Measuring Household Consumption and Poverty in 60 Minutes: The Mogadishu High Frequency Survey

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28th January 2015

Abstract

For Mogadishu, no poverty estimates exist because security risks constrain a face-to-face interview time to 60 minutes. This excludes traditional methods to estimate poverty based on time-consuming household consumption surveys. This paper presents the first approach to estimate total consumption reliably in such a context. Based on an innovative questionnaire design, the administering time is less than one hour for any households allowing fast and cost-efficient data collection even in areas with high security risks. The questionnaire design selects core consumption items administered to all households; while remaining consumption items are algorithmically partitioned into optional modules assigned systematically to households. After data collection, multiple imputation techniques are used to estimate total household consumption. Based on *ex post* simulations, the approach is demonstrated to yield reliable estimates of poverty using household budget data from Hergeiza. The approach is then applied as part of the High Frequency Survey in Mogadishu to estimate consumption within 60 minutes of face-to-face interview time.

Introduction

Poverty is the paramount indicator to gauge socio-economic wellbeing of a population. Especially after a shock, poverty estimates can disentangle who in the population was affected how severely. As one of the main indicators for poverty, monetary poverty is measured by a welfare aggregate usually based on consumption in developing countries and a poverty line. The poverty line indicates the minimum level of welfare required for a healthy living.

Consumption aggregates are estimated traditionally by time-consuming household consumption surveys. A household consumption questionnaire records consumption and expenditures for a comprehensive list of food and non-food items. With around 300 to 400 items, the administering time of

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[1] Utz Pape and Johan Mistiaen work in the Poverty Global Practice at the World Bank. Helpful comments on this approach were received from discussions with Kathleen Beegle, Peter Lanjouw, Roy van der Weide and Nobuo Yoshida. All views are those of the authors and do not reflect the views of the World Bank or its member countries.

the questionnaire often exceeds 90 – 120 minutes. In addition to higher costs due to longer administering time, response fatigue can increase measurement error especially for items at the end of the questionnaire. In a fragile country context, security concerns can restrict the duration of a visit to less than 60 minutes.

The extensive nature of household consumption surveys make it difficult to obtain updated poverty estimates especially when they are needed the most: after a shock and in fragile countries. Therefore, approaches were developed to reduce administering time to allow collection of consumption data with significantly lower administering time. The most straight-forward approach to minimize administering time reduces the number of items either by asking for aggregates or by skipping less frequently consumed items, which we call reduced consumption methodology. However, both approaches have been shown to under-estimate consumption, which in turn over-estimates poverty.[2] Splitting up the questionnaire for multiple visits is another solution but attrition issues – especially in fragile country contexts – increase required sample size and also have a high cost implication. In addition, multiple visits to the same household can increase security concerns.

A second class of approaches utilizes a full consumption baseline survey and updates poverty estimates based on a small subset of collected indicators.[3] These approaches estimate a welfare model on the baseline survey using a small number of easy-to-collect indicators. This allows updating poverty estimates by collecting only the set of indicators instead of direct consumption data. While the approach is cost-efficient and easy to implement in normal circumstances, the approach has two major drawbacks in the context of fragility and shocks. First, the approach requires a baseline survey, which is sometimes – for example in Mogadishu – not existent. Second, the approach relies on a structural model estimated from the baseline survey.[4] In the case of shocks, the structural assumptions, which cannot be tested, are often violated. Thus, poverty updates based on the violated assumption tend to under-estimate the impact of the shock on poverty. Therefore, cross-survey imputation methodologies are not applicable in the context of shocks and fragility.

We propose a new methodology combining an innovative questionnaire design with standard imputation techniques. This reduces the administering time of a consumption survey to less than 60 minutes while at the same time credible poverty estimates are obtained. Thus, the gain in administering time is bought by the need to impute missing consumption values. Due to the design of the questionnaire, the method circumvents systematic biases as identified for alternative methodologies.

After explaining the methodology in more detail in the next section, we will assess the performance of the methodology *ex post* using collected household budget data in Hergeiza, Somalia. Next, we apply the methodology to newly collected data in Mogadishu, Somalia, where full consumption data collection was impossible due to security constraints. We evaluate the consistency of the consumption estimates by performing validity checks. We conclude with a discussion of the limitations of the methodology, the benefits especially in combination of using CAPI technology and the need for further research.

