

sae: A Stata Package for Unit Level Small Area Estimation

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Any error or omission is the authors' responsibility alone.

1 Introduction

Household surveys that are designed for national or sub-national (i.e. regions or states) level parameter estimates often lack a sufficiently large sample size to generate accurate direct estimates for smaller domains or sub-populations.¹ Any area for which the sample is not sufficiently large to produce an estimate of adequate precision is referred to as a small area. Consequently small area methods attempt to address low representativeness of surveys within areas, or the lack of data for specific areas/sub-populations. This is accomplished by incorporating information from supplementary sources. In the methodology presented by Elbers, Lanjouw, and Lanjouw (2003) the desired estimate is produced by a model done using survey data which is then linked to outside information such as a population census, administrative records, and/or geospatial information obtained through remote sensing. As Rao and Molina (2015) state, the availability of these auxiliary data as well as a valid model are essential for obtaining successful small area estimates (SAE).

In the case of poverty measures, which are nonlinear functions, small area estimation methods coupled with Monte Carlo simulations are a useful statistical technique for monitoring poverty along with its spatial distribution and evolution.² Poverty estimates are often produced by statistical agencies, and commonly are the product of a household survey. Household surveys usually are the main source of welfare (expenditure or income) used to produce poverty estimates, yet most are only reliable up to a certain geographical level. Therefore, a commonly adopted solution has been to borrow strength from a national census, administrative records, and/or geospatial information which allows for representativeness for small areas. Nevertheless, these outside data sources often lack detailed expenditure or income information required for producing estimates of poverty. Small area methods attempt to exploit each data's attributes to obtain estimators that can be used at dis-aggregated levels.

Poverty at lower geographical levels can be used to identify areas that are in need of attention, or that may be lagging behind the rest of the country. For example, the Government of Ecuador after an earthquake that occurred on April 16, 2016 relied on small area estimates of poverty to decide where help was needed most. The small area estimates of poverty for Ecuador, which were released not long before the earthquake, proved to be an invaluable resource for the rebuilding effort in the country.

One of the most common small area methods used for poverty estimates is the one proposed by Elbers, Lanjouw, and Lanjouw (2003, henceforth ELL).³ This methodology has been widely adopted by the World Bank and has been applied in numerous poverty maps⁴ conducted by the institution. In its efforts to make the implementation of the ELL methodology as straightforward as possible, the World Bank created a software package that could be easily used by anyone. The software, PovMap (Zhao, 2006),⁵ has proven to be an invaluable resource for the World Bank as well as for many statistical agencies, line ministries, and other international organizations seeking to create their own small area estimates of poverty. The software is freely available and has a graphical user interface which simplifies its use. Nevertheless, more advanced

¹For example districts, municipalities, migrant populations, or populations with disabilities.

²Poverty is a nonlinear function of welfare, consequently small area estimation methods of linear characteristics are invalid (Molina and Rao, 2010). A proposed solution to this problem is to use Monte Carlo simulation to obtain multiple vectors of the measure of interest (Elbers, Lanjouw, and Lanjouw, 2003).

³For a detailed discussion of different applications of small area poverty estimates by the World Bank, readers should refer to Bedi et al. (2007), for other applications readers should refer to Rao and Moline (2015).

⁴Poverty map is the common name within the World Bank for the methodology where the obtained estimates are mapped for illustrative purposes.

⁵downloadable from: <http://iresearch.worldbank.org/PovMap/PovMap2/setup.zip>

practitioners who may wish for more functionality and options may have to program it themselves. In an effort to simplify the process, we have created a family of Stata commands which implement small area estimation methods, and provide users with a valid, modular, and flexible alternative to PovMap. All of the results produced with `sae` have been bench-marked with the well established PovMap software, and are an exact match.⁶

In the following section we discuss the linking model and focus on the first stage of the estimation. How the variance of the location effect present in the linking model is accounted for is discussed afterwards. This is initiated by presenting the ELL methodology for decomposing the first stage residuals’s variance parameters. Afterwards, this is followed by Henderson’s Method III decomposition of the residual’s variance parameters and the adaptation of Huang and Hidirolou’s (2003) GLS and implemented by Van der Weide (2014) in an update to the PovMap software. Then we present Empirical Bayes prediction of the location effects. We finally present the command’s syntax along with examples of its use.

2 First Stage: Model

When survey data is not sufficiently precise for reliable estimates at low geographical levels, small area estimation can be implemented. This commonly relies on borrowing strength from outside sources to generate indirect estimates (Rao and Molina, 2015). For example, when attempting to obtain welfare estimates at low geographical levels, it is possible to borrow strength from census data. Censuses in most cases do not collect sufficient information on incomes and/or expenditures. On the other hand household surveys tend to collect detailed information on incomes and/or expenditures which allows the generation of welfare statistics such as poverty and inequality measures. Although welfare statistics can be obtained using household surveys, these are rarely sufficiently large to allow for statistics corresponding to small areas (Tarozzi and Deaton, 2009). Small area estimation methods attempt to exploit the large sample size of census data and combine this with the information from household surveys in an attempt to obtain reliable statistics for small areas.

In its essence the small area estimation presented here relies on using household survey data to estimate a joint distribution of the variable of interest and observed correlates, and use the parameters to simulate welfare using census data (Demombynes et al., 2008). Throughout the text we focus on welfare imputation, since this is what the Elbers, Lanjouw, and Lanjouw (2003) methodology focused on, nevertheless it can be applied for other continuous measures aside from welfare.

The first step towards small area welfare simulation is a per-capita⁷ welfare model, estimated via ordinary least squares (*OLS*), or weighted least squares (*WLS*):

$$\ln Y = X\beta_{ols} + u \tag{1}$$

where $\ln Y$ is a $N \times 1$ matrix indicating the household’s welfare measure (usually in logarithms, but not necessarily),⁸ X is a $N \times K$ matrix of household characteristics, and u which is a $N \times 1$ matrix of disturbances. To achieve valid small area estimates it is necessary that the set of explanatory variables, X , used in the

⁶For the 1st stage of the analysis. The second stage relies on Monte-Carlo simulations, and thus differences are likely to arise.

⁷Other household equivalization methods are also feasible, for example adult equivalent household welfare.

⁸Logarithmic transformation is usually preferred since it makes the data more symmetrical (Haslett et al., 2010).

first stage model can also be found in the census data. It is important that the variables are compared beforehand to verify that not only their definitions are in agreement, but also their distributions.⁹

In the design of household surveys, clusters are commonly the primary sampling unit. Households within a cluster are usually not independent from one another, to allow for the clustering of households and their interrelatedness it is possible to specify equation (1) for a household as:

$$\ln y_{ch} = x_{ch}\beta + u_{ch}$$

, – where the indexes c and h stand for cluster and observation, respectively – and disturbances (u_{ch}) are assumed to have the following specification (Haslett et al., 2010):

$$u_{ch} = \eta_c + e_{ch} \tag{2}$$

where η_c and e_{ch} , are assumed to be independent from each other with different data generating processes (Haslett et al., 2010).¹⁰ Therefore the resulting model we wish to estimate is a linear mixed model (Van der Weide, 2014).¹¹

The literature has suggested different methods for estimating the unconditional variances of these parameters;¹² for the purposes of this paper focus is given to the methods presented by Elbers, Lanjouw, and Lanjouw (2003), and the adaptation of Henderson’s Method III by Huang and Hidirolou (2003) detailed and expanded upon by Van der Weide (2014). The next section describes in detail these two approaches.

3 Estimating the unconditional variance of the residual parameters

3.1 The ELL Methodology

The methodology for estimating the location’s unconditional variance detailed by ELL (2002 and 2003) is presented in the discussion below. The method consists of two steps. The initial step relies on estimating a welfare model (Eq:1) using household survey data, and then obtaining generalized least square (*GLS*) estimates for the model. Given the interrelatedness between households in a cluster, ordinary least squares is not the most efficient estimator. The second stage consists in utilizing the parameter estimates from the first stage and applying these to census data to obtain small area poverty and inequality measures.

Because the motivation is to implement the methodology into a Stata command, where possible, we also follow the methods implemented by PovMap (Zhao, 2006). It must be noted, however, that the methodology utilized by ELL is not necessarily the one followed by the PovMap software. Places where methodologies differ will be indicated in footnotes.

⁹This point is crucial, and the quality of a good poverty map is highly dependent on these two criteria being met. For further discussion and motivation refer to: Tarozzi and Deaton (2009).

¹⁰Note that the interrelatedness of η_c across observations is already a violation of *OLS* assumptions.

¹¹Molina and Rao (2010) follow the naming convention of a nested error linear regression model. Regardless of its name, standard *OLS* is invalid under this structure.

¹²Rao and Molina (2015).

