Small Area Estimation of Poverty in Somalia : A Fay Herriot Model Approach

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### 0.0.1 Introduction

Household surveys are often representative at the national level or at the level of the first administrative division (region/state level). National Statistical Offices and government entities can benefit from poverty estimation at a higher level of resolution, such as the district or district level. This note describes the small area estimation (SAE) methodology implemented to estimate poverty rates in Somalia at the district level. SAE is a statistical method that can be used to improve the reliability of survey estimates by combining survey data with geographically comprehensive auxiliary data, such as census when available or geospatial, remotely sensed data. In Burundi, we show that SAE generates poverty estimates that are sufficiently precise to report at the district level instead of the regional level. This has the potential to improve the targeting and evaluation of interventions intended to achieve poverty reduction in the future. Ideally, SAE combines survey data with household-level data from a recent census. Countries often aim to collect census data every 10 years. However, many African countries take more years between consecutive censuses, and indeed Somalia’s last census was conducted in 1986. Therefore, this exercise relies on contemporaneous geospatial data derived from a variety of sources. (Battese, Harter, and Fuller 1988) were the first to use geospatial satellite data in the context of crop production. Other studies (Georganos et al. 2019), (Chi et al. 2022) have used satellite imagery to predict wealth indices. However, the use of geo-referenced data is less ideal than the traditional microdata obtained from household surveys or administrative datasets. (Van Der Weide et al. 2023) used satellite imagery to predict monetary poverty in Malawi and noted the less than ideal nature of geospatial data. (Corral, Henderson, and Segovia 2025) also find tat remotely sensed data may not be ideal for poverty mapping due to the relatively lower predictive power.

In this note, we present the approach that models poverty rates at the district level in Somalia using the model of (Fay III and Herriot 1979). The area level model approach allows us to relate district level direct survey poverty rates to auxiliary variables (geospatial indicators) to estimate poverty rates in all districts within Somalia. (Seitz 2019) provides district level poverty rates in the Central Asia region using Fay Herriot modelling approach using auxiliary geospatial data. The World Bank has employed the SAE methodology extensively to estimate poverty and other socioeconomic indicators of interest at more granular levels and continues to produce these estimates in combination with other non-monetary measures of poverty. At this point, SAE has been applied in a wide variety of contexts across many developing countries. This note is subdivided as follows. In section 2, we present survey data (specifically the household consumption data) and why SAE is necessary for district level poverty estimation in Somalia. We also present the Fay-Herriot model as described by (Seitz 2019). Section 3 describes the geospatial databases sourced and indicators created as well as the model selection process employed. Sections 4 and 5 describes the FH model results and the poverty maps for the country.

### 0.0.2 The Data

For Somalia, the 2022 Somalia Integrated Household Budget Survey (SIHBS) is representative at the regional level. The development of the SIHBS-22 sampling frame followed a stratified multi-stage probability cluster sample design. Urban and rural areas followed a three-stage stratified cluster sample design, while in nomadic areas the design was a two-stage stratified cluster sample design. The primary sampling units (PSUs) were selected with a probability proportional to the number of dwelling structures which constituted the sampling frame. The secondary sampling units (SSUs) for rural and urban areas were selected with a probability proportional to the number of listed households which constituted the frame. The ultimate sampling units (USUs) for rural, urban, and nomadic areas were randomly selected from listed households in the cluster.

District level poverty rate estimates computed from this survey will be insufficiently precise and unreliable for publication. Table 1 illustrates why it is necessary to use SAE to report poverty rates at more disaggregated geographic levels in Somalia. We use the mean coefficient of variation (CV) as a standardized measure of precision (i.e.the square root of the estimated mean square error divided by the poverty rate). Differing thresholds for mean or median CVs, often ranging from 0.1 to 0.3, have been applied by National Statistics Offices to determine if statistics are sufficiently reliable to report. The median and mean direct CVs in Somalia at the district level are approximately 0.098 and 0.099[[1]](#footnote-1). While this is within the acceptable range of reliability for some countries, it is not considered reliable enough to publish by the Somalia National Statistics Office.

Table 1: Descriptive Statistics

| **Indicator** | **Estimate** |
| --- | --- |
| Population (in millions) | 13.6 |
| Population Number of HHs (in millions) | 2.0 |
| Sample # of HHs | 6221 |
| Poverty Rate (IPL) | 0.514 |
| Latest Census Year | 1986 |
| Number of Regions | 17 |
| Region Median CV | 0.098 |
| Region Mean CV | 0.097 |
| Number of Targets (Population) | 74 |
| Number of Targets (Sample) | 48 |

We utilize freely available geospatial data for this small area estimation exercise since the last census carried out is outdated (from 1986). The goal of the SAE exercise is to estimate more reliable district level poverty rates in Somalia by using a Fay Herriot model based on relating the target area direct estimate poverty rates and district level geospatial indicators. Given that any recent developments in Somalia might not be captured by its 15-year-old census, it would be difficult to make a case for area poverty rates estimated using the 1986 census particularly to guide current policy interventions.