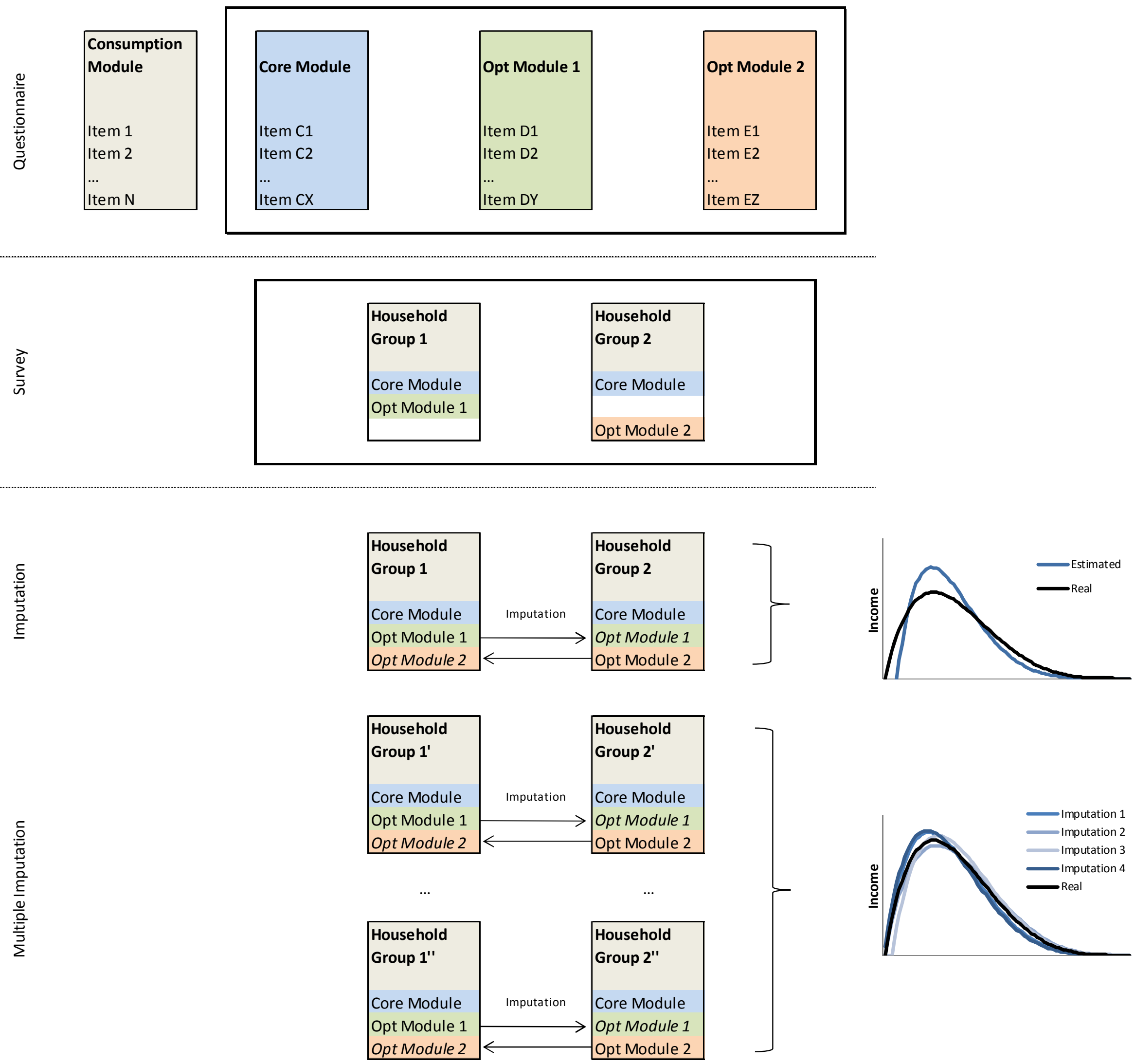
[2] Beegle et al, 2012.
[3] Douidich et al, 2013; SWIFT
[4] Christiaensen et al, 2010; Christiaensen et al, 2011.

Methodology

Overview

The rapid survey consumption methodology consists of five main steps (Figure 1). First, core items are selected based on their importance for consumption. Second, the remaining items are partitioned into optional modules. Third, optional modules are assigned to groups of households. After data collection, fourth, consumption of optional modules is imputed for all households. Fifth, the resulting consumption aggregate is used to estimate poverty indicators.

Figure 1: Illustration of the rapid consumption survey methodology (using illustrative data only). The consumption module is partitioned into core and optional modules, which in turn are assigned to households. Consumption is imputed utilizing the sub-sample information of the optional modules either by single or multiple imputation methods.



First, core consumption items are selected. Consumption in a country bears some variability but usually a small number of a few dozen items captures the majority of consumption. These items are assigned to the core module, which will be administered to all households. Important items can be identified by its average food share per household or across households. Previous consumption surveys in the same country or consumption shares of neighboring / similar countries can be used to estimate food shares.[5]

Second, non-core items are partitioned into optional modules. Different methods can be used for the partitioning into optional modules. In the simplest case, the remaining items are ordered according to their food share and assigned one-by-one while iterating the optional module in each step. A more sophisticated method would take into account correlation between items and partition them into orthogonal sets per module. This would lead to high correlation between modules supporting the total consumption estimation.

