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Proxy Means Testing vulnerability to measurement errors?

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Abstract

Proxy Means Testing (PMT) is a popular method to target the poor in developing countries. PMT usually relies on survey-based consumption data and assumes they are measured with random errors – an assumption that has been challenged by recent literature. This paper brings causal evidence on the impact of non-random errors on PMT performances. Using a survey experiment conducted in Tanzania in which eight alternative consumption questionnaires were randomly distributed across households, I compare the performances of PMT relying on error-prone consumption data with those of a PMT using gold standard consumption data. Results show that non-random errors reduce the predictive performances of PMT by a magnitude ranging from 5 to 27 percent, which in turn induce a 10 to 34 percent increase in the incidence of targeting errors (using the typical PPP \$1.25 poverty line). Impacts on the relative distribution of households are nonetheless small and non-significant.

Keywords

Social protection, Targeting, Proxy Means Testing (PMT), Measurement errors.

JEL Codes

I32, I38, O12, O20.

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1 Introduction

Social safety nets programs (SSNP) such as cash and in-kind transfers have become an important tool for achieving poverty alleviation in developing countries. Based on the World Bank Aspire database, in the last two decades, the number of developing countries with SSNP doubled from 72 to 149 so that today almost every developing country has at least one SSNP.¹ However, with an average spending of 1.6 percent of GDP, coverage is far from universal. Governments and development practitioners often use targeting tools in an effort to concentrate the benefits of SSNP on the poorest. Poor households targeting is an inherently inexact and challenging practice, especially in low-income countries which face a lack of verifiable records on earnings. This lack of records makes means-testing impractical.

Against this backdrop, Proxy Means Testing (PMT thereafter) has become an increasingly popular targeting method.² PMT has been implemented in the SSNP of more than 20 sub-Saharan countries since the year 2000 (Cirillo and Tebaldi, 2016). In PMT, a survey-based measure of well-being (usually consumption) is regressed on household covariates to estimate a proxy for well-being, and this proxy is in turn used for targeting out of the sample. Typically, the implementation of PMT has two distinct phases. First, an in-depth survey is administered to a sample of households to collect data on consumption as well as some easily observable and verifiable correlates of consumption (such as demographic characteristics and home attributes). These data are used to estimate a regression of log consumption per capita on correlates of consumption. Second, a short survey is administered to all potential beneficiary households to collect information on the same correlates of consumption, compute PMT scores based on coefficients estimates, and determine the list of beneficiaries based on resulting PMT scores.

Recently, PMT has been the subject of a lively debate among policy makers, civilian stakeholders and academics. The most debated issue is probably the claim that PMT is one of the best mechanisms, if not the best mechanism available for identifying households living in poverty. PMT advocates argue that it “can accurately and cost-effectively target the chronic poor” (Del Ninno and Mills, 2015, p.20), and that its performances can be improved by combining PMT with other targeting methods such as demographic targeting, geographical targeting or CBT (Coady et al., 2004; Grosh et al., 2008; Leite, 2014;

¹ASPIRE database — Consulted on: www.worldbank.org/aspire.

²In addition to means tests and PMT, other methods include demographic targeting (targeting of specific categories such as elderly, widowed and children), community-based targeting or CBT (groups of community leaders and members determine eligibility), geographic targeting (location determines eligibility) and self-targeting (benefits and transaction costs are set so that only needy households enrol). For a detailed overview on PMT and other targeting methods used in developing countries see Grosh (1994); Grosh et al. (2008); Del Ninno and Mills (2015); Devereux et al. (2017).

Stoeffler et al., 2016). A recent World Bank report in Namibia recommends the use of PMT to target beneficiaries of social benefits because it “could provide better coverage at existing spending levels, providing a greater poverty and inequality impact” (Sulla et al., 2017). In contrast, critics often point to PMT high built-in errors, implementation issues and lack of transparency (Kidd and Wylde, 2011; Kidd et al., 2017).

This debate has been feeded by a surge of careful studies assessing the performances of PMT. In these studies, performances are typically displayed in terms of “errors of inclusion” (providing benefits to households which should not be eligible) and “errors of exclusion” (not providing benefits to households that should be eligible). Brown et al. (2016) provide a systematic assessment of PMT performances for nine countries in Sub-Saharan Africa (SSA). Overall, they find that PMT reduce inclusion errors but this comes at the cost of substantial exclusion errors. Comparisons of PMT with Community Based Targeting (CBT) suggest some gains in terms of accuracy but some loss in terms of community satisfaction with the beneficiary list (Alatas et al., 2012; Basurto et al., 2017; Karlan and Thuysbaert, 2016; Stoeffler et al., 2016). For instance, Alatas et al. (2012) in Indonesia report that PMT allowed a 10 percent reduction in the error rate relative to CBT, while CBT resulted in 60 percent fewer complaints than PMT.³

An implicit assumption made by these studies is that consumption data underlying PMT regressions are error-free or measured with random errors – an assumption that has been challenged by recent literature. In particular, Gibson et al. (2015) show that measurement errors in consumption have a mean-reverting negative correlation with true values. According to the typical textbook on the impact of measurement errors, this would lead to biased PMT estimates.⁴ However, the magnitude of the bias and its implications on targeting accuracy are not clear.

The goal of this paper is to assess the implications of the violation of this assumption for PMT. As with many impact evaluations, the key challenge here is to construct the most credible counterfactual of what would happen with random measurement errors in consumption. I exploit a unique survey experiment which randomly assigned eight different designs of consumption module to more than 4000 households in Tanzania. This experiment has been used to explore the relative performances of different survey designs in terms of mean consumption, inequality, poverty, the prevalence of hunger and measure-

³Some studies assess PMT targeting outcomes beyond accuracy and satisfaction. Cameron and Shah (2013) show that PMT had significant negative social consequences such as an increase in the prevalence of crime within communities and a decline of the participation in community groups. In the context of a subsidy program in Malawi, Basurto et al. (2017) report that local leaders allocate input subsidies to farmers with larger returns compared to the PMT counterfactual.

⁴See Bound et al. (2001) for a discussion on the impact of measurement errors on regression estimates. In section 2.2, I present in more details how Bound et al. (2001) speak to the present study.

ment errors (Beegle et al., 2012; De Weerd et al., 2016; Friedman et al., 2016; Gibson et al., 2015), but never with an explicit focus on the implications for targeting accuracy. One design of the consumption module involved the distribution of individual diaries to each adult member of households to track all commodity in-flows (harvests, purchases, gifts, destocking) and outflows (sales, gifts, restocking, food fed to animals). In addition, each adult member was provided with tight supervision by interviewers specifically trained to cross-check and query reported information. This resource intensive design is believed to approximate a “gold standard” for consumption estimates in that it minimizes the prevalence of various sources of measurement errors. My empirical strategy compares the performances of PMT relying on the gold standard consumption data with those of PMT using the more error-prone consumption data.

This paper contributes to the ongoing debate on the methods to target poor households. It provides empirical evidence on one largely ignored aspect of PMT targeting, namely its vulnerability to non-random measurement error in survey-based consumption data. I estimate that coefficients from PMT regressions are biased in the presence of non-random errors, which result in a reduction in both the predictive and targeting performances of PMT. Specifically, using a typical \$1.25 poverty line, the incidence of targeting errors increase by a magnitude ranging from 10 to 34 percent depending on how consumption data is collected. This latter result is largely driven by an increase in inclusion errors, which suggest that PMT typically overestimates poverty rates. More reassuringly, I find rather small and non-significant effects on targeting performances when poverty is defined in relative terms (such as with the typical 30% threshold used in many development projects). This means that non-random errors in consumption have if anything a limited impact on the ranking of households.

It is always difficult to extrapolate the results derived from one context. The findings presented in this article may not hold in other contexts. However, the focus on measurement errors due to survey design (as opposed to other type of errors such as fraud or fabrication) provides some reassurance that the results are not too specific. Indeed, it is quite reasonable to assume that survey design has a core mechanism that affects respondents answers regardless of the context.

The remainder of the paper is organised as follows. Section 2 walks through a number of error sources that can be expected to arise when measuring consumption and how some of these sources likely differ by survey design. That section also introduces the expected impact of measurement error on PMT performances. Section 3 describes the experimental set-up. Section 4 presents the empirical strategy. Section 5 reports the findings. Section 6 draws the main conclusions.

2 Measurement Errors and PMT Performances

Before moving on to a description of the survey experiment, I briefly introduce some of the evidence found in the literature on measurement errors in household consumption. Consumption is generally used in PMT as a measure of household well-being, i.e. the dependent variable in PMT regressions, so I focus on how measurement error in the dependent variable is expected to affect model estimates, and thus how PMT performances may be impacted by errors in consumption.

2.1 Consumption measurement errors

Consider the following typical survey questions about some consumed item X :

“How much X did your household consume in the past 14 days? How much came from purchases? How much did you spend? How much came from own-production? How much came from gifts and other sources?”

Often, individuals trying to answer these questions will struggle to give accurate figures, leading to imprecise data.

Why should one expect consumption estimates to deviate from actual consumption?⁵ First, it is well documented in the literature that retrospective reports on expenditures can cause both recall and telescoping errors. In the one hand, a household under-reports true consumption over the period of recall because it may forget certain events. The longer the period of recall the greater the likelihood events are forgotten or not precisely remembered. In the other hand, a respondent recalls consumption that occurred before the reference period, resulting in reported consumption greater than the actual one. A second source of error is the inability of respondents to accurately report individual consumption by other household members, which may be particularly salient in the context of SSA where households are larger and the unitary model has been challenged empirically.⁶ This source of error is likely to be more compelling for certain types of consumption such as

⁵I only consider deviations that are caused by the insufficient ability of respondents to acquire, process and recall information. However, it should be noted that deviations can also arise from other sources, such as social desirability bias (e.g. under-reporting of “bad” consumption such as spending on alcohol or cigarettes), strategic responses (e.g. understatements of consumption because of the belief that responses may be used to determine eligibility for some future social program; negative answers bias in order to avoid follow-up questions) and untrained, inadvertent or strategic enumerators (e.g. enumerators guiding respondents to give answers that minimize interview length).

⁶Anderson and Baland (2002) and Duflo and Udry (2004) are two examples of empirical evidence inconsistent with the unitary model of household decision making, which assumes all household members have the same utility function.

alcohol, tobacco, meals eaten outside the home, telecommunication or personal toiletries. Lastly, for longer recall periods or items involving frequent transactions, respondents may resort to inference rather than memory to estimate consumption, resulting in what can be termed rule of thumb errors. This source of error has no obvious direction of bias but it is probably more important in hypothetical scenarios requiring high cognitive readiness such as consumption during a usual month.

These various sources of errors may be more or less prevalent depending on the features of data collection instruments used. In recent years, a number of empirical studies confirmed that measurement of consumption is fairly sensitive to survey design. I focus here on evidence on four key dimensions in which survey design vary: the method of data capture (diary versus recall questionnaires), the length of the recall period, the number of items on which data are collected and the level of respondent (individual versus household). This focus is motivated by the specific experiment exploited in this paper and described in the next section, which randomly assigned households to eight survey designs differing along the four dimensions above-mentioned.⁷

While diaries are generally believed to overcome some sources of error such as recall errors or rule of thumb errors, some concerns related to their implementation in the field exist. Specifically, in the case of illiterate, unmotivated or non-cooperative respondents, a diary survey with a lack of supervision may be equivalent to a recall survey if the information is gathered by the enumerator at the end of the period. In a survey in Canada, where households reported their food expenditures during the past month and then filled in a diary during the following two weeks, Ahmed et al. (2006) identify substantial measurement errors in recall food consumption with properties inconsistent with random measurement error. However, it also found some discrepancies in the diary survey and concludes that the “superiority of the diary may not be as obvious as the literature suggests.” Implementation of diary in developing countries may be even more challenging. Beegle et al. (2012) mention stylized facts from two diary household budget surveys in Tanzania (2002) and Malawi (1998) consistent with poor supervision, respondent fatigue and incomplete or unreliable data. The same authors wrap up that “the implications of variation in literacy, motivation, and other factors, although not well-documented, suggest it can be quite difficult to conduct high-quality diary survey.”

There is a wide understanding that an inverse relationship exists between the length of time over which respondents are asked to recall events and the accuracy of the reported estimates. Events are less likely to be precisely remembered with time due to recall errors and telescoping (see above). While these errors work in opposite directions, experimental

⁷For more detailed discussions on the sensitivity of consumption expenditures to survey design, see for instance Deaton (1997), Deaton and Grosh (2000), Gibson and Kim (2007) and Beegle et al. (2012).

studies of self-reported consumption show that under-reporting is more widespread than over-reporting. In an experiment in Ghana, Scott and Amenuvegbe (1991) varied recall periods and find that the reported spending on a basket of the 13 most frequently purchased items decreased by 2.9% for every additional day of recall. Similarly, Beegle et al. (2012) in Tanzania report that a 7-day recall design measured a 11% higher mean food consumption than a 14-day recall design. Hence, both studies suggest that telescoping is less prevalent than recall error.

Shorter versus longer lists of items included in questionnaires has also been shown to influence consumption estimates. Observational work by Lanjouw and Ravallion (1996) in Ecuador estimated a decline in poverty of seven percentage points between 1994 and 1995 while the country did not experience any policy to reduce poverty nor significant growth, suggesting that the observed decline in poverty was more related to the change of design in the questionnaire (more than 25 percent additional items were added between the two survey rounds). This positive relationship between the number of items and the level of recorded consumption has been confirmed by experimental work in El Salvador by Jolliffe (2001), where longer, more detailed questions on consumption resulted in an estimate of mean household consumption that was 31% higher than estimates derived from a condensed version of the questionnaire.

Finally, the identity of the respondent to survey questions may influence consumption records due to the difficulty for a sole respondent to perfectly capture the consumption by other household members for items such as alcohol, tobacco, meals eaten outside the home, telecommunication or personal toiletries. As reported by Beegle et al. (2012), personal diaries have been used in Russia for a random sample of households during the 2003 Household Budget Survey, and this yielded 6–11% higher expenditure levels, even if the survey was plagued with non-respondent problems.

These examples of diverging consumption estimates when different survey designs are used in the same setting are indicative of measurement error. However, because of a lack of data on actual consumption, there is only scant evidence on the nature of measurement error in estimates of household consumption. One of the main contributions of the survey experiment conducted by Gibson et al. (2015) is that they collect benchmark consumption data allowing them to make such investigations.⁸ They find that errors in measured consumption are non-random and negatively correlated with true values – a pattern that Bound and Krueger (1991) also found for earnings data and labelled *mean-reverting measurement error*. In what follows, I present how non-random error in consumption may affect PMT performances.

⁸As noted above, this paper rests on the same data as Gibson et al. (2015). More details on the design of the survey are presented in the next section.

