survey (IFLS) only cover most—but not all—of the population in the respective countries, as does the 2011/12 round of the Ethiopia Socioeconomic Survey (ERSS).

Finally, all these surveys collect some form of consumption (or income data), but opinion varies on their suitability to produce the national poverty rate. For example, Gustafsson *et al.* (2014) argue that out of all the listed Chinese surveys (and some others), the cross-sectional CHIP provides the most comprehensive measure of different household income components. Dang and Lanjouw (in press) also point out that compared to the cross-sectional Indian National Sample Survey (NSS),[13] the panel India Human Development Survey (IHDS) collects a much-reduced version of household consumption data (i.e., covering 47 consumption items vs. more than 400 items in the NSS). This suggests that constructing synthetic panels using the cross-sectional surveys that are nationally representative and have a more comprehensive consumption module may still offer an advantage that is unavailable with the less-than-perfect actual panel data. In this regard, Category C data situations where panel data are missing may be more common than expected.

Notably, although the countries discussed in Table 2 are just low-income and middle-income countries that account for more than two-thirds of the global poor, there are other countries that are (far) worse off in terms of data. Some countries in Sub-Saharan Africa, again, can serve as particularly relevant examples. Beegle *et al.* (2016) observe that during the period 1990-2012, no data exist that can be employed to measure poverty for several countries including Equatorial Guinea, Eritrea, Somalia, South Sudan, and Zimbabwe. The same study further notes that even for countries that could implement household surveys, the quality of their (survey and price) data was so poor that surveys were incomparable over time. Indeed, Guinea and Mali each fielded four surveys since the mid-1990s, but no two of these surveys is considered comparable for measuring poverty trends. These examples further highlight the existing various data-scarce environments in the world, and point to an increasingly stronger need for alternative poverty measurement methods such as poverty imputation in the absence of (comparable) consumption data.

We turn to discussing the general analytical framework and the specific imputation techniques in the next section.

III. Analytical Framework

III.1. General Setup

Following Deaton and Muellbauer (1980), we assume that a household maximizes utility subject to an income budget constraint that includes choice variables such as quantities of goods, durables, and leisure (or labor supply). These in turn are determined by different factors, such as household tastes. This results in the common practice in most, if not all, household consumption surveys of constructing total household consumption as an aggregate of consumption of different items such as food, non-food (including clothing, education, and/or health expenses), durable goods, and housing (Deaton and Zaidi, 2002).

For brevity, let x_j be a vector of characteristics that represent all these factors, where j indicates the survey type. More generally, j can indicate either another round of the same household expenditure survey, or a different survey (census), for j= 1, 2.[14] Subject to data availability, x_j can include household variables such as the household head's age, sex, education, ethnicity, religion, language (i.e., which can represent household tastes), occupation, and household assets or incomes. Occupation-related (or labor supply) characteristics can generally include whether household heads work, the share of household members that work, the type of work that household members participate in, as well as context-specific variables such as the share of female household members that participate in the labor force. Other community or regional variables can also be added since these can help control for different labor market conditions.[15]

It follows that household consumption is typically estimated using the following reduced-form linear model

$$y_{ij} = \beta' x_{ij} + \mu_{ij} \tag{1}$$

for household *i* in survey *j*, for *i*= 1,…, N (see, e.g., Elbers, Lanjouw, and Lanjouw (2003), Ravallion (2016)). Equation (1) thus provides a standard linear model that can be estimated using most available statistical packages. We will examine various versions of Equation (1) in the following sub-sections.

III.2. Completely Missing Consumption Data

In the absence of consumption data, wealth indexes can be constructed that can offer a measure of household welfare. We discuss in this sub-section the construction and some main properties of the wealth index, with the corresponding example being offered in Section IV.2 (*Illustrative Example 2*). An empirical application of the wealth index to tracking household welfare over time is also offered in the same sub-section (*Illustrative Example 3*).

Wealth indexes were used in earlier studies to measure household consumption and poverty (see, e.g., Montgomery *et al.* (2000)), but perhaps the study by Filmer and Pritchett (2001) helps significantly popularize its usage. Non-consumption surveys such as the DHS now automatically offer some version of wealth indexes in all their new data releases. Perhaps the main reason behind its popularity is—compared to the typical survey module that consists of hundreds of consumption items required to construct the consumption aggregate—data on a list of assets are both cheaper and easier to collect.

The idea behind a wealth index is, in fact, rather straightforward: it is a single-variable measure for household wealth that can be used to rank household welfare. In practice, it is essentially some combination of the various components of household wealth such as household assets (e.g., whether the household has a television, a car, and a telephone), the living area of the house, and the physical materials out of which the walls (or roof) of the house are constructed (e.g., whether more durable materials such as cement or bricks or less durable materials such as mud or grass are used). The types of a house's facilities such as the toilet are also commonly used since a better type of toilet such as a flush toilet is often observed to proxy for more wealth than other flimsier or less modern facilities such as pit latrines or no toilet at all.

To be more precise, consider a variant of Equation (1) where the left-hand side variable, household consumption y_{ij}, is now missing, but we have data on household assets a_{ij}—a subset of x_{ij}. Still, we want to generate a wealth index w_{ij} which offers the best combination of (the elements of the different) household assets a_{ij}. Our problem can then be expressed as follows

$$\gamma' a_{ij} = w_{ij} \tag{2}$$

where we now place the term $\gamma' a_{ij}$ on the left-hand side to emphasize that γ are the (vector of) weights we place on the a_{ij} in an effort to generate the best possible measure of wealth. Note that household assets are just a component of the household and community characteristics x_{ij} in Equation (1).

There are two common approaches to obtaining these weights: the first is to simply let all of them equal 1 (i.e., using simple aggregation that provides a count of the number of assets a household possesses), and the second is to search for a (linear) combination of weights that captures the most variation of the a_{ij} by statistical techniques such as the principal component analysis (PCA). Put differently, the PCA method offers a data reduction technique that obtain linear combinations of the a_{ij} with the greatest variance possible (out of the total variance of these household assets). The first linear combination, or principal component, has maximal overall variance; the second principal component has the second largest variance and is uncorrelated to the first principal component, and so on.

Some remarks are, however, in order. The PCA method is data-driven by definition, and offers weights that vary depending on the specific data set that is analyzed. For example, a motorbike would be given a small and perhaps statistically insignificant weight in a setting where it is a commonplace asset (i.e., all households have a motorbike), but would be given a larger weight in another setting where the opposite is true. On the other hand, the simple aggregation method would apply the same equal weights in all the settings. As such, the PCA method appears to be best suited for analysis that is restricted to one setting, while the simple aggregation method may be better for comparison of results across different settings.[16]

Wealth indexes are a useful substitute for household consumption in the absence of the latter, since almost all surveys these days collect the relevant information on household assets and housing characteristics. However, note that wealth indexes are less accurate than household consumption in proxying for household welfare.[17] Since poverty is a function of household consumption, wealth indexes offer biased estimates as well. These results intuitively follow from our assumption that household consumption provides the benchmark measure of household welfare, but can be formalized in the following proposition.

Proposition 1: *Wealth indexes tend to provide biased estimates of poverty rates (as measured by household consumption).*
Proof: Appendix 1.

III.3. Partially Missing Consumption Data[18]

To operationalize our estimation framework for the case where consumption data are partially missing, we extend Equation (1) to a more general model

$$y_j = \beta_j' x_j + \upsilon_{cj} + \varepsilon_j \tag{3}$$

where the error term μ_{ij} is now broken down into two components, one (υ_{cj}) a cluster random effects and the other (ε_j) the idiosyncratic error term. Note that we also suppress the subscript that indexes households to make the notation less cluttered in this sub-section. Conditional on household characteristics, the cluster random effects and the error terms are usually assumed uncorrelated with each other and to follow a normal distribution such that $\upsilon_{cj}|x_j \sim N(0, \sigma_{\upsilon_j}^2)$ and $\varepsilon_j|x_j \sim N(0, \sigma_{\varepsilon_j}^2)$. While the normal distribution assumption results in the standard linear random effects model that is more convenient for mathematical manipulations and computation, it is not necessary for this type of model. As can be seen later, we can remove this assumption and use the empirical distribution of the error terms instead, albeit at the cost of somewhat more computing time.

Without loss of generality, assume for now that consumption data are available for survey 1 but missing for survey 2, for which we are most interested in the poverty estimates. Let z_2 be the poverty line in period 2, and y_2^1 be the imputed consumption for survey 2, the poverty rate p_2 in this period could be estimated with the following quantity

$$P(y_2^1 \leq z_2) \tag{4}$$

where $P(.)$ is the probability (or poverty) function that gives the percentage of the population that are under the poverty line z_2 in survey 2. Note that the poverty rate p_2 (and the poverty function $P(.)$) can also be regarded as an expectation function.

Imputation methods differ in how they estimate y_2^1. We discuss in this sub-section methods that have been developed to impute consumption, either within the same type of surveys or across different survey types. We start first with discussing a commonly used method, proxy means testing, before discussing how consumption can be imputed to measure poverty trends.

III.3.1. Proxy Means Testing

Most of the estimates based on proxy means testing are usually estimated as

$$y_{ij}^{p} = \beta_j^{p\prime} x_{ij,p} \tag{5}$$

where the vector of coefficients β_j^p is often obtained from the regression using another data set (see, e.g., Grosh *et al.* (2008), Coady *et al.* (2014), Brown, Ravallion, and van de Walle (2016)). For example, β_j^p can be obtained from a regression using the household consumption data, and then be imposed on the data from a special—and often smaller—survey that aims at targeting poor households for a social protection program. Alternatively, β_j^p can also be obtained from a regression using data from a neighboring country. But regardless of the specific application, the error terms $\upsilon_{cj} + \varepsilon_j$ (in Equation (3)) are often omitted in Equation (5). As a result, the mean and the variance of the predicted consumption based on proxy means testing would likely provide biased estimates of those of household consumption. Put differently, the better $x_{ij,p}$ can capture the variables in x_{ij}, the less biased the predicted consumption-based proxy means tests is. When $x_{ij,p}$ is identical to x_{ij}, (that is, the estimation model for Equation (5) is fully specified except for the error terms $\upsilon_{cj} + \varepsilon_j$), there is no bias in the estimated mean consumption, but there is still bias in the estimated variance.

These results have direct implications for poverty estimation, and are formally stated in Proposition 2 below.

Proposition 2: *Proxy means testing tends to offer biased poverty estimates.*
Proof: (Appendix 1).