From the estimation of equation 1 we obtain the residuals \hat{u}_{ch} , and by defining \hat{u}_c as the weighted average of \hat{u}_{ch} for a specific cluster we can obtain \hat{e}_{ch} .¹³

$$\hat{u}_{ch} = \hat{u}_c + (\hat{u}_{ch} - \hat{u}_c) = \hat{\eta}_c + \hat{e}_{ch} \quad (3)$$

where \hat{u}_c is equal to $\hat{\eta}_c$.¹⁴

The unconditional variance of the location effect η_c given by ELL (2002) is:

$$\hat{\sigma}_\eta^2 = \max \left(\frac{\sum_c w_c (u_{c.} - u_{..})^2 - \sum_c w_c (1 - w_c) \hat{\tau}_c^2}{\sum_c w_c (1 - w_c)}; 0 \right) \quad (4)$$

where $u_{..} = \sum_c w_c u_{c.}$ (where w_c represents the cluster's weight, i.e. $w_c = \sum_h w_{hc}$) and

$$\hat{\tau}_c^2 = \frac{\sum_h (e_{ch} - e_{c.})^2}{n_c (n_c - 1)} \quad (5)$$

where $e_{c.} = \frac{\sum_h e_{ch}}{n_c}$.¹⁵

3.1.1 Estimating the Alpha Model (heteroskedasticity)¹⁶

The variance of the idiosyncratic error (e_{ch}) is specified by ELL (2003) through a parametric form of heteroskedasticity:¹⁷

$$E[e_{ch}^2] = \sigma_{e_{ch}}^2 = \left[\frac{A \exp^{Z'_{bh} \alpha} + B}{1 + \exp^{Z'_{bh} \alpha}} \right] \quad (6)$$

In ELL (2003) this is simplified by setting $B = 0$ and $A = 1.05 \max(\hat{e}_{ch}^2)$, and thus the simpler form is estimated via *OLS*.¹⁸

$$\ln \left[\frac{e_{ch}^2}{A - e_{ch}^2} \right] = Z'_{ch} \alpha + r_{ch} \quad (7)$$

This approach resembles that of Harvey (1976), nevertheless the prediction is bounded.

By defining $\exp^{(Z'_{ch} \alpha)} = D$ and using the delta method,¹⁹ the household specific conditional variance estimator for e_{ch} is equal to (Elbers, Lanjouw, and Lanjouw, 2002):

¹³ \hat{e}_{ch} denotes the household specific error component.

¹⁴Although, ELL (2003) notes that weights are to be used, the PovMap software does not utilize weights when obtaining \hat{u}_c .

¹⁵ n_c is the number of observations in cluster c .

¹⁶The heteroskedastic model is relevant for the variance estimation under ELL's method, as well as the one under Henderson's method III. In its current form, the methodology is from ELL (2003).

¹⁷Users have the option to allow for homoskedasticity, in which case $\hat{\sigma}_e = \hat{\sigma}_u - \hat{\sigma}_\eta$, where $\hat{\sigma}_u$ is the estimated variance of the residuals from the consumption model (equation 1). If the user chooses homoskedasticity, equations 6 through 8 are omitted.

¹⁸This is the actual model used by PovMap, which we also implement.

¹⁹The result is the outcome from a second order Taylor expansion for the $E[\sigma_{e_{ch}}^2]$.

$$\hat{\sigma}_{e,ch}^2 \approx \left[\frac{AD}{1+D} \right] + \frac{1}{2} \widehat{\text{Var}}(r) \left[\frac{AD(1-D)}{(1+D)^3} \right] \quad (8)$$

where $\widehat{\text{Var}}(r)$ is the estimated variance from the residuals of the model in equation (7).

3.1.2 Estimating the distribution of $\hat{\sigma}_\eta^2$

ELL (2002) proposes two methods to obtain the variance of $\hat{\sigma}_\eta^2$:

1. By simulation (ELL, 2002):

- (a) Estimate σ_η^2 from equation (4) which yields $\hat{\sigma}_\eta^2$
- (b) Estimate $\sigma_{e,ch}^2$ from equation (8) which yields $\hat{\sigma}_{e,ch}^2$
- (c) Assuming η_c and e_{ch} are independent and normally distributed with mean 0, new values for u_{ch} are generated using equation (2)
- (d) Compute a new estimate σ_η^2 from equation (4)
- (e) Repeat (a) - (d) and keep all simulated values of $\hat{\sigma}_\eta^2$

From the simulated values of σ_η^2 , the sampling variance of $\hat{\sigma}_\eta^2$ ($\text{Var}(\hat{\sigma}_\eta^2)$) can be obtained directly.

2. The sampling variance of $\hat{\sigma}_\eta^2$ can also be obtained by the following formula (ELL, 2002):²⁰

$$\text{Var}(\hat{\sigma}_\eta^2) = \sum_c 2 \left\{ a_c^2 \left[(\hat{\sigma}_\eta^2)^2 + (\hat{\tau}_c^2)^2 + 2\hat{\sigma}_\eta^2 \hat{\tau}_c^2 \right] + b_c^2 \frac{(\hat{\tau}_c^2)^2}{n_c - 1} \right\} \quad (9)$$

where $a_c = w_c / [\sum_c w_c (1 - w_c)]$, and $b_c = w_c (1 - w_c) / [\sum_c w_c (1 - w_c)]$.

- (a) This is noted by ELL to be an approximation of the sampling variance of $\hat{\sigma}_\eta^2$. It assumes within cluster homoskedasticity of the household error component. For a more comprehensive discussion on this matter refer to ELL (2002).

The command, in its present form only allows for estimation using the second method,²¹ when estimating the unconditional variance of σ_η^2 using the ELL methodology.

3.1.3 ELL's GLS Estimator

The GLS estimator offered in ELL's paper is presented in this section. Although not implemented,²² the estimator is presented for completeness of the original methodology presented by ELL.

Once $\hat{\sigma}_{e,ch}^2$ (8) and $\hat{\sigma}_\eta^2$ (4) are estimated these are used to construct a matrix $(\hat{\Omega})$ of dimension $N \times N$. The matrix for $\hat{\Omega}_c$ is a square block matrix corresponding to cluster c , where the rows and columns are the

²⁰This is the only option available in PovMap software.

²¹This is also true for the PovMap software.

²²This is due to the lack of symmetry of the resulting variance covariance matrix when weights differ across observations in a cluster.

number of observations in the cluster. Within cluster covariance is given by $\hat{\sigma}_\eta^2$. On the diagonal $\hat{\sigma}_{e,ch}^2$ is added to obtain the observation specific disturbance variance. The resulting **cluster block** of this $N \times N$ matrix is equal to:

$$\hat{\Omega}_c = \begin{pmatrix} \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 & \hat{\sigma}_\eta^2 & \cdots & \hat{\sigma}_\eta^2 \\ \hat{\sigma}_\eta^2 & \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 & \cdots & \hat{\sigma}_\eta^2 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\sigma}_\eta^2 & \hat{\sigma}_\eta^2 & \cdots & \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 \end{pmatrix}$$

$$\Rightarrow \hat{\Omega} = \begin{pmatrix} \hat{\Omega}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \hat{\Omega}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \hat{\Omega}_C \end{pmatrix}$$

where $\mathbf{0}$ is a block of zeroes; the number of columns equals the $\hat{\Omega}_c$ from above, and the number of rows to the $\hat{\Omega}_c$ next to it.

Ω is the variance-covariance matrix of the error vector necessary to estimate equation (1) via GLS and obtain $\hat{\beta}_{GLS}$ and $\text{Var}(\hat{\beta}_{GLS})$. The estimates for the GLS detailed by ELL (2003) are:

$$\hat{\beta}_{GLS} = (X'W\Omega^{-1}X)^{-1}X'W\Omega^{-1}Y \quad (10)$$

and

$$\text{Var}(\hat{\beta}_{GLS}) = (X'W\Omega^{-1}X)^{-1}(X'W\Omega^{-1}WX)(X'W\Omega^{-1}X)^{-1} \quad (11)$$

where W is a $N \times N$ diagonal matrix of sampling weights. Because $W\Omega^{-1}$ is usually not symmetric,²³ as noted by Haslett et al. (2010), the variance covariance matrix must be adjusted to obtain a symmetric matrix. This is done by obtaining the average of the variance covariance matrix and its transpose (Haslett et al., 2010).

Newer versions of the PovMap software no longer obtain *GLS* estimates using this approach. Adjustments have been made in order to better incorporate the survey weights into Ω . The newest version of PovMap uses the *GLS* estimator presented by Huang and Hidirolou (2003), which is discussed below.

3.2 Henderson's Method III decomposition

After a decade of use of PovMap, and numerous poverty maps completed by the World Bank using the original ELL small area methodology; the software was updated with Henderson's Method III (H3) decomposition of the variance components and an update of the *GLS* with a modification of Huang and Hidirolou (2003).²⁴ Obtaining the *GLS* estimates once again requires the estimation of the variance components, which are

²³The lack of symmetry is due to the difference in sampling weights between observations.

²⁴This is detailed in Van der Weide (2014).

estimated using a variation of Henderson's Method III (Henderson, 1953). The variation takes into account the use of survey weights and was presented by Huang and Hidirolou (2003). We follow the presentation offered by Van der Weide (2014) which builds on Huang and Hidirolou (2003).