Conceptual division into core and optional items should not be reflected in the layout of the questionnaire. More complicated partition patterns can result in a set of very different items in each module. However, the modular structure should not influence the layout of the questionnaire. Instead, all items per household will be grouped into categories of consumption items (like cereals) and different recall periods. Therefore, it is recommended to use CAPI technology, which allows hiding the modular structure of the consumption module from the enumerator.

Third, optional modules will be assigned to groups of households. Assignment of optional modules will be performed randomly stratified by enumeration areas to ensure appropriate representation of optional modules in each enumeration area. This step is followed by the actual data collection.

Fourth, household consumption will be estimated by imputation. The average consumption of each optional module can be estimated based on the sub-sample of households assigned to the optional module. In the simplest case, a simple average can be estimated. More sophisticated techniques can employ a welfare model based on household characteristics and consumption of the core items. We present six techniques in the next section and perform their performance on the dataset from Hergeiza.

Single imputation of the consumption aggregate under-estimates the variance of household consumption. Depending on the location of the poverty line relative to the consumption distribution, this can either consistently under- or over-estimate poverty. Multiple imputation based on boot-strapping can mitigate the problem but will render analysis more complicated. We use single as well as multiple imputation techniques for the evaluation of the methodology.

Module Construction

Consumption for a household is estimated by the sum of expenditures for a set of items

$$y_i = \sum_{j=1}^{m} y_{ij}$$

[5] As shown later, the assignment of items to modules is very robust and, thus, even rough estimates of consumption shares are sufficient to inform the assignment without requiring a baseline survey.

where y_{ij} denotes the consumption of item j in household i. The list of items can be partitioned into M+1 modules each with m_k items:

$$y_i = \sum_{k=0}^{M} y_i^{(k)} \text{ with } y_i^{(k)} = \sum_{j=1}^{m_k} y_{ikj}$$

For each household, only the core module $y_i^{(0)}$ and one additional optional module $y_i^{(k^*)}$ are collected.

The item assignment to the modules should be based on either a previous survey or a survey in a related country with similar consumption behavior. As the core module is administered to all households, it should include items covering the largest shares of consumption. Optional modules can be constructed in different ways. Currently, an algorithm is used to assign items iteratively to optional modules so that items are orthogonal within modules and correlated between modules. In each step, an unassigned item with highest consumption share is selected. For each module, total per capita consumption is regressed on household size, the consumption of all assigned items to this module as well as the new unassigned item. The item will be assigned to the module with the highest increase in the R2 relative to the regression excluding the new unassigned item. The sequenced assignment of items based on their consumption share can lead to considerable differences in the captured consumption share across optional modules. Therefore, a parameter is introduced ensuring that in each step of the assignment procedure the difference in the number of assigned items per module does not exceed *d*. Using *d=1* assigns items to modules (almost) maximizing equal consumption share across modules.[6] Increasing *d* puts increasing weight on orthogonality within and correlation between modules.

The assignment of optional modules must ensure that a sufficient number of households are assigned to each optional module. Household consumption can then be estimated using the core module, the assigned module and estimates for the remaining optional modules

$$\hat{y}_i = y_i^{(0)} + y_i^{(k^*)} + \sum_{k \in K^*} \hat{y}_i^{(k)}$$

where $K^* := \{1, \dots, k^* - 1, k^* + 1, \dots, M\}$ denotes the set of non-assigned optional modules.

Consumption Estimation

Consumption of non-assigned optional modules can be estimated by different techniques. Three classes each with two techniques are presented differing in their complexity and theoretical underpinnings. The first class of techniques simply uses summary statistics like the average to impute missing data. The second class is based on multiple univariate regression models. The third class uses multiple imputation techniques taking into account the variation absorbed in the residual term.

[6] Even with *d=1*, equal consumption share across modules is not maximized because among the modules with the same number of assigned items, the new item will be assigned to the module it's most orthogonal to; rather than to the module with lowest consumption share.

Summary Statistics (average and median)

This class of techniques applies a summary statistic on the collected module-specific consumption and applies the result to the missing modules. For each module k, the summary statistic f can be computed as

$$\hat{y}^{(k)} = f\left(\langle y_i^{(k)} \rangle_i\right).$$

For household i, household consumption is estimated as

$$\hat{y}_i = y_i^{(0)} + y_i^{(k^*)} + \sum_{k \in K^*} \hat{y}^{(k)}.$$

Thus, each household is assigned the same consumption per missing module. In the following, the average and the median are used as summary statistics. The median has the advantage of being more robust against outliers but cannot capture small module-specific consumption if more than half of the households have zero consumption for the module.

