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Small Area Estimation in the Structural Survey: New contract, Phase I - with Coverage of GREG Confidence Intervals Work for the Swiss Federal Statistical Office

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1 Introduction

Under a previous contract, several estimators of the proportions of active people in Swiss districts were compared in model-based and design-based simulation studies that were performed in a realistic way, using data from the Structural Survey. Based on the obtained results, the empirical best linear unbiased predictor (EBLUP) under a linear mixed model (LMM) was the selected estimator, together with its benchmarked (BM) version that adds up to the corresponding national estimate. Parametric and non parametric bootstrap procedures were proposed for estimation of the mean squared error (MSE) of these two small area estimators. A simulation study was carried out to analyze the performance of the parametric bootstrap procedure. These selected estimation methods were applied to the real data from the Structural Survey, using the values of the auxiliary variables from the STATPOP data, in order to produce estimates of the proportions of active people in Swiss districts and of their MSEs by the two bootstrap approaches.

This document describes the work carried out under Phase I of the new contract, in which confidence intervals are studied for the proportions of active people in Swiss districts. We propose to consider normality-based confidence intervals that use benchmarked EBLUPs based on the LMM as estimates together with MSE estimates based on new bootstrap procedures. Again, model-based and design-based simulation studies are carried out to analyze whether the intervals cover the target parameters with probability $1-\alpha$ as they are designed for. We have also studied the coverage of confidence intervals obtained using GREG estimates (considering GREG weights as fixed) together with analytical MSE estimates of these GREG estimators. Confidence intervals are finally applied to the real data.

Under the previous contract, districts with sample sizes smaller than 150 in the Structural Survey data were discarded, and the remaining data in that survey was treated as the population data. Simulations were based on drawing smaller samples from that "population", but taking sample sizes as small as the smallest district sample sizes in the Structural Survey. Note that in simulation studies, true values must be approximated with the highest possible precision because they are the reference values for comparison. Previous design-based simulation studies carried out to analyze the performance of the parametric bootstrap procedure for estimation of the design MSE evidenced some lack of stability of the true design MSEs for the smallest districts, see Figure 2 from report on Phase II of previous project. The source of this problem is that "population" sizes for those districts (between 150 and 300) are not large enough to approximate correctly the true MSEs. Note that in the real Swiss population, the district with smallest population size is 1839, so it is much more realistic to consider larger population sizes. For this reason, we have repeated the previous simulation studies for analyzing the performance of the parametric bootstrap MSE as estimator of the design MSE, but considering as "population" only the set of districts with sample sizes in the Structural Survey greater than 300, so that true MSEs can be approximated with better precision. The resulting number of districts is now $D = 132$. Still, when drawing samples from this "population", district sample sizes have been taken exactly as small as in the previous simulation studies, with the minimum district sample size approximately equal to the smallest sample size in the original Structural Survey.

For completeness, in this document we include some of the material from the report on Phase II of the previous contract. Thus, Section 2 describes again the considered estimators of the proportions of active people. Sections 3 and 4 introduce the parametric and non-parametric bootstrap approaches for MSE estimation. Section 5 proposes new bootstrap procedures designed for estimation of design MSE. Section 6 summarizes the results of the new simulation studies that study the performance of the parametric bootstrap method for estimation of the model MSE and also of the design MSE for districts with larger population sizes. The parametric bootstrap MSE estimates are applied to obtain the normality-based confidence intervals and simulation studies include the analysis of the coverage of those confidence intervals, again both under the model-based and design-based setups. Section 7 describes simulation results for the new bootstrap procedures. Section 8 deals with calculation of intervals using the GREG estimates assuming that GREG weights are fixed. Section 9 comments all the obtained results (point estimates, MSE estimates and confidence intervals) when applying the methods to the whole Structural Survey and STATPOP data. Finally, the conclusions of all the work carried out so far are given in Section 10.

2 Point estimators and confidence intervals

Let U be the target population of size N; in this project, U is the set of individuals in the STATPOP data set. This population is composed of D non-overlapping areas $U_1,\dots,U_D$; in this case, the Swiss districts, of sizes $N_1,\dots,N_D$ with $N=\sum_{d=1}^{D} N_d$. Let s be a sample of size n drawn from U; in this case, s is the set of individuals in the Structural Survey. Let s_d the subsample from area (or district) d of size n_d, $d=1,\dots,D$, where $n=\sum_{d=1}^{D} n_d$. Let $\bar{s}_d = U_d - s_d$ denote the complement of the sample from area d. Let $Y_{di} \in \{0,1\}$ be the target variable for unit i in area d; here, $Y_{di}=1$ stands for "active" and $Y_{di}=0$ for "non-active". The target parameters are the area proportions

$$P_d = N_d^{-1}\sum_{i=1}^{N_d} Y_{di}, \quad d=1,\dots,D.$$

Let w_{di} be the calibrated sampling weight of i-th unit within d-th area. We consider the GREG estimator given by

$$\hat{P}_d^{GREG} = \frac{1}{\hat{N}_d} \sum_{i \in s_d} w_{di} Y_{di},$$

where $\hat{N}_d = \sum_{i \in s_d} w_{di}$. This estimator is (practically) design unbiased; however, it is inefficient for areas with small sample sizes because it uses only the area-specific sample data.

Phase I has shown that the empirical best linear unbiased predictors (EBLUPs) based on a LMM with selected covariates perform significantly better than the GREG estimators in terms of MSE, both under the model and the design approaches, for practically all districts. The LMM assumes that the population variables Y_{di} satisfy a linear regression model including random district effects representing the unexplained between-area variability. More specifically, it assumes that

$$\begin{aligned} &Y_{di} = \mathbf{x}'_{di} \boldsymbol{\beta} + u_d + e_{di}, \\ &u_d \overset{iid}{\sim} N(0, \sigma_u^2), \quad e_{di} \overset{iid}{\sim} N(0, \sigma_e^2), \quad i = 1, \ldots, N_d, \quad d = 1, \ldots, D, \end{aligned} \tag{1}$$

where u_d is the random effect for district d. Although normality is specified in (1), the best linear unbiased predictor (BLUP) derived from this model does not require normality. Moreover, even if normality does not hold, maximum likelihood (ML) and restricted ML (REML) estimates of the model parameters obtained from the normal likelihood are still consistent under regularity assumptions (Jiang 1996). In fact, we have seen in Phase I of the project that a LMM provides practically the same small area estimates as a logistic GLMM with the same set of covariates due to the fact that the true proportions of active people are in the interval (0.2,0.8), in which the logit function is approximately linear.

For details on the ML fitting of mixed models, see Hartley and Rao (1967). Here we focus on REML estimates (Patterson and Thompson 1971; 1974), which have smaller bias for finite sample size. Let $\hat{\boldsymbol{\beta}}$ be the weighted least squared estimator of $\boldsymbol{\beta}$ and $\hat{\sigma}_u^2$ and $\hat{\sigma}_e^2$ be the restricted ML (REML) estimators of σ_u^2 and σ_e^2 based on the normal likelihood. The EBLUP of P_d under this model is given by

$$\hat{P}_d^{EBLUP} = \frac{1}{N_d} \left(\sum_{i \in s_d} Y_{di} + \sum_{i \in \bar{s}_d} \hat{Y}_{di} \right), \quad d = 1, \ldots, D, \tag{2}$$

where $\hat{Y}_{di} = \mathbf{x}'_{di} \hat{\boldsymbol{\beta}} + \hat{u}_d$ is the predicted value of Y_{di} obtained by fitting the model. Here, $\hat{u}_d = \hat{\gamma}_d (\bar{y}_d - \bar{\mathbf{x}}'_d \hat{\boldsymbol{\beta}})$ is the BLUP of u_d, where $\hat{\gamma}_d = \hat{\sigma}_u^2 / (\hat{\sigma}_u^2 + \hat{\sigma}_e^2 / n_d)$, $\bar{y}_d = n_d^{-1} \sum_{i \in s_d} Y_{di}$ and $\bar{\mathbf{x}}_d = n_d^{-1} \sum_{i \in s_d} \mathbf{x}_{di}$.