In order to obtain the variance components of the β_{GLS} it is necessary to first estimate a model which subtracts each of the cluster's means from the variables. To achieve this we first need to define the left hand side of the model. For each cluster in our estimation the left hand side is (omitting the natural logarithm only for display purposes):

$$\tilde{y}_c = Y_c - (\bar{Y}_c \otimes \mathbf{1}_T)$$

where Y_c is a $T \times 1$ vector (where T is the number of surveyed observations in the cluster), corresponding to cluster c , of our welfare variable used in equation 1. \bar{Y}_c is a scalar which is the weighted mean value of Y_c for cluster c . $\mathbf{1}_T$ is a $T \times 1$ vector of 1s, and \otimes is the Kroenecker product. Finally, we define $\tilde{\mathbf{y}}$ as a $N \times 1$ matrix which is a vector of all the cluster \tilde{y}_c s.

For the right hand side we follow the same de-meaning procedure and obtain a matrix $\tilde{\mathbf{x}}$. Additionally, define $\bar{\mathbf{x}}$ of dimensions $C \times K$ where C is the number of areas in the survey, with each row representing the demeaned \bar{x}_c for a specific cluster. With these in hand it is possible to define the following:

$$\begin{aligned} SSE &= \tilde{\mathbf{y}}' W \tilde{\mathbf{y}} - \tilde{\mathbf{y}}' W \tilde{\mathbf{x}} (\tilde{\mathbf{x}}' W \tilde{\mathbf{x}})^{-1} \tilde{\mathbf{x}}' W \tilde{\mathbf{y}} \\ t_2 &= \text{tr} \left[(\tilde{\mathbf{x}}' W \tilde{\mathbf{x}})^{-1} (\tilde{\mathbf{x}}' (W \circ W) \tilde{\mathbf{x}})^{-1} \right] \\ t_3 &= \text{tr} \left[(X' W X)^{-1} X' (W \circ W) X \right] \\ t_4 &= \text{tr} \left[(X' W X)^{-1} \bar{\mathbf{x}}' (W_c \circ W_c) \bar{\mathbf{x}} \right] \end{aligned}$$

where W_c is a $C \times C$ diagonal matrix of cluster weights, and \circ represents the Hadamard product. Using SSE , t_2 , t_3 , and t_4 it is possible to estimate the variances σ_e^2 and σ_η^2 :

$$\hat{\sigma}_e^2 = \frac{SSE}{\sum_{ch} w_{ch} - \sum_c \left(\frac{\sum_h w_{ch}^2}{\sum_h w_{ch}} \right) - t_2} \quad (12)$$

$$\hat{\sigma}_\eta^2 = \frac{Y' W Y - Y' W X (X' W X)^{-1} X' W Y - (\sum_{ch} w_{ch} - t_3) \hat{\sigma}_e^2}{\sum_{ch} w_{ch} - t_4} \quad (13)$$

To obtain the estimates of $\hat{\eta}_c$ Van der Weide (2014) provides the following for each cluster c :

$$\gamma_{c,w} = \frac{\hat{\sigma}_\eta^2}{\hat{\sigma}_\eta^2 + \hat{\sigma}_e^2 \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right)}$$

consequently the $\hat{\eta}_c$ for a particular cluster is:

$$\hat{\eta}_c = \gamma_{c,w} \sum_h w_{ch} \hat{u}_{ch} - \frac{1}{C} \sum_c \gamma_{c,w} \left(\sum_h w_{ch} \hat{u}_{ch} \right) \quad (14)$$

With the updated estimate of $\hat{\eta}_c$ it is possible to update the estimate of \hat{e}_{ch} :

$$\hat{e}_{ch} = \hat{u}_{ch} - \hat{\eta}_c - \sum_{ch} (\hat{u}_{ch} - \hat{\eta}_c) \quad (15)$$

Additionally the distribution of \hat{e}_{ch} is adjusted such that its variance is equal to $\hat{\sigma}_e^2$.

3.3 The GLS Estimator

With the idiosyncratic error terms in hand the heteroskedasticity of the observation specific residual may be specified.²⁵ In this instance we follow the same steps detailed above for equation 7, from which we can obtain observation specific $\hat{\sigma}_{e,ch}^2$ by using equation 8.

The estimated variances are then used to construct a pair of matrices used to obtain the *GLS* estimates. The *GLS* estimator for β is:

$$\hat{\beta}_{GLS} = \left(X' \hat{\Omega}^{-1} X \right)^{-1} X' \hat{\Omega}^{-1} Y \quad (16)$$

and the variance-covariance matrix of the *GLS* estimator is:

$$\text{Var} \left[\hat{\beta}_{GLS} \right] = \left(X' \hat{\Omega}^{-1} X \right)^{-1} \left(X' \hat{\Omega}^{-1} \hat{V} \hat{\Omega}^{-1} X \right) \left(X' \hat{\Omega}^{-1} X \right)^{-1} \quad (17)$$

where $\hat{\Omega}$ as opposed to the one detailed in the ELL method above, incorporates the survey weights into the matrix. $\hat{\Omega}$ for each cluster is equal to:

$$\hat{\Omega}_c = \begin{pmatrix} \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_{e,ch}^2}{w_{ch}} & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 & \dots & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 \\ \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_{e,ch}^2}{w_{ch}} & \dots & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 \\ \vdots & \vdots & \ddots & \vdots \\ \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 & \dots & \left(\frac{\sum_h w_{ch}}{\sum_h w_{ch}^2} \right) \hat{\sigma}_\eta^2 + \frac{\hat{\sigma}_{e,ch}^2}{w_{ch}} \end{pmatrix}$$

$$\Rightarrow \hat{\Omega} = \begin{pmatrix} \hat{\Omega}_1 & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \hat{\Omega}_2 & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \hat{\Omega}_C \end{pmatrix}$$

where $\mathbf{0}$ is a block of zeroes; the number of columns equals the $\hat{\Omega}_c$ from above, and the number of rows to the $\hat{\Omega}_c$ next to it. The \hat{V} for a particular cluster is equal to:

²⁵The user may also choose to forego the modeling of household level heteroskedasticity, in which case $\hat{\sigma}_e^2$ is constant for all observations.

$$\hat{V}_c = \begin{pmatrix} \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 & \hat{\sigma}_\eta^2 & \cdots & \hat{\sigma}_\eta^2 \\ \hat{\sigma}_\eta^2 & \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 & \cdots & \hat{\sigma}_\eta^2 \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\sigma}_\eta^2 & \hat{\sigma}_\eta^2 & \cdots & \hat{\sigma}_\eta^2 + \hat{\sigma}_{e,ch}^2 \end{pmatrix}$$

$$\Rightarrow \hat{V} = \begin{pmatrix} \hat{V}_1 & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \hat{V}_2 & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \hat{V}_C \end{pmatrix}$$

where $\mathbf{0}$ is a block of zeroes; the number of columns equals the \hat{V}_c from above, and the number of rows to the \hat{V}_c next to it.

The \hat{V} matrix is similar to the $\hat{\Omega}$ matrix from the ELL methodology. In the most current version of PovMap users no longer have the option to use the *GLS* estimator originally offered by ELL (2003), and independently of how users choose to model the location effect, the manner in which the *GLS* estimators are obtained is using the estimators from equations 16 and 17.

4 The Second Stage: Simulation

The final goal of the process described up to this point is to simulate values for the variable of interest. In the Elbers, Lanjouw, and Lanjouw (2003) context, this entailed log welfare and poverty rates for specific locations using the census data. Monte Carlo simulation is used to obtain the expected welfare measures given the first stage model (ELL, 2003). This is done by applying the parameter and error estimates from the survey to the census data. The goal is to obtain a sufficient number of simulations in order to obtain reliable levels of welfare. The section begins by introducing Empirical Bayes prediction as is done by Van der Weide (2014).

4.1 Empirical Bayes Prediction Assuming Normality

Along with the *GLS* and Henderson's Method III additions to the ELL approach mentioned before, Empirical Bayes (EB) prediction was also added. EB prediction makes use of the survey data in order to improve predictions on the location effect. Since EB makes explicit use of data from the survey, its use only improves predictions for areas that are included in the survey.

If we assume that η_c and e_{ch} (from equation 1) are normally distributed, then the distribution of η_c conditional on e_c will also be normally distributed (Van der Weide, 2014). The distribution of the random location effect, η_c , is obtained conditional on the observation specific residuals of the observations sampled in the location. Van der Weide (2014) indicates that the assumption of normality for both components of the residual is necessary to derive the distribution of the random location effects. In order to proceed, Van der Weide (2014) defines the following:

$$\gamma_{c,w} = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sum_h w_{ch}^2 \left(\sum_h w_{ch} \sum_h \frac{w_{ch}}{\sigma_{e, ch}^2} \right)^{-1}}$$

With this defined, the expected value of the location effect conditional on the residuals of the households within the location can be obtained:

$$E[\eta_c | e_c] = \hat{\eta}_c = \gamma_{c,w} \left(\frac{\sum_h \left(\frac{w_{c,h}}{\sigma_{e, ch}^2} \right) e_{ch}}{\sum_h \frac{w_{c,h}}{\sigma_{e, ch}^2}} \right)$$

as well as the variance:

$$\text{Var}[\hat{\eta}_c] = \sigma_\eta^2 - \gamma_{c,w}^2 \left(\sigma_\eta^2 + \sum_h \left(\frac{\frac{w_{c,h}}{\sigma_{e, ch}^2}}{\sum_h \frac{w_{c,h}}{\sigma_{e, ch}^2}} \right)^2 \sigma_{e_{ch}}^2 \right)$$

EB prediction is expected to perform well in the presence of large η , if many of the locations are covered by the survey, and if the distributions of the error terms approximate a normal distribution (Van der Weide, 2014).