As discussed above, if the estimation model is fully specified (i.e., $x_{ij,p}$ is a smaller subset of x_{ij}), there is no bias in the estimated mean consumption. This result, however, generally does not translate directly into poverty estimates, unless the poverty line is exactly set at the mean consumption level. Nevertheless, proxy means testing offers better estimates of household consumption than those offered by wealth indexes. The intuition is rather straightforward: since we employ an estimation model that is more closely related to household consumption (e.g., β_j^p is obtained from a regression using household consumption as the dependent variable) with the former, we should expect to have better estimates for household consumption.[19]

Since the empirical example for proxy means testing is closely related to our discussion of imputed consumption below, we return to more discussion with the next illustrative example.

III.3.2. Monitoring Poverty Trends over Time with Imputed Consumption

One of the very first ambitious targets of the Sustainable Development Goals (SDGs) is to eliminate extreme poverty and reducing national poverty levels at least by half by 2030. Such efforts are predicated on an ability to reliably assess and monitor progress since tracking poverty trends can help us understand which policies work and which do not work, and how efficient they are. Producing reliable poverty estimates by conducting household expenditure (consumption) or income surveys, however, requires significant financial and technical resources. As a result, consumption surveys are typically conducted by statistical agencies every few years, and poverty estimates are not available in those intervening years when no survey is available. Another challenge to tracking poverty trends is that questionnaire design may change over time, thus making consumption data and poverty estimates not comparable between different rounds.

A notable example of incomparable consumption data over time is perhaps India's NSSs. In the late 1990s, the National Sample Survey Office (NSSO) revised the questionnaire of the NSS in 1999/2000 (55th round) to make household survey consumption data more consistent with those from national accounts. Major changes to the questionnaire were implemented such as changing the recall period for household durables and education expenses from a 30-day interval to a 365-day interval, and using both the traditional 30-day recall period as well as a new 7-day recall period for food items. The Government of India subsequently estimated that the poverty rate fell by 10 percentage points between 1993/1994 and 1999/2000. However, researchers provided different estimates ranging from only somewhat lower than the official estimates to a mere three percentage point decline in poverty during the decade of the 1990s (see, e.g., Deaton and Kozel (2005)).[20]

Where consumption data are either incomparable across two survey rounds or missing in one survey round but not the other, but other characteristics (x_j) that can help predict consumption data are available in both survey rounds, we can apply survey-to-survey imputation methods. In particular, Dang, Lanjouw, and Serajuddin (2017) propose a simple imputation framework that builds on earlier studies (Elbers, Lanjouw, and Lanjouw, 2003; Tarozzi, 2007).[21] Compared to previous studies, the Dang *et al.* (2017) method provides a more explicit theoretical modeling framework, with new features such as model selection and standardization of surveys of different designs (e.g., for imputing from a household survey into a labor force survey).

Assume that the explanatory variables x_j are comparable for both surveys (Assumption IV.1), and that the changes in x_j between the two periods can capture the change in poverty rate in the next period (Assumption IV.2). Suppressing the subscript for households in the following equations, Dang *et al.* (2017) define the imputed consumption y_2^1 as

$$\mathrm{y}_2^1 = \beta_1' x_2 + \upsilon_1 + \varepsilon_1 \tag{6}$$

and estimate it as

$$\hat{\mathrm{y}}_{2,s}^1 = \hat{\beta}_1' x_2 + \tilde{\hat{\upsilon}}_{1,s} + \tilde{\hat{\varepsilon}}_{1,s} \tag{7}$$

where the parameters β_1' are estimated using Equation (3), and $\tilde{\hat{v}}_{1,s}$ and $\tilde{\hat{\varepsilon}}_{1,s}$ represent the s^th random draw from their estimated distributions, for s= 1,…, S. Using the same notation as in Equation (4), the poverty rate p_2 in period 2 and its variance can then be estimated as

$$\text{i) } \hat{P}_2 = \frac{1}{S}\sum_{s=1}^{S} P(\hat{y}_{2,s}^{1} \leq z_1) \quad (8)$$

$$\text{ii) } V(\hat{P}_2) = \frac{1}{S}\sum_{s=1}^{S} V(\hat{P}_{2,s}|x_2) + V(\frac{1}{S}\sum_{s=1}^{S} \hat{P}_{2,s}|x_2) \quad (9)$$

Indeed, these estimates of poverty are unbiased, and improve on those offered by proxy means testing method. This result is formalized in the following proposition.

Proposition 3: *Given assumptions IV.1 and IV.2, the imputed household consumption in equation (7) offers unbiased poverty estimates.*
Proof: Appendix 1.

We can test for Assumption IV.2 if consumption data exist in both survey rounds. We can use a decomposition that is similar in spirit to the Oaxaca-Blinder framework (Oaxaca, 1973; Blinder, 1973), where the change in poverty between the survey rounds can be broken down into two components, one due to the changes in the estimated coefficients (the first term in square brackets in Equation (10) below) and the other the changes in the *x* characteristics (the second term in square brackets in Equation (10) below). Assumption IV.2 would be satisfied if the poverty change is mostly explained by the latter component. This can be expressed as

$$\begin{aligned} P(y_2) - P(y_1) &= [P(y_2) - P(y_2^1)] + [P(y_2^1) - P(y_1)] \\ &= \left[P\left(\beta_2^{'}x_2 + \eta_2\right) - P\left(\beta_1^{'}x_2 + \eta_1\right)\right] + \left[P\left(\beta_1^{'}x_2 + \eta_1\right) - P\left(\beta_1^{'}x_1 + \eta_1\right)\right] \end{aligned} \quad (10)$$

where η_j is defined as $\nu_j + \varepsilon_j$, j= 1, 2, for less cluttered notation.

However, we want to predict poverty rate for the current period where consumption data are missing. Thus, a practical use of Assumption IV.2 is model selection; in particular, we can test for this assumption in contexts where consumption data exist for earlier survey rounds (i.e., there are two earlier survey rounds with consumption data), and select the imputation model that offers estimation results that are most satisfactory for this assumption. We offer the corresponding empirical example for this imputation method, which is *Illustrative Example 4* in Section IV.3.

This imputation method is also related to a larger literature on missing data (or multiple) imputation (MI) in statistics (see, e.g., Little and Rubin, 2002; Carpenter and Kenward, 2013). Official agencies such as the U.S. Census Bureau routinely use imputation to fill in important missing data on various statistics for income (Census Bureau, 2014a) and labor (Census Bureau, 2014b). However, several differences exist between the two literatures. First, MI studies often impute missing data within the same survey where usually less than half of the data are missing, rather than imputing consumption for a whole new survey (census) round. Second, MI studies, unsurprisingly, do not use economic theory for model selection. Finally, MI studies often employ Bayesian techniques for their estimation, which requires multiple drawing from posterior distributions and, consequently, is more computing-intensive. These differences have perhaps contributed to the growth of the economic literature on poverty imputation we review in this paper.[22]

A recent champion of the application of MI methods to poverty is the SWIFT method (Survey of Well-being via Instant and Frequent Tracking), which is developed by Yoshida *et al.* (2015). This method consists of three key steps. The first step is to identify between 10 and 12 variables that can be used to predict household consumption. The second step is to collect data on these variables, and the final step is to apply MI methods on these variables to obtain poverty estimates. Another notable feature of SWIFT is its statistical approach to model selection (see, e.g., James *et al.* (2013)), and building estimating models (say, by using stepwise regression to screen out variables with low p-values, rather than selecting these variables based on economic theory on household consumption).[23]

However, it can be useful to note some potential limitations of SWIFT. First, the (distributions of the) parameters β_1 , υ_1, and ε_1 are likely to change more over longer time periods. Consequently, these parameters would need to be updated more frequently for better predictions, which would effectively require a more regular implementation of the full household consumption survey rather than just a reduced set of variables. Second, a full household survey (with or without consumption data) may likely offer more precision with reproducing the whole income distribution and related welfare measures (such as inequality measures). Consequently, SWIFT's advantages of less expensive data collection costs and potentially faster poverty imputation should be carefully balanced against these limitations. Furthermore, more validation of this method is needed.[24]

III.4. Missing Panel Consumption Data

We now turn to the last category of missing panel data (Table 1, Category C). Pseudo-panels analysis has been developed to deal with situations with missing panel household consumption (see, e.g., Deaton (1985)), but these methods are rather data-demanding, and require multiple rounds of cross sections for analysis. Furthermore, perhaps because of their emphasis on cohorts rather than the household or individual, these methods have not been applied to the study of many dynamic situations involving persistent low consumption spells (Browning *et al.*, 2003). New methods have recently been proposed to address these limitations, by constructing synthetic panels from as few as two rounds of cross sections that can help provide insights into the dynamics of poverty (Dang *et al.*, 2014; Dang and Lanjouw, 2013) and other related welfare outcomes such as vulnerability and shared prosperity (Dang and Lanjouw, 2016 and 2017). These synthetic panels have been increasingly employed in a variety of contexts.[25]

Let x_{ij} be a vector of household characteristics observed in survey round *j* (j= 1 or 2) that are also observed in the other survey round for household i, i= 1,…, N. These household characteristics can include such time-invariant variables as ethnicity, religion, language, place of birth, parental education, and other time-varying household characteristics if retrospective questions about the round-1 values of such characteristics are asked in the second-round survey. To reduce spurious changes due to changes in household composition over time, we usually restrict the estimation samples to household heads age, say 25 to 55 in the first cross section and adjust this age range accordingly in the second cross section. Note that this age range is usually used in traditional pseudo-panel analysis but can vary depending on the cultural and economic factors in each specific setting.

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

$$y_{ij} = \beta_j' x_{ij} + \varepsilon_{ij} \tag{11}$$

Let z_j be the poverty line in period j. We are interested in knowing the unconditional measures of poverty mobility such as

$$P(y_{i1} < z_1 \; and \; y_{i2} > z_2) \tag{12}$$

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

$$P(y_{i2} > z_2 | y_{i1} < z_1) \tag{13}$$

which represents the percentage of poor households in the first round that escape poverty in the second round.[26]

If panel data are available, we can estimate the quantities in (12) and (13); but in the absence of such data, we can use synthetic panels to study mobility. To operationalize the framework, we make two standard assumptions. First, we assume that the underlying populations being sampled in survey rounds 1 and 2 are identical such that their time-invariant characteristics remain the same over time (Assumption V.1). More specifically, coupled with Equation (11), this implies the conditional distribution of expenditure in a given period is identical whether it is conditional on the given household characteristics in period 1 or period 2 (i.e., $x_{i1} = x_{i2}$ implies $y_{i1}|x_{i1}$ and $y_{i1}|x_{i2}$ have identical distributions). Second, we assume that ε_{i1} and ε_{i2} have a bivariate normal distribution with positive correlation coefficient ρ and standard deviations σ_{ϵ_1} and σ_{ϵ_2} respectively (Assumption V.2). Quantity (12) can be estimated by

$$P(y_{i1} < z_1 \; and \; y_{i2} > z_2) = \Phi_2(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, -\frac{z_2-\beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, -\rho) \quad (14)$$

where $\Phi_2(.)$ stands for the bivariate normal cumulative distribution function (cdf)) (and $\phi_2(.)$ stands for the bivariate normal probability density function (pdf)). Note that in Equation (14), the estimated parameters obtained from data in both survey rounds are applied to data from the second survey round (x_2) (or the base year) for prediction, but we can use data from the first survey round as the base year as well. It is then straightforward to estimate quantity (13) by dividing quantity (12) by $\Phi(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon_1}})$, where $\Phi(.)$ stands for the univariate normal cumulative distribution function (cdf).