2.2 The impact of non-random error in the dependent variable on parameter estimates

A significant amount of attention has been devoted to measurement error and its effects on model estimates. Because this paper is primarily interested in measurement error in consumption, which is used as a left-hand-side variable in PMT regressions, I confine attention to the impact of errors in the dependent variable.⁹ Assume the true model is:

$$y = \alpha + \beta X + \varepsilon \quad (1)$$

where y is the dependent variable, X a vector of independent variables, β the associated coefficients and ε a pure random error. Instead of y , the observed value of the outcome variable is y^* , which is related to the true value y by:

$$y^* = \theta + \lambda y + v \quad (2)$$

The estimator of the response coefficient with the error-ridden dependent variable is:

$$\beta_{y^*X} = \frac{\text{cov}(y^*, X)}{\text{var}(X)} = \frac{\text{cov}(\lambda\alpha + \lambda\beta X + \lambda\varepsilon - v, X)}{\text{var}(X)} \quad (3)$$

One has to assume random error in order to get consistent estimates of β from equation 3. Random error is a special case which adds variability to the data but does not affect average performance for the sample. The following assumptions are made under random error: $\theta = 0$, $\lambda = 1$ and $E(v) = \text{cov}(y, v) = \text{cov}(X, v) = \text{cov}(\varepsilon, v) = 0$. In contrast, mean-reverting measurement error in y^* assumes $0 < \lambda < 1$ which makes estimates of β inconsistent – from equation 3 it is now equal to $\lambda\beta$.

Thus, with $0 < \lambda < 1$, estimates of equation 1 will be attenuated. In other words, mean-reverting measurement error in consumption data is expected to bias downward the coefficients of consumption correlates derived from PMT estimates. As noted in the introduction, some general assessments of PMT targeting are already available in the literature. However, I am not aware of any previous work looking at the severity of this bias and to what extent it affects PMT performances. One exception is Brown et al. (2016), which exploits panel data in Ethiopia, Malawi, Nigeria, Tanzania and Uganda to reduce any bias due to measurement errors. They use time-mean consumption instead of current consumption and find that PMT performances slightly improve. However, as noted by the authors themselves, this exercise is unlikely to completely eliminate measurement errors. Griliches and Hausman (1986) argue that a crucial parameter in such cases is the correlation over time in the true values of the dependent variable (y in equation 1) and in

⁹The framework presented in this section is adapted from Bound et al. (2001), Hausman (2001) and Gibson et al. (2015).

the measurement errors (v in equation 2). Specifically, if true values of y are highly correlated over time while the measurement errors v are more or less uncorrelated (which is quite reasonable), moving from cross-sectional estimates to panel estimates would actually intensify the bias due to measurement errors in y .

3 The Survey Experiment

I exploit the same survey experiment as Beegle et al. (2012); De Weerd et al. (2016); Friedman et al. (2016); Gibson et al. (2015). It is a unique experiment developed by the Living Standards Measurement Study (LSMS) Team in the World Bank in collaboration with the University of Dar es Salaam and the Economic Development Initiatives (EDI thereafter), a leading research company established in 2002 in Tanzania. This section summarizes the experiment and its implementation. More details can be found in Beegle et al. (2012).

3.1 Sample

The sample for the experiment consists of 4,032 households spread across seven Tanzanian districts: one district in the regions of Domona, Pwani, Dar es Salaam, Manyara, and Shinyanga and two districts in the Kagera Region. While the districts in the regions of Dodoma and Dar es Salaam are urban areas, other districts are rural.¹⁰ Within these seven districts, a probability-proportional-to-size sample of 24 villages was selected using data from the 2002 Census. In each selected village, Enumeration Areas (EA) were listed in cooperation with local informants, and one of these EA was randomly chosen for the experiment. These EA are best thought of as sub-villages or neighbourhoods. Finally, in each selected EA, all households were listed, and 24 households were randomly sampled for the survey experiment. According to Beegle et al. (2012), “the sample was constructed to be representative at the district level, but not at the national level,” however “the basic characteristics of the sampled households generally match the nationally representative estimates from the 2006/2007 Household Budget Survey.”

¹⁰According to Beegle et al. (2012), “districts were purposively selected to capture variations between urban and rural areas as well as across socio-economic dimensions to inform survey design related to labor statistics and consumption expenditure for low-income settings.” Table A1 shows basic descriptive statistics.

3.2 Experimental design

In each sub-village, three households were randomly assigned to each of the eight consumption modules summarized in Table A4. Households were assigned to a single module to prevent potential cross-module spillovers. The designs of these eight modules vary along five key dimensions: the method of data capture (diary versus recall questionnaires), the length of the recall period, the number of items in the recall list, the level of respondent (individual versus household) and the degree of supervision received. These eight survey designs were strategically selected to reflect the most common methods used in low-income countries and the scope of variation one is likely to find in practice (Beegle et al., 2012).

Modules 1–5 rely on a recall design and modules 6–8 on diaries. Modules 1 and 2 use a long list of 58 commodities with a recall period of 14 and 7 days respectively. Module 3 uses a subset list consisting of the 17 most important commodities and representing 77 percent of the food consumption expenditure in Tanzania (based on the national Household Budget Survey 2000-2001).¹¹ Module 4 includes a list of 11 comprehensive categories, which corresponds to an aggregated version of the list of 58 commodities. Module 5 inquires about “usual” consumption over the list of 58 commodities. In particular, households reported the number of months in which the commodity is typically consumed, the quantity usually consumed, and the average value of what is consumed in those months. Module 6 and 7 are household diaries (i.e. a single diary was used to record all household consumption) with different intensity of supervision. Households assigned to module 6 were visited by a trained survey staff every other day, while those assigned to module 7 were only visited weekly. Module 8 is a personal diary in which each adult member was provided with his or her own diary while children were placed on the diaries of the adults who knew most about their daily activities. Each adult was visited every other day.

Non-food items were divided into two categories based on frequency of purchase. Frequently purchased items such as charcoal, soap, cigarettes and communications were collected using a 14-day recall period for modules 1–5 and the 14-day diary for modules 6–8. Non-frequent expenditures such as durables, education and health were collected using the same design across modules (i.e. a one or 12-month recall period depending on the item in question).

¹¹To make data comparable, reported expenditures for module 3 were scaled up by a factor equal to $1/0.77$, as is commonly done in practice.

3.3 Data

The data were collected between September 2007 and August 2008 by EDI. Each interviewer implemented all eight modules in equal proportion in order to avoid to confound module effects with interviewer effects. In each EA, households assigned to the recall modules were surveyed in the span of the 14 days the survey team was in the EA to collect the data based on the diaries. Interviewers were provided with an extensive training starting in June 2007 and including intensive sessions on how to check and correct individual diaries for the issue of double-counting. The survey was administered on paper but maximum control was made possible by the relatively small number of a dozen interviewers and the long 12-month period of data collection. Specifically, back-checks as well as direct observations were carried out on regular basis by supervisors. The same double blind data entry protocol was used for all modules in order to avoid any systematic error to arise and bias the results. Refusal and attrition were negligible: there were only 13 replacements due to refusals and only three households that started a diary were dropped because they did not complete their final interview. Another five households were dropped because of missing data, yielding a final sample size of 4,025 households. A summary of key statistics for the sample is reported in Table A1.

4 Empirical Strategy

I seek to quantify the impact of measurement errors in consumption on PMT estimates and to assess how PMT performances are impacted. As with many impact evaluation, the key challenge here consists in constructing the most credible counterfactual of what would happen without measurement errors in consumption. Ideally, we would like to have error-free *and* error-prone consumption data for each household. Most studies on measurement error rely on validation data such as administrative records for income (Bound and Krueger, 1991). However, the lack of data on actual consumption makes validation studies impractical for consumption. The survey experiment described in section 3 offers a rare opportunity to study measurement errors in consumption.

4.1 Identification strategy

A key assumption of the identification strategy is that the personal diary (module 8) provides “gold standard” (or “benchmark”) data on consumption. In the personal diary, there is a smaller scope for recall errors, telescoping and missed individual consumption. In addition, three measures have been undertaken to avoid double counting – the main stated weakness of personal diaries. First, the personal diary has been designed as a record

of food brought into the household instead of food consumed, which is likely to reduce the scope for double-counting purchased or self-produced items. Second, as discussed, interviewers were trained to cross-check individual diaries for similar items and apply the appropriate corrections when the same item was accidentally recorded by two individuals. Third, each adult member was visited every other day in order to provide him or her with adequate supervision. Reassuringly, some statistics, such as the daily consumption, show no diary fatigue.

My identification strategy exploits this benchmark consumption and the random assignment of the different survey designs across households. Table A3 shows the results of randomization balance checks across a set of core household characteristics. Overall, randomized assignment of households to the eight different designs seem successful. Six of the differences are statistically significant at conventional levels. These differences, while significant, are not too worrying because they are small in size. Consequently, any systematic difference in measured consumption across modules can be attributed to measurement error due to alternative survey designs. Comparisons of error prone survey designs with the benchmark give estimates of the effect of measurement error on PMT targeting.

4.2 Estimation procedure and construction of the outcomes of interest

While I recognize that poverty is multidimensional in nature, I rely on per capita consumption as the main welfare indicator for the analysis because it is generally considered as a good predictor of neediness (Deaton, 1997) and because it is used in most PMT targeting exercises. Per capita consumption is aggregated on an annual basis using data collected on food consumption and frequent non-food consumption.¹² Total food consumption from module 3 is scaled up by a factor equal to $1/0.77$ (i.e. 29.87%) to make data comparable across modules.

First, I create a set of variables that are long-term determinants or correlates of poverty, encompassing household's demographic characteristics (household size, number of

¹²Results are robust using food consumption only (see Tables A5, A9, A13 and A17) or consumption per adult equivalent (see Tables A6, A10, A14 and A18). In both cases, the consumption of non-frequently purchased items such as durables, education and health was excluded because it was collected using the same design across modules (i.e. there is no benchmark) and because it is usually not included in PMT. That said, it would be quite reasonable to assume that measurement errors for these items are more prevalent because of the longer recall period (one month or 12 months depending on the items considered). Unfortunately, I am not able to check this assumption because there are no benchmark data on actual non-frequent consumption.

children, etc.), home attributes (floor type, wall type, etc.) and household head's features (education, occupation, etc.). These variables have been selected to be representative of the variables typically included in PMT targeting.¹³ Then, using OLS with a backward stepwise selection of the variables, I estimate the relationship between this set of variables and log consumption per capita (the so-called PMT formula) by module type.¹⁴ The following regression is estimated eight times (one for each sample of households assigned to module type k):

$$y_i = \alpha_k + \beta_k X_i + \varepsilon_i \quad (4)$$

where y_i is the log consumption per capita of household i (with $i = 1, \dots, N_k$), N_k the sample size of households assigned to module k (with $k = 1, \dots, 8$) and X_i the set of correlates of consumption I created. Estimates from equation 4 are then used to predict PMT scores of household i for each PMT formula k :

$$\hat{y}_{ik} = \hat{\alpha}_k + \hat{\beta}_k X_i \quad (5)$$

Note that each PMT formula is used to compute PMT scores “in and out of sample” (e.g. formula 1 is used to predict PMT scores of households assigned to module 1 but also for the sample of households assigned to the other modules). As a result, I obtain eight PMT scores per household (one from each of the eight PMT formulas) which form the basis to assess the impact of measurement errors on PMT performances. Then, I restrict the analysis to the sample of households for which benchmark consumption data are available, i.e. those assigned to the personal diary (module 8), and compare how each formula perform to predict their consumption and which households are poor. Under the identifying assumption that the personal diary approximates a benchmark for true consumption, formula 8 can be interpreted as the closest to the counterfactual scenario, i.e. the PMT formula one would obtain if consumption was measured without errors.

In a first part, I compare the predictive performances of the alternative PMT formulas. I estimate an equation of the following form using a linear probability model:

$$\hat{y}_{ik} = \gamma_k M_{ik} + v_{ik} \quad (6)$$

where \hat{y}_{ik} is the PMT score of household i derived from formula k (see equation 5) and M_{ik} a vector of dummy variables indicating if \hat{y}_{ik} is derived from formula k . I also compute the mean squared prediction error $\hat{\mu}_{ik} = (y_i - \hat{y}_{ik})^2$, where y_i is the actual consumption, and regress it on the same variables:

$$\hat{\mu}_{ik} = \gamma_k M_{ik} + v_{ik} \quad (7)$$

¹³In an extended version, I also include variables on assets and livestock which are good correlates of consumption but are more difficult to verify and may be vulnerable to strategic responses. The results are similar (see Tables A7, A11, A15 and A19).

¹⁴Tables A8, A12, A16 and A20 show that results are largely similar without the stepwise option.

In both estimates, standard errors are clustered at the village level to account for the correlation between the error terms of observations from the same village. The comparison of γ_k ($k = 1, \dots, 7$) with γ_8 gives a sense of the impact of measurement errors on PMT predictive performances by survey design.

In a second part, I compare the performances of the alternative PMT formulas against different measures of targeting accuracy. As discussed in the introduction, there are two types of targeting errors: Inclusion Errors (IE), i.e. identifying a non-poor household as poor, and Exclusion Errors (EE), i.e. identifying a poor household as non-poor. The Inclusion Error Rate (IER), defined as the proportion of the non-poor households identified as poor, for module k , can be written as:

$$IER_k = \frac{\sum_{i=1}^{N_k} \mathbb{1}(\hat{y}_{ik} \leq z \mid y_i > z)}{\sum_{i=1}^{N_k} \mathbb{1}(y_i > z)} \quad (8)$$

where N_k is the sample size, z the poverty line, y_i the measured per capita consumption of household i , \hat{y}_{ik} its PMT score using PMT formula k and $\mathbb{1}(\cdot)$ an indicator function which takes the value one when the condition in parentheses is true and zero otherwise.¹⁵

Similarly, the Exclusion Error Rate (EER), defined as the proportion of the poor households not identified as poor, can be written as:

$$EER_k = \frac{\sum_{i=1}^{N_k} \mathbb{1}(\hat{y}_{ik} > z \mid y_i \leq z)}{\sum_{i=1}^{N_k} \mathbb{1}(y_i \leq z)} \quad (9)$$

The IER and the EER do not consider how far from the poverty line beneficiary and non-beneficiary households lie. For instance, the EER would be the same if a given household i , excluded by mistake, is just below or very far below the poverty line. Hence, mean squared errors, which allocate a higher weight for errors farther from the poverty line, is perhaps richer for measuring targeting errors. The Mean Squared IE (MSIE) and Mean Squared EE (MSEE) for module k are given by:

$$MSIE_k = \frac{\sum_{i=1}^{N_k} \mathbb{1}(\hat{y}_{ik} \leq z \mid y_i > z) * (z - y_i)^2}{\sum_{i=1}^{N_k} \mathbb{1}(y_i > z)} \quad (10)$$

$$MSEE_k = \frac{\sum_{i=1}^{N_k} \mathbb{1}(\hat{y}_{ik} > z \mid y_i \leq z) * (z - y_i)^2}{\sum_{i=1}^{N_k} \mathbb{1}(y_i \leq z)} \quad (11)$$

The IER, the EER, the Targeting Error Rate (TER), defined as the weighted sum of the IER and the EER (weights are the share of poor/non-poor households), the MSIE,

¹⁵I use the same definition as Alatas et al. (2012). IER could also be defined as Brown et al. (2016), i.e. the proportion of those identified as poor who are not poor. The latter definition is less practical in the present study. Indeed, the sample of households identified as poor is likely to vary across PMT formulas.

the MSEE and the MSTE, defined as the weighted sum of the MSIE and the MSEE, form the basis to assess the targeting performances of the alternative PMT formulas. From the rates and means defined hereinabove, I construct variables which can fit in typical regression frameworks. Specifically, for the IER, the EER and the TER, I create dummies equal to one if household i with consumption derived from formula k is mistargeted, and zero otherwise. For instance, IE_{ik} is equal to one for all households i which are considered as poor by mistake using PMT formula k . Similarly, for the MSIE, the MSEE and the MSTE, I create variables equal to the squared targeting error if household i with consumption derived from PMT formula k is mistargeted, and zero otherwise. For instance, IE_{ik}^2 is equal to the squared inclusion error (i.e. $(y_i - \hat{y}_{ik})^2$) for all households i which are considered as poor by mistake using PMT formula k . Each of these outcomes of interest is estimated with the same specification as equations 6 and 7. Importantly, the poverty line z in equations 8–11 can be defined in absolute or in relative terms. With a poverty line defined in absolute terms, e.g. PPP\$1.25, beneficiaries are those with a PMT score below PPP\$1.25. With a poverty line defined in relative terms, e.g. the poorest 30%, beneficiaries are those with a PMT score equal or below the PMT score of the 30th percentile. I start by assessing PMT targeting performances with respect to the typical PPP\$1.25 poverty line. Then I use a poverty line defined in relative terms as a 30% threshold. Specifically, for each PMT formula, I rank households from lowest to highest PMT scores and consider as eligible those with PMT scores equal or below the PMT score of the 30th percentile.