### 0.0.3 The Methodology

(Corral et al. 2022) recommends implementing an area level Fay Herriot level model with geospatial indicators for poverty mapping. Imagine a finite population for Somalia, , that consists of households that are subdivided into districts with sizes . A random sample of households can be drawn from the commune (i.e., . The Fay-Herriot (FH) model comprises of two levels. The first is a sample model which assumes a direct survey estimator:

is design unbiased for the small area parameter, the population indicator of interest, in this case, the poverty rate each district, . We assume a sample error with the usual independently and normally distribution properties.

In the second level, a linking model is assumed to relate to auxiliary variables via a linear regression. Both levels of the model together are presented as follows:

The empirical best linear unbiased estimators (EBLUP) are computed with by weighted least squares regression. The EBLUP of is obtained by substituting the variance parameter with an estimate. The resulting estimator can then be written as:

The EBLUP/FH estimator can be understood as a weighted average of the direct estimator and a regression synthetic part. The estimated shrinkage factor puts more weight on the direct estimator when the sampling variance is small and vice versa. Areas for which no direct estimation results are called out-of-sample domains. For those domains the prediction reduces the regression-synthetic component (Molina and Rao 2010). This model is then fit via a restricted maximum likelihood (REML) method.

This method is widely used by the Small Area Income and Poverty Estimates (SAIPE) program of the US census bureau and has been thoroughly validated in (Corral Rodas, Henderson, and Segovia 2023). This approach improves the error efficiency rates over the direct estimates at the target area level. Inter-area unexplained heterogeneous area effects are accounted for within the model. Section 3.3 in (Corral et al. 2022) provides a full list of pros and cons of the Fay-Herriot modelling approach.

For this small area estimation exercise, 48 of the 74 Somalia Districts are included in the SIHBS. As a result, these in-sample districts will benefit from the information available in the sample. In some cases with FH models, districts with low sample sizes can result in all households from a specific sample district being all poor or not poor ( = 1 or 0) or only one Enumeration Area in a district is sampled. The common practice of sample variance smoothing (You and Hidiroglou 2012; You and Hidiroglou 2023) in the SAE literature is typically implemented to solve this problem. The variance smoothing approach of (You and Hidiroglou 2012) applies a log linear model of the direct sampling variance{} as a function of the sampling size, .

Assuming and to be the simple OLS estimators for the regression coefficients and . Applying the exponential of the equation produces the naive variance estimator (Dick 1995) as follows:

(Rivest and Belmonte 2000) show that the naive estimator can underestimate sampling variance. They propose correction as follows:

since the naive variance estimator can be easily shown to overestimate sampling variance by a factor of . For the purposes of our analysis, there are no districts without variances or extreme case poverty rates ( = 1 or 0). Consequently, we do not remove districts from the analysis. However, the National Statistical Office flagged predicted poverty rates in 3 areas as being too low. 2 of these 3 districts have low sample sizes and with only 1 and 2 primary sampling units as well. In the supplementary section, we re-estimate the Fay Herriot model without these areas and present the results. Below, we simply show the sample distribution of PSUs and households within districts and how this varies with the direct district poverty rates.

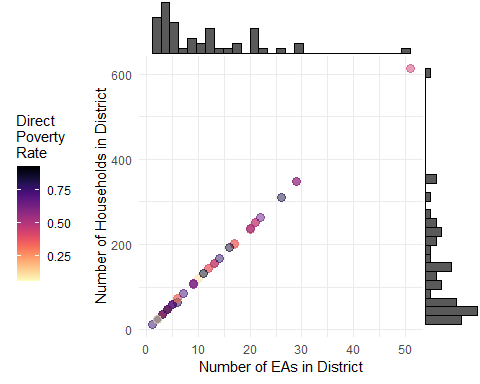


Figure 1: Joint Distribution of EAs and Households (District-Level)

### 0.0.4 The Geospatial Data and Model Selection Process

The process leading up to model selection involves sourcing freely available geospatial indicators that might be correlated with household welfare and poverty. The geospatial features were sourced at native resolution and then zonal statistics were computed at the target area level (districts). 2 shows all the geospatial features and the data sources employed.

Table 2: EBP Model (Regression Results)

| **Feature** | **Source** | **Original\_Data\_Resolution** | **Year** |
| --- | --- | --- | --- |
| Built-settlement extent area | WorldPop Building Footprints | 1km | 2001 - 2020 |
| Gridded Population & Density | WorldPop Gridded Population Counts & Density | 90m | 2020 |
| Share of area planted by crop for banana, beans, cassava, maize, sesame seed, sorghum, sugar cane, temperature fruit,  tropical fruit, vegetables | IFPRI Spatial Production Allocation Model (SPAM) | 10km | 2009, 2017, 2020 |
| Production quantity for each crop for banana, beans, cassava, maize, sesame seed, sorghum, sugar cane, temperature  fruit, tropical fruit, vegetables | IFPRI Spatial Production Allocation Model (SPAM) | 10km | 2009, 2017, 2020 |
| % production as a total crop production for banana, beans, cassava, maize, sesame seed, sorghum, sugar cane,  temperature fruit, tropical fruit, vegetables | IFPRI Spatial Production Allocation Model (SPAM) | 10km | 2009, 2017, 2020 |
| Standardized precipitation evaporation index, 12 month | Global SPEI database, version 4.03 | 0.5 degrees | 2020 |
| Drought exposure, Drought hazard, Drought risk index, Drought vulnerability | (Carrao et al. 2018) | 0.5 degrees | 2000-2014 |
| Drought hazard, risk for irrigated agricultural systems | Drought risk for rainfed, irrigated agric. systems aggregated as an average per polygon based on the data from  (Meza et al. 2020) |  | 2020 |
| Percent of area (with Vegetation Index below 40) for the Gu season (April - June) | STAR - Global Vegetation Health Products |  | 2017-2022 |
| Average travel time in nearest urban areas with 5000km, 20000km and 50000km | Computed based on population data from WorldPop and accessibility data from (Nelson et al. 2019) |  | 2019 |