In Equation (14), the parameters β_j and σ_{ε_j} are estimated from Equation (1), and ρ can be estimated using an approximation of the correlation of the cohort-aggregated household consumption between the two surveys, which yields an estimate for $\rho_{y_{i1}y_{i2}}$. The partial correlation coefficient ρ can then be estimated by

$$\rho = \frac{\rho_{y_{i1}y_{i2}}\sqrt{var(y_{i1})var(y_{i2})} - \beta_1' var(x_i)\beta_2}{\sigma_{\varepsilon_1}\sigma_{\varepsilon_2}} \quad (15)$$

Note that the standard errors of estimates based on the synthetic panels can in fact be even smaller than that of the true (or design-based) rate if there is a good model fit (or the sample size in the target survey is significantly larger than that in the base survey; see Dang and Lanjouw (2013) for more discussion).

Equation (14) can be extended to the more general case of vulnerability. For example, we can estimate the percentage of poor households in the first period that escape poverty but still remain vulnerable in the second period (joint probability) as

$$P(y_{i1} < z_1 \; and \; z_2 < y_{i2} < v_2) = \Phi_2\left(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, \frac{v_2-\beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right) - \Phi_2\left(\frac{z_1-\beta_1' x_{i2}}{\sigma_{\varepsilon_1}}, \frac{z_2-\beta_2' x_{i2}}{\sigma_{\varepsilon_2}}, \rho\right) \quad (16)$$

Other formulae and more detailed derivations for other measures of vulnerability dynamics are provided in Dang and Lanjouw (2017) (which also offers formulas for the more general income transition matrix). We further offer *Illustrative Example 5* in Section IV.4 to discuss an application of synthetic panels in measuring poverty mobility.

IV. Empirical Analysis

We start first with briefly discussing the data sources, before offering the illustrative examples in this section.

IV.1. Data Sources

We use the latest three rounds of the household survey data from Vietnam—the Vietnam Household Living Standards Surveys (VHLSSs)—in 2010, 2012, and 2014. Being similar to the Living Standards Measurement Study (LSMS) surveys supported by the World Bank, these surveys are implemented biennially by Vietnam's General Statistical Office (GSO) and collect rich data on household demographics, education, occupation, assets, and consumption. These surveys are regularly employed by the Government of Vietnam and international organizations to provide estimates on household welfare and poverty measures.[27] Since the VHLSSs collect panel data, these surveys offer an ideal setting for us to evaluate the different imputation methods. The key idea is to construct each welfare measure as if we did not have consumption data, and then evaluate the former against the latter.

In particular, we construct a wealth index and compare how it performs against the actual consumption data in measuring poverty (Category A), impute consumption from one previous round to the next round and compare the imputed consumption against the actual consumption (Category B), and compare the synthetic panels against the actual panel data (Category C). For this category, a particularly useful feature of the VHLSSs is that it has a rotating panel design, whereby approximately half of the households are followed and half are refreshed in each new survey round. We will make use of this feature to provide poverty estimates using the synthetic panels constructed from the cross-sectional component of the VHLSSs, and then validate these estimates against the "true" rates that are based on the panel component of the VHLSSs.

IV.2. Completely Missing Consumption Data

Illustrative Example 2

We provide an illustrative example where the wealth index is generated using both the simple aggregation (Table 3, Model 1) and the PCA method (Table 3, Models 2 and 3) on the VHLSSs in 2012 and 2014. (Further details on the implementation are provided in Appendix 2.) Each cell in the first five rows shows the proportion of each quintile of the consumption distribution that is correctly captured by each quintile of the wealth index. These quintile divisions may also be considered as different poverty lines. The list of assets for Model 1 includes (whether the household has) a car, a motorbike, a bicycle, a desk phone, a mobility phone, a DVD player, a television set, a computer, a refrigerator, an air conditioner, a washing machine, and an electric fan. Model 2 adds to Model 1 the construction materials for the house's roof and walls, Model 3 adds to Model 2 the type of water and toilet the household has access to.

Estimation results concur with Proposition 1, where each of the quintiles based on the wealth index can only capture around half of the corresponding quintile based on the consumption distribution. For example, the poorest wealth index quintile in Model 3 can correctly capture only 57 and 47 percent of the poorest consumption quintile respectively in 2012 and 2014. Alternatively, we also show the proportion of the cumulative consumption distribution that is correctly captured by the wealth quintiles in Appendix 3, Table 3.1.[28] Estimation results are, however, qualitatively similar where taken altogether, the wealth quintiles can correctly capture between 60 percent and 80 percent of the corresponding consumption quintiles. Notably, the correlation between asset indexes and household consumption is higher for the PCA wealth index than for the simple aggregation method (e.g., this correlation is 0.61 for Model 1 in 2012, but increases to 0.67 and 0.70 respectively for Models 2 and 3 in the same year).

These results are broadly consistent with the empirical evidence offered in recent studies. Reviewing 17 studies that analyze 36 different data sets, Howe *et al.* (2009) observe a poor correlation between wealth indexes and household consumption. Filmer and Scott (2012) analyze survey data from 11 countries from four continents and find a similar result. Furthermore, Filmer and Scott (2012) also find that the correlation between wealth indexes and consumption is only stronger under certain, and more demanding, conditions such as urban settings, limited measurement errors, and a small share of individually consumed goods (e.g., food) in total expenditures.[29] The latter caveats can perhaps also be partly explained by the fact that, wealth indexes are a stock measure, rather than a flow measure as with household consumption.[30]

Tracking Welfare over Time with Wealth Indexes

Illustrative Example 3

As earlier discussed, since wealth indexes are biased estimates of household consumption levels, they appear likely to provide biased estimates of consumption trends as well. We provide an illustrative example in Table 4, where we compare the growth of consumption (second column) against those of wealth indexes. We use two versions of the wealth indexes, the first is the simple aggregation method (or wealth index 1), and the second the PCA method (or wealth index 2, same as Model 3 in Table 3) after pooling all data for the three survey years. The list of the assets that are used is the same as that used for Model 1 in Table 3.[31] Table 4 shows that the growth rate of mean per capita consumption widely differs from that of the wealth indexes between 2010 and 2012: while the former is around 2 percent, the growth rate of wealth index 1 is higher at 10 percent, and even negative at -11 percent for wealth index 2 (Panel A). The growth rate of mean per capita consumption and the growth rate of the wealth indexes differs as well between 2012 and 2014 (Panel B), but a different result emerges where the former is now larger than that of wealth index 1 but still smaller than that of wealth index 2.

This empirical result qualitatively concurs with that offered by Harttgen, Klasen, and Vollmer (2013), who analyze 160 DHS surveys from 33 African and 34 non-African countries and construct wealth indexes in different ways as well. In particular, Harttgen *et al.* (2013) argue that employing wealth indexes as a proxy for trends in household consumption is subject to several different types of biases. For example, one is due to changing preferences for certain assets (e.g., the increasing ownership of smart phones), another changing relative prices among different assets leading to more demand for one asset at the expense of others (e.g., the dramatically decreasing price of smart phones).[32]

Still, we end this section on an optimistic note that more methods have recently been developed in an effort to provide more comparable wealth indexes over time. For example, a promising direction of research is offered by Rutstein and Staveteig (2014), who adjust, relative to a reference country, a country-specific wealth index using the country-level relationship between some "unsatisfied basic needs" and ownership of certain basic assets such as a car, a refrigerator, a landline telephone, and a television. This study builds on earlier studies that employ asset indexes to analyze poverty trends over time (e.g., Sahn and Stifel (2000)), but it does not use consumption data to validate its estimates based on the asset indexes.

IV.3. Partially Missing Consumption Data

We discuss the empirical results that correspond to the theory in Section III.3.1 and Section III.3.2 with the illustrative example below.

Illustrative Example 4

We start with checking Assumptions IV.1 and IV.2 before discussing estimation results. Since all the 2010, 2012, and 2014 rounds of the VHLSS share the same sampling frame based on the 2009 Population and Housing Census, and their questionnaire design remains almost identical,[33] Assumption IV.1 for a similar survey design is satisfied. We can test for Assumption IV.2 for the period 2010-2012 using the decomposition provided in Equation (10).

We start first with building the estimation models on a cumulative basis for illustration purposes, with later models sequentially adding more variables to earlier models. Model 1 is the most parsimonious model and consists of household size, household heads' age, gender, highest completed levels of schooling, a dummy variable indicating whether the head belongs to the ethnic majority group, and a dummy variable indicating urban residence. Model 2 adds to Model 1 the household demographics such as the shares of household members in the age ranges 0-14, 15-24, and 25-59 (with the reference group being those 60 years old and older), a dummy variable indicating whether the head worked in the past 12 months. Model 3 adds to Model 2 asset variables, the construction materials for the house's roof and walls, and the type of water and toilet the household has access to, which are the same as those employed in our earlier analysis of wealth indexes. Full model specifications are provided in Appendix 3, Table 3.2.

We then predict consumption, using the estimated coefficients from the preceding years (i.e., the estimated coefficients are respectively from 2010 and 2012 for our predicted consumption in 2012 and 2014). Decomposition results, shown in Table 3.3, suggest that as the list of control variables becomes richer, the change in poverty that can be explained by the *x* characteristics grows proportionately larger. For example, this component increases from around 60 percent in Model 1 to 62 percent in Model 2, and then close to 100 percent in Model 3 for the period 2010-2012. For the period 2012-2014, Models 1 and 2 do not perform as well with less than 20 percent of the change in poverty being explained by the *x* characteristics under these models. However, Model 3 offers a good estimation model and can explain almost all the change in poverty.[34] This indicates that Assumption 2 is largely satisfied with Model 3 for both periods, and less likely to be satisfied with the remaining models.

Table 5 provides the estimation results for the predicted poverty rates based on the imputed data. Estimation results show that our estimates using Model 3 indeed fall within one standard error of the true poverty rates for both 2012 and 2014. For example, our predicted poverty rate for 2014 is 13.1 percent using the normal linear regression model, which is inside the one-standard-error interval of the true poverty rate of [13.0, 14.0] for the same year. As a further robustness check, we also show the estimation results where we predict consumption for 2014, but use the estimated coefficients from 2010 (instead of those from 2012). The longer time interval may reduce the precision of the estimates if the changes in the estimated coefficients dominate the change in the *x* characteristics. Indeed, the estimates shown under Models 1 and 2 in Table 3.4 are much farther from the true poverty rate than the corresponding figures in Table 5. But the estimates under Model 3 in Table 3.4 show that we have similar, or slightly better, results. The latter results may perhaps suggest that variable omission is more important to obtain good estimates than a shorter interval between the survey rounds, but certainly more evidence is needed on this area.