Module-wise Regression (OLS and tobit regression)

Module-wise estimation applies a regression model for each module. This allows capturing differences in core consumption as well as other household characteristics

$$\hat{y}_i^{(k)} = \beta_0^{(k)} y_i^{(0)} + x_i^T \beta^{(k)} + u_i^{(k)}$$

With x_i^T representing a vector of household characteristics and $u_i^{(k)}$ an error term assumed to be normally distributed with $N\left(0, \sigma^{(k)}\right)$. Thus, module-wise estimation uses a regression separately for each module. Coefficients are estimated only based on the subsample assigned to module k. In general, a bootstrapping approach using the residual distribution could mimic multiple imputations; but is not applied here. Given the impossibility of negative consumption, a tobit regression with a lower bound of 0 is used in addition to a standard OLS regression approach. For the OLS regression, negative imputed values are set to zero.

Multiple Imputation Chained Equations (MICE)

Multiple Imputation Chained Equations (MICE) uses a regression model for each variable and allows missing values in the dependent and independent variables. As missing values are allowed in the independent variables, the consumption of all optional modules can be used as explanatory variables:

$$\hat{y}_i^{(k)} = \beta_0^{(k)} y_i^{(0)} + \sum_{k' \in K^*} \beta_{k'}^{(k)} y_i^{(k')} + x_i^T \beta^{(k)} + u_i^{(k)}$$

Missing values in the explanatory variable ($y_i^{(k')}$) are drawn randomly in the first step. Iteratively, these values are substituted with imputed values drawn from the posterior distribution estimated from the regression for $\hat{y}_i^{(k')}$. While the technique of chained equations cannot be shown to converge in distribution theoretically, practical results are encouraging and the method is widely used.

Multi-Variate Normal Regression (MImvn)

Multiple Imputation Multi-variate Normal Regression uses an EM-like algorithm to iteratively estimate model parameters and missing data. In contrast to chained equations, this technique is guaranteed to converge in distribution to the optimal values. An EM algorithm draws missing data from a prior (often non-informative) distribution and runs an OLS to estimate the coefficients. Iteratively, the coefficients are updated based on re-estimation using imputed values for missing data drawn from the posterior distribution of the model. Multiple Imputation Multi-variate Normal Regression employs a Data-Augmentation (DA) algorithm, which is similar to an EM algorithm but updates parameters in a non-deterministic fashion unlike the EM algorithm. Thus, coefficients are drawn from the parameter posterior distribution rather than chosen by likelihood maximization. Hence, the iterative process is a Monte-Carlo Markov –Chain (MCMC) in the parameter space with convergence to the stationary distribution that averages over the missing data. The distribution for the missing data stabilizes at the exact distribution to be drawn from to retrieve model estimates averaging over the missing value distribution. The DA algorithm usually converges considerably faster than using standard EM algorithms:

$$\hat{y}_i^{(k)} = \beta_0^{(k)} y_i^{(0)} + x_i^T \beta^{(k)} + u_i^{(k)}$$

Estimation Performance

The performance of the different estimation techniques is compared based on the relative bias (mean of the error distribution) and the relative standard error. We define the relative error as the percentage difference of the estimated consumption and the reference consumption (based on the full consumption module):

$$e_i = \frac{\hat{y}_i - y_i}{y_i}$$

The relative bias is the average of the relative error:

$$\bar{e} = \frac{1}{n} \sum_{i=1}^{n} e_i$$

The relative standard error is the standard deviation of the relative error:

$$se = \sqrt{\frac{1}{n} \sum_{i=1}^{n} {e_i}^2}$$

For estimation based on multiple imputations, e_i is averaged over all imputations.

Each proposed estimation procedure is run on random assignments of households to optional modules. A constraint ensures that each optional module is assigned equally often to a household per enumeration. The relative bias and the relative standard error are reported across all simulations.

The performance measures can be calculated at different levels. At the household level, the relative error is the relative difference in the household consumption. At the cluster level, the relative error is defined as the relative difference of the average reference household consumption and average estimated household consumption across the households in the cluster. Similarly, the global level compares total average consumption for all households.

Results

In this section, the rapid consumption methodology will first be applied to a dataset including a full consumption module from Hergeiza, Somalia. This will be used to assess the performance of the rapid consumption methodology compared to the traditional full consumption. Subsequently, we present results from the High Frequency Survey in Mogadishu. Security risks restrict face-to-face interview time to less than one hour. Therefore, we employed the rapid consumption methodology to derive the first ever consumption estimates for Mogadishu. We present the resulting consumption aggregate and perform consistency checks for its validation.

Ex-post Simulation

The rapid consumption methodology is applied *ex post* to household budget data collected in Hergeiza, Somalia. Hergeiza was chosen as it is the most similar city to Mogadishu. Using the full consumption dataset from Hergeiza allows a full-fledged assessment of the new methodology. Based on selected indicators, we compare the results after estimating consumption based on the rapid consumption methodology with the results from using the traditional full consumption module. We add a comparison with the results for a reduced consumption module.