5 Results

5.1 PMT estimates

Table 1 presents the results of PMT regressions by module type. Adjusted- R^2 range from 0.45 for the sample assigned to household diary with infrequent supervision (module 7), to 0.64 for the sample assigned to the usual month recall (module 5). Column 9 displays the PMT on the full sample of households and Adjusted- R^2 is 0.54, which is slightly lower than the 0.59 Adjusted- R^2 obtained by Brown et al. (2016) in Tanzania using LSMS-ISA data, and somewhat higher than the 0.40 obtained in Indonesia by Alatas et al. (2012). Interestingly, while coefficients and variables selected through the backward stepwise procedure vary somewhat across specifications, signs do not change (with a few exceptions). Overall, coefficients are larger for households assigned to the benchmark (module 8), which is consistent with the assumption that non-random measurement errors in consumption data bias downward PMT estimates (see Section 2.2 above).

5.2 PMT predictive performances

Simple comparisons of distributions of PMT scores using different formulas in Figure 1 show that the benchmark PMT formula yields relatively higher scores. The distribution of scores is shifted to the right compared to other formulas.¹⁶ This is confirmed by the results of regressions presented in Table 2. Overall, formulas 1–7 yield significantly lower PMT scores and higher squared prediction errors than formula 8 (derived from the benchmark personal diary). The results in column 1 show that formulas 1–7 predict between 5 and 27 percent lower PMT scores compared with the benchmark formula 8. Similarly, formulas 1–7 produce mean prediction errors between 12 and 49 percent higher compared with the benchmark. PMT formulas derived from the long list 7-day recall (module 2) and the subset list (module 3) appear to yield slightly better predictions compared with formulas derived from the collapsed list (module 4) and usual month (module 5). Non-random measurement errors in consumption have thus a significant and rather large impact on the predictive performances of PMT. In the next section I will investigate how these relate to targeting performances.

5.3 PMT targeting performances

Regressions in Table 3 compare the targeting performances of each of the seven formulas against the benchmark formula derived from the sample of households assigned to the personal diary (module 8), using the PPP\$1.25 poverty line. The results in column 1 show that measurement errors in formulas 1–7 increase the TER by a magnitude ranging from 2.4 and 8.3 percentage point. Given that the TER derived from formula 8 is 24.7 percent, these effects are equivalent to an increase in TER of 10 to 34 percent. In columns 2 and 3, I examine the error rates separately for the non-poor and the poor (defined as the households above/below the PPP\$1.25 poverty line). The results show that the IER increase and the EER decrease for all formulas compared with formula 8, which is not surprising given that Table 2 found that formulas 1–7 predict lower PMT scores. This means that the number of poor households is overestimated when formulas 1–7 are used.

I further investigate whether this pattern (higher TER and EER and lower IER) hold when the poverty line is defined in relative terms. Figure 2 looks at whether a household position in the distribution of PMT scores is influenced to some extent by the formula being used to predict her score. Each point in the graphs represent the percentile of a household in the consumption distribution when PMT formula 8 is used against the percentile in the consumption distribution for the same household when PMT formula k

¹⁶Figure A1 similarly compares raw distributions of consumption before PMT regressions and shows that households assigned to module 8 have higher scores.

(with $k = \{1, 7\}$) is used. If measurement errors had no distributive impacts, each point should be on the diagonal. Households are relatively well distributed around the diagonal, even though large deviations exist for some households. Spearman correlations range from 0.83 for PMT scores derived from formula 7 (household diary with infrequent supervision) to 0.93 for PMT scores derived from formula 2 (7 day recall with the long list of items) and formula 4 (7 day recall with the collapsed list of items). Table 4 refines the insights from Figure 2 by investigating the results of regressions. Poverty is defined in relative terms, using a typical 30% threshold. Interestingly, the coefficients are now much smaller in magnitudes and not statistically significant (except formula 5, derived from the usual month recall module). Point estimates correspond to a 0.4 to 3.2 percentage point increase in TER using formulas 1–7. Similarly, both the IER and EER estimates find small and statistically insignificant coefficients (columns 2 and 3). These results provide evidence that if anything measurement errors in consumption does not affect to a great extent the distribution of poor households. In other words, measurement errors in consumption seem to have relatively weak implications on the distribution of PMT scores.

The results presented in columns 4–6 in tables 3 and 4 suggest the effects of measurement errors in consumption on the MSTE, the MSIE and the MSEE are similar to those found for the TER, the IER and the EER.

Measurement errors in consumption may be correlated with household characteristics. For instance, the number of adults in the household may affect the relative prevalence of measurement errors across modules (individual consumption from other adult household members may be missed in designs with a sole respondent). Table 5 explores the potential effects that interactions between key household characteristics (household size, number of adults, literacy, urban/rural location) and the formulas dummies could have on the TER. The poverty line is defined in absolute terms in Panel A and in relative terms in Panel B. Household size and the number of adult members do not seem to mediate the impact of measurement errors on targeting accuracy. No interaction term is significant for any formula except formula 5 (the usual month recall) in Panel A and formulas 4–6 in Panel B. Column 3 shows that literate households seem more vulnerable to targeting errors (due to measurement errors) vis-à-vis the benchmark (module 8). For six out of seven formulas in Panel A interaction terms are significantly different from zero. Finally, household vulnerability to targeting errors (due to measurement errors) does not seem to depend on urban/rural location.

6 Conclusions

In this paper, I have investigated the impact of non-random measurement error on PMT performances. Assessments of PMT performances rely on the assumption that consumption data underlying PMT regressions are error-free or measured with random error – an assumption that has been challenged by recent literature. Using a unique survey experiment in Tanzania, I show that the presence of non-random measurement error in consumption reduces the predictive performances of PMT by a magnitude ranging from 5 to 27 percent, which in turn induces a 10 to 34 percent increase in the incidence of targeting errors (using the typical PPP \$1.25 poverty line). More reassuringly, when poverty is defined in relative terms, impacts on the relative distribution of households are small and non-significant, meaning that measurement errors in consumption have weak implications on the distribution of PMT scores.

Some unresolved questions remain. First, I only discussed one dimension of PMT, i.e. its predictive and targeting performances, and more attention on cost-efficiency, transparency, fairness and acceptance would be welcome. Second, I only considered measurement errors in the dependent variable, while measurement errors in the independent variables could also impact PMT performances. Third, I do not take into account PMT vulnerability to data fraud or data fabrication by interviewers. I chose instead to focus on measurement errors due to survey design, which are likely to have more external validity. However, the problem of data fabrication in surveys has been shown to be prevalent (Finn and Ranchhod, 2017) and documenting the vulnerability of PMT to this other form of measurement errors is a potential avenue for further research. Finally, recent works such as McBride and Nichols (2016) have shown that new tools from machine learning outperform PMT. These new tools are typically trained on survey-based data and future research could investigate whether they are also vulnerable to measurement errors.

Nevertheless, the results presented in this paper provide empirical evidence on one largely ignored aspect of PMT, namely its vulnerability to non-random errors due to survey design. The results may be of relevant interest to researchers in their assessments of PMT performances or in their comparisons of the different targeting mechanisms available. It also has implications for development practitioners and governments designing the targeting devices of the many SSNP implemented in developing countries. If the objective is to target people below the poverty the line, then PMT performances are quite vulnerable to measurement errors. However, if the objective is to target a fixed share of the population (regardless of whether they are above or below the poverty line), PMT performances are quite robust to the presence of measurement errors.

References

- Ahmed, N., Brzozowski, M., and Crossley, T. F. (2006). Measurement errors in recall food consumption data. Working Paper 06/21, Institute for Fiscal Studies (IFS).
- Alatas, V., Banerjee, A., Hanna, R., Olken, B. A., and Tobias, J. (2012). Targeting the poor: Evidence from a field experiment in Indonesia. *The American Economic Review*, 102(4):1206–1240.
- Anderson, S. and Baland, J.-M. (2002). The economics of roscas and intrahousehold resource allocation. *The Quarterly Journal of Economics*, 117(3):963–995.
- Basurto, P. M., Dupas, P., and Robinson, J. (2017). Decentralization and efficiency of subsidy targeting: Evidence from chiefs in rural Malawi. Working Paper 23383, National Bureau of Economic Research.
- Beegle, K., De Weerd, J., Friedman, J., and Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania. *Journal of development Economics*, 98(1):3–18.
- Bound, J., Brown, C., and Mathiowetz, N. (2001). Measurement error in survey data. *Handbook of Econometrics*, 5:3705–3843.
- Bound, J. and Krueger, A. B. (1991). The extent of measurement error in longitudinal earnings data: Do two wrongs make a right? *Journal of Labor Economics*, 9(1):1–24.
- Brown, C., Ravallion, M., and Van De Walle, D. (2016). A poor means test? Econometric targeting in Africa. Working paper 22919, National Bureau of Economic Research.
- Cameron, L. and Shah, M. (2013). Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. *Economic Development and Cultural Change*, 62(2):381–415.
- Cirillo, C. and Tebaldi, R. (2016). Social protection in Africa: inventory of non-contributory programmes. *IPC-IG*.
- Coady, D., Grosh, M. E., and Hoddinott, J. (2004). *Targeting of transfers in developing countries: Review of lessons and experience*. World Bank Publications.
- De Weerd, J., Beegle, K., Friedman, J., and Gibson, J. (2016). The challenge of measuring hunger through survey. *Economic Development and Cultural Change*, 64(4):727–758.
- Deaton, A. (1997). *The analysis of household surveys: a microeconomic approach to development policy*. World Bank Publications.

- Deaton, A. and Grosh, M. (2000). Consumption. In *Designing Household Questionnaires for Developing Countries: Lessons from Fifteen Years of the Living Standard Measurement Study*, volume 15, pages 91–133.
- Del Ninno, C. and Mills, B. (2015). *Safety Nets in Africa: Effective Mechanisms to Reach the Poor and Most Vulnerable*. World Bank and Agence Française de Développement Publication.
- Devereux, S., Masset, E., Sabates-Wheeler, R., Samson, M., Rivas, A.-M., and te Lintelo, D. (2017). The targeting effectiveness of social transfers. *Journal of Development Effectiveness*, 9(2):162–211.
- Dufló, E. and Udry, C. (2004). Intrahousehold resource allocation in Cote d’Ivoire: Social norms, separate accounts and consumption choices. Working paper 10498, National Bureau of Economic Research.
- Finn, A. and Ranchhod, V. (2017). Genuine fakes: The prevalence and implications of data fabrication in a large South African survey. *The World Bank Economic Review*, 31(1):129–157.
- Friedman, J., Beegle, K., De Weerd, J., and Gibson, J. (2016). Decomposing response errors in food consumption measurement. *Food Policy*. Forthcoming.
- Gibson, J., Beegle, K., De Weerd, J., and Friedman, J. (2015). What does variation in survey design reveal about the nature of measurement errors in household consumption? *Oxford Bulletin of Economics and Statistics*, 77(3):466–474.
- Gibson, J. and Kim, B. (2007). Measurement error in recall surveys and the relationship between household size and food demand. *American Journal of Agricultural Economics*, 89(2):473–489.
- Griliches, Z. and Hausman, J. A. (1986). Errors in variables in panel data. *Journal of Econometrics*, 31(1):93–118.
- Grosh, M., Del Ninno, C., Tesliuc, E., and Ouerghi, A. (2008). *For protection and promotion: The design and implementation of effective safety nets*. World Bank Publications.
- Grosh, M. E. (1994). *Administering targeted social programs in Latin America: From platitudes to practice*, volume 94. World Bank Publications.
- Hausman, J. (2001). Mismeasured variables in econometric analysis: problems from the right and problems from the left. *The Journal of Economic Perspectives*, 15(4):57–67.