For further comparison, we also provide estimates using MI methods in Table 3.5. Two imputation models are used, one is the normal linear regression and the other the predictive mean matching, which offer the closest corresponding modeling options to the normal linear regression model and the empirical distribution of the error terms model provided in Table 5. Estimation results suggest that both methods, in particular the predictive mean matching method, work reasonably well (using our preferred Model 3). In fact, the predictive mean matching method may offer even slightly better estimates than those in Table 5. However, there are two limitations with MI methods: the variance for MI estimates are larger than those offered in Table 5, and it takes more computer time to obtain these estimates which, particularly in low-capacity geographies, can still be a somewhat of a constraint.[35]

It can be useful to briefly discuss estimation results based on proxy means testing. As discussed earlier, proxy means testing would likely provide biased poverty estimates (Proposition 2). The intuition behind this result is that predicted poverty does not appropriately adjust for the error term, and is based on the deterministic part of Equation 1 only (see Equation 5). Indeed, estimation results (Table 3.6) show that the estimated poverty rates are much lower than the true poverty rates, with the difference ranging around 5 percentage points for Model 3 in both years.

IV.4. Missing Panel Consumption Data

Illustrative Example 5

Table 6 provides the estimates for both unconditional and conditional poverty mobility using the synthetic panels, and then compares these estimates with those based on the true panels. Several remarks are in order for this table. First, the synthetic panel estimates approximate those of the true panel estimates reasonably well. In particular, all the point estimates based on the synthetic panels fall within the 95 percent confidence intervals (CIs) of those based on the true panels, and even fall within one standard error of the latter in one case. That is, the unconditional probability estimate for those who remain poor in both years is 10.8 percent, which is almost identical to the corresponding estimate based on the true panel of 10.7 percent. Second, all the 95 percent CIs of the synthetic panel estimates overlap with those of the true panels for at least half or more. This is due to the fact that the synthetic panel estimates are model-based estimates, thus these estimates generally should have smaller standard errors than those using the actual panels (which are usually referred to in the survey statistics literature as the design-based estimates). Finally, estimates for the conditional probabilities are somewhat less accurate than those for the unconditional probabilities since obtaining the latter entails prediction for both the numerator and the denominator of (12)-type quantities.[36]

V. Further Discussion and Conclusion

We offer in this paper a review of poverty measurement methods in contexts where consumption data are missing or have inadequate quality. Some of the methods we reviewed are more established, but some are rather recent. While micro survey data are becoming more widely available and collected more frequently in developing countries, we expect these methods to be useful for the foreseeable future, including for backcasting consumption from a more recent survey for better comparison with older surveys.

In addition, these imputation methods may also be appropriate in contexts where survey costs and/or survey implementation pose a challenge. For example, perhaps most national statistical agencies are keen on producing annual poverty statistics. But few, if any, developing countries can afford the associated expenses and demanding logistics of fielding a household consumption survey every year; rather, they are likely to implement the household consumption survey every few years. Furthermore, poverty-reduction projects are often hard-pressed to measure the welfare impact of a given intervention but face severe constraints in terms of capacity and resources to field complex surveys. In such contexts, poverty rates can be imputed for the intervening years between the surveys, or for project zones of influence, at just a fraction of the cost of fielding a full-fledged consumption survey by, say, using other non-consumption data or implementing a lighter (non-consumption) version of the survey.[37]

Seen in this light, imputation techniques can offer a low-cost and arguably wieldy approach to poverty estimation. While we should be mindful of the various assumptions underlying imputation methods as discussed in this paper, we would earnestly call for more attention to further developing these methods, and particularly validation studies to provide richer evidence on contexts where these methods may or may not work, or how well these methods work. In this paper we have attempted to review the state of the art, offer some new theoretical results, and put forth some practical prescriptions based on the analysis of a unique dataset enabling the validation and comparison of different methods. Beside the need for further validation, the challenge is also how to scale up the adoption of these somewhat complex methods in low-capacity geographies. Besides supporting the more traditional (national or regional) capacity building programs for staff from national statistical offices and other local stakeholders, a complementary and possibly more effective approach would be through selective pairing of international experts with these staff, who can form small teams that provide further analysis with low costs. Yet, another approach is to incorporate these imputation methods in existing popular software platforms with an accompanying guidebook (see, for example, Foster *et al.* (2013)) that can provide user-friendly and self-contained access to development practitioners.

Finally, we would like to conclude by noting a promising area for further research on the use of subjective well-being data to provide richer analysis of poverty. While there appears no consensus yet on the use of such data,[38] it can be argued that if poverty is multi-dimensional, subjective assessment of poverty can further enrich its measurement.

Notes

[1] For details see https://sustainabledevelopment.un.org/sdg1.

[2] Throughout this paper we are focused primarily on consumption as this is the measure of well-being that is most frequently used in the world for assessing poverty status, but we also note that income is used as a measure of well-being in many cases. For example, the 2012 global poverty estimates reported in Ferreira *et al.* (2016) are based on data from 131 countries, of which 99 use consumption as the measure of well-being and 32 use income. In an abuse of terminology, we refer to "consumption" and "income" interchangeably as the measure of household living standards in this paper. We also focus on the poverty headcount ratio as our main poverty measure. See also Ravallion (2016) for a comprehensive discussion on the history of thought on poverty and other measurement approaches.

[3] The observed pattern between missing data and national income is also particularly relevant for estimates of the global poverty rate produced by international organizations such as the World Bank. In particular, Jolliffe *et al.* (2015) indicate that the approach used by the World Bank to imputing poverty rates for those countries with missing poverty data is simply to assume that the data are missing at random within each region (e.g., replacing the missing poverty rate for the Democratic People's Republic of Korea with the average poverty rate in East Asia). The systematic correlation between missing survey data and national income observed in Figure 1 suggests that this assumption is untenable, and can result in a downward bias in the global poverty count.

[4] We also make available the Stata do files that generate the estimation results in this paper.

[5] There is perhaps some strong consensus among policy makers regarding this as well. For example, the United Nations most recently decided to monitor the global poverty rate as the proportion of the population living below the international poverty line of US$1.90 per day. But see also Alkire *et al.* (2015) for a comprehensive discussion of the alternative approach of multi-dimensional poverty.

[6] Household consumption data may not exactly be comparable across different countries without a common conversion system for prices of goods and services. The International Comparison Program (ICP) is an international effort to address this issue (World Bank, 2015). See also Crossley and Winter (2015) and the 2015 special issue of the *Journal of Development Studies* for further discussion on survey comparability issues.

[7] Beegle *et al.* (2016) offer a review of studies that use the existing panel data for African countries and find much variation in the estimates for chronic poverty and transient poverty. Furthermore, it is argued that a considerable proportion of these estimates of poverty mobility are subject to measurement errors in income or consumption (Dercon and Krishnan, 2000; Glewwe, 2012; Lee *et al.*, 2017). See also Dercon and Shapiro (2007) for a brief discussion of various panel data sources for developing countries.

[8] See Grosh and Glewwe (2000) for a systematic treatment of the different steps involved in fielding an LSMS-type survey.

[9] Unless otherwise noted, for brevity we hereafter follow the common practice and do not use the term "cross sectional" when referring to such data, but we explicitly mention the term "panel data" when discussing these data.

[10] There is thus some overlap between this sub-case and the non-consumption surveys in Group A. But note that we focus on the *absence* of consumption data in Group A, and the *similarity* between consumption surveys and other surveys in Group B. Put differently, we consider non-consumption surveys on their own in Group A but highlight their relationship with other consumption surveys in Group B.

[11] See also Gustafsson, Shi, and Sato (2014) for a detailed discussion of the various consumption surveys in China.

[12] Our estimates are based on figures from the PovCalNet database for the period 2010-2014. Also note that all the surveys in Tables fall under Category B(iii), since they are by design not census. Category B(i) applies to earlier rounds of the NSS as discussed earlier.

[13] Although we mark the NSS as belonging to Category B (since the design of the consumption module changed between the 2009/10 and 2011/2 rounds), Dang and Lanjouw (in press) suggest that these differences are negligible in practice.

[14] More generally, *j* can indicate any type of relevant surveys that collect household data sufficiently relevant for imputation purposes such as labor force surveys or demographic and health surveys. To make notation less cluttered, we suppress the subscript for each household in the following equations.

[15] Regional characteristics related to macroeconomic trends such as (un)employment rates or commodity prices can also be included if such data are available.

[16] See, for example, Jolliffe (2002) for a comprehensive treatment of PCA methods.

[17] In addition, assets take time to depreciate and to be sold/ bought so they are not as smooth as consumption in capturing household welfare.

[18] Government agencies in richer countries such as the U.S. Census Bureau regularly rely on statistical techniques known as "small-area" estimation methods (see, e.g., Bell *et al.* (2007)) to impute poverty numbers at different administrative levels. These methods essentially impute from a household (income or) consumption survey into a population census to provide more spatially disaggregated measures of consumption and poverty for better targeting purposes. Interested readers are encouraged to refer to the studies by Elbers *et al.* (2003), Tarozzi and Deaton (2007), and Rao and Molina (2015) on spatial targeting with poverty map, or "small-area" estimation methods. We offer further discussion in the working paper version of this paper (Dang, Jolliffe, and Carletto, 2017).

[19] We offer more formal discussion of these results in the proof for Proposition 2 in Appendix 1.

[20] See also Dang and Lanjouw (in press) for a discussion of more recent, albeit less severe, comparability issues with the NSSs in the late 2000s.

[21] Elbers *et al.* (2003) provide a method that imputes household consumption from a survey into a population census. Adapting this approach for survey-to-survey imputation, Christiaensen *et al*. (2012) impute poverty estimates using data from several countries, including China, Kenya, the Russian Federation, and Vietnam; other studies analyze data from Uganda (Mathiassen, 2013).

[22] Douidich *et al.* (2016) offer an early application of MI methods to poverty imputation. See also Davey, Shanahan, and Schafer (2001) and Jenkins *et al.* (2011) for studies that apply MI techniques to economic issues. More discussion on the differences between the two literatures and references to earlier imputation studies are provided in Table 1 in Dang *et al.* (2014) and Dang *et al*. (2017), which also provides poverty estimates using MI methods for comparison purposes.