We begin by transforming all indicators as necessary to minimize the risk of divergence in model parameter estimation. For indicator with values greater than 100, we take the natural logarithm. We have avoiding feature scaling to avoid excessive distortion or loss of information for the scaled variables.

The geospatial data listed under the previous header was used to construct candidate features, at the grid and target area level. In addition, we include regional dummy variables. In all, we created ~157 potential geospatial candidate indicators. Using all these features in the linear mixed model risks potentially leads to over-fitting the survey sample and generates poor out-of-sample estimations.

Next, we employ a stepwise (both-ways method) selection approach which picks the most predictive set of indicators from the pool of candidate indicators. The both-ways method was used, enabling iterative testing of each variable’s contribution by alternatively adding and removing variables based on statistical significance criteria at each step. This approach begins with an constant term and tests the inclusion of variables one-by-one; then it considers each for potential removal, thus optimizing the model’s explanatory power while controlling for over-fitting. The both-ways method provides flexibility, more so than the forward or backward algorithm, to achieve an optimal balance of predictive power and model parsimony, ensuring the only variables with significant and robust relationships to the outcome are retained.

### 0.0.5 Fay Herriot Model Estimation Results

The final selected model includes covariates share of the population within a 2km grid as well as the share of total production that is tropical fruit production. The regression results are as follows:

Table 3: EBP Model (Regression Results)

| **Variables** | **Coefficients** | **Standard Error** |
| --- | --- | --- |
| Intercept | 0.151 | 0.134 |
| Rural Reachability Index | 0.003\*\* | 0.001 |
| Drought Hazard (Carrao et al. 2016 estimates) | 0.206 | 0.124 |
| Hiraan Region | 0.296\*\* | 0.106 |
| Bakool Region | 0.271\*\* | 0.089 |
| % of area with vegetation health index (VHI) below 40 during the 2020 season | 0.005\*\* | 0.002 |
| Population density per sqkm of populated area | 0.0000019 | 0.0000053 |
| Harvest area for maize as a share of all crops | 0.014\*\*\* | 0.004 |
| Gedo Region | -0.23\*\* | 0.072 |
| Production quantity for maize as a share of all crops | -0.0078\*\*\* | 0.002 |
| Harvest area for vegetable as a share of all crops | -0.031\*\*\* | 0.009 |
| Nugaal Region | -0.08 | 0.082 |
| **Sample Size (n) = 48** | | |

Table 4: Assessing Normality Assumptions

| **Model R²** | | **(Error Term) ε** | | **(Random Effect) μ** | |
| --- | --- | --- | --- | --- | --- |
| **marginal** | **conditional** | **skewness** | **kurtosis** | **skewness** | **kurtosis** |
| 0.433 | 0.577 | 0.653 | 3.002 | -0.215 | 3.054 |

The regression coefficients have the expected sign. The Hiraan and Bakool regions appear on average to be poorer on average than other regions. While the Nugaal region appears to be more well-off than the average region, although this later result is not statistically significant. Several agriculture related variables appear to be significant predictors of poverty rates in Somalia. The production quantity for maize is associated with lower poverty rates while largest harvest areas appear to be increasing in poverty rates. Maize cultivation, and most crop production in Somalia, is heavily rural which might explain the direction of the sign for maize harvest area shares with respect to poverty. The proportion of area with vegetation health indices (a geospatial proxy for crop production) below 40 (in 2020) is increasing in poverty rates. Consequently, less greener areas are more likely to be less well off. In addition, drought hazards appear to be also unsurprisingly increasing in poverty rates, although this result is not statistically significant.

Several assumptions are made in this model which needed to be verified. The Fay Herriot model equals 57.7% with an adjusted of 43.3% which is typical for the FH model particularly with only 48 in-sample districts used in the regression of only geospatial features. We assume independent normal distributions for the area effects as well as error terms. The table shows the skewness and kurtosis which should be approximately 0 and 3 for normally distributed random variables.

The normality assumptions proposed in the method section matter for the noise estimates but the EB methodology ensures that the poverty estimates are unbiased. The residual analysis suggests that the skewness and kurtosis of the idiosyncratic and district level area effects match the normality assumptions. However, there appears to be few outliers within the error term normal density plot 4. The residual plots for both the random error and idiosyncratic errors can be found below:

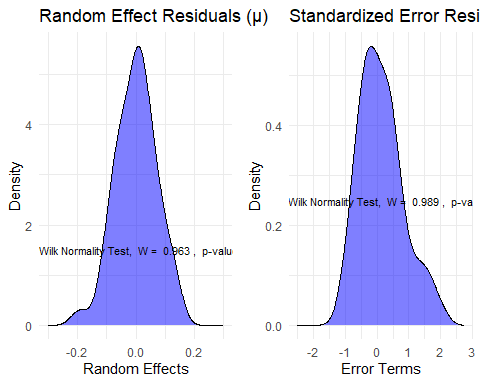


Figure 2: Fay-Herriot Residual Plots

We employ the Shapiro-Wilks measure to test the null hypothesis that random variables, and , come from a normality distributed populations. The test results, 0.963 ( 0.129); 0.989 ( 0.916) suggest normally distributed random effects and idiosyncratic error terms. We cannot reject the null hypothesis at the 5% level (although the standardized error residuals are significant at 10%).