A desirable property of small area estimators is that the estimated totals for the areas add up to a reliable estimator of the population total. This property is called the benchmarking property. A reliable estimator of the population total $Y = \sum_{d=1}^{D} \sum_{i=1}^{N_d} Y_{di}$ is the GREG estimator

$$\hat{Y}^{GREG} = \sum_{d=1}^{D} \sum_{i \in s_d} w_{di} Y_{di} = \sum_{d=1}^{D} \hat{N}_d \hat{P}_d^{GREG}.$$

A simple adjustment of the EBLUP based on the LMM to make it satisfy the benchmarking property is the ratio-adjustment

$$\hat{P}_d^{BM} = \hat{P}_d^{EBLUP} \frac{\hat{Y}^{GREG}}{\sum_{d=1}^{D} N_d \hat{P}_d^{EBLUP}}, \quad d = 1, \ldots, D. \tag{3}$$

This estimator is called hereafter benchmarked EBLUP.

Let $\text{mse}(\hat{P}_d^{EBLUP})$ be an estimate of the MSE of the EBLUP $\hat{P}_d^{EBLUP}$. A $(1-\alpha)\%$ normality-based confidence interval (CI) for the true district proportion P_d based on $\hat{P}_d^{EBLUP}$ is given by

$$\text{CI}_{1-\alpha}(P_d) = \left[\hat{P}_d^{EBLUP} - z_{\alpha/2}\sqrt{\text{mse}(\hat{P}_d^{EBLUP})}, \hat{P}_d^{EBLUP} + z_{\alpha/2}\sqrt{\text{mse}(\hat{P}_d^{EBLUP})}\right],$$

where $z_{\alpha/2}$ is the critical $\alpha/2$ point of a standard normal distribution. If the reported estimates of the district proportions P_d are the benchmarked EBLUPs $\hat{P}_d^{BM}$ instead of the unadjusted EBLUPs $\hat{P}_d^{EBLUP}$, one might wish confidence intervals that are centered around the reported estimates $\hat{P}_d^{BM}$. The one can use the $(1-\alpha)\%$ normality-based confidence interval for P_d given by

$$\text{CI}_{1-\alpha}(P_d) = \left[\hat{P}_d^{BM} - z_{\alpha/2}\sqrt{\text{mse}(\hat{P}_d^{BM})}, \hat{P}_d^{BM} + z_{\alpha/2}\sqrt{\text{mse}(\hat{P}_d^{BM})}\right],$$

where $\text{mse}(\hat{P}_d^{BM})$ is an estimate of the MSE of the benchmarked EBLUP $\hat{P}_d^{BM}$. The bootstrap procedures of Sections 3–... provide suitable estimators $\text{mse}(\hat{P}_d^{EBLUP})$ and $\text{mse}(\hat{P}_d^{BM})$ of $\text{MSE}(\hat{P}_d^{EBLUP})$ and $\text{MSE}(\hat{P}_d^{BM})$ respectively.

Note that these confidence intervals rely on normality of the EBLUPs or bechmarked EBLUPs. Although normality of these estimators cannot be ensured even if the target variable was continuous (here it is actually binary), model-based simulation results described in Section 6 show that the coverage of these normality-based CIs is approximately correct. Since the number of areas in simulations is not small ($D = 132$), the central limit theorem must be acting to ensure approximate coverage.

3 Parametric bootstrap estimator of the model MSE

Analytical approximations to the model MSE of the EBLUP are obtained in the literature only when normality holds and for the number of areas D tending to infinity. In our problem, target variables Y_{di} are binary and therefore the available analytical approximations are not valid. Moreover, even if an analytical formula was available for the estimated MSE of the unadjusted EBLUP, this MSE estimator is not necessarily good for the benchmarked estimator. Note that the adjustment factor for the EBLUP given in (3) is random and therefore analytical approximation of the MSE of the benchmarked estimator is not straightforward. Thus, here we appeal to a bootstrap procedures that can handle complex estimators similarly as in the case of simple estimators. In this section we describe a parametric bootstrap procedure especially designed for finite populations that was first introduced by González-Manteiga *et al.* (2008). This procedure follows the steps below:

1) Fit the LMM model (1) to the available sample data $\{(\mathbf{x}_{di}, Y_{di}); i \in s_d,\ d = 1,\ldots,D\}$, obtaining model parameter estimates $\hat{\boldsymbol{\beta}}$, $\hat{\sigma}_u^2$ and $\hat{\sigma}_e^2$.

2) Generate bootstrap random effects as $u_d^* \overset{iid}{\sim} N(0, \hat{\sigma}_u^2)$, $d = 1,\ldots,D$.

3) Generate bootstrap population values as

$$Y_{di}^* \overset{ind.}{\sim} N(\mathbf{x}_{di}'\hat{\boldsymbol{\beta}} + u_d^*, \hat{\sigma}_e^2), \quad i = 1,\ldots,N_d,\ d = 1,\ldots,D.$$

Although normality does not really hold because Y_{di} are binary, a bootstrap procedure in which the bootstrap population values Y_{di}^* are generated from a logistic GLMM was also implemented and the simulation results were practically identical to those obtained from this bootstrap procedure.

4) Calculate the true bootstrap proportions of interest

$$P_d^* = \frac{1}{N_d}\sum_{i=1}^{N_d} Y_{di}^*, \quad d = 1,\ldots,D.$$

5) Select the part of the bootstrap population corresponding to the sample units, called bootstrap sample data: $\{(\mathbf{x}_{di}, Y_{di}^*); i \in s_d,\ d = 1,\ldots,D\}$. Now fit the LMM model (1) to the bootstrap sample data, obtaining bootstrap model parameter estimates $\hat{\boldsymbol{\beta}}^*$, $\hat{\sigma}_u^{2*}$, $\hat{\sigma}_e^{2*}$, and predicted random effects $\hat{u}_d^*$, $d = 1,\ldots,D$. Calculate the EBLUPs $\hat{P}_d^{EBLUP*}$ using the bootstrap sample data, as

$$\hat{P}_d^{EBLUP*} = \frac{1}{N_d}\left(\sum_{i\in s_d} Y_{di}^* + \sum_{i\in \bar{s}_d} \hat{Y}_{di}^*\right), \quad d = 1,\ldots,D,$$

where $\hat{Y}_{di}^* = \mathbf{x}_{di}'\hat{\boldsymbol{\beta}}^* + \hat{u}_d^*$ is the predicted value of Y_{di}^* obtained by fitting the LMM to the bootstrap sample data. Calculate also the benchmarked EBLUPs $\hat{P}_d^{BM*}$ as

$$\hat{P}_d^{BM*} = \hat{P}_d^{EBLUP*}\frac{\hat{Y}^{GREG}}{\sum_{d=1}^{D} N_d \hat{P}_d^{EBLUP*}},$$