4.2 Monte Carlo Simulations

ELL (2003) use various specifications in their paper. The options and methods differ depending on how the variance for the decomposed error terms is obtained. The simulation may be done via parametric drawing of the parameters, and via bootstrap. The PovMap manual (Zhao, 2006) only details the parametric approach. Nevertheless, the newest version of the software has incorporated a bootstrap approach to obtaining the parameters. The steps for the simulation are:

1. Obtain GLS coefficients by drawing from $\tilde{\beta}_{GLS} \sim N\left(\hat{\beta}_{GLS}, \text{Var}\left(\hat{\beta}_{GLS}\right)\right)$. For reasons that will become apparent in the following steps, this approach is only possible when the user chooses ELL variance estimation.
 - (a) A different approach relies on obtaining bootstrapped samples of the survey data used in the first stage, this is repeated for every single simulation. The latter method yields a set of $\tilde{\beta}$ for every single simulation.
2. Under the ELL variance estimation approach the cluster component of the error term, $\tilde{\eta}_c$ is obtained by drawing from $\tilde{\eta}_c \sim N(0, \hat{\sigma}_\eta^2)$ where we:
 - (a) Draw $\hat{\sigma}_\eta^2 \sim \text{Gamma}\left(\hat{\sigma}_\eta^2, \text{Var}\left(\hat{\sigma}_\eta^2\right)\right)$ ²⁶
 - i. With each $\hat{\sigma}_\eta^2$ in hand it is possible to draw the location effects from $\tilde{\eta}_c \sim N(0, \hat{\sigma}_\eta^2)$.

²⁶As described in Demombynes et al. (2008), $\text{Var}\left(\hat{\sigma}_\eta^2\right)$ may be estimated by simulation as detailed above, or from equation 9. In its present form the only available option is that from equation 9.

- ii. Additionally, $\tilde{\eta}_c$ could be drawn from those estimated in the first stage (semi-parametric), this is possible to do in the parametric and bootstrapped simulation.

Under Henderson's method III (H3) there is no defined distribution for the $\hat{\sigma}_\eta^2$ parameter. Consequently, bootstrapped samples of the survey data are used to obtain $\hat{\sigma}_\eta^2$ and all other parameters for every single simulation. This approach is also available under ELL methods. The bootstrap is also necessary for the instances when EB is chosen. When EB is chosen, the bootstrap produces a vector of η s and of $\hat{\sigma}_{\eta c}^2$ for each of the clusters included in the survey and thus for every simulation we draw $\tilde{\eta}_c \sim N(\hat{\eta}_c, \hat{\sigma}_{\eta c}^2)$. For clusters not included in the survey the drawing is: $\tilde{\eta}_c \sim N(0, \hat{\sigma}_\eta^2)$.

- 3. \tilde{e}_{ch} can be drawn from a normal distribution with variance such as the one specified in equation 8. This is done by:

- (a) Drawing $\alpha \sim N(\hat{\alpha}, \text{Var}(\hat{\alpha}))$ (it may also be the product of the bootstrap process) and using it on the census data, we obtain a new $D = \exp^{(Z'_{ch}\alpha)}$, and using the new D we obtain in conjunction with the first stage $A = 1.05 \max(\hat{e}_{ch}^2)$ and $\widehat{\text{Var}}(r)$ we get:

$$\tilde{\sigma}_{e,ch}^2 \approx \left[\frac{A\hat{D}}{1 + \hat{D}} \right] + \frac{1}{2} \widehat{\text{Var}}(r) \left[\frac{A\hat{B}(1 - \hat{D})}{(1 + \hat{D})^3} \right]$$

From this it is possible to draw $\tilde{e}_{ch} \sim N(0, \tilde{\sigma}_{e,ch}^2)$.

- (b) As an alternative it is also possible to draw from the estimated \hat{e}_{ch} from the first phase (semi-parametric). In the case of the ELL variance estimation with a parametric drawing of β 's then this will be done from one $N \times 1$ vector, when performing bootstrap the drawing is done from the $N \times 1$ vector corresponding to each simulation.
- (c) Under the assumption of homoskedasticity, the error terms are drawn from $\tilde{e}_{ch} \sim N(0, \tilde{\sigma}_e^2)$.
- 4. Once all simulated parameters have been obtained, it is possible to obtain the simulated vector of target values:

$$\tilde{Y}_{ch} = X\tilde{\beta}_{GLS} + \tilde{\eta}_c + \tilde{e}_{ch} \quad (18)$$

- (a) This is repeated multiple times (usually 100) in order to obtain a full set of simulated household welfare vectors.

If the interest is small area estimates of income and poverty, once all simulations are finalized a set of incomes for all observations in the target data may be used to obtain R simulated poverty, or inequality rates for each domain of interest. Making use of the R indicators produced, it is possible to obtain the mean indicator for each domain of interest (i.e. municipality in the context of a poverty map), as well as the associated standard errors for the indicator.

5 Computational Considerations

The first stage of the analysis is standard procedure among the typical Stata commands, since the analysis is done on survey data. There are no considerable computational requirements, and the analysis may likely

be performed using the majority of computers available to users. On the other hand, the Monte Carlo simulation requires the use of the census data. Census data, depending on the country, can range from anywhere between roughly 30,000 observations to almost half a billion. Depending on a user's computer setup, a couple million observations can really slow down the computer to a crawl. Assuming variables in double type precision, a 5 million observation dataset with 30 variables will require roughly 1.1 GB of memory. Therefore, in order to speed up the second stage operation and to be able to operate with larger datasets, a couple of modifications are implemented.

The first modification concerns importing the census data and formatting it in a more memory friendly way. Along with the main command we supply a sub-command that allows the user to import the census data for the second stage, `sae data import`. The data is imported one vector at a time and saved into a Mata format file which is used for the processing of each regressor at a time for each simulation to obtain the predicted welfare. Proceeding in this manner, the maximum number of observations that can be used in the simulation stage is increased. As shown in the examples section, this setup requires preparing the target dataset beforehand. Due to this setup, the Monte Carlo simulations are executed one vector at a time. For smaller datasets it is likely that performing all simulations in one go results in quicker execution times,²⁷ once we move on to larger census data this method provides faster execution times and allows for more efficient memory management.

The second modification, is a plugin for processing the simulations and producing the required indicators. This is only used/necessary for processing indicators. The processing is also done one simulation at a time, just like the Monte Carlo simulations. The plugin speeds up the process considerably, especially when requesting Gini coefficients.²⁸

6 The `sae` Command and Sub-Commands

The `sae` command and sub-commands for modeling, simulating, and data manipulation are introduced below. The common syntax for the command is:

```
sae [routine] [sub routine]
```

Currently available routines and subroutines are:

- `sae data import||export` : This is used to import the target dataset to a more manageable format for the simulations. It is also used to export the resulting simulations to a dataset of the user's preference.
- `sae model lmm/povmap` : This routine is for obtaining the *GLS* estimates of the first stage. The sub-routines, `lmm` (linear mixed model) and `povmap` are used interchangeably.²⁹
- `sae simulate lmm/povmap` : This routine and sub-routine obtains the *GLS* estimates of the first stage, and goes on to perform the Monte Carlo simulations.

²⁷This is particularly true for the MP version of Stata, which makes use of more than one core for its operations.

²⁸Gini coefficients require sorting at every level, this is done much faster using a C plugin. Stata's sorting speed (as of this writing), including Mata's, is much slower than that of many other software.

²⁹Future work aims to incorporate additional methodologies, such as models for discrete left hand side variables .

- **sae proc stats||inds** : The stats and inds sub-routines are useful for processing Mata formatted simulation output and producing indicators with new thresholds or weights, as well as profiling.

The routines and sub-routines are described in the sections below.

6.1 Preparing the Target Dataset

Due to the potential large size of the target data set, the **sae** command comes with an ancillary sub-command (**sae data import**) useful for preparing the target dataset and converting it into a Mata format dataset to minimize the overall burden put on the system. The command's syntax is as follows:

```
sae data import, datain(string) varlist(string) area(string) uniqid(string)
dataout(string)
```

The options of the command are all required.