The Fay Herriot model employs direct estimates in predicting poverty rates. The shrinkage factor measures the ratio of the random effect to the total variance within the model. Full shrinkage = 1 means predicted poverty rates are simply the direct estimates while the other extreme uses a purely synthetic predictions, = 0. We present a scatter plot of the as a function of sample size.

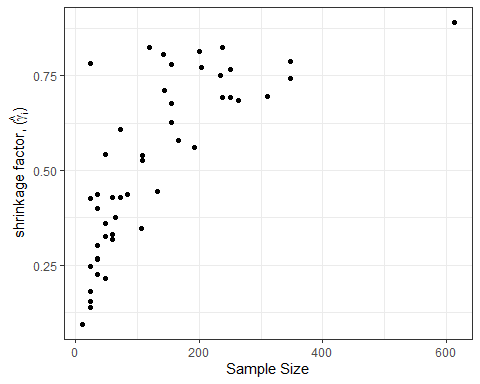


Figure 3: Scatter Plot of Shrinkage Factor vs Sample Size

In a final check, we attempt to validate the model by perform the Remove-One Model validation. Since our sample only contains 48 target areas, the typical n-fold validation process would have to split an already limited sample into 2 smaller training and test sets. Instead, the Remove-One validation process, trains a Fay Herriot model on 47 districts and removes 1 until every district has been excluded once. We compare show a plot comparing model validation estimates with the actual FH model predictions to check the stability of the model.

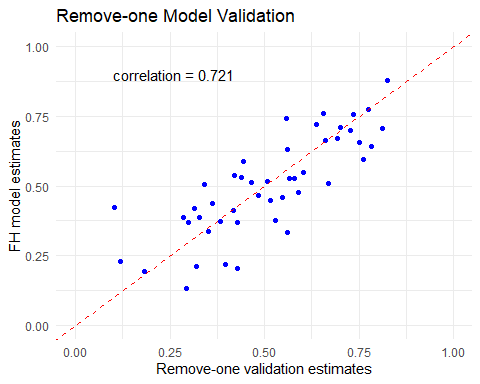
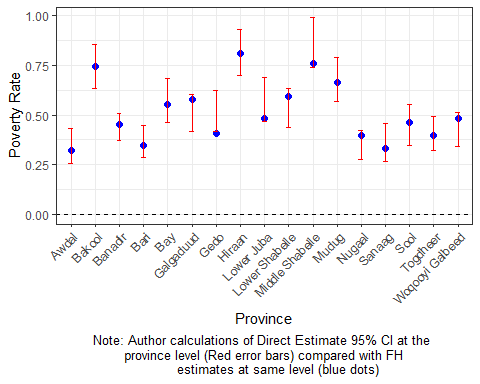


Figure 4: Remove-One Model Valiadation Plot

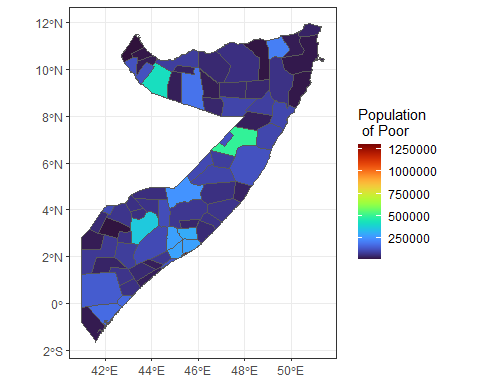
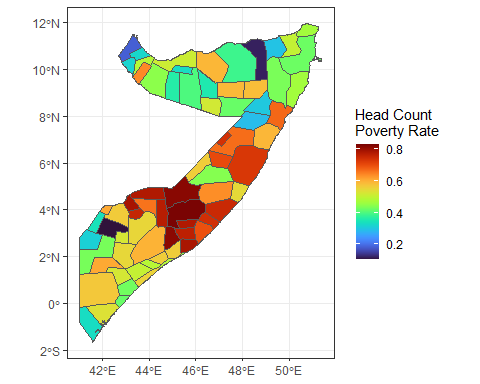
Figure 4 plots the FH model estimates against their corresponding estimates as a result of the remove-one validation model. The correlation between the set of FH model estimates and the validation estimates stands at 0.75 as shown in above chart.

### 0.0.6 Poverty Maps

As a final check, the FH poverty rates at the district level are aggregated to the regional level to compare against the direct estiamtes. The regional level is the highest level of resolution at which survey design specifies national representativeness. The direct estimates in 5 are shown as 95% confidence intervals (in red) which are plotted in comparison with Fay Herriot poverty estimates.

 It should be noted that all the model based regional estimates appear to basically lie within the direct estimates confidence intervals in all the regions.