[23] Due to various post-survey data quality control procedures such as data entry, cleaning and checking, household survey data are usually unavailable for use from until half a year to longer with most household surveys. But this situation may improve with the increased use of tablet-based (or hand-held devices-based) data collection.

[24] An additional technical limitation is that SWIFT has to rely more heavily on the assumption of constant parameters than most other previous studies. As yet, there appear to be no published validation studies besides those offered in Yoshida *et al.* (2015).

[25] Since these synthetic panels are constructed using repeated cross sections, they may be less affected by issues specific to actual panel data such as measurement errors and attrition. Recent applications and further validations include Ferreira *et al.* (2013), Cruces *et al.* (2015) and Vakis *et al.* (2015) for Latin American countries, Martinez *et al.* (2013) for the Philippines, Garbero (2014) for Vietnam, Bourguignon and Moreno (2015) and Foster and Rothbaum (2015) for Mexico, Cancho *et al.* (2015) for countries in Europe and Central Asia, Dang and Ianchovichina (forthcoming) for countries in the Middle East and North Africa region, Dang and Dabalen (in press) and Dang, Lanjouw and Swinkels (2017) for countries in Suh-Saharan Africa, and Dang and Lanjouw (2017 and in press) for India, Vietnam, and the United States. Researchers at international organizations including the UNDP and the Asian Development Bank have also applied these methods for analysis of welfare mobility (UNDP, 2016; Jha *et al.*, 2018); see also OECD (2015) for an application by the OECD to study labor transitions in richer countries.

[26] We examine a specific form of poverty and vulnerability transitions as shown in Equations (12), (13), and (16). Dang and Dabalen (in press) offer some further decomposition of these poverty transitions. For discussion on other types of poverty dynamics, see also Rodgers and Rodgers (1993), Jalan and Ravallion (2000), McCuloch and Calandrino (2003), Hulme and Shepherd (2003), and Foster (2009). One option to estimate these other poverty dynamics is to construct synthetic panels with household consumption level (using the techniques in Dang *et al.* (2014) or Bourguignon and Moreno (2015) instead of the probabilistic formulae in Equation (12)), which we leave for future research.

[27] An additional advantage of these data is the availability of community targeting, i.e., a household poverty status as classified by the local government. We will make use of this feature and present it together with the analysis based on consumption data.
[28] In this case, the poverty line can equal the 20th, 40th, or 60th (and so on) percentile of the wealth index distribution.
[29] Some other practical issues with using wealth indexes to measure poverty are that it is unclear how to set the poverty line for wealth indexes (compared with the more established calorie-intake or cost-of-basic-needs with the consumption-based poverty line) or that asset ownership may also be affected by factors related to supply but not household consumption (e.g., inadequate water supply may result in less ownership of flush toilets or washing machines).
[30] Various alternative approaches have been implemented for surveys that have no consumption data, but mostly in the context of richer countries. For example, one alternative approach is to collect data on a reduced set of consumption items that may offer strong correlation with the total consumption aggregate (Morris *et al.*, 2000), or simply ask an overall question for the household's total consumption in the past (calendar) month (Browning, Weber, and Crossley, 2003). A related approach is to impute total household consumption in one survey, using the predicted coefficients from a reduced set of consumption items in another survey (Skinner, 1987; Blundell, Pistaferri, and Preston, 2008). But Friedman *et al.* (2017) offer recent evidence for Tanzania that collecting data on a reduced set of food consumption items does not save time but introduces substantial errors to the total consumption. Another approach is to produce households' ranks in the population with the number of consumption items they own, if we make the additional assumption that households place an order of importance on their consumption items when having to reduce their consumption expenditure (Deutsch, Silber, and Wang, 2017). We return to more discussion on the survey imputation approach in Section IV.
[31] The reason we pool the data is to make the wealth indexes comparable over time, since applying the PCA method to each year separately as with Table 3 would standardize these indexes to a mean 0 for each year. We use the same assets as in Model 1, Table 3 for easier interpretation with the count index; estimation results (not shown) using additional assets in the other models (Models 2 and 3) provide qualitatively similar results.
[32] Although providing biased poverty estimates in a static period, wealth indexes may not necessarily provide biased estimates of trends in household consumption (or poverty) over time. If the degree of bias for both wealth indexes and household consumption is similar over time, wealth indexes can provide unbiased estimates. As an (extreme) example, if the bias of the mean of a wealth index as a measure of mean household consumption remains constant at 10 percent for all time periods, this bias would cancel out for estimates of the trends in consumption—or the relative growth of the mean. We provide more formal discussion of this result in the proof for Proposition 1.
[33] The VHLSSs have a rotating module that collect more detailed data on certain topic in each survey round. For example, the 2014 VHLSS collects more data on land access and ownership. But more importantly for our purposes, the core modules that collect data on household demographics, education, assets, and house materials remain the same over these survey rounds.
[34] Table 3.3 also shows that the R^2 is much higher with Model 3 at 0.69 for both periods, compared with a range of 0.41-0.46 for Models 1 and 2. The switch from positive to negative of these models can suggest that Assumption IV.2 is more flexible compared to the commonly made assumption of constant parameters in previous studies. This is further supported by the Wald test that rejects the latter assumption for all models (Table 3.3). But also note that model specifications where the changes in the explanatory variables x can explain much more than 100 percent of the changes in poverty may also indicate model overfitting. Furthermore, Dang *et al.* (2017) observe that it is generally ill-advisable to include certain assets whose correlations with consumption change dramatically over the two periods due to other factors such as technology. A notable example is that in certain developing countries cell phones could get mass produced quickly and their prices were lowered to the extent that they could no longer be considered a luxury good in the second period.
[35] Furthermore, as earlier discussed, these estimates are based on Model 3, which is selected using the method proposed in Dang *et al.* (2017). These results are also consistent with MI estimation results using household survey data from Jordan offered in this study.
[36] This is also consistent with the theoretical and empirical evidence provided in Dang and Lanjouw (2013).
[37] Kilic *et al.* (2017) estimate the average cost of implementing a recent household consumption survey (in 2014 or later) to range from approximately US$800,000 to US$5 million, depending on the context and sample sizes. On the other hand, applying poverty imputation methods would most likely require only researchers' time costs.

[38] It is even proposed that a "social subjective poverty line", below which people tend to think they are poor, can be a conceptual alternative to defining poverty (Ravallion, 2014). Other researchers are more optimistic, and support the employment of subjective wellbeing data at both the national level (Allin and Hand, 2017) and the global level (Helliwell, Layard, and Sachs, 2017). On the other hand, some empirical evidence suggests that poverty may not necessarily overlap with unhappiness or other subjective assessments in a number of countries (see, e.g., Banerjee and Duflo (2007), Rojas (2008), Graham, (2010), and Dang and Ianchovichina (forthcoming)). More specifically, some researchers even suggest that cross-country rankings based on self-reported happiness in the World Value Surveys can be rather sensitive to the assumption made to transform it from the unobserved latent and continuous variable into an observed discrete variable (Bond and Lang (2014); Gibson (2016)). A left-skew transformation indicates that some countries in the OECD (Organization for Economic Cooperation and Development) are happiest, while some African countries such as Ghana are least happy. But a right-skew transformation would place Ghana as the happiest country and reduce the rankings of the OECD countries that were at the top under the assumption of a left-skew distribution by more than 20 places. This sensitivity would require further explorations into an appropriate imputation model that is more robust to assumptions about the functional form of the distribution of the error terms (e.g., using the empirical distribution of the error terms). But these technical challenges with analyzing subjective well-being data, if overcome, may open up new applications such as producing a "happiness map" for different regions within a country or globally. See also Dang *et al.* (2017) for discussion on other promising topics for future research, including measurement errors and big data.

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Table 1: Categories of Missing Household Consumption Data and Commonly Employed Imputation Methods

Type	Extent of Missing Consumption Data	Typical Situation	Example	Imputation Method
A	Completely missing	i) Non-consumption surveys ii) Most small-scale surveys	Demographic and Health Surveys	Wealth index
B	Partially missing	i) Consumption data not comparable across survey rounds	Some rounds of India's National Sample Surveys	Survey-to-survey imputation
		ii) Consumption data unavailable in current survey but available in another related survey	The annual LFS does not have consumption data, but the household consumption survey is implemented every few years	
		iii) Consumption data unavailable at more disaggregated administrative levels than those in current survey	Population census data are representative at lower administrative level than a household consumption survey, but does not collect consumption data.	Survey-to-census imputation or poverty "mapping"
C	Available cross sections, but missing panel data	Most surveys in developing countries do not offer panel data		Synthetic panels

Note: LFS stands for Labor Force Surveys.

Table 2: Examples of Recent Household Consumption Surveys Assigned to Different Data Categories

No	Country	Survey	Category	Survey Years	Main Host Agency	Website
1	**China**					
1.1		China Household Income Project (CHIP)	C	2002, 2007, 2013	Beijing Normal University	http://ciid.bnu.edu.cn/index.asp?lang=EN
1.2		China Health and Nutrition Survey (CHNS)	P	2000*, 2004*, 2006*	University of North Carolina at Chapel Hill	http://www.cpc.unc.edu/projects/china
1.3		Chinese Family Panel Studies (CFPS)	P	2010, 2012, 2014, 2016	Peking University	http://www.isss.pku.edu.cn/cfps/EN/About/
2	**Ethiopia**					
2.1		Demographic and Health Survey (DHS)	A	2000, 2005, 2011, 2016	ORC Macro	https://dhsprogram.com/data/available-datasets.cfm
2.2		Household Consumption Expenditure Survey (HCE)	C	2000, 2004, 2011, 2016	Central Statistical Agency	http://www.csa.gov.et/survey-report/category/350-hice-2016
2.3		Ethiopia Socioeconomic Survey (ERSS)	P	2011/12*, 2013/14, 2015/16	World Bank's Survey Unit & Central Statistical Agency	http://surveys.worldbank.org/lsms/integrated-surveys-agriculture-ISA/ethiopia
3	**India**					
3.1		Demographic and Health Survey (DHS)	A	2005/06, 2015/16	ORC Macro	https://dhsprogram.com/data/available-datasets.cfm
3.2		National Sample Survey (NSS)	B, C	2004/05, 2009/10, 2011/12	National Sample Organization	http://www.mospi.gov.in/national-sample-survey-office-nsso
3.3		India Human Development Survey (IHDS)	P	2004/05, 2011/12	University of Maryland	https://ihds.umd.edu/
4	**Indonesia**					
4.1		Demographic and Health Survey (DHS)	A	2002/03, 2007, 2012	ORC Macro	https://dhsprogram.com/data/available-datasets.cfm
4.2		National Socio-Economic Survey (SUSENAS)	C	2000-2017 (annually)	Directorate of Social Welfare & Education Statistics	https://microdata.bps.go.id/mikrodata/index.php/catalog/756
4.3		Indonesian Family Life Survey (IFLS)	P	2000*, 2007/08*, 2014/15*	Rand Corporation	https://www.rand.org/labor/FLS/IFLS.html

Note: We use the same notation for data categories as with Table 1, with the additional Category P representating panel data. A star "*" sign on the survey year indicates that the data for that year are not nationally representative. We restrict the sample to surveys that were implemented in 2000 or later and that are publicly available.