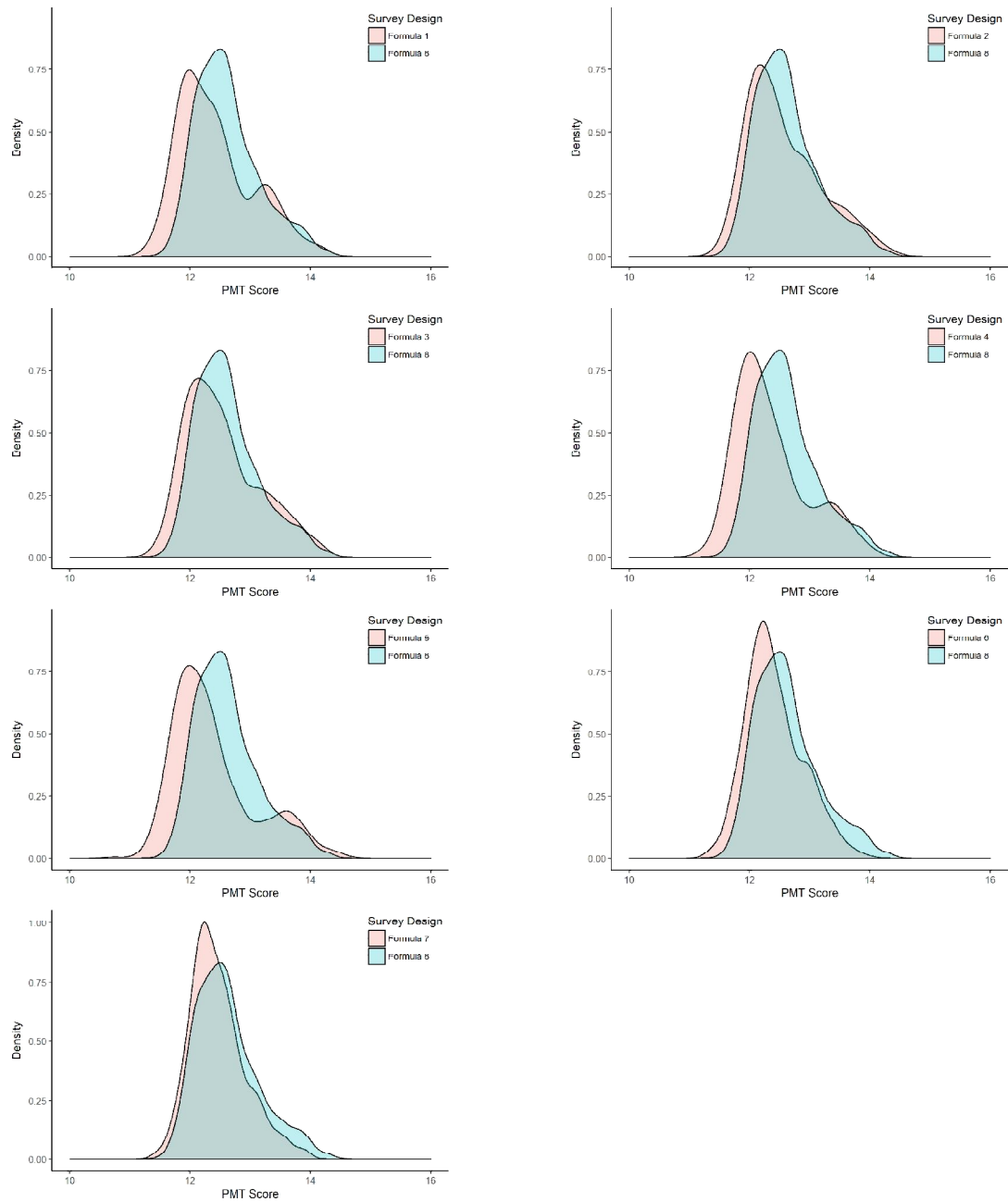
- Jolliffe, D. (2001). Measuring absolute and relative poverty: the sensitivity of estimated household consumption to survey design. *Journal of Economic and Social Measurement*, 27(1, 2):1–23.
- Karlan, D. and Thuysbaert, B. (2016). Targeting ultra-poor households in Honduras and Peru. *The World Bank Economic Review*, Lhw036.
- Kidd, S., Gelders, B., and Bailey-Athias, D. (2017). Exclusion by design. Social protection department, International Labour Office, Geneva.
- Kidd, S. and Wylde, E. (2011). Targeting the poorest: An assessment of the proxy means test methodology. Ausaid research paper, Australian Agency for International Development, Canberra, Australia.
- Lanjouw, P. and Ravallion, M. (1996). How should we assess poverty using data from different surveys? *Poverty Lines*, (3).
- Leite, P. (2014). Effective targeting for the poor and vulnerable. Social protection and labor technical note, The World Bank.
- McBride, L. and Nichols, A. (2016). Retooling poverty targeting using out-of-sample validation and machine learning. *The World Bank Economic Review*, Lhw056.
- Scott, C. and Amenuvegbe, B. (1991). Recall loss and recall duration: an experimental study in Ghana. *Inter-Stat*, 4(1):31–55.
- Stoeffler, Q., Mills, B., and Del Ninno, C. (2016). Reaching the poor: Cash transfer program targeting in Cameroon. *World Development*, 83:244–263.
- Sulla, V., Zikhali, P., Schuler, P., and Jellema, J. (2017). Does fiscal policy benefit the poor and reduce inequality in Namibia? Working Paper 116029, World Bank.

Table 1: PMT Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7	Module 8	All
<i>Hhsize</i>	-0.249*** (0.033)	-0.289*** (0.031)	-0.176*** (0.041)	-0.231*** (0.030)	-0.212*** (0.036)	-0.158*** (0.019)	-0.184*** (0.022)	-0.249*** (0.027)	-0.197*** (0.014)
<i>Hhsize</i> ²	0.011*** (0.002)	0.014*** (0.002)	0.010*** (0.003)	0.009*** (0.002)	0.011*** (0.003)	0.007*** (0.001)	0.007*** (0.001)	0.003*** (0.002)	0.009*** (0.001)
<i>Elderly</i>		0.110* (0.056)						-0.156*** (0.048)	
<i>Young Children</i>	-0.076*** (0.029)	-0.072** (0.030)	-0.150*** (0.030)	-0.063** (0.030)	-0.132*** (0.029)	-0.089*** (0.028)	-0.059** (0.027)		-0.100*** (0.012)
<i>Children</i>			-0.049* (0.029)						-0.023** (0.012)
<i>Mud/Dirt Floor</i>		-0.118* (0.060)				-0.146*** (0.056)			-0.074** (0.031)
<i>Thatch Roof</i>				-0.159*** (0.060)		-0.134** (0.052)	-0.187*** (0.057)		-0.066** (0.026)
<i>Mud Walls</i>	-0.308*** (0.082)		-0.326*** (0.058)	-0.253*** (0.071)	-0.266*** (0.065)	-0.249*** (0.076)		-0.164** (0.081)	-0.193*** (0.031)
<i>N Rooms</i>		0.042** (0.020)		0.041** (0.018)			0.072*** (0.016)	0.098*** (0.017)	0.039*** (0.008)
<i>Electricity</i>		0.234** (0.096)	-0.138** (0.069)	0.186** (0.091)		0.307*** (0.080)	0.343*** (0.096)	0.393*** (0.092)	0.072* (0.044)
<i>Urban</i>	0.126* (0.076)	0.289*** (0.072)						0.283*** (0.085)	0.101** (0.040)
<i>Water</i>			0.122** (0.061)						
<i>Flushed Toilet</i>					0.185* (0.098)	0.206** (0.097)	0.356*** (0.090)		0.161*** (0.052)
<i>Cooking</i>	0.575*** (0.112)	0.505*** (0.086)	0.590*** (0.070)	0.665*** (0.090)	0.787*** (0.073)			0.216** (0.105)	0.418*** (0.050)
<i>Married</i>	-0.238** (0.117)		-0.223*** (0.082)			-0.236** (0.094)	-0.353*** (0.117)	0.189*** (0.060)	-0.149*** (0.042)
<i>Widowed</i>	-0.171* (0.102)	-0.129* (0.074)							-0.105*** (0.039)
<i>Age</i>		0.023** (0.009)		0.019* (0.010)					
<i>Age</i> ²		-0.000*** (0.000)		-0.000** (0.000)	-0.000*** (0.000)				-0.000*** (0.000)
<i>Male</i>	0.347*** (0.119)		0.315*** (0.081)	0.195*** (0.063)		0.370*** (0.097)	0.332*** (0.117)		0.179*** (0.039)
<i>Primary</i>		0.120** (0.058)				0.142** (0.056)	0.197*** (0.054)		0.077*** (0.025)
<i>Secondary</i>			0.287*** (0.109)		0.449*** (0.097)		0.291*** (0.092)		0.154*** (0.041)
<i>Primary Max</i>	0.222** (0.096)				0.260** (0.105)				
<i>Secondary Max</i>	0.249*** (0.068)	0.260*** (0.069)	0.151** (0.070)	0.165** (0.066)				0.235*** (0.071)	0.106*** (0.028)
Ajusted- <i>R</i> ²	0.58	0.60	0.62	0.59	0.64	0.46	0.45	0.47	0.54
Observations	503	504	504	504	504	502	501	503	4025

Notes: This table reports regressions of per capita consumption (in log) as reported in different survey designs. Sequential selection of variables has been done using backward stepwise regression. Definition of the variables are provided in Table A2. The sample in columns 1–8 is restricted to households assigned to a certain consumption module. Results for the full sample are reported in column 9. OLS estimator is used for all regressions. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Comparing distributions of PMT scores by survey design



Notes: Each sub-figure compares the distribution of PMT scores derived from Formula 8 (the benchmark) with distributions of PMT scores of households derived from Formula k (with $k = \{1, 7\}$).

Table 2: Predictive Performances

	(1)	(2)
	\hat{y}_{ik}	$\hat{\mu}_{ik}$
<i>Formula 1</i>	-0.195*** (0.014)	0.100*** (0.017)
<i>Formula 2</i>	-0.050*** (0.011)	0.034*** (0.012)
<i>Formula 3</i>	-0.089*** (0.015)	0.073*** (0.015)
<i>Formula 4</i>	-0.269*** (0.013)	0.105*** (0.019)
<i>Formula 5</i>	-0.239*** (0.020)	0.145*** (0.024)
<i>Formula 6</i>	-0.210*** (0.014)	0.089*** (0.018)
<i>Formula 7</i>	-0.159*** (0.017)	0.080*** (0.018)
F-statistics	193.98***	7.20***
Observations	4024	4024
Number of Households	503	503
Mean in <i>Formula 8</i>	12.621	0.293

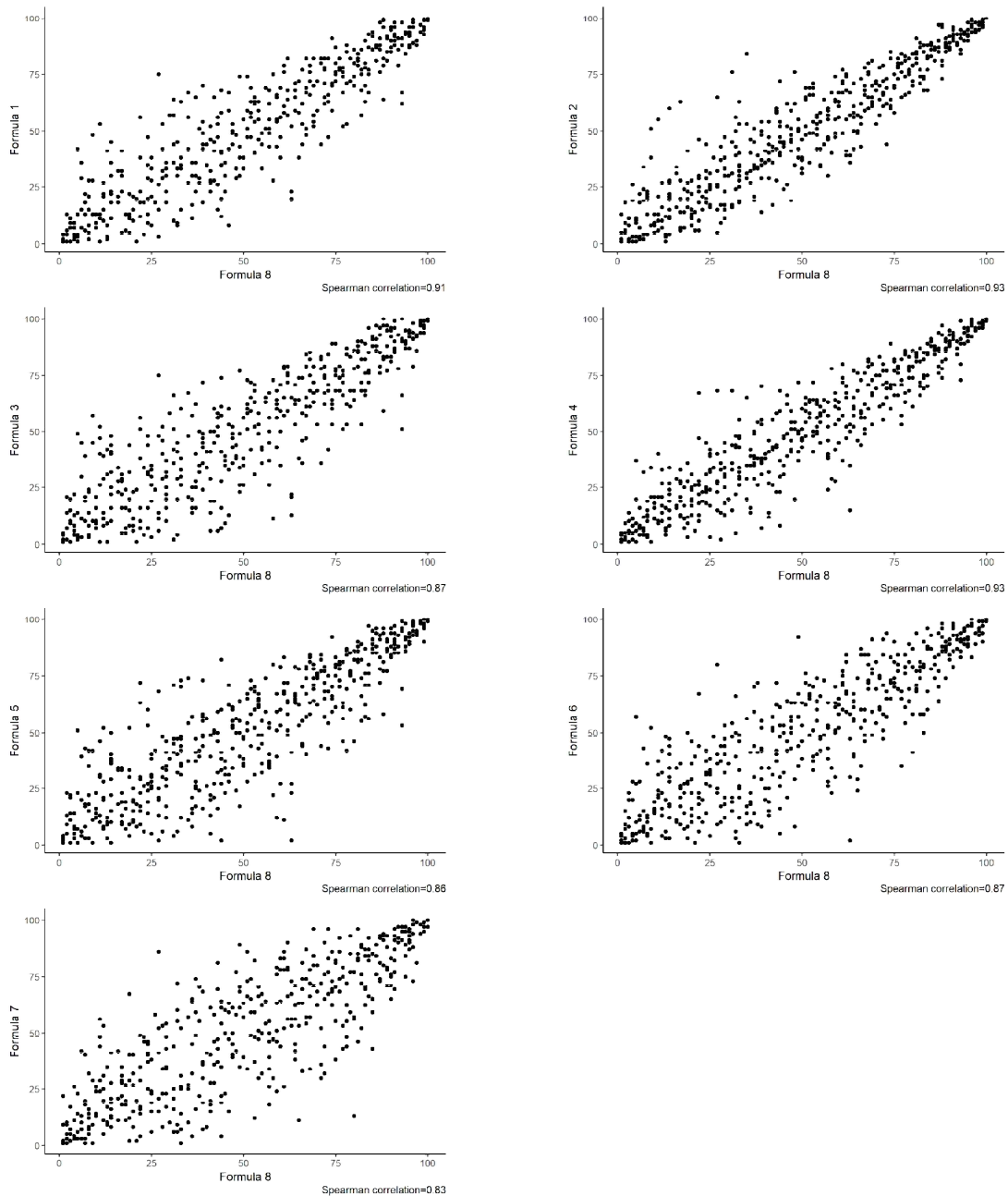
Notes: This table reports regressions of predictive performances of PMT by survey design. \hat{y}_{ik} is the predicted value of the log consumption per capita (PMT score) of household i for formula k . $\hat{\mu}_{ik}$ is the squared prediction error for household i and formula k . Formula k (with $k = \{1, 8\}$) is a dummy variable taking the value of 1 if PMT Formula k is used to derive \hat{y}_{ik} . All coefficients are interpretable relative to formula 8, which is the omitted category and the benchmark to assess the impact of measurement error on the predictive performances by survey design. OLS estimator is used for both regressions. Robust standard errors clustered at the village level in parentheses. F-test is performed on the null hypothesis that the coefficients of all controls are jointly zero. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Targeting Performances, \$1.25 Poverty Line

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.054** (0.023)	0.200*** (0.025)	-0.266*** (0.036)	0.034*** (0.012)	0.072*** (0.016)	-0.049*** (0.014)
<i>Formula 2</i>	0.040** (0.017)	0.116*** (0.020)	-0.127*** (0.032)	0.021** (0.010)	0.046*** (0.013)	-0.034** (0.014)
<i>Formula 3</i>	0.050** (0.020)	0.136*** (0.024)	-0.139*** (0.037)	0.021** (0.010)	0.044*** (0.013)	-0.029** (0.012)
<i>Formula 4</i>	0.058** (0.024)	0.238*** (0.026)	-0.335*** (0.038)	0.037*** (0.014)	0.085*** (0.017)	-0.070*** (0.018)
<i>Formula 5</i>	0.083*** (0.024)	0.261*** (0.027)	-0.304*** (0.039)	0.060*** (0.016)	0.120*** (0.020)	-0.070*** (0.019)
<i>Formula 6</i>	0.024 (0.021)	0.130*** (0.024)	-0.209*** (0.038)	0.007 (0.011)	0.040*** (0.012)	-0.065*** (0.023)
<i>Formula 7</i>	0.044** (0.019)	0.104*** (0.022)	-0.089** (0.043)	0.014 (0.011)	0.041*** (0.010)	-0.043* (0.026)
F-statistics	2.25**	17.75***	13.74***	2.68**	6.99***	3.77***
Observations	4024	2760	1264	4024	2760	1264
Number of Households	503	345	158	503	345	158
Mean in <i>Formula 8</i>	0.247	0.139	0.481	0.059	0.029	0.124

Notes: This table reports regressions of targeting performances of PMT by survey design. The dependent variable in column 1 is a dummy equal to 1 if household i with consumption derived from PMT Formula k is mistargeted, and 0 otherwise. Dependent variable in column 4 is equal to mean squared error if household i with consumption derived from PMT Formula k is mistargeted, and 0 otherwise. Columns 2–3 and 5–6 disaggregate the results by error type. Formula k (with $k = \{1, 8\}$) is a dummy variable taking the value of 1 if PMT Formula k is used to predict Y_{ik} . All coefficients are interpretable relative to formula 8, which is the omitted category and the benchmark to assess the impact of measurement error on the predictive performances by survey design. The mean of the dependent variable in formula 8 is shown in the bottom row. LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. F-test is performed on the null hypothesis that the coefficients of all controls are jointly zero. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2: Correlation between PMT score's percentile predicted by the benchmark PMT formula (formula 8) and the seven other formulas



Notes: Each point in the graphs represent the percentile of the household in the consumption distribution when PMT formula 8 is used (x-axis) against the percentile in the consumption distribution for the same household when PMT formula k (with $k = \{1, 7\}$) is used (y-axis).