6) Repeat Steps 2–5 for $b = 1,\ldots,B$, where B is large. Let $P_d^{*(b)}$ be the true proportion, $\hat{P}_d^{EBLUP*(b)}$ be the EBLUP and $\hat{P}_d^{BM*(b)}$ be the benchmarked EBLUP obtained in b-th bootstrap replicate. The parametric bootstrap (PB) estimator of the model MSE of the EBLUP, $\hat{P}_d^{EBLUP}$, is given by

$$\mathrm{mse}_{PB}(\hat{P}_d^{EBLUP}) = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{EBLUP*(b)} - P_d^{*(b)}\right)^2. \tag{4}$$

Similarly, for the benchmarked EBLUP $\hat{P}_d^{BM}$, the PB MSE estimator is given by

$$\mathrm{mse}_{PB}(\hat{P}_d^{BM}) = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{BM*(b)} - P_d^{*(b)}\right)^2. \tag{5}$$

Quantile-bootstrap CIs for P_d can also be constructed using the previous parametric bootstrap approach. These intervals are based on selecting the $\alpha/2$ and $1-\alpha/2$ quantiles $\hat{P}^{BM}_{d(\alpha/2)}$ and $\hat{P}^{BM}_{d(1-\alpha/2)}$ from the set of bootstrap estimates $\{\hat{P}^{BM*(b)}_d; b=1,\ldots,B\}$. The $(1-\alpha)\%$ quantile-bootstrap CI for P_d based on the benchmarked EBLUP estimates is then

$$\mathrm{CI}^{PB}_{1-\alpha}(P_d) = \left[\hat{P}^{BM}_{d(\alpha/2)}, \hat{P}^{BM}_{d(1-\alpha/2)}\right].$$

Analogous CIs can be computed based on the unadjusted EBLUPs. Chatterjee, Lahiri and Li (2008) obtained similar intervals for the case of continuous target variable and showed that the coverage is correct up to terms of order D^{-1}. However, the number of bootstrap replicates needed to approximate correctly the 0.025 and 0.975 quantiles if $\alpha = 0.05$ is really large and computational time overflows. In our simulation results with $B = 500$, coverage of quantile-bootstrap CIs intervals was poor and, for that reason, results are not shown.

4 Nonparametric bootstrap estimator of the design MSE

The design MSE is obtained by averaging the squared errors over the possible samples drawn from a fixed population using the considered sampling design. Here we propose a nonparametric bootstrap for the estimation of this design MSE. This procedure follows the steps below:

1) Replicate each data point $(\mathbf{x}_{di}, Y_{di})$ from the sample a number of times equal to the rounded calibrated sampling weight w_{di}. This leads to the bootstrap population data set $\{(\mathbf{x}^*_{di}, Y^*_{di}); i=1,\ldots,\hat{N}_d,\ d=1,\ldots,D\}$.

2) Calculate the true bootstrap proportions of interest

$$P^*_d = \frac{1}{\hat{N}_d}\sum_{i=1}^{\hat{N}_d} Y^*_{di}, \quad d=1,\ldots,D.$$

3) Draw a simple random sample (SRS) s^*_d from each district d. Select the corresponding bootstrap elements for that sample: $\{(\mathbf{x}^*_{di}, Y^*_{di}); i\in s^*_d,\ d=1,\ldots,D\}$. Now fit the LMM model (1) to these bootstrap sample data, obtaining bootstrap model parameter estimates $\hat{\boldsymbol{\beta}}^*$, $\hat{\sigma}^{2*}_u$, $\hat{\sigma}^{2*}_e$, and predicted random effects $\hat{u}^*_d$, $d=1,\ldots,D$. Calculate the EBLUPs $\hat{P}^{EBLUP*}_d$ using the bootstrap sample data,

$$\hat{P}^{EBLUP*}_d = \frac{1}{N_d}\left(\sum_{i\in s^*_d} Y^*_{di} + \sum_{i\in \bar{s}^*_d} \hat{Y}^*_{di}\right), \quad d=1,\ldots,D,$$

where $\hat{Y}^*_{di} = \mathbf{x}^{*\prime}_{di}\hat{\boldsymbol{\beta}}^* + \hat{u}^*_d$ is the predicted value of Y^*_{di} obtained by fitting the LMM. Calculate also the benchmarked EBLUPs $\hat{P}^{BM*}_d$ as

$$\hat{P}^{BM*}_d = \hat{P}^{EBLUP*}_d \frac{\hat{Y}^{GREG}}{\sum_{d=1}^{D}\hat{N}_d\hat{P}^{EBLUP*}_d},$$

4) Repeat Step 3 for $b = 1, \dots, B$, where B is large. Note that here the true bootstrap proportions P_d^* are constant over bootstrap replicates because the bootstrap population in Step 1 is fixed. Let $\hat{P}_d^{EBLUP*(b)}$ be the EBLUP and $\hat{P}_d^{BM*(b)}$ be the benchmarked EBLUP obtained in b-th bootstrap replicate. A nonparametric bootstrap estimator of the design MSE of $\hat{P}_d^{EBLUP}$ is given by

$$\widetilde{\mathrm{mse}}_{NPB}(\hat{P}_d^{EBLUP}) = \frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{EBLUP*(b)} - P_d^*\right)^2.$$

Note that in Step 1, data are replicated to get the bootstrap population and, in Step 3, a SRS without replacement is drawn from the bootstrap population. This is equivalent to drawing a SRS with replacement of size n_d from the original data. However, an estimator based on a SRS with replacement of size n_d is less efficient than the same estimator based on a SRS of the same size, but obtained without replacement. In this case, the NPB estimator is actually approximating the design MSE of an estimator based on a SRS with replacement of size n_d, which has smaller effective sample size than the desired sample size n_d if the sampling was without replacement. Thus, for areas with non negligible sampling fraction $f_d = n_d/N_d$, the NPB estimator will be overestimating the true MSE. For this reason, we correct the NPB estimator using the "finite population correction factor" $f_d = n_d/N_d$. Hence, we will finally consider the following corrected nonparametric bootstrap (NPB) estimator given by

$$\mathrm{mse}_{NPB}(\hat{P}_d^{EBLUP}) = (1 - f_d)\, \widetilde{\mathrm{mse}}_{NPB}(\hat{P}_d^{EBLUP}).$$

Similarly, for the benchmarked EBLUP $\hat{P}_d^{BM}$, we consider the NPB estimator of the design MSE given by

$$\mathrm{mse}_{NPB}(\hat{P}_d^{BM}) = (1 - f_d)\frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{BM*(b)} - P_d^*\right)^2. \tag{6}$$

In contrast with the parametric bootstrap of Section 3, which generates new population data in each bootstrap replicate, note that this nonparametric bootstrap procedure is based only on the original sample data, which is simply replicated using the sampling weights. In fact, the average over the bootstrap replicates in (6) actually estimates the average over the possible subsamples s_d from district d, which are all based on the same set of n_d units. Thus, the nonparametric bootstrap MSE estimate (6) for district d might be inefficient for a district with small sample size n_d.