Table 3: Population Distribution by Asset Indexes vs. Consumption, Vietnam 2012-2014 (percentage)

Per capita consumption	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Poorest quintile	64.3	52.9	57.1	43.8	43.2	46.6
Quintile 2	24.7	29.7	30.5	42.4	26.3	29.2
Quintile 3	24.6	27.4	28.7	23.5	32.0	28.6
Quintile 4	36.5	30.7	31.0	19.5	32.9	36.7
Richest quintile	39.6	55.4	57.2	47.2	60.8	62.9
Correlation with household consumption	0.61	0.67	0.70	0.59	0.64	0.67
N	9,396	9,324	9,324	9,399	9,348	9,348

Note: Each cell in the first five rows shows the percentage of the population that would be correctly captured for each consumption quintile if asset index was used. Model 1 provides a simple count of the number of assets a household possesses, while Models 2 and 3 construct the asset index using principal component method. The list of assets for Model 1 include car, motorbike, bicycle, desk phone, mobility phone, DVD player, television set, computer, refrigerator, air conditioner, washing machine, and electric fan. Model 2 adds to Model 1 the construction materials for the house's roof and wall, Model 3 adds to Model 2 the type of water and toilet the household has access to. All estimates are weighted by population weight.

Table 4: Growth in Asset Indexes vs. Growth in Consumption, Vietnam 2010- 2014 (percentage)

	Year/ Growth	Consumption (D'000)	Wealth index 1	Wealth index 2
	2010	18,683	5.24	0.16
Panel A	2012	19,026	5.76	0.14
	Growth rate	1.8	9.9	-10.5
	2012	19,026	5.76	0.14
Panel B	2014	20,941	6.08	0.18
	Growth rate	10.1	5.6	28.0

Note: Wealth index 1 provides a simple count of the number of assets a household possesses, while Wealth index 2 constructs the asset index using principal component method after pooling data for all three years. The list of assets for both wealth indexes include car, motorbike, bicycle, desk phone, mobility phone, DVD player, television set, computer, refrigerator, air conditioner, washing machine, and electric fan. All estimates are weighted by population weight.

Table 5: Predicted Poverty Rates Based on Imputation, Vietnam 2012-2014 (percentage)

Method	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
1) Normal linear regression model	21.3	21.1	17.5	16.7	16.6	13.1
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.4)
2) Empirical distribution of the error terms	21.1	20.9	17.5	16.4	16.4	13.0
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.4)
Control variables						
Parsimonious	Y	Y	Y	Y	Y	Y
Demographics & employment	N	Y	Y	N	Y	Y
Household assets & house characteristics	N	N	Y	N	N	Y
True poverty rate		17.2			13.5	
		(0.5)			(0.5)	

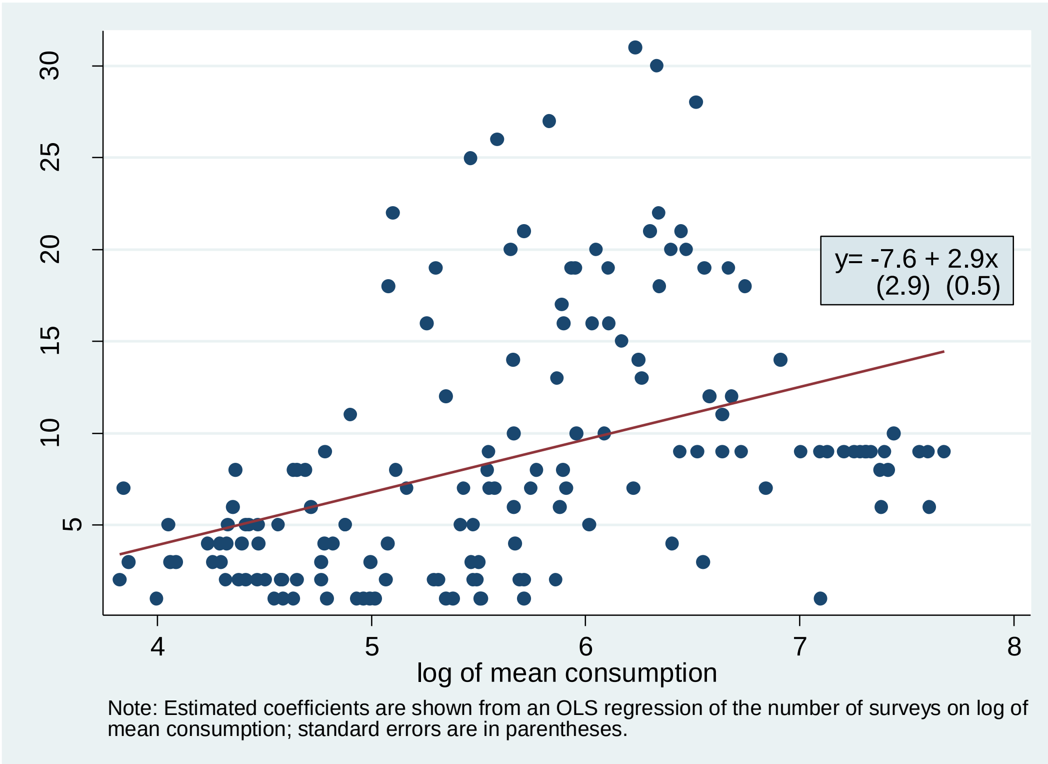
Note: Standard errors in parentheses are adjusted for complex survey design. All estimates are obtained with population weights. Method 1 uses the normal linear regression model with the theoretical distribution of the error terms and Method 2 uses the empirical distribution of the error terms. Both methods employ commune random effects. Imputed poverty rates for 2012 use the estimated parameters based on the 2010 data, and imputed poverty rates for 2014 use the estimated parameters based on the 2012 data. 1,000 simulations are implemented. The underlying regression results are provided in Appendix 3, Table 3.2. True poverty rate is the estimate directly obtained from the survey data.

Table 6: Poverty Dynamics Based on Synthetic Data, Vietnam 2012-2014 (percentage)

Panel A: Unconditional Probabilities			Panel B: Conditional Probabilities		
Poverty Status	**Actual panel**	**Synthetic panel**	**Poverty Status**	**Actual panel**	**Synthetic panel**
Poor, Poor	10.7	10.8	Poor--> Poor	61.1	64.9
	(0.8)	(0.3)		(2.2)	(1.3)
Poor, Nonpoor	6.8	5.9	Poor--> Nonpoor	38.9	35.1
	(0.5)	(0.1)		(2.2)	(0.6)
Nonpoor, Poor	4.6	4.0	Nonpoor--> Poor	5.6	4.8
	(0.5)	(0.1)		(0.6)	(0.1)
Nonpoor, Nonpoor	77.9	79.3	Nonpoor-->Nonpoor	94.4	95.2
	(1.0)	(0.4)		(0.6)	(0.3)
Goodness-of-fit Tests			*Goodness-of-fit Tests*		
Within 95% CI	4/4		Within 95% CI	4/4	
Within 1 standard error	1/4		Within 1 standard error	0/4	
Coverage of 50% or more	4/4		Coverage of 50% or more	4/4	
Coverage of 100%	2/4		Coverage of 100%	1/4	
N	2,639	3,519	N	2,639	3,519

Note: Synthetic panels are constructed from the cross-sectional component. The first survey round is used as the base year for imputation. Standard errors are obtained adjusting for complex survey design. All estimates are obtained with population weights. Household heads' ages are restricted to between 25 and 55 for the first survey round and adjusted accordingly with the year difference for the second synthetic panels fall within the 95% confidence interval (CI) of the estimates based on the actual panels; the "Within 1 standard error" row shows a similar figure but using one standard error around the estimates based on the actual panels. The "Coverage of 50% or more" row shows the number of times that half or more of the 95% CI around the synthetic panel estimates overlap with those based on the actual panels overlap with those based on the actual panels; the "Coverage of 100%" row shows a similar figure for the number of times that the former fall completely inside the latter.

Figure 1: Number of Household Surveys vs. Countries' Income Level, 1981- 2014



Data source: PovCalNet, 2017.

Appendix 1: Proofs
Proposition 1

The linear projection of household consumption onto household (and community) characteristics x_{ij} is given as follows (Equation (1))

$$y_{ij} = \beta' x_{ij} + \mu_{ij} \tag{1.1}$$

We provide three following sets of results in this proof

1a. the wealth index w_{ij} provides a biased estimator of household consumption y_{ij}

1b. poverty estimates based on w_{ij} tend to provide biased estimates of the poverty rates based on y_{ij}, and

1c. wealth indexes may not necessarily provide biased estimates of trends in household consumption (or poverty) over time (as discussed in footnote 20).

Part 1a. The wealth index w_{ij} provides a biased estimator of household consumption y_{ij}

Since x_{ij} is composed of different characteristics such as household tastes, labor supply, and assets (Deaton and Muellbauer, 1980; Deaton and Zaidi, 2002), we can also write out x_{ij} more clearly as consisting of two components, assets (a_{ij}) and non-assets variables (z_{ij})

$$y_{ij} = \beta_1' a_{ij} + \beta_2' z_{ij} + \mu_{ij} \tag{1.2}$$

Thus by the Gauss-Markov theorem (see, e.g., Greene (pp. 60, 2012)), the least square estimator $\hat{\beta}$, which is ($\hat{\beta}_1'$, $\hat{\beta}_2'$)', provides the (minimum variance) linear unbiased estimator of β.