The simulation assigns each household to one optional module. The consumption data for the modules not assigned to the household is deleted. Multiple simulations are performed with varying assignment of modules to households. Across the simulations, we calculate three consumption and four poverty and inequality indicators. The consumption indicators capture the accuracy of the estimation at three different levels: the household level, the cluster level (consisting of about 9 households) and the level of the dataset. In addition, we calculate the poverty headcount (FGT0), poverty depth (FGT1) and poverty severity (FGT2) as well as the Gini coefficient to capture inequality.

The six proposed estimation techniques presented in the previous section are compared based on 20 simulations with respect to their relative bias and relative standard error. All simulations used the same item assignment to modules using the algorithm as described with parameter *d=3* (see Table 1 for the resulting consumption shares per module).[7] The estimation techniques differ considerably in terms of performance. We also compare the techniques to using a reduced consumption module where the same consumption items are collected for all households. The number of items is equal to the size of the core and one optional module implying a comparable face-to-face interview time to the Rapid Consumption methodology.

[7] We performed robustness checks with different item assignment to modules including setting the parameter *d=1* and *d=2*. The estimation results are extremely robust to changes in the item assignment to modules.

Table 1: Number of items and consumption share captured per module.

	Food		Non Food	
	Number of Items	Share of Consumption	Number of Items	Share of Consumption
Core	33	92%	25	88%
Module 1	17	3%	15	3%
Module 2	17	2%	15	3%
Module 3	15	2%	15	4%
Module 4	17	2%	15	3%

Comparing the reduced consumption approach with the full consumption as reference, the reduced consumption approach suffers from an under-estimation of the consumption (Figure 2 and Table 3 in the appendix). This is not surprising because the approach only collects consumption from a subset of items. Applying the median as a summary statistic also results in an under-estimation of consumption. As consumption distributions have a long right tail, the median consumption belongs to a poorer household than the average household. In the case of Hergeiza, several optional modules have a median of zero consumption. Thus, the median underestimates the consumption similarly to the reduced consumption approach. In contrast, the average consumption of households is larger than the consumption of the median household. Thus, it is not surprising that the technique using the average as summary statistic over-estimates total consumption at the household and cluster level.

The regression techniques have a similar performance with a considerable upward bias at all levels. The tobit regression performs slightly better especially at the global level. In contrast, both multiple imputation techniques perform exceptionally well with a bias of around 1% at the household level, virtually unbiased at the cluster level and a minor downward bias of 0.7% at the global level.

Figure 2: Average Relative Bias at household, cluster, and simulation level for six estimation techniques.

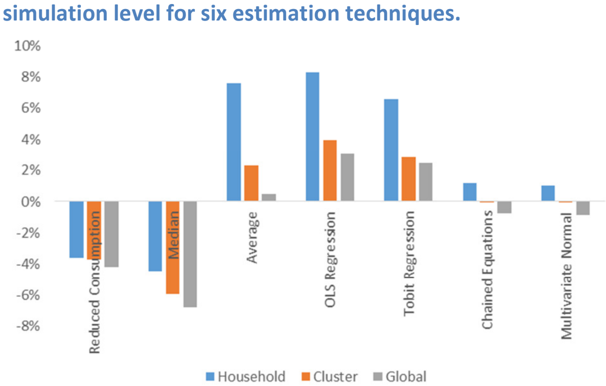
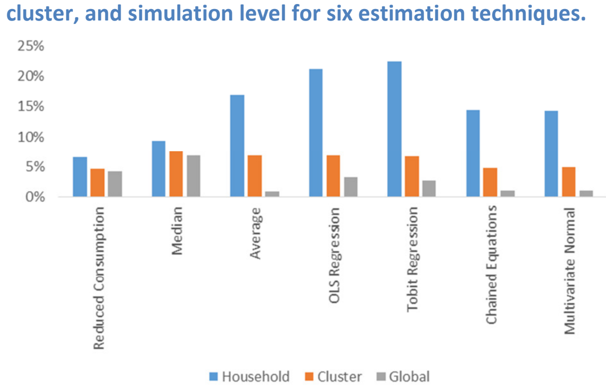


Figure 3: Average Relative Standard Error at household, cluster, and simulation level for six estimation techniques.



While the bias is important to understand systematic deviation of the estimation, the relative standard error helps to understand the variation of the estimation. Except in a simulation setting, the standard error of the estimation cannot be calculated as only one assignment of households to optional modules is available (Figure 3 and Table 3 in the appendix). Thus, it is important that the estimation technique delivers a small relative standard error.

Generally, the relative standard error reduces when moving from the household level over the cluster level to the global level. The relative standard error for the reduced consumption methodology is smaller than for the summary statistic techniques because the reduced consumption is not subject to the variation from the module assignment to households. The regression techniques have large relative standard errors at the household level of around 20% while the multiple imputation techniques vary around 15%. At the cluster level, the relative standard error drops to 7% for regression techniques and 5% for multiple imputation techniques. At the global level, the relative standard error is around 3% for regression techniques and 1% for multiple imputation techniques.