The poverty map corresponding to the 2022 for Somalia at the district level in the subsequent figures:



Upon review of the initial estimates in collaboration with SNBS, 3 districts were identified as having unrealistically low estimates of poverty as the surrounding districts within each region had significantly higher poverty rates. These districts were Garbahaarey, Lassqoray and Zeylac in Gedo, Sanaag and Awdal regions respectively. Three benchmarking approaches were implemented in attempts to solve the problem:

1. First, the raking benchmarking method iteratively adjusts district estimates until convergence is reached with the regional poverty rate. However, the FH model regional poverty rates are all within 5% percent of the direct estimates, as a result this had little effect in changing the district poverty rates.
2. Next, the ratio method adjusts the district estimates using a constant factor
3. Finally, a method which incorporates the MSE estimates was also applied.

All three methods had minimal effect on the district poverty rates as they all sensitive to the accuracy of sampling in the specific districts. The decision was made to treat all three districts as out of sample, which resulted in poverty rates more aligned with the neighboring districts. The results of this exercise can be found in the supplementary section.

### 0.0.7 Appendix

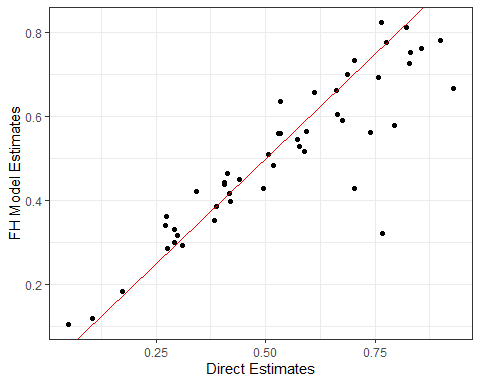


Figure 8: Correlation between FH Model Estimates and Direct Estimates at District Level

Table 5: Comparing FH Estimates to Direct Estimates at Regional Level

|  | **Survey** | **FH Estimate 95% Confidence Intervals** | |
| --- | --- | --- | --- |
| **Province** | **Direct Estimate** | **Lower Bound** | **Upper Bound** |
| Awdal | 0.343 | 0.254 | 0.432 |
| Woqooyi Galbeed | 0.427 | 0.340 | 0.515 |
| Togdheer | 0.406 | 0.322 | 0.490 |
| Sool | 0.450 | 0.348 | 0.553 |
| Sanaag | 0.363 | 0.266 | 0.460 |
| Bari | 0.366 | 0.285 | 0.447 |
| Nugaal | 0.349 | 0.276 | 0.422 |
| Mudug | 0.679 | 0.568 | 0.789 |
| Galgaduud | 0.509 | 0.416 | 0.602 |
| Hiraan | 0.815 | 0.700 | 0.931 |
| Middle Shabelle | 0.866 | 0.739 | 0.992 |
| Banadir | 0.440 | 0.374 | 0.505 |
| Lower Shabelle | 0.534 | 0.436 | 0.631 |
| Bay | 0.572 | 0.462 | 0.681 |
| Bakool | 0.743 | 0.632 | 0.855 |
| Gedo | 0.521 | 0.419 | 0.624 |
| Lower Juba | 0.578 | 0.468 | 0.689 |