- The **datain()** option indicates the path and file name of the Stata format dataset to be converted into a Mata format dataset.
- The **varlist()** option specifies all the variables to be imported into the Mata format dataset. The variables specified will be available for the simulation stage of the analysis. Variables must have similar names between datasets. Additionally, users should include here any additional variables they wish to include, as well as expansion factors for the target data.
- The **uniqid()** option specifies the numeric variable that indicates the unique identifiers in the target dataset. This is necessary to ensure replicability of the analysis, and the name should match the one of the unique identifier from the source dataset.
- The **area()** option is necessary and specifies at which level the clustering is done, it indicates at which level the η_c is obtained. The only constraint is that the variable must be numeric and should match across datasets, although it is recommended it follows a hierarchical structure similar to the one proposed by Zhao (2006).
 - The hierarchical id should be of the same length for all observations. For example: AAMMEEE.³⁰ This structure facilitates getting final estimates at different aggregation levels.
- The **dataout()** option indicates the path and filename of the Mata format dataset that will be used when running the Monte Carlo simulations.

6.1.1 Example: Preparing the Target Data

The **sae** command requires users to import the target data into a Mata data format file. This is done to facilitate the process of simulations in the second stage due to the potential large size of the target data.

³⁰In the case this were done for a specific country, AA stands for the highest aggregation level, MM stands for the second highest aggregation level, and EEE, stands for the lowest aggregation level.

```
. sae data import, varlist(`xvar` p_hhsize_hh `zvar` pline pline2 rdef rdef2 rentdef rdef_rentroom2 rdef_rent
> tall2) area(localityid_n) uniqid(hhid) datain(`censo`) dataout(`matadata`)
Saving data variables into mata matrix file (38)
----- 1 ----- 2 ----- 3 ----- 4 ----- 5
.....
```

6.2 Model

In this section the command for the modeling stage of the analysis is presented. The syntax of this is as follows:

```
sae model lmm/povmap depvar indepvar [if] [in] [aw pw fw] , area(varname numeric)
varest(string) [zvar(varlist) yhat(varlist) yhat2(varlist) alfatest(string) vce(string)]
```

- **area()**: The **area** option is necessary and specifies at which level the clustering is done, it indicates at which level the η_c is obtained. The only constraint is that the variable must be numeric and should match across datasets, although it is recommended it follows a hierarchical structure similar to the one proposed by Zhao (2006).
 - The hierarchical id should be of the same length for all observations for example: AAMMEEE.³¹
- **varest()**: The **varest** option allows the user to select between *H3* or *ELL* methods for obtaining the variance of the decomposed first stage residuals. The selection has repercussions on the options available afterwards. For example, if the user selects *H3*, parameters must be obtained via bootstrapping.

The following are optional. In the case of homoskedasticity, the **zvar**, **yhat**, and **yhat2** options should not be specified.

- **zvar()**: The **zvar** option is necessary for specifying the alpha model, the user must place the independent variables of the alpha model under the option.
- **yhat()**: The **yhat** option is also a part of the alpha model. Variables listed here will be interacted with the predicted $\hat{y} = X\beta$ from the OLS model.
- **yhat2()**: The **yhat2** option is also a part of the alpha model. Variables listed here will be interacted with the predicted $\hat{y}^2 = (X\beta)^2$ from the OLS model.
- **alfatest()**: The **alfatest** option may be run in any stage, but is useful for selecting a proper first stage. It requests the command to output the dependent variable of the alpha model for users to model for heteroskedasticity.
- **vce()**: The **vce** option allows users to replicate the variance covariance matrix from the *OLS* in the PovMap 2.5 software. The default option is the variance covariance matrix from the PovMap software, **vce(ell)**, the user may specify robust or clustered variance covariance matrix to replicate the results from the **regress** command.³²

³¹In the case this were done for a specific country, AA stands for the highest aggregation level, MM stands for the second highest aggregation level, and EEE, stands for the lowest aggregation level.

³²The variance covariance matrix presented by the PovMap software is not standard in the literature. The variance covariance

6.2.1 Running the First Stage (welfare model)

The entire process of small area estimation may be run in two stages. It is possible to test the first stage of the analysis before moving on to the simulation which makes use of the target data. To obtain the first stage of the analysis, the user must have the data ready, and it is recommended that the user has predefined as macros the variables to be used.

```
. sae model povmap `y' `xvar' [aw=hhw], area(localityid_n) zvar(`zvar') ///
> varest(h3) vce(ell) alfatest(pp)
note: p_age omitted because of collinearity
WARNING: 76 observations removed due to less than 3 observations in the cluster.
```

OLS model:

lny	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dw_bath	.1397767	.0200267	6.98	0.000	.100525	.1790283
dw_btype_d3	.0496587	.0211568	2.35	0.019	.0081921	.0911253
edu_postsec	.0816588	.0883387	0.92	0.355	-.0914818	.2547994
edu_prim	-.8848284	.1744707	-5.07	0.000	-1.226785	-.5428722
j_firm_access1	.0382874	.0129973	2.95	0.003	.0128132	.0637616
jud_erate	.8928555	.2215139	4.03	0.000	.4586962	1.327015
jud_occup_el_sh	-1.333666	.2481222	-5.38	0.000	-1.819977	-.8473555
p_activity_1_sh	-.204576	.0306396	-6.68	0.000	-.2646285	-.1445235
p_age	.0134131	.0023387	5.74	0.000	.0088293	.0179968
p_age2	-.0000788	.0000238	-3.31	0.001	-.0001255	-.0000321
p_ecstat_2_sh	-.2178931	.0840416	-2.59	0.010	-.3826117	-.0531745
p_ecstat_4_sh	.4529504	.0297431	15.23	0.000	.394655	.5112458
p_ecstat_hh_2	-.1803367	.0690036	-2.61	0.009	-.3155813	-.0450921
p_elder_sh	.4871691	.0363326	13.41	0.000	.4159585	.5583797
p_hhsize_1	-.1331209	.0253237	-5.26	0.000	-.1827544	-.0834874
p_isced_max_0	-.5169389	.0540608	-9.56	0.000	-.6228961	-.4109817
p_isced_max_1	-.3758244	.0257253	-14.61	0.000	-.426245	-.3254037
p_isced_max_2	-.221132	.0191942	-11.52	0.000	-.2587519	-.1835122
p_isced_max_4	.138612	.0286283	4.84	0.000	.0825016	.1947225
p_isced_max_5	.2343928	.024233	9.67	0.000	.1868969	.2818887
p_isced_max_6	.237176	.0802218	2.96	0.003	.0799442	.3944078
p_male	.1836228	.0218718	8.40	0.000	.140755	.2264906
p_marital_hh_1	-.052893	.030501	-1.73	0.083	-.1126738	.0068878
p_marital_hh_3	-.0809455	.0206275	-3.92	0.000	-.1213747	-.0405163
p_occup_pr_sh	.3670144	.0363299	10.10	0.000	.2958092	.4382196
p_workstat_1_sh	.5260943	.0270113	19.48	0.000	.4731532	.5790354
rooms_pc	.0470549	.0109036	4.32	0.000	.0256843	.0684255
_cons	7.132082	.1597874	44.63	0.000	6.818904	7.445259

Alpha model:

Residual	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
p_activity_1_sh	-.3447938	.1425119	-2.42	0.016	-.624112	-.0654756
p_ecstat_4_sh	-.8035096	.1585224	-5.07	0.000	-1.114208	-.4928114
p_ecstat_hh_4	-.3006224	.118973	-2.53	0.012	-.5338051	-.0674397

matrix presented by the PovMap software is equal to $\sigma^2 [(X'WX)^{-1} (X'W^2X) (X'WX)^{-1}]$ where σ^2 is an estimate of $\text{Var}(w_{ch}u_{ch})$. It is easy to see that the weights are included twice in the variance covariance estimator, which makes it non-standard.

p_elder_sh	-.8877215	.1511032	-5.87	0.000	-1.183878	-.5915647
p_isced_max_1	-.1701583	.10368	-1.64	0.101	-.3733673	.0330507
p_isced_max_5	.2211589	.1155722	1.91	0.056	-.0053584	.4476762
p_male	.156548	.1078049	1.45	0.146	-.0547458	.3678417
p_marital_hh_1	.1685545	.1322579	1.27	0.203	-.0906662	.4277752
p_occup_pr_sh	.5477886	.1793579	3.05	0.002	.1962536	.8993236
p_workstat_1_sh	-1.289935	.1263831	-10.21	0.000	-1.537641	-1.042228
rooms_pc	.124589	.0411818	3.03	0.002	.0438741	.2053038
_cons	-6.317578	.13152	-48.04	0.000	-6.575353	-6.059804