5 Mixed bootstrap estimators of design MSE

The nonparametric bootstrap MSE estimator (6) proposed in Section 4 depends on the domain-specific sample data and is thus "direct". Then, it becomes highly inefficient for domains with small sample sizes, see Figure 20. On the other hand, the parametric bootstrap MSE estimator (5) of Section 3 is unbiased for the model MSE, but it becomes too stable (e.g. biased) as an estimator of the design MSE. If the model is correct, it is design-unbiased for the design MSE when averaging over a large number of domains, but not in each particular one. To balance the design-bias of the parametric bootstrap MSE estimator for the large areas and the instability of the nonparametric bootstrap for the smaller areas, we propose to mix them by making a convex linear combination of the two. In a domain with large sample size, the mixed estimator automatically approaches the nonparametric bootstrap MSE estimator, and in a domain with a small sample size it gets closer to the parametric bootstrap MSE estimator. The idea is to "borrow strength" from other domains when estimating the design MSE in a given domain, similarly as we do for estimation of the domain proportions. As weight for the combination, we consider the same domain-specific weight γ_d used to obtain the EBLUP as a combination of the direct survey-regression estimator and the synthetic regression estimator. Thus, the mixed bootstrap (MB) estimator of the design MSE of the benchmarked EBLUP for domain d is obtained from (6) and (5) as

$$\mathrm{mse}_{MB}(\hat{P}_d^{BM}) = \hat{\gamma}_d\, \mathrm{mse}_{NPB}(\hat{P}_d^{BM}) + (1-\hat{\gamma}_d)\mathrm{mse}_{PB}(\hat{P}_d^{BM}), \tag{7}$$

where $\hat{\gamma}_d = \hat{\sigma}_u^2/(\hat{\sigma}_u^2 + \hat{\sigma}_e^2/n_d)$. For the unadjusted EBLUP, the MB estimator of the design MSE is obtained analogously. The only prior drawback of this mixed MSE estimator is that is requires to run both bootstrap procedures for each area, which makes it computationally slower.

Another way to "borrow strength" is to consider a mixed estimator based on a parametric bootstrap for estimating directly the design MSE. In the nonparametric bootstrap, the population is generated by replicating the sample. This method is not using the whole set of population values of auxiliary variables, which are actually available. However, it estimates the design-MSE because it is averaging over all the possible samples drawn from a fixed population. On the other hand, the parametric bootstrap uses the whole set of population values of auxiliary variables, but it really estimates the model MSE, because the expectation is approximated by the average over all simulated populations from the model. Here we propose a completely new bootstrap procedure that uses the stability provided by the model to estimate directly the design MSE instead of the model MSE. In this bootstrap procedure, the fixed population is generated from the fitted model to the original sample (conditioning on the observed sample data), and then different samples are drawn from this fixed population to approximate by Monte Carlo the expectation under the sampling design. However, if the model is not perfectly correct, the population generated from the model is not exactly equal to the true population and therefore true proportions are not actually available in this bootstrap procedure. We propose to estimate the true values with the EBLUPs for domains with small sample size, and with the "direct" estimators obtained by fitting the LMM with fixed domain effects, denoted $\hat{P}_d^{FIX}$, for the domains with large sample size. Thus, the parametric design bootstrap (PDB) estimator of the design MSE of the EBLUP is obtained as follows:

1) Fit the LMM model (1) to the available sample data $\{(\mathbf{x}_{di}, Y_{di}); i \in s_d,\ d = 1,\dots,D\}$, obtaining model parameter estimates $\hat{\boldsymbol{\beta}}$ and $\hat{\sigma}_e^2$, and estimated random effects $\hat{u}_d$.

2) Generate a bootstrap population from the fitted model as

$$Y_{di}^* \overset{ind.}{\sim} N(\mathbf{x}_{di}'\hat{\boldsymbol{\beta}} + \hat{u}_d, \hat{\sigma}_e^2), \quad i = 1,\dots,N_d,\ d = 1,\dots,D.$$

3) Draw a simple random sample s_d^* from each district d. Select the corresponding bootstrap elements for that sample: $\{(\mathbf{x}_{di}^*, Y_{di}^*); i \in s_d^*,\ d = 1, \ldots, D\}$. Now fit the LMM model (1) to these bootstrap sample data, obtaining bootstrap model parameter estimates $\hat{\boldsymbol{\beta}}^*$, $\hat{\sigma}_u^{2*}$, $\hat{\sigma}_e^{2*}$, and predicted random effects $\hat{u}_d^*$, $d = 1, \ldots, D$. Calculate the EBLUPs $\hat{P}_d^{EBLUP*}$ using the bootstrap sample data,

$$\hat{P}_d^{EBLUP*} = \frac{1}{N_d}\left(\sum_{i\in s_d^*} Y_{di}^* + \sum_{i\in \bar{s}_d^*} \hat{Y}_{di}^*\right), \quad d = 1, \ldots, D,$$

where $\hat{Y}_{di}^* = \mathbf{x}_{di}^{*\prime}\hat{\boldsymbol{\beta}}^* + \hat{u}_d^*$ is the predicted value of Y_{di}^* obtained by fitting the LMM. Calculate also the benchmarked EBLUPs $\hat{P}_d^{BM*}$ as

$$\hat{P}_d^{BM*} = \hat{P}_d^{EBLUP*}\frac{\hat{Y}^{GREG}}{\sum_{d=1}^{D} N_d \hat{P}_d^{EBLUP*}},$$

4) Repeat Step 3 for $b = 1, \ldots, B$, where B is large. Let $\hat{P}_d^{EBLUP*(b)}$ be the EBLUP and $\hat{P}_d^{BM*(b)}$ be the benchmarked EBLUP obtained in b-th bootstrap replicate. The parametric design bootstrap (PDB) estimator of the design MSE of $\hat{P}_d^{EBLUP}$ is given by

$$\begin{aligned}\mathrm{mse}_{PDB}(\hat{P}_d^{EBLUP}) &= \hat{\gamma}_d \frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{EBLUP*(b)} - \hat{P}_d^{FIX}\right)^2 \\ &+ (1-\hat{\gamma}_d)\frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{EBLUP*(b)} - \hat{P}_d^{EBLUP}\right)^2,\end{aligned}$$

where $\hat{P}_d^{FIX}$ is the EBLUP obtained by fitting model (1), but considering domain effects u_d as fixed instead of random, that is, considering the domain variable (district) as an additional (fixed) factor in the model. Since domain effects are estimated with the domain observations only, this estimator is "direct", but uses the regression to improve its efficiency, so it is actually a kind of GREG estimator. Similarly, for the benchmarked EBLUP $\hat{P}_d^{BM}$, the PDB estimator of the design MSE is given by

$$\begin{aligned}\mathrm{mse}_{PDB}(\hat{P}_d^{BM}) &= \hat{\gamma}_d \frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{BM*(b)} - \hat{P}_d^{FIX}\right)^2 \\ &+ (1-\hat{\gamma}_d)\frac{1}{B}\sum_{b=1}^{B}\left(\hat{P}_d^{BM*(b)} - \hat{P}_d^{EBLUP}\right)^2.\end{aligned}$$

6 Simulation studies for the parametric bootstrap MSE

A model-based simulation study was performed to analyze the performance of (4) and (5) as estimators of the model MSEs of the EBLUP and the benchmarked EBLUP, and also to analyze the actual coverage of 95% normality-based confidence intervals. Since the target variable is actually binary, in this simulation study we consider that the population data are generated by the GLMM

$$Y_{di}|v_d \sim \mathrm{Bern}(p_{di}),\ \log\left(\frac{p_{di}}{1-p_{di}}\right) = \mathbf{x}'_{di}\boldsymbol{\alpha} + v_d$$
$$v_d \overset{iid}{\sim} N(0,\sigma_v^2). \tag{8}$$

In this way, the true MSE in this simulation study will incorporate any potential bias due to considering a LMM instead of a GLMM in the parametric bootstrap procedure.