Table 6: District-Level Poverty Map Table

| **Region** | **District** | **Direct Estimate** | **FH Model Estimate** |
| --- | --- | --- | --- |
| Awdal | Borama | 0.298 | 0.316 |
| Awdal | Baki | 0.519 | 0.483 |
| Awdal | Lughaye | 0.768 | 0.321 |
| Awdal | Zeylac | 0.173 | 0.181 |
| Woqooyi Galbeed | Hargeysa | 0.406 | 0.443 |
| Woqooyi Galbeed | Berbera | 0.506 | 0.508 |
| Woqooyi Galbeed | Gebiley | 0.534 | 0.636 |
| Togdheer | Burco | 0.419 | 0.397 |
| Togdheer | Buuhoodle | 0.590 | 0.515 |
| Togdheer | Owdweyne | 0.273 | 0.361 |
| Togdheer | Sheikh | 0.291 | 0.329 |
| Sool | Laas Caanood | 0.418 | 0.417 |
| Sool | Caynabo | 0.383 | 0.352 |
| Sool | Taleex | 0.795 | 0.579 |
| Sool | Xudun | NA | 0.586 |
| Sanaag | Ceerigaabo | 0.388 | 0.384 |
| Sanaag | Ceel Afweyn | 0.675 | 0.589 |
| Sanaag | Laasqoray | 0.105 | 0.118 |
| Bari | Bossaso | 0.310 | 0.293 |
| Bari | Bandarbeyla | NA | 0.463 |
| Bari | Caluula | 0.412 | 0.464 |
| Bari | Iskushuban | 0.342 | 0.420 |
| Bari | Qandala | NA | 0.498 |
| Bari | Qardho | 0.496 | 0.429 |
| Nugaal | Garoowe | 0.292 | 0.300 |
| Nugaal | Burtinle | 0.276 | 0.286 |
| Nugaal | Eyl | 0.929 | 0.668 |
| Mudug | Gaalkacyo | 0.662 | 0.662 |
| Mudug | Galdogob | 0.703 | 0.734 |
| Mudug | Hobyo | 0.829 | 0.726 |
| Mudug | Jariiban | NA | 0.588 |
| Mudug | Xarardheere | NA | 0.541 |
| Galgaduud | Dhuusamarreeb | 0.405 | 0.438 |
| Galgaduud | Cabudwaaq | 0.528 | 0.559 |
| Galgaduud | Cadaado | 0.688 | 0.700 |
| Galgaduud | Ceel Buur | NA | 0.632 |
| Galgaduud | Ceel Dheer | NA | 0.746 |
| Hiraan | Belet Weyne | 0.821 | 0.812 |
| Hiraan | Bulo Burto | 0.765 | 0.824 |
| Hiraan | Jalalaqsi | NA | 0.775 |
| Middle Shabelle | Jowhar | 0.855 | 0.761 |
| Middle Shabelle | Adan Yabaal | NA | 0.736 |
| Middle Shabelle | Balcad | 0.899 | 0.782 |
| Middle Shabelle | Cadale | 0.758 | 0.692 |
| Banadir | Banadir | 0.440 | 0.451 |
| Lower Shabelle | Marka | NA | 0.483 |
| Lower Shabelle | Afgooye | 0.534 | 0.558 |
| Lower Shabelle | Baraawe | NA | 0.551 |
| Lower Shabelle | Kurtunwaarey | NA | 0.485 |
| Lower Shabelle | Qoryooley | NA | 0.558 |
| Lower Shabelle | Sablaale | NA | 0.500 |
| Lower Shabelle | Wanla Weyn | NA | 0.810 |
| Bay | Baydhaba | 0.572 | 0.546 |
| Bay | Buur Hakaba | NA | 0.593 |
| Bay | Diinsoor | NA | 0.544 |
| Bay | Qansax Dheere | NA | 0.520 |
| Bakool | Xudur | 0.613 | 0.656 |
| Bakool | Ceel Barde | 0.776 | 0.775 |
| Bakool | Tayeeglow | NA | 0.768 |
| Bakool | Waajid | 0.831 | 0.752 |
| Bakool | Rab Dhuure | NA | 0.784 |
| Gedo | Garbahaarey | 0.050 | 0.104 |
| Gedo | Baardheere | 0.702 | 0.428 |
| Gedo | Belet Xaawo | 0.272 | 0.340 |
| Gedo | Ceel Waaq | NA | 0.310 |
| Gedo | Doolow | 0.663 | 0.604 |
| Gedo | Luuq | 0.739 | 0.561 |
| Lower Juba | Kismaayo | 0.576 | 0.529 |
| Lower Juba | Afmadow | 0.592 | 0.565 |
| Lower Juba | Badhaadhe | NA | 0.330 |
| Lower Juba | Jamaame | NA | 0.417 |

### 

Supplementary Section: Re-estimating FH Model without Garbahaarey, Lassqoray and Zeylac in SIHBS sample

The National Statistical Office in Somalia flagged the aforementioned areas as possessing abnormally low poverty rates. Upon further inspection, Garbahaarey and Zeylac have only 2 enumeration areas. Table S1 presents the fewest 10 districts in number of EAs sampled.

Sparsely Sampled Districts

| **District Code** | **District Name** | **Number of Households** | **Number of EAs** |
| --- | --- | --- | --- |
| SO1103 | Lughaye | 12 | 1 |
| SO1102 | Baki | 24 | 2 |
| SO1104 | Zeylac | 24 | 2 |
| SO1403 | Taleex | 24 | 2 |
| SO1803 | Hobyo | 24 | 2 |
| SO2104 | Cadale | 24 | 2 |
| SO2601 | Garbahaarey | 24 | 2 |
| SO1303 | Owdweyne | 36 | 3 |
| SO1402 | Caynabo | 36 | 3 |
| SO1502 | Ceel Afweyn | 36 | 3 |
| *The colored districts were flagged by the NSO* | | | |

We remove the 3 districts flagged by the SNBS and re-iterate the entire modelling exercise previously described including both the model/variable selection process and the FH model estimation. The results are as follows:

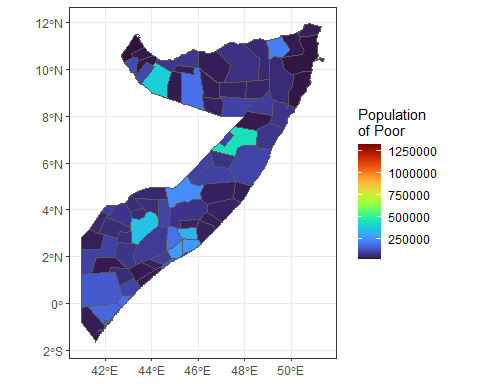
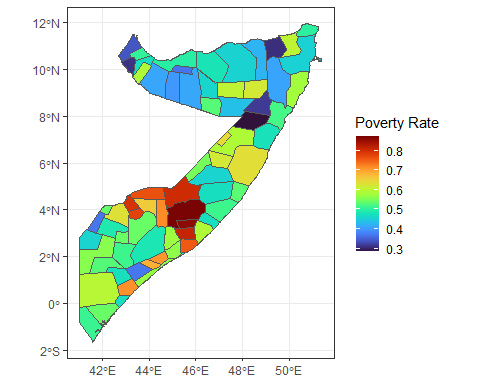
Table S1: EBP Model (Regression Results)

| **Variables** | **Coefficients** | **Standard Error** |
| --- | --- | --- |
| Intercept | 0.148 | 0.180 |
| Hiraan Region | 0.350\*\*\* | 0.094 |
| Bakool Region | 0.207\*\* | 0.078 |
| Rural Accessibility Index | 0.004\*\* | 0.002 |
| Production quantity for banana as a share of all crops | 0.026\*\*\* | 0.008 |
| Share of people living within 5km from conflicts | 0.002\*\* | 0.001 |
| Number of Schools | -0.0057\*\*\* | 0.002 |
| Nugaal Region | -0.15\*\* | 0.069 |