The distributional shape of the estimated household consumption can be compared to the reference household consumption by employing standard poverty and inequality indicators. The poverty headcount (FGT0) is 24.6% for the reference distribution. Not surprisingly, the reduced consumption and the median summary statistic overestimate poverty by several percentage points due to the under-estimation of consumption (Figure 4 and Table 4 in the appendix). The average summary statistic and the regression techniques underestimate poverty since they overestimate consumption. The multiple imputation techniques over-estimate poverty but only by 0.3 percentage points performing significantly better than the reduced consumption approach with a more than five times larger bias. The reduced consumption and the median summary statistic as well as the multiple imputation techniques deliver good results for the FGT1 and FGT2 emphasizing that not only the headcount can be estimated reasonably well but also the distributional shape is conserved. Except for the median summary statistic, these techniques also perform well estimating the Gini coefficient with a bias of less than 0.5 percentage points. The relative standard errors show similar results as for the estimation of the consumption (Figure 5 and Table 4 in the appendix).While the relative standard error of the reduced consumption for FGT0 is double compared to the multiple imputation techniques, the relative standard errors for FGT1 are comparable but larger for FGT2 and Gini for the multiple imputation techniques.

Figure 4: Average Bias for FGT0, FGT1, FGT2 and Gini coefficient.

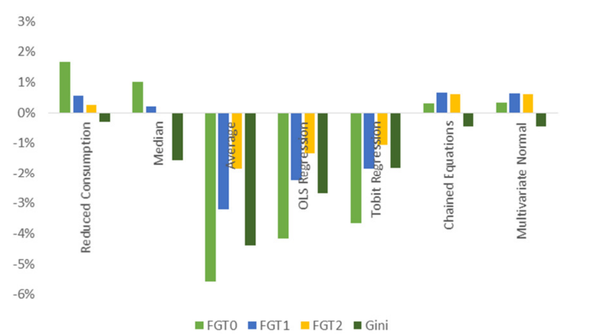
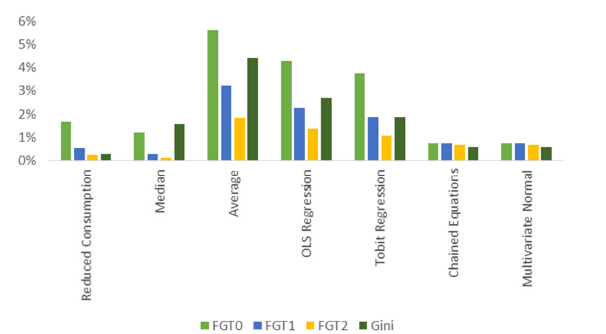


Figure 5: Average Standard Error for FGT0, FGT1, FGT2 and Gini coefficient.



In summary, the average summary statistic and the regression approaches cannot deliver convincing estimations. While the reduced consumption and the median summary statistic perform considerably better, they both over-estimate poverty by construction. Only the multiple imputation techniques can convince in all estimation exercises. Especially in the estimation of the important poverty headcount (FGT0), the multiple imputation techniques are virtually unbiased.

Application to Mogadishu

In late 2014, consumption data using the proposed rapid methodology was collected in Mogadishu using CAPI. After data cleaning and quality procedures, 675 households with consumption data were retained.[8] A welfare model was built to predict missing consumption in optional modules. We test the welfare model on the core consumption (after removing the core consumption as explanatory variable). The model for food consumption retrieves an R2 of 0.24 while non-food consumption is modeled with an R2 of 0.16 (see Table 5). It is important to emphasize that these models give a lower bound of the R2 compared to the models used in the prediction as the prediction models include the core consumption as explanatory variable. Given the assessment of the different estimation techniques in the last section, the multivariate normal approximation using multiple imputations is applied to the Mogadishu dataset.

For the Mogadishu dataset, the assignment of items to modules had to be refined manually.[9] The refinement has minor impact on the share of consumption per module (Table 2). It is peculiar though that the share of consumption per module is different for Hergeiza and Mogadishu. Using the Hergeiza dataset, 91% of food consumption (76% for non-food consumption) is captured in the core module. In contrast, the core food consumption share is only 64% (for non-food consumption 62%) in Mogadishu before imputing consumption of non-assigned modules. Thus, employing a reduced consumption module based on consumption shares identified in Hergeiza would have crudely under-estimated consumption in Mogadishu without the possibility to evaluate the inaccuracy.

Table 2: the number of items and consumption share captured per module simulated for Hergeiza, estimated for Mogadishu before imputation of non-assignment modules (normalized to 100%) and after imputing full consumption.