Table 4: Targeting Performances, 30% Poverty Threshold

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.024 (0.016)	0.026 (0.018)	0.020 (0.036)	0.006 (0.008)	0.002 (0.010)	0.015 (0.014)
<i>Formula 2</i>	0.004 (0.012)	0.003 (0.013)	0.007 (0.031)	0.004 (0.006)	0.007 (0.007)	-0.002 (0.014)
<i>Formula 3</i>	0.024 (0.016)	0.017 (0.020)	0.040 (0.040)	0.002 (0.008)	0.000 (0.009)	0.008 (0.015)
<i>Formula 4</i>	0.012 (0.015)	0.009 (0.018)	0.020 (0.035)	0.002 (0.005)	-0.003 (0.005)	0.013 (0.014)
<i>Formula 5</i>	0.032* (0.016)	0.023 (0.020)	0.053 (0.038)	0.008 (0.007)	0.003 (0.008)	0.018 (0.014)
<i>Formula 6</i>	0.022 (0.019)	0.017 (0.022)	0.033 (0.047)	0.000 (0.010)	0.001 (0.010)	-0.001 (0.026)
<i>Formula 7</i>	0.010 (0.018)	0.009 (0.021)	0.013 (0.048)	0.000 (0.010)	0.009 (0.010)	-0.019 (0.026)
F-statistics	0.65	0.40	0.54	0.62	0.59	0.82
Observations	4024	2816	1208	4024	2816	1208
Number of Households	503	352	151	503	352	151
Mean in <i>Formula 8</i>	0.258	0.185	0.430	0.065	0.044	0.114

Notes: Inclusion threshold is adjusted to obtain 30% of the household targeted for each module. LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 3 for other details.

Table 5: Interaction of PMT formula and select household characteristics

	(1)	(2)	(3)	(4)
	Household size	Number of adults	Literacy	Urban
Panel A:				
Targeting Error (\$1.25 poverty line)				
Interaction 1	0.009 (0.006)	0.005 (0.011)	0.078* (0.041)	-0.038 (0.043)
Interaction 2	0.002 (0.004)	-0.002 (0.010)	0.014 (0.035)	-0.017 (0.030)
Interaction 3	0.010 (0.006)	0.010 (0.013)	0.080** (0.040)	-0.014 (0.039)
Interaction 4	0.004 (0.008)	-0.001 (0.014)	0.110** (0.047)	0.009 (0.046)
Interaction 5	0.014** (0.007)	0.031** (0.013)	0.101** (0.048)	0.014 (0.047)
Interaction 6	0.009 (0.007)	0.010 (0.014)	0.072* (0.043)	0.017 (0.043)
Interaction 7	0.004 (0.006)	-0.008 (0.012)	0.088** (0.043)	0.013 (0.036)
Panel B:				
Targeting Error (30% poverty threshold)				
Interaction 1	0.008 (0.005)	0.011 (0.011)	0.022 (0.036)	0.017 (0.031)
Interaction 2	0.003 (0.004)	0.002 (0.011)	0.015 (0.030)	0.020 (0.021)
Interaction 3	0.006 (0.005)	0.002 (0.012)	0.047 (0.038)	0.043 (0.033)
Interaction 4	0.012** (0.005)	0.017* (0.009)	0.036 (0.031)	0.043 (0.031)
Interaction 5	0.017*** (0.006)	0.032*** (0.012)	0.026 (0.035)	0.013 (0.034)
Interaction 6	0.013* (0.007)	0.011 (0.014)	0.052 (0.039)	0.011 (0.040)
Interaction 7	0.002 (0.006)	-0.010 (0.012)	0.058 (0.042)	0.029 (0.036)
Observations	4024	4024	4024	4024
Number of Households	503	503	503	503

Notes: This table represents the results of (separate) LPM estimates of a selected measure of targeting performances (mentioned in panels' title) on PMT formula dummies, a single selected household characteristic (mentioned in the column headings) and their interactions. Only the interaction terms are reported due to space limitations. Interaction k (with $k = \{1, 8\}$) is an interactive variable between the characteristic mentioned in the column heading and formula k dummy. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 3 and 4 for other details.

Appendix

Table A1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Ln conso	12.48	0.79	10.21	15.65	4025
hhsize	5.28	2.88	1	23	4025
children5	1.08	1.1	0	8	4025
children14	1.42	1.41	0	12	4025
elderly	0.33	0.59	0	3	4025
age	46.65	16.3	17	96	4025
male	0.8	0.4	0	1	4025
litteracy	0.65	0.48	0	1	4025
primary	0.72	0.45	0	1	4025
secondary	0.09	0.29	0	1	4025
primarymax	0.92	0.26	0	1	4025
secondarymax	0.2	0.4	0	1	4025
married	0.74	0.44	0	1	4025
widowed	0.13	0.34	0	1	4025
floor	0.57	0.49	0	1	4025
roof	0.34	0.47	0	1	4025
wall	0.72	0.45	0	1	4025
room	3.57	1.8	1	18	4025
electricity	0.14	0.34	0	1	4025
water	0.27	0.44	0	1	4025
flushedtoilet	0.1	0.31	0	1	4025
cooking	0.22	0.42	0	1	4025
urban	0.34	0.48	0	1	4025
mobile	0.3	0.46	0	1	4025
tv	0.1	0.29	0	1	4025
radio	0.6	0.49	0	1	4025
watch	0.43	0.5	0	1	4025
bicycle	0.44	0.5	0	1	4025
iron	0.25	0.43	0	1	4025
refrigerator	0.05	0.22	0	1	4025
mattress	0.83	0.38	0	1	4025
sewing_machine	0.07	0.26	0	1	4025
improved_stove	0.12	0.33	0	1	4025
motorecycle	0.02	0.14	0	1	4025
car	0.02	0.14	0	1	4025
wheelbarrow	0.04	0.21	0	1	4025
cattle	0.15	0.36	0	1	4025
sheep	0.05	0.22	0	1	4025
goat	0.25	0.43	0	1	4025
chicken	0.5	0.5	0	1	4025
land_owned	0.8	0.4	0	1	4025
land_rented	0.28	0.45	0	1	4025

Table A2: Description of variables

<i>Dependent variables</i>	
Inconso	Consumption per capita (in log)
<i>Demographic characteristics</i>	
hhsz	Household size
hhsz ²	Squared household size
young children	Number of children (0-5)
children	Number of children (6-14)
elderly	Number of elderly (65+)
primary max	=1 if at least one household member attended primary
secondary max	=1 if at least one household member attended secondary
<i>Household head characteristics</i>	
married	Household head is married
widowed	Household head is widowed
age	Household head's age
age ²	Squared household's head age
primary	Household head attended primary
secondary	Household head attended secondary
male	Household head is male
<i>Dwelling characteristics</i>	
mud/dirt floor	Floor is mud or dirt
thatch roof	Roof is thatched
mud walls	Walls are mud
n rooms	Number of rooms
electricity	Household has access to electricity
urban	Household is urban
water	Water is from piped or from covered well or from vendor
flushed toilet	Household has flushed toilet
cooking	Main fuel for cooking is not firewood
<i>Assets</i>	
mobile	Household has a mobile phone
TV	Household has a TV
radio	Household has a radio
watch	Household has a watch
bicycle	Household has a sewing machine
iron	Household has an improved stove
refrigerator	Household has a refrigerator
mattress	Household has a mattress
sewing machine	Household has a sewing machine
improved stove	Household has an improved stove
motorcycle	Household has a motorcycle
car	Household has a car
wheelbarrow	Household has a wheelbarrow
cattle	Household has cattle
sheep	Household has sheep
goat	Household has goat
chicken	Household has chicken
land ownership	Household owns land
land rented	Household rents land

Table A3: Balance Table

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	T-test						
	Module 1 Mean/SE	Module 2 Mean/SE	Module 3 Mean/SE	Module 4 Mean/SE	Module 5 Mean/SE	Module 6 Mean/SE	Module 7 Mean/SE	Module 8 Mean/SE	(8)-(1)	(8)-(2)	(8)-(3)	(8)-(4)	(8)-(5)	(8)-(6)	(8)-(7)
<i>Hhsizc</i>	5.227 (0.157)	5.153 (0.140)	5.155 (0.140)	5.460 (0.142)	5.282 (0.139)	5.337 (0.153)	5.317 (0.157)	5.280 (0.151)	0.054	0.128	0.126	-0.180	-0.001	-0.056	-0.037
<i>Young Children</i>	1.083 (0.060)	1.016 (0.053)	1.065 (0.055)	1.141 (0.053)	1.069 (0.053)	1.068 (0.059)	1.070 (0.058)	1.093 (0.058)	0.010	0.078	0.028	-0.047	0.024	0.026	0.024
<i>Children</i>	1.429 (0.071)	1.333 (0.062)	1.440 (0.071)	1.498 (0.070)	1.444 (0.069)	1.444 (0.067)	1.355 (0.075)	1.433 (0.071)	0.004	0.100	-0.007	-0.065	-0.011	-0.011	0.078
<i>Elderly</i>	0.370 (0.030)	0.339 (0.029)	0.278 (0.025)	0.312 (0.026)	0.347 (0.025)	0.331 (0.030)	0.339 (0.030)	0.336 (0.029)	-0.034	-0.003	0.058	0.024	-0.011	0.005	-0.003
<i>Married</i>	0.742 (0.022)	0.732 (0.021)	0.720 (0.022)	0.730 (0.021)	0.718 (0.021)	0.747 (0.020)	0.737 (0.021)	0.763 (0.021)	0.022	0.031	0.043	0.033	0.045	0.016	0.027
<i>Widowed</i>	0.125 (0.015)	0.113 (0.015)	0.133 (0.016)	0.135 (0.015)	0.143 (0.016)	0.124 (0.016)	0.160 (0.017)	0.135 (0.016)	0.010	0.022	0.002	0.000	-0.008	0.012	-0.024
<i>Age</i>	47.628 (0.838)	46.192 (0.756)	46.048 (0.762)	46.419 (0.751)	46.532 (0.717)	46.629 (0.765)	46.988 (0.809)	46.803 (0.809)	-0.825	0.611	0.756	0.385	0.271	0.174	-0.185
<i>Male</i>	0.811 (0.019)	0.802 (0.019)	0.794 (0.019)	0.792 (0.018)	0.784 (0.019)	0.819 (0.018)	0.788 (0.019)	0.791 (0.019)	-0.020	-0.010	-0.002	-0.000	0.008	-0.027	0.003
<i>Primary</i>	0.710 (0.022)	0.726 (0.022)	0.738 (0.023)	0.710 (0.023)	0.708 (0.022)	0.731 (0.021)	0.715 (0.024)	0.706 (0.022)	-0.004	-0.020	-0.032	-0.005	-0.003	-0.025	-0.009
<i>Secondary</i>	0.082 (0.014)	0.101 (0.014)	0.087 (0.015)	0.097 (0.016)	0.091 (0.015)	0.088 (0.014)	0.102 (0.016)	0.099 (0.017)	0.018	-0.002	0.012	0.002	0.008	0.012	-0.002
<i>Primary Max</i>	0.913 (0.013)	0.919 (0.013)	0.927 (0.011)	0.933 (0.012)	0.940 (0.010)	0.914 (0.014)	0.942 (0.011)	0.913 (0.012)	0.000	-0.006	-0.014	-0.020	-0.028*	-0.002	-0.030*
<i>Secondary Max</i>	0.195 (0.020)	0.208 (0.022)	0.208 (0.021)	0.196 (0.021)	0.204 (0.021)	0.211 (0.021)	0.210 (0.022)	0.195 (0.021)	0.000	-0.014	-0.014	-0.002	-0.010	-0.016	-0.015
<i>Mud/Dirt Floor</i>	0.571 (0.033)	0.577 (0.033)	0.581 (0.033)	0.565 (0.033)	0.571 (0.033)	0.572 (0.034)	0.561 (0.034)	0.577 (0.033)	0.006	-0.001	-0.005	0.011	0.005	0.005	0.016
<i>Thatch Roof</i>	0.328 (0.028)	0.321 (0.027)	0.331 (0.028)	0.345 (0.029)	0.323 (0.029)	0.339 (0.030)	0.357 (0.028)	0.340 (0.028)	0.012	0.019	0.009	-0.005	0.017	0.001	-0.017
<i>Mud Walls</i>	0.698 (0.029)	0.714 (0.029)	0.712 (0.029)	0.732 (0.028)	0.710 (0.029)	0.735 (0.029)	0.739 (0.029)	0.702 (0.030)	0.004	-0.012	-0.011	-0.030	-0.009	-0.033*	-0.037**
<i>N Rooms</i>	3.529 (0.103)	3.581 (0.100)	3.492 (0.087)	3.615 (0.095)	3.558 (0.089)	3.614 (0.103)	3.607 (0.095)	3.598 (0.095)	0.070	0.017	0.106	-0.017	0.041	-0.015	-0.008
<i>Electricity</i>	0.161 (0.022)	0.125 (0.020)	0.133 (0.021)	0.129 (0.021)	0.151 (0.022)	0.135 (0.021)	0.128 (0.020)	0.133 (0.021)	-0.028	0.008	0.000	0.004	-0.018	-0.002	0.005
<i>Urban</i>	0.203 (0.031)	0.202 (0.031)	0.202 (0.031)	0.202 (0.031)	0.202 (0.031)	0.203 (0.031)	0.200 (0.031)	0.201 (0.031)	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	0.001
<i>Water</i>	0.264 (0.031)	0.264 (0.031)	0.266 (0.032)	0.268 (0.031)	0.274 (0.032)	0.267 (0.032)	0.267 (0.031)	0.270 (0.031)	0.006	0.006	0.005	0.003	-0.003	0.003	0.003
<i>Flushed Toilet</i>	0.119 (0.021)	0.097 (0.017)	0.111 (0.020)	0.103 (0.019)	0.111 (0.020)	0.092 (0.018)	0.108 (0.020)	0.093 (0.018)	-0.026*	-0.004	-0.018	-0.010	-0.018	0.002	-0.014
<i>Cooking</i>	0.229 (0.031)	0.240 (0.031)	0.234 (0.030)	0.222 (0.029)	0.226 (0.030)	0.221 (0.030)	0.204 (0.029)	0.215 (0.030)	-0.014	-0.025**	-0.019	-0.008	-0.011	-0.006	0.011
N	503	504	504	504	504	502	501	503							
Clusters	168	168	168	168	168	168	168	168							