Table S2: Assessing Normality Assumptions

| **Model R²** | | **(Error Term) ε** | | **(Random Effect) μ** | |
| --- | --- | --- | --- | --- | --- |
| **marginal** | **conditional** | **skewness** | **kurtosis** | **skewness** | **kurtosis** |
| 0.313 | 0.488 | 0.256 | 2.729 | -0.251 | 2.524 |

Figure S1: Predicted Head Count Poverty Rate & Population of Poor



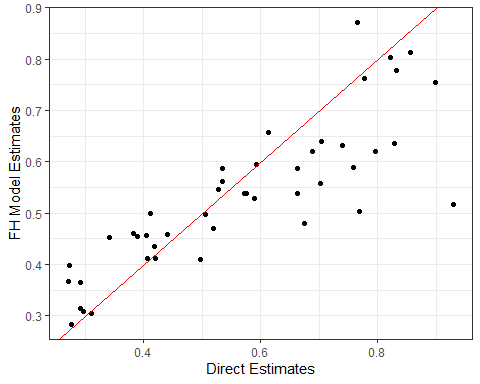


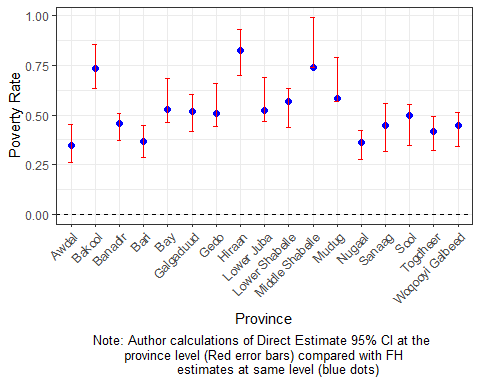
Figure S2: Correlation between FH Model Estimates and Direct Estimates at District Level

Table S3: Comparing FH Estimates to Direct Estimates at Regional Level

|  | **Survey** | **FH Estimate 95% Confidence Intervals** | |
| --- | --- | --- | --- |
| **Province** | **Direct Estimate** | **Lower Bound** | **Upper Bound** |
| Awdal | 0.357 | 0.263 | 0.452 |
| Woqooyi Galbeed | 0.427 | 0.340 | 0.515 |
| Togdheer | 0.406 | 0.322 | 0.490 |
| Sool | 0.450 | 0.348 | 0.553 |
| Sanaag | 0.436 | 0.314 | 0.558 |
| Bari | 0.366 | 0.285 | 0.447 |
| Nugaal | 0.349 | 0.276 | 0.422 |
| Mudug | 0.679 | 0.568 | 0.789 |
| Galgaduud | 0.509 | 0.416 | 0.602 |
| Hiraan | 0.815 | 0.700 | 0.931 |
| Middle Shabelle | 0.866 | 0.739 | 0.992 |
| Banadir | 0.440 | 0.374 | 0.505 |
| Lower Shabelle | 0.534 | 0.436 | 0.631 |
| Bay | 0.572 | 0.462 | 0.681 |
| Bakool | 0.743 | 0.632 | 0.855 |
| Gedo | 0.549 | 0.441 | 0.658 |
| Lower Juba | 0.578 | 0.468 | 0.689 |

Table S4: District-Level Poverty Map Table (Comparing Poverty Rates with and without the 3 SIHBS flagged areas)