On the other hand, reversing the two sides of Equation (2) for presentation purposes, we obtain wealth indexes using the following equation

$$w_{ij} = \gamma' a_{ij} \tag{1.3}$$

where $\hat{\gamma}$ provides the estimator for γ using PCA methods. Taking the expectations of (1.2) and (1.3) and comparing results, we have

$$E(y_{ij}) = E(\beta_1' a_{ij} + \beta_2' z_{ij} + \mu_{ij}) = E(\beta_1' a_{ij} + \beta_2' z_{ij}) \neq E(w_{ij}) = E(\gamma' a_{ij}) \tag{1.4}$$

Thus the wealth index w_{ij} provides a biased estimator of household consumption y_{ij}. Intuitively, this result is due to two reasons. First, the wealth index w_{ij} does not include the non-asset component z_{ij}, which is equivalent to the well-known issue of omitted variable bias. Second, β_1 and γ are generally different from each other, since the estimator for γ maximizes the variance in x_{ij}, while the estimator for β maximizes the variance in y_{ij}.[39]

Part 1b. Poverty estimates based on w_{ij} tend to provide biased estimates of the poverty rates based on y_{ij}

Since the wealth index w_{ij} provides a biased estimator for household consumption y_{ij}, poverty estimates based on w_{ij} tend to provide biased estimates of the poverty rates based on y_{ij}. Put differently, let *P(.)* denote the poverty function, and z_w and z_y respectively the poverty lines for the wealth index and household consumption, the following equation would generally hold true

$$P(w_{ij} \leq z_w) \neq P(y_{ij} \leq z_y) \tag{1.5}$$

Furthermore, while Equation (1.5) may be violated under some rare theoretical circumstance (e.g., by choosing a cutoff point below which the proportions of the population are equal for both w_{ij} and y_{ij}), the identification of z_w is no easy task. While there is an established theory underlying the construction of z_y (say, using a minimum basic needs or calorie-intake approach (see, e.g., Ravallion, 2016)), no such reliable theory currently exists for the construction of z_w. In practice, identifying z_w usually involves assuming a given level of poverty rate and set z_w at the corresponding percentile in the distribution (see, for example, Sahn and Stifel (2000)).

Part 1c. Wealth indexes may not necessarily provide biased estimates of trends in household consumption (or poverty) over time

It is in fact rather straightforward to see that wealth indexes may not necessarily provide biased estimates of trends in household consumption (or poverty) over time (as discussed in footnote 20). Let us specify the bias between the wealth index $w_{ij,t}$ and household consumption $y_{ij,t}$ at time *t* as follows

$$E(y_{ij,t}) - E(w_{ij,t}) = B_{ij,t} \quad (1.6)$$

Given the assumption that the degree of bias is similar for each cross-sectional survey round, or equivalently, we have the following hold regardless of time *t*

$$B_{ij,t} = B_{ij} \quad (1.7)$$

Thus, taking the difference between time *t* and time *t-1* for Equation (1.4), and plugging in Equation (1.5), we can estimate the trends in household consumption as follows

$$E\left(y_{ij,t}\right) - E\left(y_{ij,t-1}\right) = \left[E\left(w_{ij,t}\right) - B_{ij,t}\right] - \left[E\left(w_{ij,t-1}\right) - B_{ij,t-1}\right] = E(w_{ij,t}) - E(w_{ij,t-1}) \quad (1.8)$$

A similar result follows for poverty where we replace the wealth index $w_{ij,t}$ and household consumption $y_{ij,t}$ with the poverty function *P(.)* in Equation (1.6).

Proposition 2

Household consumption is predicted using proxy means tests as follows (i.e., Equation (5))

$$y_{ij}^{p} = \beta^{p\prime} x_{j,p} \quad (1.9)$$

We provide two following sets of results in this proof

2a. Proxy means testing tends to offer biased poverty estimate.

2b. The extent of bias using proxy means testing tends to be less than those using wealth indexes

Part 2a. Proxy means testing tends to offer biased poverty estimate.

Taking the expectation of (1.1), and (1.9) we have

$$E\left(y_{ij}\right) = E\left(\beta' \, x_{ij} + \mu_{ij}\right) = \beta' \, x_{ij} \quad (1.10)$$

$$E\left(y_{ij}^{p}\right) = \beta^{p\prime} x_{ij,p} \quad (1.11)$$

When the model is fully specified, the estimator for β^p is identical for that for β (i.e. using the same nationally representative household survey). When the model is not fully specified, $x_{ij,p}$ is a smaller subset of x_{ij}. This would result in β^p being a biased estimate for β, the mean of household consumption based on proxy means testing would provide a biased estimate for mean household consumption.

For the variance, taking the variance of (1.1), and (1.9) we have

$$V\left(y_{ij}\right) = V\left(\beta' \, x_{ij} + \mu_{ij}\right) = V(\beta' \, x_{ij}) + \mathrm{V}(\mu_{ij}) \quad (1.12)$$

$$V\big(y_{ij}^{p}\big) = V(\beta^{p\prime} x_{ij,p}) \quad (1.13)$$

When the model is not fully specified, we have

$$V(\beta_{x_{ij,p}}^{p'}) \leq V(\beta' \ x_{ij}) \leq V(\beta' \ x_{ij}\ ) + V(\mu_{ij}) = V\big(y_{ij}\big) \quad (1.14)$$

since $x_{ij,p}$ is a smaller subset of x_{ij}.

Following a similar argument as with Equation (1.5), the results above imply that proxy means testing tends to offer biased estimates of poverty.

Part 2b. The extent of bias using proxy means testing tends to be less than those using wealth indexes

The bias between household consumption and predicted consumption obtained by proxy means testing methods is

$$E\big(y_{ij}\big) - E\big(y_{ij}^{p}\big) = E(\beta' \ x_{ij}) - E(\beta^{p'} x_{ij,p}) \quad (1.15)$$

On the other hand, the bias between household consumption and the wealth index is

$$E\big(y_{ij}\big) - E\big(w_{ij}\big) = E(\beta' \ x_{ij}) - E(\gamma' a_{ij}) \quad (1.16)$$

If the estimation model is fully specified for the proxy means test, the bias in Equation (1.15) would be zero. However, if the estimation model is not fully specified, assume that $x_{ij,p}$ includes all the household assets a_{ij} and some other relevant household characteristics (e.g., education). By the Gauss-Markov theorem, the least square estimator for β^{p} provides the linear unbiased estimator, while γ is not. Consequently, the bias in Equation (1.15) is smaller than that in Equation (1.16). Replacing the expectation function in Equations (1.15) and (1.16), and using a similar argument as with Equation (1.5), the results above imply that proxy means testing tends to offer less biased estimates of poverty.

Proposition 3

The poverty rate P_2 in period 2 and its variance can then be estimated as

$$\hat{P}_2 = \frac{1}{S}\sum_{s=1}^{S} P(\hat{y}_{2,s}^{1} \leq z_1) \quad (1.17)$$

where the imputed consumption y_2^1 is estimated as

$$\mathrm{y}_2^1 = \beta_1' x_2 + \upsilon_1 + \varepsilon_1 \quad (1.18)$$

We provide two following sets of results in this proof

- *3a. Given assumptions IV.1 and IV.2, the imputed household consumption in equation (1.17) offers unbiased poverty estimates*
- *3b. The imputed consumption provides less bias and a better variance than the predicted consumption obtained by proxy means testing methods.*

Part 3a. Given assumptions IV.1 and IV.2, the imputed household consumption in equation (1.17) offers unbiased poverty estimates

The proof for this part is given in Dang *et al.* (2017).

Part 3b. The imputed consumption provides less bias and a better variance than the predicted consumption obtained by proxy means testing methods.

If the estimation model is fully specified for the proxy means test, there would be no bias between household consumption and imputed household consumption. Indeed, writing out the notation for each period, the bias between household consumption and imputed consumption is

$$E(y_2) - E(y_2^1) = E(\beta_2' x_{i2} + \mu_{i2}) - E(\beta_1' x_{i2} + \mu_{i1}) = E(\beta_2' x_{i2}) - E(\beta_1' x_{i2}) \qquad (1.19)$$

The corresponding bias between household consumption and predicted consumption obtained by proxy means testing methods is

$$E(y_2) - E\left(y_2^p\right) = E(\beta_2' x_{i2}) - E(\beta_1^{p\prime} x_{i2,p}) \qquad (1.20)$$

If the estimation model for the proxy means test is identical to that used for imputing consumption, the biases in Equations (1.19) and (1.20) are the same. But if the estimation model for the proxy means test is not fully specified (i.e., $x_{ij,p}$ is a subset of x_{ij}), we know from Proposition 2 that $E(\beta_1' x_{i2})$ would provide a better estimator for $E(\beta_2' x_{i2})$ than $E(\beta_1^{p\prime} x_{i2,p})$. Consequently, the bias is smaller for imputed household consumption.

From Equation (1.14), we have

$$V\left(y_{ij}^p\right) = V\left(\beta_1^{p'} x_{i2,p}\right) \le V(\beta_1' x_{i2} + \mu_{i1}) = V(y_2^1) \qquad (1.21)$$

Regardless of whether the estimation model for the proxy means test is fully specified or not, it is smaller than, or at most equal to, the variance of the imputed household consumption. In particular, the variance $V\left(y_{ij}^p\right)$ does not take into account the variance of the unobserved household effects, which can be considerable in practice. Thus the variance of the imputed household consumption is likely to provide a better approximation for the variance of household consumption.

[39] See also Rencher (2002, pp. 389) for a graphical illustration of the general difference between principal component analysis and OLS methods.

Appendix 2: Practical Note for Implementation

We provide some quick examples for the different poverty imputation methods that are reviewed in this paper.

2.1. Principal component analysis (PCA) method for generating wealth indexes

Let a_{ij} represent the list of household assets for household *i* in survey *j*. The list of assets includes (whether the household has) a car, a motorbike, a bicycle, a desk phone, a mobility phone, a DVD player, a television set, a computer, a refrigerator, an air conditioner, a washing machine, an electric fan, the construction materials for the house's roof and wall, and the type of water and toilet the household has access to. We use the Stata command "*pca*" to estimate the parameters in Equation (2) as follows

pca varlist, components (1) vce(norm)

The first component is specified using the option "*components(1)*", and the VCE of the eigenvalues and vectors is computed assuming multivariate normality.
After the model is estimated, the wealth index can be generated using the following command

predict wind3

More detailed discussion on the options available with the "*pca*" command is provided in the Stata (2016) manual.

2.2. Imputing consumption when consumption is partially missing

To implement the Dang *et al.* (2017) imputation method, we can install the "*povimp*" (Dang and Nguyen, 2014) from within Stata by typing

ssc install povimp

We can stack the different years of data such that the same variables have the same names, and use a year variable to indicate the different years. For example, let this year variable have two values 2010 and 2012, and assume that household consumption is unavailable for 2012, but are available for 2010.[40]

We have different modeling options for imputing household consumption in 2012 based on Equations (8) and (9). We can estimate the normal linear regression model as

povimp depvar varlist, by(year) from(2010) to(2012) pline(pline) cluster(com) strata(strata) wt(hhszwt) method(normal) rep(1000)

where "*pline*" is a variable indicating the poverty line. Other survey design variables are specified as cluster ("*com*"), strata ("*strata*"), and population weight ("*hhszwt*"). We use 1,000 simulations.

We can estimate the model with the empirical distribution of the error terms as

povimp depvar varlist, by(year) from(2010) to(2012) pline(pline) cluster(com) strata(strata) wt(hhszwt) method(empirical) rep(1000)

More detailed discussion on the options available with the "*povimp*" command is provided in its associated help file (i.e., type "*help povimp*" after installing it in Stata).