GLS model:

lny	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dw_bath	.1397681	.018897	7.40	0.000	.1027307	.1768054
dw_btype_d3	.043487	.0194832	2.23	0.026	.0053006	.0816734
edu_postsec	.2515946	.1255387	2.00	0.045	.0055434	.4976459
edu_prim	-.4613187	.2236142	-2.06	0.039	-.8995944	-.023043
j_firm_access1	.077631	.0206401	3.76	0.000	.0371772	.1180849
jud_erate	.8129607	.3335183	2.44	0.015	.1592769	1.466644
jud_occup_el_sh	-1.238829	.352069	-3.52	0.000	-1.928872	-.5487866
p_activity_1_sh	-.1952054	.0310771	-6.28	0.000	-.2561153	-.1342954
p_age	.0146863	.0021284	6.90	0.000	.0105146	.0188579
p_age2	-.0000884	.0000208	-4.25	0.000	-.0001292	-.0000477
p_ecstat_2_sh	-.1790066	.090007	-1.99	0.047	-.3554171	-.0025961
p_ecstat_4_sh	.3970182	.0272502	14.57	0.000	.3436088	.4504275
p_ecstat_hh_2	-.1760779	.0761019	-2.31	0.021	-.3252349	-.0269209
p_elder_sh	.408984	.0333136	12.28	0.000	.3436906	.4742775
p_hhsize_1	-.1450279	.0228201	-6.36	0.000	-.1897545	-.1003014
p_isced_max_0	-.4641431	.0497277	-9.33	0.000	-.5616076	-.3666786
p_isced_max_1	-.3250672	.022455	-14.48	0.000	-.3690782	-.2810562
p_isced_max_2	-.1953666	.0172695	-11.31	0.000	-.2292142	-.1615191
p_isced_max_4	.1499224	.0233206	6.43	0.000	.1042149	.1956299
p_isced_max_5	.2418694	.0224473	10.77	0.000	.1978734	.2858654
p_isced_max_6	.2282902	.0750887	3.04	0.002	.0811191	.3754613
p_male	.1945154	.0199999	9.73	0.000	.1553163	.2337145
p_marital_hh_1	-.046479	.0299398	-1.55	0.121	-.1051599	.0122019
p_marital_hh_3	-.0799847	.0177162	-4.51	0.000	-.1147078	-.0452616
p_occup_pr_sh	.3263021	.0359602	9.07	0.000	.2558214	.3967828
p_workstat_1_sh	.4861585	.0257385	18.89	0.000	.4357121	.536605
rooms_pc	.0572602	.0106962	5.35	0.000	.036296	.0782244
_cons	6.668453	.2825154	23.60	0.000	6.114733	7.222173

Comparison between OLS and GLS models:

Variable	bOLS	bGLS
dw_bath	.13977666	.13976806
dw_btype_d3	.04965872	.04348699
edu_postsec	.0816588	.25159463
edu_prim	-.88482838	-.46131871
j_firm_acc_1	.03828739	.07763102
jud_erate	.89285555	.81296068
jud_occup_h	-1.333666	-1.2388292
p_acti_1_sh	-.20457601	-.19520536
p_age	.01341306	.01468626

p_age2	-.00007879	-.00008844
p_ecstat_2_h	-.21789309	-.17900661
p_ecstat_4_h	.45295039	.39701819
p_ecstat_h_2	-.18033673	-.17607789
p_elder_sh	.48716911	.40898405
p_hhsize_1	-.13312094	-.14502795
p_isced_ma_0	-.51693886	-.4641431
p_isced_ma_1	-.37582438	-.32506718
p_isced_ma_2	-.22113204	-.19536665
p_isced_ma_4	.13861204	.14992238
p_isced_ma_5	.23439281	.24186941
p_isced_ma_6	.23717604	.22829018
p_male	.1836228	.19451539
p_marital_1	-.05289303	-.04647901
p_marital_3	-.0809455	-.0799847
p_occup_pr_h	.36701439	.32630214
p_works_1_sh	.52609429	.48615854
rooms_pc	.04705493	.0572602
_cons	7.1320819	6.6684532

Model settings

Error decomposition	H3
---------------------	----

Beta model diagnostics

Number of observations	=	7564
Adjusted R-squared	=	.55294896
R-squared	=	.55454493
Root MSE	=	.45080868
F-stat	=	347.46412

Alpha model diagnostics

Number of observations	=	7564
Adjusted R-squared	=	.03563669
R-squared	=	.03703931
Root MSE	=	2.2858123
F-stat	=	26.407274

Model parameters

Sigma ETA sq.	=	.02312296
Ratio of sigma eta sq over MSE	=	.11377818
Variance of epsilon	=	.18255558

<End of first stage>

6.3 Monte Carlo Simulation

The simulation part of the analysis requires more inputs from the user. Depending on the details given and the purpose of the analysis, the user may obtain poverty rates by the different locations specified or just output the simulated vectors to a dataset of her choosing. The syntax for the simulation stage is:

```
sae simulate lmm/povmap depvar indepvar [if] [in] [aw pw fw], area(varname numeric)
varest(string) eta(string) epsilon(string) uniqid(varname numeric) [vce(string)
```

```

zvar(varlist numeric) yhat(varlist numeric) yhat2(varlist numeric) psu(varname numeric)
matin(string) pwcensus(string) rep(integer 1) seed(integer 123456789) bootstrap ebest
colprocess(integer 1) lny addvars(string) ydump(string) plinevar(varname numeric)
plines(numlist sort) aggids(numlist sort) indicators(string) results(string) allmata]

```

The possible options are:

- **area()**: The **area** option is necessary and specifies at which level the clustering is done, it indicates at which level the η_c is obtained. The only constraint is that the variable must be numeric and should match across datasets, although it is recommended it follows a hierarchical structure similar to the one proposed by Zhao (2006).
 - The hierarchical id should be of the same length for all observations for example: AAMMEEE.³³
- **varest()**: The **varest** option allows the user to select between *H3* or *ELL* methods for obtaining the variance of the decomposed first stage residuals. The selection has repercussions on the options available afterwards. For example, if the user selects *H3*, parameters must be obtained via bootstrapping.
- **eta()**: The **eta** option allows users to specify how they would like to draw η_c for the different clusters in the second stage of the analysis. The available options are *normal* and *non-normal*. If *non-normal* is chosen empirical Bayes is not available to users.
- **epsilon()**: The **epsilon** option allows users to specify how they would like to draw ε_{ch} for the different observations in the second stage of the analysis. The available options are *normal* and *non-normal*. If *non-normal* is chosen empirical Bayes is not available to users.
- **uniqid()**: The **uniqid** option specifies the numeric variable that indicates the unique identifiers in the source and target datasets. This is necessary to ensure replicability of the analysis.
- **vce()**: The **vce** option allows users to replicate the variance covariance matrix from the *OLS* in the PovMap 2.5 software. The default option is the variance covariance matrix from the PovMap software (*ell*), the user may specify robust or clustered variance covariance matrix to replicate the results from the **regress** command.³⁴
- **zvar()**: The **zvar** option is necessary for specifying the alpha model, the user must place the independent variables of the alpha model under the option.
- **yhat()**: The **yhat** option is also a part of the alpha model. Variables listed here will be interacted with the predicted $\hat{y} = X\beta$ from the OLS model.
- **yhat2()**: The **yhat2** option is also a part of the alpha model. Variables listed here will be interacted with the predicted $\hat{y}^2 = (X\beta)^2$ from the OLS model.

³³In the case this were done for a specific country, AA stands for the highest aggregation level, MM stands for the second highest aggregation level, and EEE, stands for the lowest aggregation level.

³⁴The variance covariance matrix presented by the PovMap software is not standard in the literature. The variance covariance matrix presented by the PovMap software is equal to $\sigma^2 [(X'WX)^{-1} (X'W^2X) (X'WX)^{-1}]$ where σ^2 is an estimate of $\text{Var}(w_{ch}u_{ch})$. It is easy to see that the weights are included twice in the variance covariance estimator, which makes it non-standard.

- **psu()**: The **psu** option indicates the numeric variable in the source data for the level at which bootstrapped samples are to be obtained. This option is required for the cases when obtaining bootstrapped parameters is necessary. If not specified, the level defaults to the cluster level, that is the level specified in the **area** option.
- **matin()**: The **matin** option indicates the path and filename of the Mata format target dataset. The dataset is created from the **sae data import** command; it is necessary for the second stage.
- **pwccensus()**: The **pwccensus** option indicates the variable which corresponds to the expansion factors to be used in the target dataset, it must always be specified for the second stage. The user must have added the variable to the imported data (**sae data import**) i.e. the target data.
- **rep()**: The **rep** option is necessary for the second stage, and indicates the number of Monte-Carlo simulations to be done in the second stage of the procedure.
- **seed()**: The **seed** option is necessary for the second stage of the analysis and ensures replicability. Users should be aware that Stata's default pseudo-random number generator in Stata 14 is different than that of previous versions.
- **bootstrap**: The **bootstrap** option indicates that the parameters used for the second stage of the analysis are to be obtained via bootstrap methods. If this option is not specified the default method is parametric drawing of the parameters.
- **ebest**: The **ebest** option indicates that empirical Bayes methods are to be used for the second stage. If this option is used, it is necessary that **eta(normal)**, **epsilon(normal)**, and **bootstrap** options be used.
- **colprocess()**: The **colprocess** option is related to the processing of the second stage. Because of the potential large size of the target data set the default is one column at a time, this however may be increased with potential gains in speed.
- **lny**: The **lny** option indicates that the dependent variable in the welfare model is in log form. This is relevant for the second stage of the analysis in order to get appropriate simulated values.
- **addvars()**: The **addvars** option allows users to add variables to the dataset created from the simulations. These variables must have been included into the target dataset created with the **sae data import** command.
- **ydump()**: The **ydump** option is necessary for the second stage of the analysis. The user must provide path and filename for a Mata format dataset to be created with the simulated dependent variables.
- **plinevar()**: The **plinevar** option allows users to indicate a variable in the target data set which is to be used as the threshold for the Foster Greer Thorbeck indexes (Foster, Greer, and Thorbeck 1984) to be predicted from the second stage simulations. The user must have added the variable in the **sae data import** command when preparing the target dataset. Only one variable may be specified.
- **plines()**: The **plines** option allows users to explicitly indicate the threshold to be used, this option is preferred when the threshold is constant across all observations. Additionally, it is possible to specify multiple lines, separated by a space.