| **Region** | | **District** | | **FH Model Estimate** | | **Original FH Model Estimate** | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Awdal | | Borama | | 0.308 | | 0.3158937 | |
| Awdal | | Baki | | 0.470 | | 0.4834294 | |
| Awdal | | Lughaye | | 0.504 | | 0.3212016 | |
| Awdal | | Zeylac | | 0.337 | | 0.1814266 | |
| Woqooyi Galbeed | | Hargeysa | | 0.411 | | 0.4433516 | |
| Woqooyi Galbeed | | Berbera | | 0.497 | | 0.5079388 | |
| Woqooyi Galbeed | | Gebiley | | 0.586 | | 0.6362767 | |
| Togdheer | | Burco | | 0.412 | | 0.3970575 | |
| Togdheer | | Buuhoodle | | 0.528 | | 0.5153860 | |
| Togdheer | | Owdweyne | | 0.398 | | 0.3612637 | |
| Togdheer | | Sheikh | | 0.365 | | 0.3290785 | |
| Sool | | Laas Caanood | | 0.435 | | 0.4165817 | |
| Sool | | Caynabo | | 0.460 | | 0.3523711 | |
| Sool | | Taleex | | 0.620 | | 0.5787886 | |
| Sool | | Xudun | | 0.601 | | 0.5860947 | |
| Sanaag | | Ceerigaabo | | 0.455 | | 0.3843609 | |
| Sanaag | | Ceel Afweyn | | 0.480 | | 0.5890278 | |
| Sanaag | | Laasqoray | | 0.423 | | 0.1177883 | |
| Bari | | Bossaso | | 0.305 | | 0.2932197 | |
| Bari | | Bandarbeyla | | 0.577 | | 0.4632127 | |
| Bari | | Caluula | | 0.500 | | 0.4643615 | |
| Bari | | Iskushuban | | 0.453 | | 0.4197501 | |
| Bari | | Qandala | | 0.600 | | 0.4980277 | |
| Bari | | Qardho | | 0.409 | | 0.4291898 | |
| Nugaal | | Garoowe | | 0.315 | | 0.2997191 | |
| Nugaal | | Burtinle | | 0.283 | | 0.2860153 | |
| Nugaal | | Eyl | | 0.517 | | 0.6675905 | |
| Mudug | | Gaalkacyo | | 0.587 | | 0.6619848 | |
| Mudug | | Galdogob | | 0.640 | | 0.7338951 | |
| Mudug | | Hobyo | | 0.635 | | 0.7257320 | |
| Mudug | | Jariiban | | 0.476 | | 0.5881161 | |
| Mudug | | Xarardheere | | 0.532 | | 0.5414604 | |
| Galgaduud | | Dhuusamarreeb | | 0.457 | | 0.4380751 | |
| Galgaduud | | Cabudwaaq | | 0.547 | | 0.5593798 | |
| Galgaduud | | Cadaado | | 0.620 | | 0.7002371 | |
| Galgaduud | | Ceel Buur | | 0.470 | | 0.6315186 | |
| Galgaduud | | Ceel Dheer | | 0.512 | | 0.7459147 | |
| Hiraan | | Belet Weyne | | 0.804 | | 0.8117509 | |
| Hiraan | | Bulo Burto | | 0.872 | | 0.8241094 | |
| Hiraan | | Jalalaqsi | | 0.859 | | 0.7751405 | |
| Middle Shabelle | | Jowhar | | 0.813 | | 0.7609432 | |
| Middle Shabelle | | Adan Yabaal | | 0.472 | | 0.7364308 | |
| Middle Shabelle | | Balcad | | 0.755 | | 0.7819597 | |
| Middle Shabelle | | Cadale | | 0.588 | | 0.6920718 | |
| Banadir | | Banadir | | 0.458 | | 0.4506796 | |
| Lower Shabelle | | Marka | | 0.560 | | 0.4829774 | |
| Lower Shabelle | | Afgooye | | 0.562 | | 0.5583717 | |
| Lower Shabelle | | Baraawe | | 0.567 | | 0.5506913 | |
| Lower Shabelle | | Kurtunwaarey | | 0.685 | | 0.4852593 | |
| Lower Shabelle | | Qoryooley | | 0.707 | | 0.5583049 | |
| Lower Shabelle | | Sablaale | | 0.368 | | 0.5000973 | |
| Lower Shabelle | | Wanla Weyn | | 0.574 | | 0.8096928 | |
| Bay | | Baydhaba | | 0.539 | | 0.5460101 | |
| Bay | | Buur Hakaba | | 0.482 | | 0.5932554 | |
| Bay | | Diinsoor | | 0.513 | | 0.5439663 | |
| Bay | | Qansax Dheere | | 0.540 | | 0.5202485 | |
| Bakool | | Xudur | | 0.658 | | 0.6562309 | |
| Bakool | | Ceel Barde | | 0.762 | | 0.7753613 | |
| Bakool | | Tayeeglow | | 0.716 | | 0.7678550 | |
| Bakool | | Waajid | | 0.779 | | 0.7515893 | |
| Bakool | | Rab Dhuure | | 0.795 | | 0.7842077 | |
| Gedo | | Garbahaarey | | 0.487 | | 0.1040450 | |
| Gedo | | Baardheere | | 0.558 | | 0.4276045 | |
| Gedo | | Belet Xaawo | | 0.367 | | 0.3398158 | |
| Gedo | | Ceel Waaq | | 0.456 | | 0.3102931 | |
| Gedo | | Doolow | | 0.538 | | 0.6036457 | |
| Gedo | | Luuq | | 0.632 | | 0.5611038 | |
| Gedo | | Bu'aale | | 0.473 | | 0.5185329 | |
| Gedo | | Jilib | | 0.712 | | 0.4229273 | |
| Gedo | | Saakow | | 0.527 | | 0.6041703 | |
| Lower Juba | | Kismaayo | | 0.539 | | 0.5286834 | |
| Lower Juba | | Afmadow | | 0.595 | | 0.5650695 | |
| Lower Juba | | Badhaadhe | | 0.510 | | 0.3299765 | |
| Lower Juba | | Jamaame | | 0.468 | | 0.4167271 | |



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1. The coefficient of variation is the MSE divided by the poverty rate. In estimating direct variances (directs MSEs), we assume to sampling design of the SIHBS (described in Section 2). We use the svydesign function of the survey R package in computing the variances. [↑](#footnote-ref-1)