2.3. Imputing consumption when panel consumption data are missing

Do files to implement an earlier version of this method (i.e., the bounds approach in Dang *et al.* (2014)) can be downloaded on the following website

https://sites.google.com/site/decrgdmckenzie/datasets

These do files can be modified to provide point estimates of poverty mobility as proposed in Dang and Lanjouw (2013). Given a good approximation for ρ , we can use the following Stata command to estimate Equation (14)

gen double p1p2= binormal((z1- b1x2)/sigep1, -(z2- b2x2)/sigep2, -rho)

where the various parameters are defined as earlier (e.g., *z1* stands for z_1, *sigep1* for σ_{ε_1} , and so on).

Equation (16) can be estimated similar as
gen double p1v2= binormal((z1- b1x2)/sigep1, (v2- b2x2)/sigep2, rho)- binormal((z1- b1x2)/sigep1, (z2- b2x2)/sigep2, rho)

A Stata program to automate the estimation process will be made available in due course.

Appendix 3: Additional Tables

Table 3.1: Cumulative Population Distribution by Asset Indexes vs. Consumption, Vietnam 2012- 2014 (percentage)

Per capita consumption	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Poorest quintile	12.9	10.6	11.4	8.8	8.6	9.3
Bottom 40 percent	24.4	21.3	22.4	22.8	19.2	20.3
Bottom 60 percent	37.6	33.7	34.9	40.3	33.9	34.4
Bottom 80 percent	54.0	47.8	48.9	59.5	52.1	52.3
All distribution	73.1	67.1	68.2	82.8	75.4	75.6
Correlation with household consumption	0.61	0.67	0.70	0.59	0.64	0.67
N	9,396	9,324	9,324	9,399	9,348	9,348

Note: Each cell in the first five rows shows the percentage of the population that would be correctly captured by the cumulative quintiles of the consumption distribution if asset index was used. Model 1 provides a simple count of the number of assets a household possesses, while Models 2 and 3 construct the asset index using principal component method. The list of assets for Model 1 include car, motorbike, bicycle, desk phone, mobility phone, DVD player, television set, computer, refrigerator, air conditioner, washing machine, and electric fan. Model 2 adds to Model 1 the construction materials for the house's roof and wall, Model 3 adds to Model 2 the type of water and toilet the household has access to. All estimates are weighted by population weight.

Table 3.2: Estimation of Consumption Model Using the VHLSSs, Vietnam 2010-2012

	2010			2012		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Household size	-0.090***	-0.064***	-0.122***	-0.081***	-0.061***	-0.124***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Head's age	0.003***	0.001	-0.001**	0.003***	0.001***	-0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Head is female	0.022*	0.032***	0.033***	-0.007	0.012	0.039***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Head belongs to ethnic minority group	-0.436***	-0.429***	-0.232***	-0.431***	-0.428***	-0.183***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Head completed primary school	0.187***	0.168***	0.056***	0.196***	0.172***	0.053***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Head completed lower secondary school	0.320***	0.274***	0.087***	0.322***	0.273***	0.073***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Head completed upper secondary school	0.489***	0.450***	0.139***	0.481***	0.441***	0.124***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Head has (some) college education	0.787***	0.755***	0.263***	0.782***	0.756***	0.226***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Share of household members age 0-14		-0.438***	-0.445***		-0.371***	-0.360***
		(0.04)	(0.03)		(0.04)	(0.03)
Share of household members age 15-24		0.044	-0.039		0.123***	0.046*
		(0.03)	(0.03)		(0.03)	(0.03)
Share of household members age 15-24		0.278***	0.079***		0.314***	0.087***
		(0.03)	(0.02)		(0.02)	(0.02)
Head worked in the last 12 months		-0.055***	-0.020		-0.023	-0.019
		(0.02)	(0.01)		(0.02)	(0.01)
Household owns a car			0.760***			0.594***
			(0.04)			(0.03)
Household owns a motorbike			0.151***			0.149***
			(0.01)			(0.01)
Household owns a bicycle			-0.026***			-0.031***
			(0.01)			(0.01)
Household owns a desk phone			0.034***			0.066***
			(0.01)			(0.01)
Household owns a cell phone			0.117***			0.123***
			(0.01)			(0.01)
Household owns a DVD player			0.036***			0.050***
			(0.01)			(0.01)
Household owns a television			0.016			0.093***
			(0.01)			(0.01)
Household owns a computer			0.137***			0.132***
			(0.01)			(0.01)
Household owns a refrigerator			0.151***			0.154***
			(0.01)			(0.01)
Household owns an airconditioner			0.273***			0.225***
			(0.02)			(0.02)
Household owns a washing machine			0.113***			0.117***
			(0.01)			(0.01)
Household owns an electric fan			0.044***			0.035***
			(0.01)			(0.01)
Log of residential area			0.197***			0.184***
			(0.01)			(0.01)
House wall materials			0.021***			0.026***
			(0.00)			(0.00)
Access to drinking water			0.013***			0.011***
			(0.00)			(0.00)
Type of toilet			0.045***			0.047***
			(0.00)			(0.00)
Urban	0.354***	0.339***	0.087***	0.339***	0.322***	0.079***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Constant	9.395***	9.452***	8.485***	9.470***	9.403***	8.396***
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)
σ_e	0.40	0.39	0.30	0.40	0.38	0.30
σ_u	0.29	0.27	0.20	0.28	0.27	0.19
ρ	0.34	0.33	0.31	0.33	0.33	0.28
R^2	0.43	0.46	0.69	0.41	0.45	0.69
N	9,211	9,211	9,211	9,324	9,324	9,324

Note: * p<0.10, ** p<0.05 *** p<0.01. Standard errors are in parentheses. All estimation employs commune random effects models. House wall material is assigned numerical values using the following categories: 6 "cement", 5 "brick", 4 "iron/wood", 3 "earth/straw", 2 "bamboo/board", and 1 "others". The types of toilet are assigned numerical values using the following categories: 6 "septic", 5 "suilabh", 4 "double septic", 3 "fish bridge", 2 "others", and 1 "none".

[40] Incidentally, it is rather straightforward to implement poverty estimation using proxy means testing in Stata. After stacking the data from two different years in the same data set, we can obtain the estimated parameters in the household consumption model from one year, and impose these parameters on the *x* variables in the other year. For example, we can type "*xtreg depvar varlist if year== 2010, i(household id) re"*, and then "*predict depvarhat if year== 2012*". The imputed poverty rate can then be obtained using the predicted consumption variable and the appropriate poverty line.

Table 3.3: Decomposition of Changes in Poverty, Vietnam 2012-2014 (percentage)

	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
A. Normal linear regression model						
Due to characteristics	59.9	62.2	96.6	14.2	17.2	110.4
Due to coefficients	40.1	37.8	3.4	85.8	82.8	-10.4
Total	100	100	100	100	100	100
B. Wald test for constant parameters						
F value	9.5	13.4	7.2	10.2	2.9	2.0
p value	0.00	0.00	0.00	0.00	0.00	0.00
Control variables						
Parsimonious	Y	Y	Y	Y	Y	Y
Demographics & employment	N	Y	Y	N	Y	Y
Household assets & house characteristics	N	N	Y	N	N	Y
Adjusted R2	0.43	0.46	0.69	0.41	0.45	0.69
N (base survey)	9,211	9,211	9,211	9,324	9,324	9,324
N (target survey)	9,324	9,324	9,324	9,348	9,348	9,348

Note: The decomposition of the changes in poverty for Panel A is implemented using respectively Equation (10) and the Wald test as discussed in the text. All estimates adjust for complex survey design with cluster sampling and stratification. Full model specification is provided in Appendix 3, Table 3.2.

Table 3.4: Predicted Poverty Rates Based on Imputation, Vietnam 2014 (percentage)

Method	**2014**		
	Model 1	**Model 2**	**Model 3**
1) Normal linear regression model	19.8	19.8	13.2
	(0.5)	(0.5)	(0.4)
2) Empirical distribution of the error terms	19.5	19.5	13.1
	(0.5)	(0.5)	(0.4)
Control variables			
Parsimonious	Y	Y	Y
Demographics & employment	N	Y	Y
Household assets & house characteristics	N	N	Y
True poverty rate		13.5	
		(0.5)	

Note: Standard errors in parentheses are adjusted for complex survey design. All estimates are obtained with population weights. Method 1 uses the normal linear regression model with the theoretical distribution of the error terms and Method 2 uses the empirical distribution of the error terms. Both methods employ commune random effects. The imputed poverty rates for 2014 use the estimated parameters based on the 2010 data. 1,000 simulations are implemented. The underlying regression results are provided in Appendix 3, Table 3.2. True poverty rate is the estimate directly obtained from the survey data.

Table 3.5: Predicted Poverty Rates Based on MI Methods, Vietnam 2012-2014 (percentage)

Method	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
1) Normal linear regression model	21.5	21.3	17.8	16.9	16.9	13.3
	(0.7)	(0.7)	(0.6)	(0.7)	(0.6)	(0.6)
2) Predictive mean matching model	20.4	20.3	17.1	16.4	16.4	13.2
	(0.6)	(0.7)	(0.6)	(0.7)	(0.6)	(0.6)
Control variables						
Parsimonious	Y	Y	Y	Y	Y	Y
Demographics & employment	N	Y	Y	N	Y	Y
Household assets & house characteristics	N	N	Y	N	N	Y
True poverty rate		17.2			13.5	
		(0.5)			(0.5)	

Note: Standard errors in parentheses are adjusted for complex survey design. All estimates are obtained with population weights. Method 1 uses the normal linear regression model and Method 2 uses the predictive mean matching model, both with 50 simulations. Method 2 sets the number of closest observations (i.e., nearest neighbors) equal to 5. The imputed poverty rates for 2012 use the estimated parameters based on the 2010 data, and the imputed poverty rates for 2014 use the estimated parameters based on the 2012 data. True poverty rate is the estimate directly obtained from the survey data.

Table 3.6: Predicted Poverty Rates Based on Proxy Means Testing, Vietnam 2012-2014 (percentage)

Method	2012			2014		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Proxy mean tests	11.0	11.1	12.5	7.6	8.0	8.8
	(0.4)	(0.4)	(0.5)	(0.4)	(0.4)	(0.4)
Control variables						
Parsimonious	Y	Y	Y	Y	Y	Y
Demographics & employment	N	Y	Y	N	Y	Y
Household assets & house characteristics	N	N	Y	N	N	Y
True poverty rate		17.2			13.5	
		(0.5)			(0.5)	

Note: Standard errors in parentheses are adjusted for complex survey design. All estimates are obtained with population weights. The imputed poverty rates for 2012 use the estimated parameters based on the 2010 data, and the imputed poverty rates for 2014 use the estimated parameters based on the 2012 data. True poverty rate is the estimate directly obtained from the survey data.