- `indicators()`: The `indicators` option is used to request the indicators to be estimated from the simulated vectors of welfare. The list of possible indicators is:
 - The set of Foster Greer Thorbeck indexes (Foster, Greer, and Thorbeck 1984) FGT_0 , FGT_1 , and FGT_2 ; also known as poverty headcount, poverty gap, and poverty severity respectively.
 - The set of inequality indexes: Gini, and Generalized Entropy Index with $\alpha = 0, 1, 2$
 - Set of Atkinson indexes
- `aggids()`: The `aggids` option indicates the different aggregation levels for which the indicators are to be obtained, values placed here tell the command how many digits to the left to move to get the indicators at that level. Using the same hierarchical id specified in the `area` option, AAMMEEE, if the user specifies 0, 3, 5, and 7, it would lead to aggregates at each of the levels E, M, A and the national level.
- `results()`: The `results` option specifies the path and filename for users to save as a txt file the results the analysis specified in the `indicators` option.
- `allmata`: The `allmata` option skips use of the plugin and does all poverty calculations in Mata.

6.3.1 Running the Second Stage (Simulation)

The second stage of the command takes considerably longer to run, depending on the size of the target dataset and the number of simulations requested. The command for the second stage would look like the following:

```
.      sae sim povmap `y' `xvar' [aw=hhw], area(localityid_n) uniqid(hhid) psu(thepsu)  zvar(`zvar') ///
>      eta(normal) epsilon(normal) varest(h3) lny pwcensus(p_hhsize_hh) ///
>      vce(ell) rep(100) seed(89546) ydump(`sfiles') res(`result') addvars(pline ///
>      pline2 rdef rdef2 rentdef rdef_rentroom2 rdef_rentall2) ///
>      matin(`matadata')   col(10) boot ebest stage(second) aggids(0) indicators(fgt0) ///
>      plines(5291.52)
note: p_age omitted because of collinearity
Note: Dependent variable in logarithmic form
WARNING: 76 observations removed due to less than 3 observations in the cluster.

OLS model:
```

lny	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dw_bath	.1397767	.0200267	6.98	0.000	.100525	.1790283
dw_btype_d3	.0496587	.0211568	2.35	0.019	.0081921	.0911253
edu_postsec	.0816588	.0883387	0.92	0.355	-.0914818	.2547994
edu_prim	-.8848284	.1744707	-5.07	0.000	-1.226785	-.5428722
j_firm_access1	.0382874	.0129973	2.95	0.003	.0128132	.0637616
jud_erate	.8928555	.2215139	4.03	0.000	.4586962	1.327015
jud_occup_el_sh	-1.333666	.2481222	-5.38	0.000	-1.819977	-.8473555
p_activity_1_sh	-.204576	.0306396	-6.68	0.000	-.2646285	-.1445235
p_age	.0134131	.0023387	5.74	0.000	.0088293	.0179968
p_age2	-.0000788	.0000238	-3.31	0.001	-.0001255	-.0000321
p_ecstat_2_sh	-.2178931	.0840416	-2.59	0.010	-.3826117	-.0531745
p_ecstat_4_sh	.4529504	.0297431	15.23	0.000	.394655	.5112458
p_ecstat_hh_2	-.1803367	.0690036	-2.61	0.009	-.3155813	-.0450921

p_elder_sh	.4871691	.0363326	13.41	0.000	.4159585	.5583797
p_hhsize_1	-.1331209	.0253237	-5.26	0.000	-.1827544	-.0834874
p_isced_max_0	-.5169389	.0540608	-9.56	0.000	-.6228961	-.4109817
p_isced_max_1	-.3758244	.0257253	-14.61	0.000	-.426245	-.3254037
p_isced_max_2	-.221132	.0191942	-11.52	0.000	-.2587519	-.1835122
p_isced_max_4	.138612	.0286283	4.84	0.000	.0825016	.1947225
p_isced_max_5	.2343928	.024233	9.67	0.000	.1868969	.2818887
p_isced_max_6	.237176	.0802218	2.96	0.003	.0799442	.3944078
p_male	.1836228	.0218718	8.40	0.000	.140755	.2264906
p_marital_hh_1	-.052893	.030501	-1.73	0.083	-.1126738	.0068878
p_marital_hh_3	-.0809455	.0206275	-3.92	0.000	-.1213747	-.0405163
p_occup_pr_sh	.3670144	.0363299	10.10	0.000	.2958092	.4382196
p_workstat_1_sh	.5260943	.0270113	19.48	0.000	.4731532	.5790354
rooms_pc	.0470549	.0109036	4.32	0.000	.0256843	.0684255
_cons	7.132082	.1597874	44.63	0.000	6.818904	7.445259

Alpha model:

Residual	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
p_activity_1_sh	-.3447938	.1425119	-2.42	0.016	-.624112	-.0654756
p_ecstat_4_sh	-.8035096	.1585224	-5.07	0.000	-1.114208	-.4928114
p_ecstat_hh_4	-.3006224	.118973	-2.53	0.012	-.5338051	-.0674397
p_elder_sh	-.8877215	.1511032	-5.87	0.000	-1.183878	-.5915647
p_isced_max_1	-.1701583	.10368	-1.64	0.101	-.3733673	.0330507
p_isced_max_5	.2211589	.1155722	1.91	0.056	-.0053584	.4476762
p_male	.156548	.1078049	1.45	0.146	-.0547458	.3678417
p_marital_hh_1	.1685545	.1322579	1.27	0.203	-.0906662	.4277752
p_occup_pr_sh	.5477886	.1793579	3.05	0.002	.1962536	.8993236
p_workstat_1_sh	-1.289935	.1263831	-10.21	0.000	-1.537641	-1.042228
rooms_pc	.124589	.0411818	3.03	0.002	.0438741	.2053038
_cons	-6.317578	.13152	-48.04	0.000	-6.575353	-6.059804

GLS model:

lny	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
dw_bath	.1397681	.018897	7.40	0.000	.1027307	.1768054
dw_btype_d3	.043487	.0194832	2.23	0.026	.0053006	.0816734
edu_postsec	.2515946	.1255387	2.00	0.045	.0055434	.4976459
edu_prim	-.4613187	.2236142	-2.06	0.039	-.8995944	-.023043
j_firm_access1	.077631	.0206401	3.76	0.000	.0371772	.1180849
jud_erate	.8129607	.3335183	2.44	0.015	.1592769	1.466644
jud_occup_el_sh	-1.238829	.352069	-3.52	0.000	-1.928872	-.5487866
p_activity_1_sh	-.1952054	.0310771	-6.28	0.000	-.2561153	-.1342954
p_age	.0146863	.0021284	6.90	0.000	.0105146	.0188579
p_age2	-.0000884	.0000208	-4.25	0.000	-.0001292	-.0000477
p_ecstat_2_sh	-.1790066	.090007	-1.99	0.047	-.3554171	-.0025961
p_ecstat_4_sh	.3970182	.0272502	14.57	0.000	.3436088	.4504275
p_ecstat_hh_2	-.1760779	.0761019	-2.31	0.021	-.3252349	-.0269209
p_elder_sh	.408984	.0333136	12.28	0.000	.3436906	.4742775
p_hhsize_1	-.1450279	.0228201	-6.36	0.000	-.1897545	-.1003014
p_isced_max_0	-.4641431	.0497277	-9.33	0.000	-.5616076	-.3666786
p_isced_max_1	-.3250672	.022455	-14.48	0.000	-.3690782	-.2810562
p_isced_max_2	-.1953666	.0172695	-11.31	0.000	-.2292142	-.1615191
p_isced_max_4	.1499224	.0233206	6.43	0.000	.1042149	.1956299

p_isced_max_5	.2418694	.0224473	10.77	0.000	.1978734	.2858654
p_isced_max_6	.2282902	.0750887	3.04	0.002	.0811191	.3754613
p_male	.1945154	.0199999	9.73	0.000	.1553163	.2337145
p_marital_hh_1	-.046479	.0299398	-1.55	0.121	-.1051599	.0122019
p_marital_hh_3	-.0799847	.0177162	-4.51	0.000	-.1147078	-.0452616
p_occup_pr_sh	.3263021	.0359602	9.07	0.000	.2558214	.3967828
p_workstat_1_sh	.4861585	.0257385	18.89	0.000	.4357121	.536605
rooms_pc	.0572602	.0106962	5.35	0.000	.036296	.0782244
_cons	6.668453	.2825154	23.60	0.000	6.114733	7.222173

Comparison between OLS and GLS models:

Variable	bOLS	bGLS
dw_bath	.13977666	.13976806
dw_btype_d3	.04965872	.04348699
edu_postsec	.0816588	.25159463
edu_prim	-.88482838	-.46131871
j_firm_acc_1	.03828739	.07763102
jud_erate	.89285555	.81296068
jud_occup_h	-1.333666	-1.2388292
p_acti_1_sh	-.20457601	-.19520536
p_age	.01341306	.01468626
p_age2	-.00007879	-.00008844
p_ecstat_2_h	-.21789309	-.17900661
p_ecstat_4_h	.45295039	.39701819
p_ecstat_h_2	-.18033673	-.17607789
p_elder_sh	.48716911	.40898405
p_hhsize_1	-.13312094	-.14502795
p_isced_ma_0	-.51693886	-.4641431
p_isced_ma_1	-.37582438	-.32506718
p_isced_ma_2	-.22113204	-.19536665
p_isced_ma_4	.13861204	.14992238
p_isced_ma_5	.23439281	.24186941
p_isced_ma_6	.23717604	.22829018
p_male	.1836228	.19451539
p_marital_1	-.05289303	-.04647901
p_marital_3	-.0809455	-.0799847
p_occup_pr_h	.36701439	.32630214
p_works_1_sh	.52609429	.48615854
rooms_pc	.04705493	.0572602
_cons	7.1320819	6.6684532

Model settings

Error decomposition	H3
Beta drawing	Bootstrapped
Eta drawing method	normal
Epsilon drawing method	normal
Empirical best methods	Yes

Beta model diagnostics

Number of observations	=	7564
Adjusted R-squared	=	.55294896
R-squared	=	.55454493
Root MSE	=	.45080868

```

F-stat                                =    347.46412
Alpha model diagnostics
-----
Number of observations                =    7564
Adjusted R-squared                   =    .03563669
R-squared                           =    .03703931
Root MSE                            =    2.2858123
F-stat                              =    26.407274

Model parameters
-----
Sigma ETA sq.                       =    .02312296
Ratio of sigma eta sq over MSE      =    .11377818
Variance of epsilon                 =    .18255558
-----
                                <End of first stage>
-----
Initializing the Second Stage, this may take a while...
Bootstrapped drawing of betas and parameters

Number of simulations: 100. Each dot (.) represents 10 simulation(s).
-----| 1 -----| 2 -----| 3 -----| 4 -----| 5
.....
Finished running the Second Stage
-----

```

6.4 Exporting the Simulated Vectors into Stata

This subroutine is useful for bringing the simulated vectors into Stata. It provides the user the ability to further manipulate these vectors. Due to the unique structure of the Mata data, this command will only work with data created in the simulation stage.

The command's structure is:

```
sae data export, matasource(string) [numfiles(integer 1) prefix(string) saveold
datasave(string)]
```

- **matasource()**: The **matasource** option allows users to specify the source ydump file created by the **sae simulate** routine. Because the size of the file can be quite large, it is advisable to use this with the **numfiles** option.
- **numfiles()**: The **numfiles** option is to be used in conjunction with the **ydumpdta** option; it specifies the number of datasets to be created from the simulations.
- **prefix()**: The **prefix** option may be used to give a prefix to the simulated vectors.
- **saveold**: The **saveold** option can be specified in conjunction with the **ydumpdta** option, and makes the files readable by older versions of Stata.
- **datasave()**: The **datasave** option allows users to specify a path where to save the exported data, this is recommended when using the **numfiles** option.

6.5 Processing the Simulated Vectors

A set of commands that facilitate the processing of the outputs from the simulation are provided. This subroutine is useful for post-estimation calculations based on the output of Mata data created in the simulation stage (6.3). It provides the user the ability to further calculate poverty and inequality indicators. Those indicators may be based on new aggregated levels, new poverty lines, or different weights that were not implemented in the simulation stage. In the case of new weights, it is necessary for the user to have included these new weights in the `addvars` option.

6.5.1 Process Indicators

This sub-routine allows for processing the simulated vectors to obtain poverty and inequality indicators.

The command's structure is:

```
sae proc indicator, matasource(string) aggids(numlist sort) [INDicators(string) plinevar(string)
plines(numlist sort) area(string) weight(string)]
```

- `matasource()`: The `matasource` option allows users to specify the source ydump file created by the `sae simulate` routine. Because the size of the file can be quite large, it is advisable to use this with the `numfiles` option.
- `aggids()`: The `aggids` option indicates the different aggregation levels for which the indicators are to be obtained, values placed here tell the command how many digits to the left to move to get the indicators at that level. Using the same hierarchical id specified in the `area` option, AAMMEEE, if the user specifies 0, 3, 5, and 7, it would lead to aggregates at each of the levels E, M, A and the national level.
- `indicators()`: The `indicators` option is used to request the indicators to be estimated from the simulated vectors of welfare. The list of possible indicators is:
 - The set of Foster Greer Thorbeck indexes (Foster, Greer, and Thorbeck 1984) FGT_0 , FGT_1 , and FGT_2 ; also known as poverty headcount, poverty gap, and poverty severity respectively.
 - The set of inequality indexes: Gini, and Generalized Entropy Index with $\alpha = 0, 1, 2$
 - Set of Atkinson indexes
- `plinevar()`: The `plinevar` option allows users to indicate a variable in the target data set which is to be used as the threshold for the Foster Greer Thorbeck indexes (Foster, Greer, and Thorbeck 1984) to be predicted from the second stage simulations. The user must have added the variable in the `sae data import` command when preparing the target dataset. Only one variable may be specified.
- `plines()`: The `plines` option allows users to explicitly indicate the threshold to be used, this option is preferred when the threshold is constant across all observations. Additionally, it is possible to specify multiple lines, separated by a space.
- `area()`: The `area` option is necessary and specifies at which level the clustering is done, it indicates at which level the η_c is obtained. The only constraint is that the variable must be numeric and should

match across datasets, although it is recommended it follows a hierarchical structure similar to the one proposed by Zhao (2006). Note that in this step, the default is to use the defined areas from the simulation step. In this option the user is given the opportunity to change this grouping.

- The hierarchical id should be of the same length for all observations for example: AAMMEEE.
- **weight()**: The **weight** option indicates the new variable which corresponds to the expansion factors to be used in the target/ydump dataset. The default option is to use the weight variable saved in the ydump file, if a variable is specified here all results will be obtained with this new weighing. The user must have added the variable to the target data imported (**sae data import**).

6.5.2 Profiling

This sub-routine aids researchers in creating a profile from group classifications that are the outcome from the simulated census vectors. For example in the context of poverty it allows researchers to break down characteristics of the poor and non poor. In the context of anthropometric Z-scores it would allow researchers to obtain characteristics for the individuals who fall below the indicator's threshold. The command syntax is as follows:

```
sae process stats, matasource(string) aggids(numlist sort) [contvar(string) catvar(string)
plinevar(string) plines(numlist sort) area(string) weight(string)]
```

- **contvar()**: The **contvar** option indicates the continuous variables for which the user wants to estimate the mean/distribution based on poor and non-poor groups defined from the defined poverty lines in either **plines** or **plinevar**. Those statistics will be aggregated at the aggregation levels indicated in the **aggids** option. The user must have added the variable in the **sae data import** command when preparing the target dataset.
- **catvar()**: The **catvar** option indicates the categorical variables for which the user wants to estimate the two-way frequencies/distributions based on poor and non-poor groups defined from the defined poverty lines in either **plines** or **plinevar**. Those statistics will be aggregated at the aggregation levels indicated in the **aggids** option. The user must have added the variable in the **sae data import** command when preparing the target dataset.

All other options resemble those detailed for other subroutines.

7 Conclusions

As we approach the 2020 round of the population census, governments and their respective national systems of statistics have renewed their international commitments towards the Sustainable Development Goals (SDGs). The SDGs will need to be operationalized at a sub-national level or reported for specific subgroups of the population. Moreover, the expansion of the availability and use of administrative, geospatial and Big Data sources for evidence based policy making is on the rise, creating a number of important opportunities for potentially better and more up-to-date measures of social well-being. Against this backdrop, to ensure

the much needed quality and rigor of the analysis produced, the advancement and availability of statistically valid methods with proper inference such as small area estimates are required.

Direct estimates of poverty and inequality from household surveys are only reliable up to a certain regional level. When estimates are needed at lower, more disaggregated levels, the reliability of these is questionable. Under a set of specific assumptions, data from outside sources along with household survey data may be combined in order to provide policy makers with a more complete picture of poverty and inequality along with the spatial heterogeneity of these indicators.

In this paper we introduce a new family of Stata functions, **sae**, which were designed in a modular and flexible way to manage the data, estimate models, conduct simulations, and compute indicators of interest. The estimation functions have been bench-marked against the World Bank's PovMap software for full validation.

We hope that the flexibility of this new family of functions will encourage producers of SAE to document and report in a more systematic manner the robustness of their results to alternative methodological choices made, improving the replicability and increasing the transparency of this estimation process. Its modular nature creates a platform for the introduction of new estimation techniques, such as count and binary models. Additionally, the modular nature encourages collaboration from the broader Stata community.

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