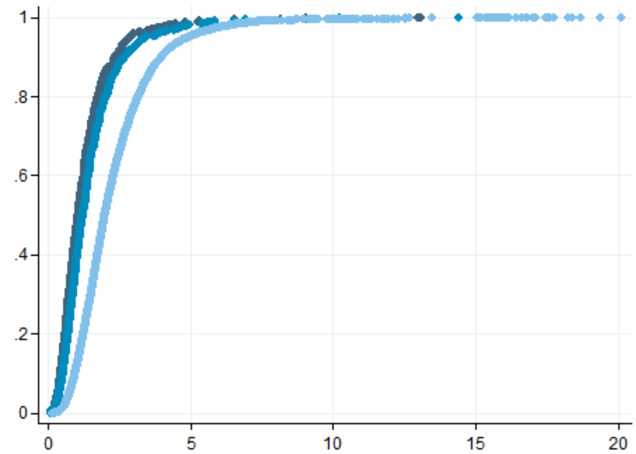
	Food Consumption				Non-Food Consumption			
	Number of Items	Share Hergeiza	Share Mogadishu	Share Mogadishu Imputed	Number of Items	Share Hergeiza	Share Mogadishu	Share Mogadishu Imputed
Core	33	91%	64%	54%	26	76%	62%	52%
Module 1	19	3%	9%	16%	15	7%	9%	12%
Module 2	20	2%	14%	14%	15	5%	9%	12%
Module 3	15	2%	5%	6%	15	6%	8%	9%
Module 4	15	2%	8%	9%	15	6%	11%	15%

The cumulative consumption distribution can be compared for the consumption captured in the core module, the consumption captured in the core and the assigned optional module and the imputed consumption (Figure 6). By construction, the core consumption shows the lowest consumption per household. Adding the consumption from the assigned optional module shifts the cumulative consumption curve slightly. The imputed consumption is shifted even further as the estimated consumption shares from the non-assigned module are added as well.

[8] While the survey also covered IDP camps, the presented analysis is restricted to households in residential areas excluding IDP camps.

[9] The manual refinement is necessary to ensure that items like 'other fruits' cannot double count type of fruits not assigned to the household. This is implemented by relabeling and manual assignment to modules. In addition, some items grouping several sub-items were split into single items, which is generally preferable for recall and recording as well as calculation of unit values.

Figure 6: Cumulative consumption distribution in current USD per day and capita for core module (dark blue), core and assigned optional module (medium blue) and imputed consumption (light blue).[10]



Without a full consumption aggregate available for Mogadishu, we can only show consistency of the retrieved consumption aggregate with other household characteristics to validate the estimates. Consumption per capita usually reduces with increasing household size. Indeed, we find that household size is significantly negatively correlated with estimated per capita consumption (coefficient: -0.04, t-statistic: -2.10, p-value: 0.04).[11] Per capita consumption also decreases with a larger share of children among the household members (coefficient: -0.28, t-statistic: -1.66, p-value: 0.098). The proportion of employed members in the household significantly increases consumption per capita (coefficient: 0.51, t-statistic: 2.77, p-value: <0.01). Thus, the retrieved consumption estimate is consistent and – using the evidence from the *ex post* simulations – highly accurate.

Conclusions

The results from the ex post simulation indicate that the rapid consumption methodology can reliably estimate consumption and poverty. At the same time, the experience in Mogadishu showed that the rapid consumption methodology can be implemented in extremely high risk areas while succeeding in limiting face-to-face interview time to less than one hour. While these results are encouraging, the rapid consumption methodology has some limitations.

The rapid consumption questionnaire varies comprehensiveness and order of items in the consumption module between households. The effect of a response bias due to this neither can be estimated from the simulations nor from the data collected in Mogadishu. However, an enhanced design with different

[10] Note that the presented consumption aggregate does not include consumption from durables goods.

[11] The reported numbers are corrected against correlation with household characteristics included in the welfare model. As the welfare model for the prediction of consumption includes household size, we have run a robustness check excluding household size from the welfare model used for prediction. The correlation between consumption per capita and household size is still significant (coefficient: -0.03, t-statistic: -2.17, p-value: 0.03).

optional modules varying in their comprehensiveness of items can shed light on this bias. Comparison between responses for the same item in a comprehensive and an incomprehensive list would indicate a lower bound for response bias. Assuming that the context of a comprehensive list is a better estimate, the response bias could be corrected for.

The rapid consumption survey methodology can increase the gap between capacity at enumerator level and complexity of survey instrument. Capacity at the enumerator level is often low in developing countries – especially in a fragile context. The rapid consumption survey methodology increases complexity of the questionnaire, which can further increase the gap between existing and required capacity at the level of enumerators. However, CAPI technology can seal off complexity from enumerator as software can automatically create the consumption module based on core and optional modules for each household without showing the partition to the enumerator. In Mogadishu, advanced CAPI technology was used generating the questionnaire automatically based on the assignment of the household to an optional module. While enumerators were made aware that different households will be asked for different items, administering the rapid consumption questionnaire did not require any additional training of enumerators beyond standard consumption questionnaires.