Notes: The value displayed for t-tests are the difference in means between households assigned to module 8 and households assigned to each of the other modules. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Survey experiment consumption modules

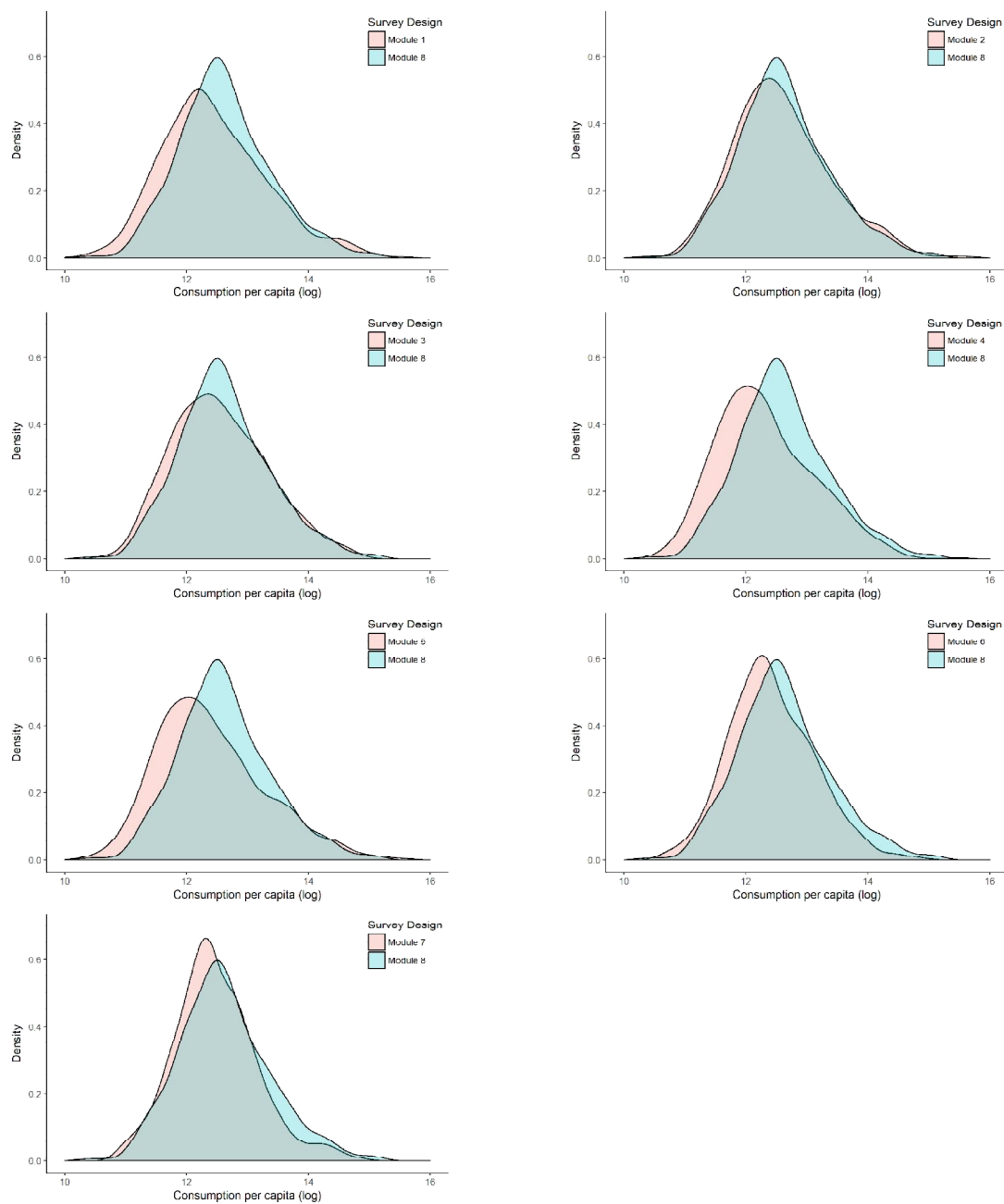
Module	Consumption measurement	Food content	N households
1	Long list (58 food items) 14 day	Quantity from purchases, own-production, and gifts/other sources; Tshilling value of consumption from purchases	504
2	Long list (58 food items) 7 day	Quantity from purchases, own-production, and gifts/other sources; Tshilling value of consumption from purchases	504
3	Subset list (17 food items; subset of 58 foods) 7 day	Quantity from purchases, own-production, and gifts/other sources; Tshilling value of consumption from purchases	504
4	Collapsed list (11 food items covering universe of food categories) 7 day	Tshilling value of consumption	504
5	Long list (58 food items) Usual 12 month	Consumption from purchases: number of months consumed, quantity per month, Tshilling value per month Consumption from own-production: number of months consumed, quantity per month, Tshilling value per month Consumption from gifts/other sources: total estimated value for last 12 months	504
6	Household diary, frequent visits 14 day diary		503
7	Household diary, infrequent visits 14 day diary		503
8	Personal diary, frequent visits 14 day diary		503
			4029

Notes: Frequent visits entailed daily visits by the local assistant and visits every other day by the survey enumerator for the duration of the 2-week diary. Infrequent visits entail 3 visits: to deliver the diary (day 1), to pick up week 1 diary and drop off week 2 diary (day 8), and to pick up week 2 diary (day 15). Households assigned to the infrequent diary but who had no literate members (about 18% of the 503 households) were visited every other day by the local assistant and the enumerator.

Non-food items are divided into two groups based on frequency of purchase. Frequently purchased items (charcoal, firewood, kerosene/paraffin, matches, candles, lighters, laundry soap, toilet soap, cigarettes, tobacco, cell phone and Internet, transport) were collected by 14-day recall for modules 1-5 and in the 14-day diary for modules 6-8. Non-frequent non-food items (utilities, durables, clothing, health, education, contributions, and other; housing is excluded) are collected by recall identically across all modules at the end of the interview (and at the end of the 2-week period for the diaries) and over the identical one or 12-month reference period, depending on the item in question.

Source: Gibson et al. (2015)

Figure A1: Comparing distributions of consumption by survey design



Notes: Each figure compares the distribution of consumption of households assigned to Module 8 (the benchmark) with distributions of households assigned to module k (with $k = \{1, 7\}$).

Table A5: PMT Regressions: food consumption only

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7	Module 8	All
<i>Hhsize</i>	-0.220*** (0.032)	-0.268*** (0.032)	-0.174*** (0.039)	-0.222*** (0.030)	-0.204*** (0.035)	-0.153*** (0.019)	-0.181*** (0.022)	-0.234*** (0.027)	-0.204*** (0.011)
<i>Hhsize</i> ²	0.010*** (0.002)	0.013*** (0.002)	0.010*** (0.002)	0.009*** (0.002)	0.010*** (0.003)	0.007*** (0.001)	0.007*** (0.001)	0.009*** (0.002)	0.009*** (0.001)
<i>Elderly</i>		0.104* (0.055)						-0.164*** (0.048)	
<i>Young Children</i>	-0.085*** (0.029)	-0.074** (0.029)	-0.145*** (0.030)	-0.061** (0.029)	-0.130*** (0.029)	-0.094*** (0.026)	-0.051** (0.025)	-0.056* (0.030)	-0.088*** (0.009)
<i>Children</i>			-0.048* (0.027)						
<i>Mud/Dirt Floor</i>						-0.132** (0.055)			-0.049* (0.030)
<i>Thatch Roof</i>				-0.142** (0.060)		-0.106** (0.053)	-0.146*** (0.054)		-0.054** (0.026)
<i>Mud Walls</i>	-0.246*** (0.078)		-0.282*** (0.056)	-0.185*** (0.069)	-0.213*** (0.064)	-0.169** (0.073)		-0.153** (0.074)	-0.153*** (0.030)
<i>N Rooms</i>		0.041** (0.019)		0.037** (0.018)			0.074*** (0.016)	0.086*** (0.017)	0.039*** (0.007)
<i>Electricity</i>		0.227** (0.089)	-0.153** (0.066)	0.167* (0.085)		0.198*** (0.071)	0.316*** (0.091)	0.401*** (0.087)	0.072* (0.041)
<i>Urban</i>		0.264*** (0.071)						0.287*** (0.076)	0.089** (0.037)
<i>Water</i>									
<i>Flushed Toilet</i>			0.157* (0.091)			0.171** (0.083)	0.291*** (0.083)		0.143*** (0.045)
<i>Cooking</i>	0.529*** (0.087)	0.434*** (0.082)	0.448*** (0.062)	0.506*** (0.092)	0.744*** (0.074)				0.324*** (0.046)
<i>Married</i>	-0.326*** (0.111)	-0.119* (0.072)	-0.270*** (0.084)			-0.279*** (0.093)	-0.317*** (0.105)	0.168*** (0.059)	-0.174*** (0.041)
<i>Widowed</i>	-0.186* (0.106)	-0.186** (0.087)							-0.107*** (0.038)
<i>Age</i>		0.016* (0.009)		0.017* (0.009)					
<i>Age</i> ²		-0.000** (0.000)		-0.000** (0.000)	-0.000*** (0.000)				-0.000*** (0.000)
<i>Male</i>	0.377*** (0.117)		0.351*** (0.082)	0.200*** (0.063)		0.377*** (0.097)	0.292*** (0.106)		0.193*** (0.038)
<i>Primary</i>		0.140** (0.058)				0.114** (0.054)	0.177*** (0.052)		0.065** (0.026)
<i>Secondary</i>	0.233* (0.118)		0.182* (0.095)		0.377*** (0.076)		0.228** (0.092)		0.118*** (0.039)
<i>Primary Max</i>					0.250** (0.104)				
<i>Secondary Max</i>	0.152** (0.076)	0.232*** (0.067)	0.147** (0.070)	0.177*** (0.064)				0.141** (0.070)	0.100*** (0.027)
Ajusted- <i>R</i> ²	0.533	0.553	0.569	0.525	0.591	0.415	0.412	0.421	0.480
Observations	503	504	504	504	504	502	501	503	4025

Notes: OLS estimator is used for all regressions. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 1 for other details.

Table A6: PMT Regressions: consumption per adult equivalent

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7	Module 8	All
<i>Hhsize</i>	-0.232*** (0.035)	-0.230*** (0.038)	-0.162*** (0.043)	-0.241*** (0.031)	-0.240*** (0.040)	-0.111*** (0.025)	-0.152*** (0.027)	-0.194*** (0.040)	-0.179*** (0.015)
<i>Hhsize</i> ²	0.013*** (0.002)	0.015*** (0.002)	0.012*** (0.003)	0.011*** (0.002)	0.013*** (0.003)	0.007*** (0.001)	0.008*** (0.001)	0.010*** (0.002)	0.010*** (0.001)
<i>Elderly</i>			-0.077* (0.044)				-0.094** (0.039)	-0.241*** (0.054)	-0.050** (0.024)
<i>Young Children</i>	-0.197*** (0.031)	-0.210*** (0.033)	-0.284*** (0.033)	-0.170*** (0.031)	-0.225*** (0.029)	-0.214*** (0.031)	-0.194*** (0.032)	-0.195*** (0.039)	-0.219*** (0.013)
<i>Children</i>	-0.044* (0.027)	-0.070*** (0.027)	-0.097*** (0.030)			-0.072** (0.030)	-0.047* (0.028)	-0.087** (0.035)	-0.064*** (0.012)
<i>Mud/Dirt Floor</i>		-0.112* (0.061)				-0.158*** (0.057)			-0.072** (0.031)
<i>Thatch Roof</i>				-0.147** (0.061)		-0.129** (0.054)	-0.185*** (0.056)		-0.067** (0.026)
<i>Mud Walls</i>	-0.306*** (0.081)		-0.317*** (0.058)	-0.267*** (0.075)	-0.257*** (0.068)	-0.222** (0.088)		-0.160* (0.083)	-0.205*** (0.032)
<i>N Rooms</i>		0.038* (0.020)		0.045** (0.018)			0.069*** (0.017)	0.092*** (0.018)	0.039*** (0.008)
<i>Electricity</i>		0.198** (0.091)	-0.135* (0.069)	0.205** (0.093)		0.323*** (0.076)	0.329*** (0.100)	0.414*** (0.094)	
<i>Urban</i>		0.294*** (0.073)				0.133* (0.072)		0.260*** (0.086)	0.100** (0.042)
<i>Water</i>			0.123** (0.062)						
<i>Flushed Toilet</i>					0.183* (0.098)		0.349*** (0.093)		0.179*** (0.050)
<i>Cooking</i>	0.673*** (0.091)	0.493*** (0.088)	0.558*** (0.071)	0.671*** (0.094)	0.786*** (0.078)			0.201* (0.106)	0.432*** (0.051)
<i>Married</i>	-0.260** (0.110)	-0.262*** (0.091)	-0.318*** (0.086)			-0.336*** (0.095)	-0.462*** (0.118)	0.184*** (0.063)	-0.243*** (0.044)
<i>Widowed</i>		-0.222** (0.092)							-0.127*** (0.040)
<i>Age</i>		0.022** (0.009)		0.019** (0.010)					0.007** (0.003)
<i>Age</i> ²		-0.000*** (0.000)		-0.000*** (0.000)	-0.000*** (0.000)				-0.000*** (0.000)
<i>Male</i>	0.470*** (0.125)	0.164* (0.085)	0.405*** (0.083)	0.236*** (0.065)	0.154** (0.068)	0.468*** (0.099)	0.441*** (0.119)		0.277*** (0.040)
<i>Primary</i>		0.123** (0.057)				0.172*** (0.057)	0.172*** (0.055)		0.074*** (0.026)
<i>Secondary</i>	0.219* (0.120)	0.180* (0.103)	0.291*** (0.109)		0.347*** (0.118)		0.277*** (0.092)		0.162*** (0.043)
<i>Primary Max</i>	0.277*** (0.098)		0.172* (0.092)		0.310*** (0.110)				
<i>Secondary Max</i>	0.166** (0.082)	0.168** (0.079)	0.158** (0.073)	0.190*** (0.068)	0.144* (0.079)			0.197*** (0.072)	0.114*** (0.029)
Ajusted- <i>R</i> ²	0.622	0.640	0.662	0.629	0.672	0.526	0.506	0.526	0.581
Observations	503	504	504	504	504	502	501	503	4025

Notes: OLS estimator is used for all regressions. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 1 for other details.