To make the simulation study realistic, we consider as true values of the model parameters $\boldsymbol{\alpha}$ and σ_v^2 in (8), those obtained by fitting the model (8) to the data from the Structural Survey. Thus, using those fitted values as the true model parameters, first we generate $L = 10,000$ Monte Carlo populations from model (8) to approximate the true model MSE with good precision. Let $P_d^{(\ell)}$ be the true proportion for d-th area in ℓ-th Monte Carlo population. From each generated population, we draw a stratified sample with districts acting as strata and simple random sampling (SRS) within each district. The district sample sizes were taken as in the simulation studies in the previous project, namely $n_d = 60+5(k-1)$, $k = 1,\dots,D$ with $D = 132$. The sample units are kept fixed over the L Monte Carlo replicates because it is a purely model-based simulation study. Let $\hat{P}_d^{EBLUP(\ell)}$ and $\hat{P}_d^{BM(\ell)}$ be the EBLUP and benchmarked EBLUP obtained using the sample data from ℓ-th population. For the benchmarked EBLUPs, the true model MSEs were approximated as

$$\mathrm{MSE}_m(\hat{P}_d^{BM}) = L^{-1}\sum_{\ell=1}^{L}(\hat{P}_d^{BM(\ell)} - P_d^{(\ell)})^2, \quad d = 1,\dots,D.$$

The true model MSEs of the unadjusted EBLUPs for each district are approximated similarly, replacing $\hat{P}_d^{BM(\ell)}$ by $\hat{P}_d^{EBLUP(\ell)}$.

Now to approximate the expected value of the parametric bootstrap MSE estimates and to obtain the actual coverage of the 95% CIs for P_d, the simulation study was repeated generating $L = 500$ Monte Carlo populations. With the sample data from ℓ-th generated population, we carried out the parametric bootstrap procedure of Section 3 with number of bootstrap replicates $B = 500$, to obtain parametric bootstrap MSE estimates for the benchmarked estimators denoted by $\mathrm{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})$. Using these MSE estimates, 95% normality-based confidence intervals for P_d were calculated as follows

$$\mathrm{CI}_{1-\alpha}(P_d^{(\ell)}) = \left[\hat{P}_d^{BM(\ell)} - z_{\alpha/2}\sqrt{\mathrm{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})}, \hat{P}_d^{BM(\ell)} + z_{\alpha/2}\sqrt{\mathrm{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})}\right],\ d = 1,\dots,D,$$

with $\alpha = 0.05$. This was repeated for $\ell = 1,\dots,L$. Then, the expected value of the MSE estimates is approximated empirically by averaging the bootstrap MSE estimates over Monte Carlo replicates as

$$L^{-1}\sum_{\ell=1}^{L}\mathrm{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM}), \quad d = 1,\dots,D.$$

Finally, the coverage rate (CR) of the 95% normality-based CIs was computed as

$$\mathrm{CR} = L^{-1}\sum_{\ell=1}^{L} I\left\{P_d^{(\ell)} \in \mathrm{CI}_{1-\alpha}(P_d^{(\ell)})\right\},$$

where $I\{\text{condition}\} = 1$ if condition is true and 0 otherwise. If the CIs perform well, CR should be approximately $1-\alpha$. For the unadjusted EBLUPs, means of MSE estimates $\text{mse}_{PB}^{(\ell)}(\hat{P}_d^{EBLUP})$ over the L Monte Carlo replicates and coverage rates of CIs are computed similarly.

True model MSEs for the benchmarked EBLUPs (labeled TRUE) and expected values of the parametric bootstrap MSE estimates (labeled BOOTSTRAP) are depicted in Figure 1 for each district in the x axis, with districts sorted by decreasing sample sizes (labels in the x axis are sample sizes). This figure shows that the parametric bootstrap MSE estimates track rather well the true model MSEs, as expected from a bootstrap procedure. For the unadjusted EBLUPs, the plot is not shown but the parametric bootstrap procedure performs very similarly. Coverage rates of the 95% CIs for each district proportion P_d are given in Figure 2. Note that the number of simulations $L = 500$ and of bootstrap replicates $B = 500$ might not be large enough for approximating correctly the true coverage rates. Still, Figure 2 shows that for all districts, CRs are never far from the nominal level $1-\alpha = 0.95$ (dashed line), with CRs roughly between 0.88 and 0.99 for all districts. Moreover, the average CR over the districts is 0.943, which indicates a good performance of the model-based CIs.

A new simulation study was carried out under the design-based setup to analyze whether the parametric bootstrap MSE is also an acceptable estimator of the design MSE, $\text{MSE}_\pi(\hat{P}_d^{BM})$, and to analyze the actual design coverage of the 95% normality-based confidence intervals for P_d, $d = 1,\dots,D$. For this purposes, we considered the Structural Survey data for the $D = 132$ districts with sample sizes larger than 300 as the (fixed) true population and samples were drawn from it. To approximate empirically the true design MSEs, a first simulation study was performed drawing $L = 10,000$ samples out of the population. The district sample sizes were taken as in the model-based simulation study described above. Let P_d be the true proportion for district d, and $\hat{P}_d^{EBLUP(\ell)}$ and $\hat{P}_d^{BM(\ell)}$ be the estimates obtained using the data from ℓ-th sample. The true design MSEs of the benchmarked EBLUPs were approximated as

$$\text{MSE}_\pi(\hat{P}_d^{BM}) = L^{-1}\sum_{\ell=1}^{L}(\hat{P}_d^{BM(\ell)} - P_d)^2, \quad d = 1,\dots,D.$$

The true design MSEs of the unadjusted EBLUPs $\hat{P}_d^{BM}$ for each district d were approximated similarly.

Now to estimate the expected value of the parametric bootstrap MSE estimates under the design-based approach, the simulation study was repeated drawing now $L = 500$ samples from the given population. With the data from ℓ-th sample, we carried out the parametric bootstrap procedure with number of bootstrap replicates $B = 500$, obtaining the parametric bootstrap MSE estimate of the benchmarked estimate $\text{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})$. With the same sample, CIs were computed as follows

$$\text{CI}_{1-\alpha}^{(\ell)}(P_d) = \left[\hat{P}_d^{BM(\ell)} - z_{\alpha/2}\sqrt{\text{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})}, \hat{P}_d^{BM(\ell)} + z_{\alpha/2}\sqrt{\text{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM})}\right],$$

This was repeated for each sample $\ell = 1,\dots,L$. Then, we averaged the bootstrap estimates over Monte Carlo samples as

$$L^{-1}\sum_{\ell=1}^{L}\mathrm{mse}_{PB}^{(\ell)}(\hat{P}_d^{BM}),\quad d=1,\ldots,D.$$

Similarly as before, to check the performance of the CIs we obtain CRs as

$$\mathrm{CR}=L^{-1}\sum_{\ell=1}^{L}I\left\{P_d\in\mathrm{CI}_{1-\alpha}^{(\ell)}(P_d)\right\},$$

Analogous formulas are applied for the unadjusted EBLUPs.

The parametric bootstrap procedure estimates the model MSE and not the design MSE. However, if the model is approximately correct, the average of these MSEs over a large number of areas should be similar, see Appendix 1 of report on Phase II of previous contract. Thus, the parametric bootstrap estimate is expected to estimate correctly the design MSE in average but not in each particular area.

Figure 3 plots the true design MSE together with the parametric bootstrap MSE estimates for each district, with districts sorted by decreasing sample sizes. Recall that to approximate well the true MSEs, only districts with "population sizes" larger than 300 are considered in the fixed "population". Recall that in the true Swiss population, the smallest district population size is 1839. Figure 3 shows that the parametric bootstrap model MSE estimates follow the trend of the design MSEs. Figure 4 shows exactly the same plot but with the scale of the y-axis equal to the one in Figure 2 of the report of Phase II of the previous contract. In that figure the true MSEs for the smallest districts were much larger than the parametric bootstrap MSE estimates. According to Figure 4, this is not happening anymore, which means that the problem was in the true MSEs and not in the estimates. True MSEs are now better approximated because the smallest district population size is larger than 300.