Analysis of rapid consumption survey data requires high capacity. Analysis capacity is usually limited in developing – and especially fragile – countries. While the general idea of assignment of optional consumption modules to households will be digestible by local counterparts, poverty analysis based on bootstrapped sample of consumption distribution is likely to overwhelm local capacity. However, even standard poverty analysis is often out of limits for local capacity in fragile countries. Therefore, capacity building usually focuses on data collection skills with a long-term perspective to increase data analysis capacity. In addition, the rapid consumption survey methodology might be the only possibility to create poverty estimates in certain areas, for example Mogadishu.

The results of the ex-post simulation and the application in Mogadishu suggest that the rapid consumption methodology can be a promising approach to estimate consumption and poverty in a cost-efficient and fast manner even in fragile areas. A similar ex-post simulation for South Sudan (data not shown) indicates that the rapid consumption methodology can also be applied at the country-level with large intra-country consumption variation.[12] Further research can help further refining the methodology and estimation techniques. A better understanding of the relationship between the number of items in the core module and the number of optional modules with the accuracy of the resulting estimates can help to further optimize the methodology. Also the algorithm for the assignment of items to modules was designed *ad hoc* and can certainly be further improved. The estimation techniques can be optimized utilizing different techniques and more appropriate welfare models, for example including locational random effects. Finally, ultimate validation of the rapid consumption methodology should come from a parallel implementation of a full consumption survey and the rapid consumption methodology to directly compare estimates.

[12] On-going field work employs the rapid consumption methodology currently in South Sudan to update poverty numbers.

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Appendix

Table 3: Bias and relative error for consumption aggregate at the household, cluster and global level.

	Household		Cluster		Global	
Method	Bias	SE	Bias	SE	Bias	SE
Reduced Consumption	-3.6%	6.5%	-3.7%	4.6%	-4.2%	4.2%
Median	-4.4%	9.3%	-5.9%	7.5%	-6.8%	6.8%
Average	7.6%	16.9%	2.3%	6.8%	0.5%	0.9%
OLS Regression	8.3%	21.1%	4.0%	6.8%	3.1%	3.2%
Tobit Regression	6.6%	22.4%	2.8%	6.7%	2.5%	2.7%
Chained Equations	1.1%	14.4%	0.0%	4.7%	-0.7%	0.9%
Multivariate Normal	1.0%	14.2%	-0.1%	4.8%	-0.9%	1.1%

Table 4: Bias and relative error for FGT0, FGT1, FGT2 and Gini for different estimation techniques.

	FGT0		FGT1		FGT2		Gini	
Method	Bias	SE	Bias	SE	Bias	SE	Bias	SE
Reduced Consumption	1.7%	1.7%	0.6%	0.6%	0.3%	0.3%	-0.3%	0.3%
Median	1.0%	1.2%	0.2%	0.3%	0.0%	0.1%	-1.6%	1.6%
Average	-5.6%	5.6%	-3.2%	3.2%	-1.8%	1.8%	-4.4%	4.4%
OLS Regression	-4.2%	4.3%	-2.3%	2.3%	-1.3%	1.4%	-2.7%	2.7%
Tobit Regression	-3.7%	3.7%	-1.8%	1.9%	-1.1%	1.1%	-1.8%	1.9%
Chained Equations	0.3%	0.8%	0.6%	0.7%	0.6%	0.7%	-0.5%	0.6%
Multivariate Normal	0.4%	0.7%	0.7%	0.7%	0.6%	0.7%	-0.4%	0.5%

Table 5: Test of Welfare Model on core consumption reporting coefficients (t-statistics) for Mogadishu.

Variable	Core Food Consumption	Core Non-Food Consumption
Core Food Consumption		
... 2nd Quartile	0.78 (1.17)	
... 3rd Quartile	0.09 (1.46)	
... 4th Quartile	0.52 (7.22)	
Core Non-Food Consumption		
... 2nd Quartile		0.07 (1.11)
... 3rd Quartile		0.12 (1.77)
... 4th Quartile		0.42 (5.81)
Household Size	-0.07 (-8.36)	-0.04 (4.34)
Household Head Education	0.16 (3.34)	0.12 (2.56)
Dwelling Characteristics		
... Shared Apartment	0.04 (0.59)	-0.13 (-2.12)
... Separated House	-0.14 (-1.13)	-0.19 (-1.55)
... Shared House	-0.07 (-0.81)	-0.14 (-1.52)
Water Access		
... Piped Water	-0.22 (-0.93)	-0.04 (-0.19)
... Public Tap	0.41 (2.47)	-0.01 (-0.08)
Insufficient Food in last 4 weeks	0.05 (1.49)	-0.05 (-1.50)
R2	0.24	0.16
N	675	675