Table A7: PMT Regressions: extended list of covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7	Module 8	All
<i>Hhsize</i>	-0.260*** (0.030)	-0.280*** (0.032)	-0.174*** (0.039)	-0.239*** (0.029)	-0.263*** (0.033)	-0.168*** (0.021)	-0.187*** (0.022)	-0.258*** (0.023)	-0.226*** (0.011)
<i>Hhsize</i> ²	0.010*** (0.002)	0.014*** (0.002)	0.010*** (0.002)	0.011*** (0.002)	0.013*** (0.002)	0.006*** (0.001)	0.007*** (0.001)	0.010*** (0.001)	0.009*** (0.001)
<i>Elderly</i>		0.104** (0.053)						-0.143*** (0.043)	
<i>Young Children</i>		-0.093*** (0.025)	-0.144*** (0.027)	-0.070*** (0.025)	-0.113*** (0.026)	-0.080*** (0.028)	-0.065** (0.026)		-0.077*** (0.009)
<i>Children</i>			-0.053* (0.027)						
<i>Mud/Dirt Floor</i>						-0.185*** (0.050)			
<i>Thatch Roof</i>				-0.133** (0.056)			-0.129** (0.053)		
<i>Mud Walls</i>	-0.185** (0.082)		-0.188*** (0.066)	-0.152** (0.068)	-0.137** (0.062)				-0.113*** (0.028)
<i>N Rooms</i>							0.047*** (0.016)	0.042** (0.017)	0.014** (0.007)
<i>Electricity</i>	-0.235*** (0.089)		-0.147** (0.063)		-0.206** (0.089)	0.218*** (0.076)	0.188** (0.087)	0.260*** (0.086)	
<i>Urban</i>		0.204*** (0.062)				0.146** (0.064)		0.285*** (0.080)	0.081** (0.036)
<i>Water</i>			0.132** (0.056)						
<i>Flushed Toilet</i>							0.251*** (0.091)		0.087** (0.043)
<i>Cooking</i>	0.413*** (0.104)	0.366*** (0.072)	0.408*** (0.079)	0.462*** (0.082)	0.567*** (0.083)			0.189* (0.104)	0.290*** (0.016)
<i>Married</i>	-0.441*** (0.109)	-0.128* (0.070)	-0.324*** (0.081)			-0.266*** (0.097)	-0.345*** (0.109)		-0.211*** (0.040)
<i>Widowed</i>	-0.204** (0.101)	-0.179** (0.083)							-0.097** (0.038)
<i>Age</i>		0.015* (0.009)				-0.003* (0.002)			
<i>Age</i> ²		-0.000** (0.000)		-0.000** (0.000)	-0.000*** (0.000)				-0.000*** (0.000)
<i>Male</i>	0.380*** (0.109)		0.288*** (0.079)	0.121** (0.057)		0.310*** (0.098)	0.258** (0.113)		0.166*** (0.037)
<i>Primary</i>							0.144** (0.056)		
<i>Secondary</i>			0.224*** (0.083)		0.187** (0.085)		0.168** (0.083)		
<i>Primary Max</i>					0.181* (0.104)				
<i>Secondary Max</i>	0.143** (0.069)	0.127** (0.064)						0.162** (0.065)	0.077*** (0.023)
<i>Iron</i>	0.198*** (0.071)		0.123** (0.057)	0.199*** (0.055)	0.112** (0.054)				0.084*** (0.022)
<i>Refrigerator</i>	0.295** (0.129)	0.403*** (0.113)		0.286** (0.118)			0.247* (0.149)	0.235* (0.138)	0.151** (0.060)
<i>Land Rented</i>	-0.130** (0.058)			-0.089* (0.053)		-0.083* (0.046)			
<i>Mobile</i>	0.220*** (0.071)	0.226*** (0.052)	0.262*** (0.073)	0.298*** (0.053)	0.251*** (0.063)	0.201*** (0.063)	0.235*** (0.060)	0.145* (0.081)	0.205*** (0.022)
<i>Cattle</i>	0.135** (0.063)	0.135** (0.056)		-0.142** (0.071)		0.192*** (0.066)	0.210*** (0.065)	0.235*** (0.061)	0.114*** (0.031)
<i>Radio</i>	0.192*** (0.055)	0.090* (0.053)	0.185*** (0.048)	0.154*** (0.048)	0.166*** (0.049)		0.124** (0.052)	0.149*** (0.050)	0.135*** (0.018)
<i>Improved Stove</i>	0.200** (0.086)	0.142* (0.073)	0.144* (0.074)	0.155** (0.075)	0.225** (0.091)				0.140*** (0.031)
<i>TV</i>	0.226* (0.123)				0.326*** (0.104)	0.205* (0.111)		0.197** (0.095)	0.136*** (0.041)
<i>Mattress</i>		0.173** (0.075)							0.076*** (0.026)
<i>Car</i>		0.269* (0.158)			0.493*** (0.177)		0.213* (0.128)		0.175** (0.072)
<i>Watch</i>		0.151*** (0.051)			0.116** (0.049)	0.119** (0.049)		0.128*** (0.048)	0.069*** (0.017)
<i>Goat</i>				0.158** (0.061)				0.242*** (0.055)	0.070*** (0.024)
<i>Sheep</i>				-0.173** (0.086)	0.196** (0.084)				
<i>Land Ownership</i>				0.122* (0.065)					
<i>Bicycle</i>						0.085* (0.047)			
<i>Sewing Machine</i>						0.266*** (0.095)		0.157* (0.083)	0.064** (0.029)
<i>Motorcycle</i>						0.280* (0.143)			
<i>Chicken</i>								0.108* (0.057)	
<i>Wheelbarrow</i>									0.080* (0.044)
Adjusted-R ²	0.639	0.643	0.651	0.654	0.695	0.516	0.494	0.548	0.580
Observations	503	504	504	504	504	502	501	503	4025

Notes: OLS estimator is used for all regressions. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 1 for other details.

Table A8: PMT Regressions: no stepwise procedure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Module 1	Module 2	Module 3	Module 4	Module 5	Module 6	Module 7	Module 8	All
<i>Hhsize</i>	-0.247*** (0.039)	-0.251*** (0.042)	-0.194*** (0.045)	-0.231*** (0.037)	-0.230*** (0.043)	-0.129*** (0.027)	-0.162*** (0.031)	-0.209*** (0.041)	-0.200*** (0.015)
<i>Hhsize</i> ²	0.012*** (0.002)	0.013*** (0.002)	0.011*** (0.003)	0.010*** (0.002)	0.011*** (0.003)	0.006*** (0.001)	0.007*** (0.001)	0.009*** (0.002)	0.009*** (0.001)
<i>Elderly</i>	0.058 (0.062)	0.114* (0.059)	-0.009 (0.072)	-0.041 (0.061)	-0.034 (0.063)	-0.013 (0.060)	-0.029 (0.063)	-0.110 (0.069)	-0.005 (0.024)
<i>Young Children</i>	-0.081** (0.038)	-0.079** (0.034)	-0.139*** (0.035)	-0.063* (0.037)	-0.122*** (0.032)	-0.110*** (0.035)	-0.081** (0.033)	-0.084** (0.038)	-0.097*** (0.012)
<i>Children</i>	-0.005 (0.028)	-0.014 (0.028)	-0.051 (0.033)	-0.010 (0.031)	-0.003 (0.034)	-0.025 (0.032)	-0.019 (0.028)	-0.047 (0.034)	-0.024** (0.012)
<i>Mud/Dirt Floor</i>	-0.117 (0.077)	-0.093 (0.065)	-0.077 (0.063)	-0.079 (0.065)	-0.058 (0.065)	-0.136** (0.057)	-0.066 (0.066)	0.004 (0.067)	-0.076** (0.031)
<i>Thatch Roof</i>	0.093 (0.065)	0.009 (0.066)	-0.061 (0.058)	-0.165*** (0.059)	-0.026 (0.062)	-0.094* (0.051)	-0.154*** (0.057)	-0.089 (0.061)	-0.068*** (0.026)
<i>Mud Walls</i>	-0.285*** (0.084)	-0.085 (0.073)	-0.285*** (0.066)	-0.221*** (0.074)	-0.227*** (0.068)	-0.175** (0.088)	-0.058 (0.086)	-0.130 (0.092)	-0.193*** (0.031)
<i>N Rooms</i>	0.021 (0.020)	0.040* (0.021)	0.007 (0.017)	0.036* (0.019)	0.028 (0.026)	0.028 (0.017)	0.070*** (0.017)	0.079*** (0.018)	0.039*** (0.007)
<i>Electricity</i>	-0.092 (0.093)	0.151 (0.103)	-0.156** (0.069)	0.176* (0.090)	-0.118 (0.094)	0.247*** (0.082)	0.289*** (0.103)	0.356*** (0.091)	0.073* (0.044)
<i>Urban</i>	0.167** (0.079)	0.262*** (0.074)	0.071 (0.077)	-0.005 (0.075)	0.091 (0.091)	0.106 (0.075)	-0.056 (0.081)	0.242*** (0.089)	0.102** (0.041)
<i>Water</i>	-0.058 (0.081)	0.071 (0.073)	0.073 (0.062)	-0.095 (0.080)	-0.091 (0.093)	0.006 (0.087)	0.027 (0.079)	0.007 (0.070)	-0.008 (0.038)
<i>Flushed Toilet</i>	0.125 (0.099)	0.129 (0.107)	0.115 (0.096)	0.031 (0.089)	0.229** (0.112)	0.124 (0.110)	0.290*** (0.101)	0.099 (0.108)	0.161*** (0.053)
<i>Cooking</i>	0.565*** (0.122)	0.422*** (0.090)	0.500*** (0.086)	0.680*** (0.100)	0.812*** (0.108)	0.095 (0.107)	0.068 (0.118)	0.153 (0.103)	0.421*** (0.051)
<i>Married</i>	-0.250** (0.119)	-0.171* (0.088)	-0.215** (0.091)	-0.077 (0.106)	0.011 (0.107)	-0.272*** (0.095)	-0.370*** (0.117)	0.172 (0.130)	-0.151*** (0.042)
<i>Widowed</i>	-0.147 (0.107)	-0.184* (0.095)	0.036 (0.077)	-0.155 (0.100)	-0.016 (0.116)	-0.121 (0.093)	-0.085 (0.118)	0.014 (0.107)	-0.107*** (0.039)
<i>Age</i>	0.003 (0.009)	0.021** (0.009)	0.007 (0.009)	0.020** (0.010)	-0.001 (0.008)	-0.009 (0.009)	0.001 (0.010)	0.001 (0.011)	0.004 (0.003)
<i>Age</i> ²	-0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)
<i>Male</i>	0.345*** (0.121)	0.084 (0.084)	0.338*** (0.085)	0.154 (0.115)	0.108 (0.108)	0.306*** (0.111)	0.277** (0.126)	-0.009 (0.121)	0.184*** (0.039)
<i>Primary</i>	0.005 (0.076)	0.120* (0.062)	-0.006 (0.061)	0.064 (0.065)	-0.006 (0.075)	0.118* (0.065)	0.148** (0.060)	0.090 (0.069)	0.072*** (0.027)
<i>Secondary</i>	0.156 (0.120)	0.144 (0.100)	0.234** (0.103)	0.036 (0.101)	0.339*** (0.124)	0.083 (0.098)	0.292** (0.116)	0.070 (0.117)	0.153*** (0.042)
<i>Primary Max</i>	0.176 (0.116)	-0.023 (0.118)	0.093 (0.102)	0.014 (0.117)	0.228** (0.113)	-0.078 (0.114)	-0.038 (0.109)	-0.064 (0.102)	0.016 (0.043)
<i>Secondary Max</i>	0.143* (0.083)	0.155** (0.077)	0.139* (0.072)	0.127 (0.090)	0.098 (0.088)	0.035 (0.079)	-0.041 (0.078)	0.146 (0.093)	0.105*** (0.028)
Ajusted- <i>R</i> ²	0.584	0.596	0.618	0.592	0.642	0.462	0.440	0.472	0.535
Observations	503	504	504	504	504	502	501	503	4025

Notes: OLS estimator is used for all regressions. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 1 for other details.

Table A9: Predictive Performances: food consumption only

	(1)	(2)
	\hat{y}_{ik}	$\hat{\mu}_{ik}$
<i>Formula 1</i>	-0.197*** (0.015)	0.105*** (0.017)
<i>Formula 2</i>	-0.045*** (0.012)	0.039*** (0.011)
<i>Formula 3</i>	-0.102*** (0.014)	0.070*** (0.013)
<i>Formula 4</i>	-0.303*** (0.012)	0.122*** (0.021)
<i>Formula 5</i>	-0.277*** (0.020)	0.168*** (0.026)
<i>Formula 6</i>	-0.210*** (0.013)	0.084*** (0.016)
<i>Formula 7</i>	-0.145*** (0.014)	0.061*** (0.015)
F-statistics	178.50***	6.89***
Observations	4024	4024
Number of Households	503	503
Mean in <i>Formula 8</i>	12.489	0.283

Notes: OLS estimator is used for both regressions. Robust standard errors clustered at the village level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 2 for other details.

Table A10: Predictive Performances: consumption per adult equivalent

	(1)	(2)
	\hat{y}_{ik}	$\hat{\mu}_{ik}$
<i>Formula 1</i>	-0.194*** (0.016)	0.112*** (0.019)
<i>Formula 2</i>	-0.061*** (0.012)	0.040*** (0.012)
<i>Formula 3</i>	-0.093*** (0.015)	0.079*** (0.016)
<i>Formula 4</i>	-0.269*** (0.013)	0.112*** (0.020)
<i>Formula 5</i>	-0.238*** (0.020)	0.149*** (0.024)
<i>Formula 6</i>	-0.216*** (0.013)	0.094*** (0.018)
<i>Formula 7</i>	-0.164*** (0.017)	0.085*** (0.018)
F-statistics	149.26***	7.78***
Observations	4024	4024
Number of Households	503	503
Mean in <i>Formula 8</i>	12.402	0.303

Notes: OLS estimator is used for both regressions. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 2 for other details.

Table A11: Predictive Performances: extended list of covariates in PMT

	(1)	(2)
	\hat{y}_{ik}	$\hat{\mu}_{ik}$
<i>Formula 1</i>	-0.200*** (0.018)	0.134*** (0.017)
<i>Formula 2</i>	-0.074*** (0.014)	0.059*** (0.012)
<i>Formula 3</i>	-0.085*** (0.018)	0.103*** (0.015)
<i>Formula 4</i>	-0.273*** (0.018)	0.157*** (0.021)
<i>Formula 5</i>	-0.231*** (0.021)	0.157*** (0.022)
<i>Formula 6</i>	-0.221*** (0.012)	0.092*** (0.015)
<i>Formula 7</i>	-0.170*** (0.015)	0.087*** (0.015)
F-statistics	192.30***	10.75***
Observations	4024	4024
Number of Households	503	503
Mean in <i>Formula 8</i>	12.621	0.249

Notes: OLS estimator is used for both regressions. Robust standard errors clustered at the village level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 2 for other details.