Although CIs are designed to have the nominal coverage under the model distribution (and not under the design), however design CRs of the CIs, plotted in Figure 5, are close to the nominal level 0.95 for most of the districts. The average coverage rate is 0.94. Additionally, Figure 6 plots averages of the CRs for districts with similar sample sizes; specifically, we have averaged the CRs for the districts with sample sizes in the classes $800-700, 700-600, \ldots, 100-60$. See that these averages are approximately in the interval (0.89,0.99). Thus, average design CRs are not far from the nominal level 0.95.

The poor design CR of the confidence intervals for some districts shown in Figure 5 could be due to a bias in the estimation of the design MSE for those domains. To find out if this is true, we calculated the design CRs of the confidence intervals based on the true design MSEs. Results are shown in Figure 7. See that the coverage of these intervals is around the nominal level $1-\alpha=0.95$. This indicates that the poor coverage of the intervals for some domains is due to a biased design MSE estimator for those domains. Section 7 studies the design-based performance of the mixed estimators of the design MSE proposed in Section 5. It also shows the design coverage of the CIs based on these MSE estimates.

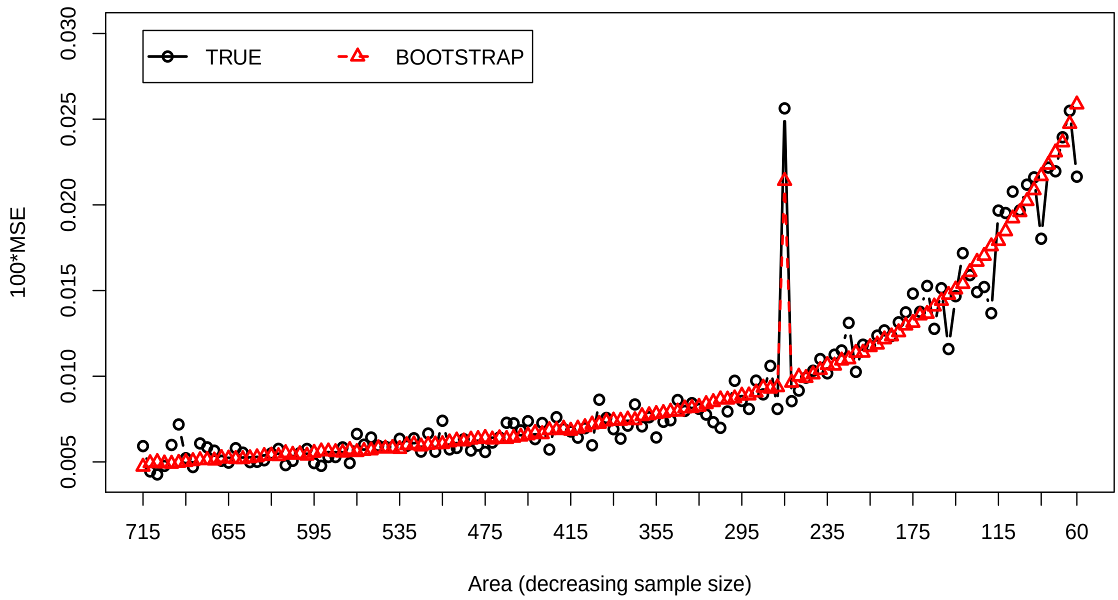

Figure 1: True model MSE (labeled TRUE) of the benchmarked EBLUP based on the LMM and parametric bootstrap estimator (labeled BOOTSTRAP). Districts sorted by decreasing sample sizes.

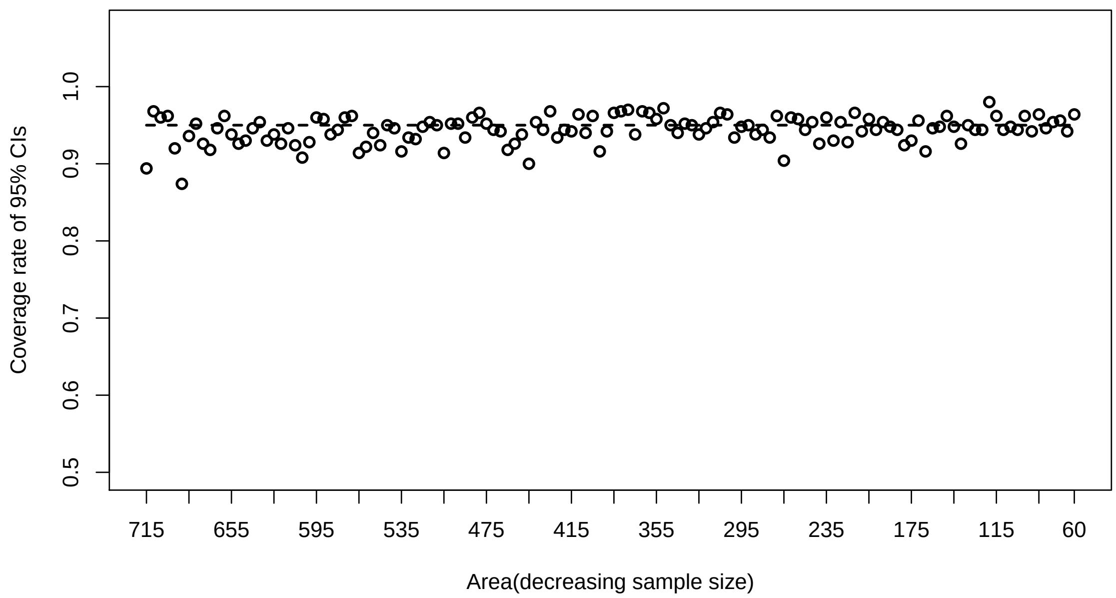

Figure 2: Model-based coverage rates of 95% normality-based CIs using the parametric bootstrap MSE estimator (Average: 0.943). Nominal level 0.95 indicated by the dashed line. Districts sorted by decreasing sample sizes.

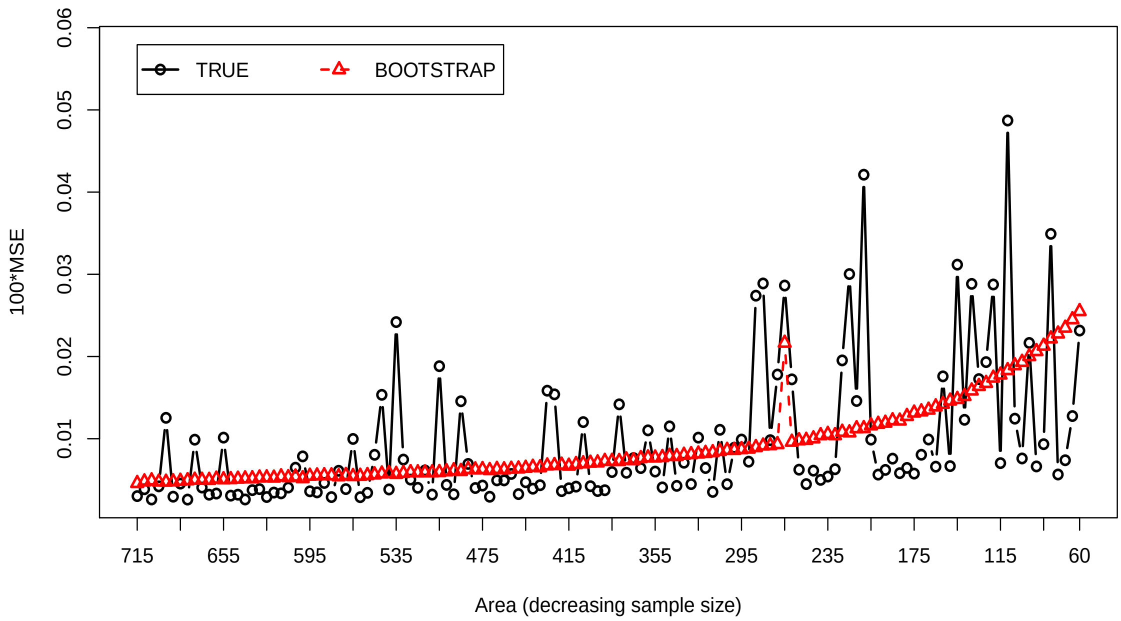

Figure 3: True design MSE (labeled TRUE) of the benchmarked EBLUP based on the LMM and parametric bootstrap estimator (labeled BOOTSTRAP). Districts sorted by decreasing sample sizes.