Table A12: Predictive Performances: no stepwise procedure in PMT

	(1)	(2)
	\hat{y}_{ik}	$\hat{\mu}_{ik}$
<i>Formula 1</i>	-0.190*** (0.014)	0.103*** (0.017)
<i>Formula 2</i>	-0.055*** (0.011)	0.042*** (0.011)
<i>Formula 3</i>	-0.090*** (0.014)	0.069*** (0.014)
<i>Formula 4</i>	-0.275*** (0.013)	0.119*** (0.020)
<i>Formula 5</i>	-0.236*** (0.018)	0.142*** (0.021)
<i>Formula 6</i>	-0.214*** (0.009)	0.075*** (0.015)
<i>Formula 7</i>	-0.155*** (0.015)	0.076*** (0.016)
F-statistics	225.52***	8.53***
Observations	4024	4024
Number of Households	503	503
Mean in <i>Formula 8</i>	12.621	0.287

Notes: OLS estimator is used for both regressions. Robust standard errors clustered at the village level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 2 for other details.

Table A13: Targeting Performances (\$1.25 Poverty Line): food consumption only

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.064*** (0.023)	0.217*** (0.029)	-0.190*** (0.035)	0.053*** (0.017)	0.092*** (0.023)	-0.014 (0.022)
<i>Formula 2</i>	0.048** (0.021)	0.140*** (0.024)	-0.106*** (0.034)	0.030*** (0.011)	0.052*** (0.014)	-0.005 (0.019)
<i>Formula 3</i>	0.048** (0.021)	0.150*** (0.026)	-0.122*** (0.033)	0.028*** (0.010)	0.051*** (0.014)	-0.011 (0.013)
<i>Formula 4</i>	0.074*** (0.026)	0.303*** (0.031)	-0.307*** (0.033)	0.039*** (0.014)	0.105*** (0.019)	-0.071*** (0.015)
<i>Formula 5</i>	0.095*** (0.027)	0.315*** (0.032)	-0.270*** (0.039)	0.079*** (0.021)	0.153*** (0.029)	-0.042* (0.022)
<i>Formula 6</i>	0.022 (0.022)	0.172*** (0.025)	-0.228*** (0.031)	0.011 (0.010)	0.048*** (0.013)	-0.052*** (0.013)
<i>Formula 7</i>	0.036* (0.019)	0.140*** (0.024)	-0.138*** (0.028)	0.013 (0.008)	0.042*** (0.011)	-0.036*** (0.013)
F-statistics	3.22	16.81	16.41	3.78	6.39	4.44
Observations	4024	2512	1512	4024	2512	1512
Number of Households	503	314	190	503	314	190
Mean in <i>Formula 8</i>	0.278	0.185	0.434	0.054	0.037	0.082

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 3 for other details.

Table A14: Targeting Performances (\$1.25 Poverty Line): consumption per adult equivalent

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.044** (0.019)	0.188*** (0.025)	-0.133*** (0.028)	0.027 (0.017)	0.084*** (0.027)	-0.042*** (0.016)
<i>Formula 2</i>	0.020 (0.014)	0.112*** (0.020)	-0.093*** (0.021)	-0.002 (0.008)	0.028*** (0.009)	-0.039*** (0.012)
<i>Formula 3</i>	0.032* (0.017)	0.097*** (0.022)	-0.049* (0.026)	0.009 (0.010)	0.031*** (0.011)	-0.018 (0.016)
<i>Formula 4</i>	0.048** (0.020)	0.242*** (0.028)	-0.190*** (0.026)	0.011 (0.013)	0.079*** (0.019)	-0.072*** (0.016)
<i>Formula 5</i>	0.054** (0.021)	0.245*** (0.029)	-0.181*** (0.027)	0.028* (0.015)	0.099*** (0.022)	-0.059*** (0.016)
<i>Formula 6</i>	0.042** (0.019)	0.188*** (0.025)	-0.137*** (0.026)	0.003 (0.011)	0.053*** (0.014)	-0.058*** (0.015)
<i>Formula 7</i>	0.028 (0.017)	0.126*** (0.023)	-0.093*** (0.026)	0.002 (0.011)	0.038*** (0.014)	-0.044*** (0.015)
F-statistics	1.10	14.13	10.96	1.71	3.91	4.05
Observations	4024	2216	1808	4024	2216	1808
Number of Households	503	277	226	503	277	226
Mean in <i>Formula 8</i>	0.247	0.139	0.481	0.059	0.029	0.124

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 3 for other details.

Table A15: Targeting Performances (\$1.25 Poverty Line): extended list of covariates in PMT

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.064*** (0.024)	0.203*** (0.028)	-0.241*** (0.037)	0.033*** (0.012)	0.065*** (0.015)	-0.038* (0.020)
<i>Formula 2</i>	0.032 (0.021)	0.113*** (0.022)	-0.146*** (0.044)	0.028*** (0.008)	0.039*** (0.011)	0.005 (0.013)
<i>Formula 3</i>	0.044** (0.021)	0.119*** (0.024)	-0.120*** (0.041)	0.021** (0.008)	0.028*** (0.010)	0.005 (0.015)
<i>Formula 4</i>	0.066** (0.026)	0.229*** (0.029)	-0.291*** (0.040)	0.046*** (0.014)	0.088*** (0.018)	-0.047** (0.018)
<i>Formula 5</i>	0.070*** (0.024)	0.232*** (0.028)	-0.285*** (0.038)	0.040*** (0.013)	0.083*** (0.016)	-0.054*** (0.019)
<i>Formula 6</i>	0.024 (0.018)	0.133*** (0.022)	-0.215*** (0.035)	0.010 (0.010)	0.036*** (0.011)	-0.046** (0.019)
<i>Formula 7</i>	0.018 (0.019)	0.087*** (0.022)	-0.133*** (0.033)	0.011 (0.009)	0.031*** (0.009)	-0.034* (0.019)
F-statistics	1.53	12.18	14.68	3.84	6.05	1.87
Observations	4024	2760	1264	4024	2760	1264
Number of Households	503	345	158	503	345	158
Mean in <i>Formula 8</i>	0.221	0.122	0.437	0.040	0.021	0.081

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 3 for other details.

Table A16: Targeting Performances (\$1.25 Poverty Line): no stepwise procedure in PMT

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.058** (0.022)	0.186*** (0.026)	-0.222*** (0.040)	0.031** (0.012)	0.061*** (0.015)	-0.035* (0.018)
<i>Formula 2</i>	0.042** (0.017)	0.125*** (0.020)	-0.139*** (0.033)	0.025** (0.010)	0.050*** (0.013)	-0.029** (0.012)
<i>Formula 3</i>	0.042** (0.019)	0.125*** (0.023)	-0.139*** (0.034)	0.026** (0.011)	0.046*** (0.015)	-0.017 (0.017)
<i>Formula 4</i>	0.056** (0.024)	0.235*** (0.026)	-0.335*** (0.037)	0.041*** (0.015)	0.090*** (0.019)	-0.066*** (0.016)
<i>Formula 5</i>	0.062** (0.024)	0.232*** (0.026)	-0.310*** (0.038)	0.039*** (0.014)	0.085*** (0.018)	-0.063*** (0.016)
<i>Formula 6</i>	0.024 (0.019)	0.145*** (0.022)	-0.241*** (0.034)	0.005 (0.010)	0.042*** (0.011)	-0.075*** (0.022)
<i>Formula 7</i>	0.032* (0.018)	0.099*** (0.021)	-0.114*** (0.035)	0.008 (0.010)	0.035*** (0.009)	-0.051** (0.022)
F-statistics	1.67	13.48	16.08	1.96	5.19	4.15
Observations	4024	2760	1264	4024	2760	1264
Number of Households	503	345	158	503	345	158
Mean in <i>Formula 8</i>	0.256	0.148	0.494	0.060	0.032	0.120

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 3 for other details.

Table A17: Targeting Performances (30% Poverty Threshold): food consumption only

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.036** (0.016)	0.026 (0.020)	0.060* (0.033)	0.019** (0.009)	0.010 (0.008)	0.041 (0.025)
<i>Formula 2</i>	-0.008 (0.014)	-0.006 (0.014)	-0.013 (0.033)	0.008 (0.009)	0.008 (0.007)	0.006 (0.026)
<i>Formula 3</i>	0.028* (0.017)	0.020 (0.021)	0.046 (0.037)	0.004 (0.009)	-0.004 (0.007)	0.022 (0.025)
<i>Formula 4</i>	0.020 (0.015)	0.014 (0.018)	0.033 (0.030)	0.011 (0.009)	0.002 (0.005)	0.032 (0.026)
<i>Formula 5</i>	0.036** (0.017)	0.026 (0.021)	0.060 (0.038)	0.015 (0.009)	0.005 (0.008)	0.036 (0.025)
<i>Formula 6</i>	0.032* (0.018)	0.023 (0.021)	0.053 (0.040)	0.008 (0.008)	0.004 (0.008)	0.015 (0.018)
<i>Formula 7</i>	0.030* (0.017)	0.026 (0.020)	0.040 (0.043)	0.005 (0.008)	0.011 (0.007)	-0.008 (0.022)
F-statistics	1.47	0.54	1.00	1.34	1.39	1.14
Observations	4024	2816	1208	4024	2816	1208
Number of Households	503	352	151	503	352	151
Mean in <i>Formula 8</i>	0.262	0.187	0.437	0.057	0.028	0.125

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 4 for other details.

Table A18: Targeting Performances (30% Poverty Threshold): consumption per adult equivalent

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.040*** (0.013)	0.028* (0.016)	0.066** (0.032)	0.021** (0.010)	0.005 (0.005)	0.060* (0.031)
<i>Formula 2</i>	0.024** (0.012)	0.017 (0.015)	0.040 (0.025)	0.021* (0.011)	0.007 (0.005)	0.053 (0.034)
<i>Formula 3</i>	0.036*** (0.014)	0.026 (0.016)	0.060* (0.034)	0.025** (0.011)	0.003 (0.005)	0.074** (0.034)
<i>Formula 4</i>	0.036** (0.015)	0.026 (0.018)	0.060* (0.033)	0.022** (0.010)	0.005 (0.005)	0.062* (0.033)
<i>Formula 5</i>	0.036** (0.015)	0.026 (0.018)	0.060* (0.033)	0.025** (0.011)	0.009 (0.007)	0.062* (0.033)
<i>Formula 6</i>	0.034** (0.016)	0.026 (0.019)	0.053 (0.035)	0.016** (0.007)	0.008 (0.005)	0.035* (0.020)
<i>Formula 7</i>	0.024 (0.015)	0.017 (0.018)	0.040 (0.038)	0.014 (0.010)	0.006 (0.005)	0.031 (0.032)
F-statistics	1.49	0.49	0.80	1.44	0.85	1.17
Observations	4024	2816	1208	4024	2816	1208
Number of Households	503	352	151	503	352	151
Mean in <i>Formula 8</i>	0.227	0.162	0.377	0.061	0.011	0.178

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 4 for other details.

Table A19: Targeting Performances (30% Poverty Threshold): extended list of covariates in PMT

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.020 (0.016)	0.017 (0.020)	0.026 (0.038)	0.031*** (0.012)	0.009 (0.009)	0.083** (0.033)
<i>Formula 2</i>	0.016 (0.016)	0.011 (0.018)	0.026 (0.038)	0.022** (0.009)	0.012 (0.010)	0.046** (0.021)
<i>Formula 3</i>	0.036* (0.019)	0.026 (0.023)	0.060 (0.041)	0.021** (0.009)	0.007 (0.009)	0.054** (0.023)
<i>Formula 4</i>	0.020 (0.017)	0.014 (0.020)	0.033 (0.040)	0.029** (0.012)	0.011 (0.010)	0.071** (0.032)
<i>Formula 5</i>	0.028 (0.018)	0.020 (0.020)	0.046 (0.047)	0.016* (0.009)	0.002 (0.009)	0.050** (0.024)
<i>Formula 6</i>	0.024 (0.017)	0.017 (0.019)	0.040 (0.040)	0.015* (0.008)	0.012 (0.010)	0.022 (0.014)
<i>Formula 7</i>	0.020 (0.018)	0.014 (0.022)	0.033 (0.041)	0.009 (0.007)	0.009 (0.009)	0.009 (0.010)
F-statistics	0.63	0.22	0.36	1.32	0.84	1.26
Observations	4024	2816	1208	4024	2816	1208
Number of Households	503	352	151	503	352	151
Mean in <i>Formula 8</i>	0.219	0.156	0.364	0.036	0.026	0.061

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See notes to Table 4 for other details.

Table A20: Targeting Performances (30% Poverty Threshold): no stepwise procedure in PMT

	(1)	(2)	(3)	(4)	(5)	(6)
	TE_{ik}	IE_{ik}	EE_{ik}	TE_{ik}^2	IE_{ik}^2	EE_{ik}^2
<i>Formula 1</i>	0.028** (0.014)	0.020 (0.016)	0.046 (0.033)	0.010 (0.008)	0.009 (0.009)	0.014 (0.016)
<i>Formula 2</i>	-0.000 (0.012)	-0.000 (0.014)	-0.000 (0.028)	0.004 (0.006)	0.004 (0.008)	0.005 (0.013)
<i>Formula 3</i>	0.024 (0.015)	0.017 (0.018)	0.040 (0.034)	0.002 (0.008)	-0.003 (0.010)	0.014 (0.015)
<i>Formula 4</i>	0.012 (0.014)	0.009 (0.016)	0.020 (0.033)	-0.003 (0.004)	-0.008 (0.005)	0.009 (0.009)
<i>Formula 5</i>	0.016 (0.014)	0.011 (0.016)	0.026 (0.033)	0.005 (0.007)	0.002 (0.008)	0.013 (0.015)
<i>Formula 6</i>	0.020 (0.013)	0.014 (0.014)	0.033 (0.030)	0.003 (0.005)	-0.000 (0.004)	0.011 (0.013)
<i>Formula 7</i>	0.024 (0.016)	0.017 (0.018)	0.040 (0.039)	-0.001 (0.008)	0.006 (0.007)	-0.018 (0.022)
F-statistics	1.07	0.40	1.02	0.51	1.25	0.45
Observations	4024	2816	1208	4024	2816	1208
Number of Households	503	352	151	503	352	151
Mean in <i>Formula 8</i>	0.254	0.182	0.424	0.064	0.044	0.111

Notes: LPM is used for regressions 1–3. OLS is used for regressions 4–6. Standard errors in parentheses are clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1. See notes to Table 4 for other details.