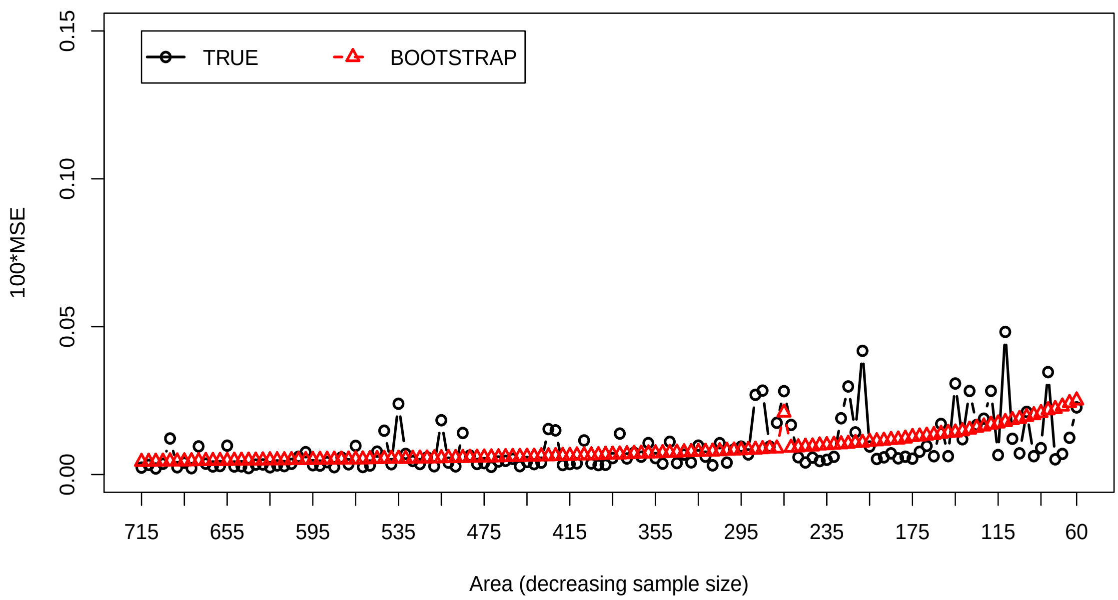

Figure 4: True design MSE (labeled TRUE) of the benchmarked EBLUP based on the LMM and parametric bootstrap estimator (labeled BOOTSTRAP). Districts sorted by decreasing sample sizes. Limits of y-axis as in Report on Phase II of previous contract.

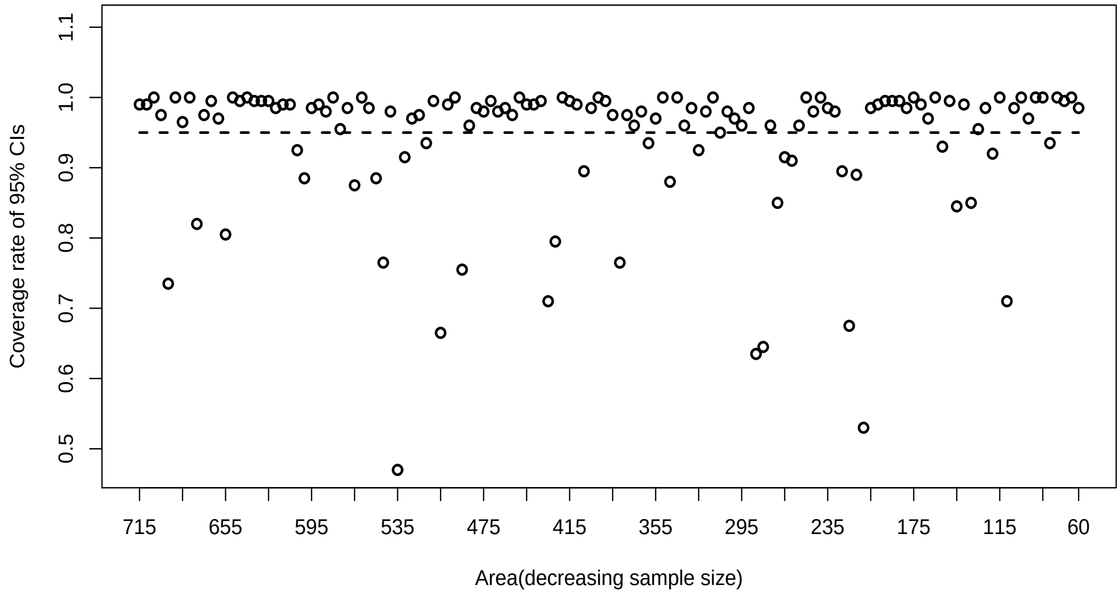

Figure 5: Design-based coverage rates of 95% normality-based CIs using parametric bootstrap MSE estimates (Average: 0.940). Nominal level 0.95 indicated by dashed line. Districts sorted by decreasing sample sizes.

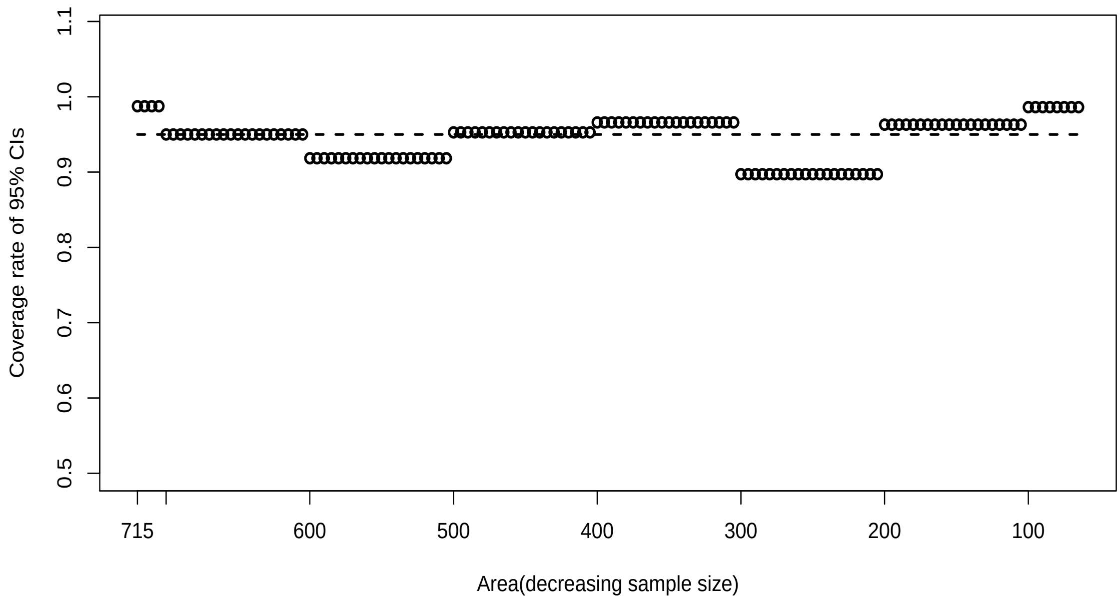

Figure 6: Design-based coverage rates of 95% normality-based CIs using parametric bootstrap MSE estimates, averaged by sample sizes in the classes $(715-700, 700-600, 600-500, \ldots)$. Nominal level 0.95 indicated by dashed line. Districts sorted by decreasing sample sizes.

7 Design-based simulation studies for mixed estimators of design MSE

A design-based simulation study was carried out exactly the same as in the one described in Section 6, to analyze the design-based performance of the mixed bootstrap MSE estimators introduced in Section 5 and the coverage of the CIs based on these MSE estimators.

Thus, the true (fixed) population is taken as the Structural Survey data for the $D = 132$ districts with sample sizes larger than 300 and samples were drawn from it. To approximate empirically the true design MSEs, namely $\text{MSE}_\pi(\hat{P}_d^{BM})$, a first simulation study was performed drawing $L = 10,000$ samples out of the population. The district sample sizes were taken as in the simulation studies described above. Let P_d be the true proportion for district d, and $\hat{P}_d^{EBLUP(\ell)}$ and $\hat{P}_d^{BM(\ell)}$ be the estimates obtained using the data from ℓ-th sample.

To estimate the expected value of the mixed bootstrap MSE estimates under the design-based approach, the simulation study was repeated drawing now $L = 500$ samples from the given population (L is small due to time limitation). With the data from ℓ-th sample, we carried out the parametric and the non-parametric bootstrap procedures with number of bootstrap replicates $B = 500$ each one, obtaining the mixed bootstrap MSE estimate of the benchmarked EBLUP given in (7), denoted here $\text{mse}_{MB}^{(\ell)}(\hat{P}_d^{BM})$. With the same sample, CIs based on the MB estimates were computed as follows

$$\text{CI}_{MB,1-\alpha}^{(\ell)}(P_d) = \left[\hat{P}_d^{BM(\ell)} - z_{\alpha/2}\sqrt{\text{mse}_{MB}^{(\ell)}(\hat{P}_d^{BM})}, \hat{P}_d^{BM(\ell)} + z_{\alpha/2}\sqrt{\text{mse}_{MB}^{(\ell)}(\hat{P}_d^{BM})}\right],$$

This calculation was repeated for each sample $\ell = 1,\ldots,L$. Then, we averaged the bootstrap estimates over Monte Carlo samples as

$$L^{-1}\sum_{\ell=1}^{L}\text{mse}_{MB}^{(\ell)}(\hat{P}_d^{BM}), \quad d = 1,\ldots,D.$$

Similarly as before, to check the performance of the CIs we obtain CRs as

$$\text{CR}_{MB} = L^{-1}\sum_{\ell=1}^{L} I\left\{P_d \in \text{CI}_{MB,1-\alpha}^{(\ell)}(P_d)\right\},$$

Analogous formulas are applied for the unadjusted EBLUPs.

Figure 8 shows the expected values of the estimated MSEs using the NPB estimator compared to true design MSEs, while Figure 9 shows the analogous plot for the MB estimates of the design MSEs. Figure 8 shows that the nonparametric bootstrap tracks the pattern of the true design MSE with some overestimation for most of the districts, but this overestimation becomes more serious for the districts of smaller sample sizes (on the right side). Figure 9 shows that the new MB estimates perform better in average, reducing the overestimation in the smaller districts. Figure 10 shows the design-based coverage rates of the confidence intervals based on the MB estimate of the design MSE. Again, average coverage rate is correct (0.953), but for some districts (11 in total) the design coverage falls between 0.6 and 0.8.

The new PDB procedure described in Section 5 for estimation of the design MSE was applied with $B = 500$ and its performance was studied with $L = 500$ Monte Carlo samples. Expected values of design MSE estimates and CRs of confidence intervals were approximated similarly as for the MB estimators.

Figure 11 shows the expected values of the PDB estimates and the true design MSEs. Despite the slight overestimation (which is less serious than underestimation), see that these MSE estimates are tracking very well the peaks of the design MSEs for practically all the districts. The PDB estimates perform in average much better than the parametric bootstrap MSEs as estimates of the design MSE, compare with Figure 3. It performs even better than the MB estimates shown in Figure 9. Figure 12 shows the coverage rates of confidence intervals based on these MSE estimates. Average coverage rate is in this case 0.89, but observe that the design CRs improves as long as the district sample size increases. Coverage is likely to improve for larger B and L, since the slight overestimation of the design MSEs should provide also slight overcoverage rather than undercoverage.

The performance of each estimator of the design MSE, namely PB, NPB, MB and PDB, has been summarized by averaging across districts. Averages across areas of absolute relative bias (ARB) and coefficient of variation (CV) of each MSE estimator, together with coverage rate (CR) and expected length (EL) of the corresponding 95% confidence intervals, for the benchmarked estimators $\hat{P}_d^{BM}$, are computed respectively as:

$$\overline{\mathrm{ARB}} = \frac{1}{D}\sum_{d=1}^{D} \frac{\left|\frac{1}{L}\sum_{\ell=1}^{L} \mathrm{mse}^{(\ell)}(\hat{P}_d^{BM}) - \mathrm{MSE}(\hat{P}_d^{BM})\right|}{\mathrm{MSE}(\hat{P}_d^{BM})},$$

$$\overline{\mathrm{CV}} = \frac{1}{D}\sum_{d=1}^{D} \frac{\sqrt{\frac{1}{L}\sum_{\ell=1}^{L} \left[\mathrm{mse}^{(\ell)}(\hat{P}_d^{BM}) - \frac{1}{L}\sum_{\ell=1}^{L} \mathrm{mse}^{(\ell)}(\hat{P}_d^{BM})\right]^2}}{\frac{1}{L}\sum_{\ell=1}^{L} \mathrm{mse}^{(\ell)}(\hat{P}_d^{BM})},$$

$$\overline{\mathrm{CR}} = \frac{1}{D}\sum_{d=1}^{D} \frac{1}{L}\sum_{\ell=1}^{L} I\left\{P_d \in \mathrm{CI}_{1-\alpha}^{(\ell)}(P_d)\right\},$$

$$\overline{\mathrm{EL}} = \frac{1}{D}\sum_{d=1}^{D} \frac{1}{L}\sum_{\ell=1}^{L} 2z_{\alpha/2}\sqrt{\mathrm{mse}^{(\ell)}(\hat{P}_d^{BM})}.$$

Since underestimation of error is more serious than overestimation, we also wanted to see which part of bias is due to each type of error. For this reason, we have computed the average across districts of the positive part of the RB as follows

$$\overline{\mathrm{PRB}} = \frac{1}{D}\sum_{d=1}^{D} \frac{\max\left(0, \frac{1}{L}\sum_{\ell=1}^{L} \mathrm{mse}^{(\ell)}(\hat{P}_d^{BM}) - \mathrm{MSE}(\hat{P}_d^{BM})\right)}{\mathrm{MSE}(\hat{P}_d^{BM})}.$$

Note that the negative part is the remainder part of the ARB. Table 1 reports these summarized results. This table indicates that the PDB estimator of the MSE is the less biased among the considered MSE estimators, with practically no underestimation. However, it turns out to be more unstable than the other MSE estimators, which might be the reason for the poorer coverage rate. The instability might arise from the fact that it uses a kind of direct estimator of the area proportion, the one based on the model with fixed district effects

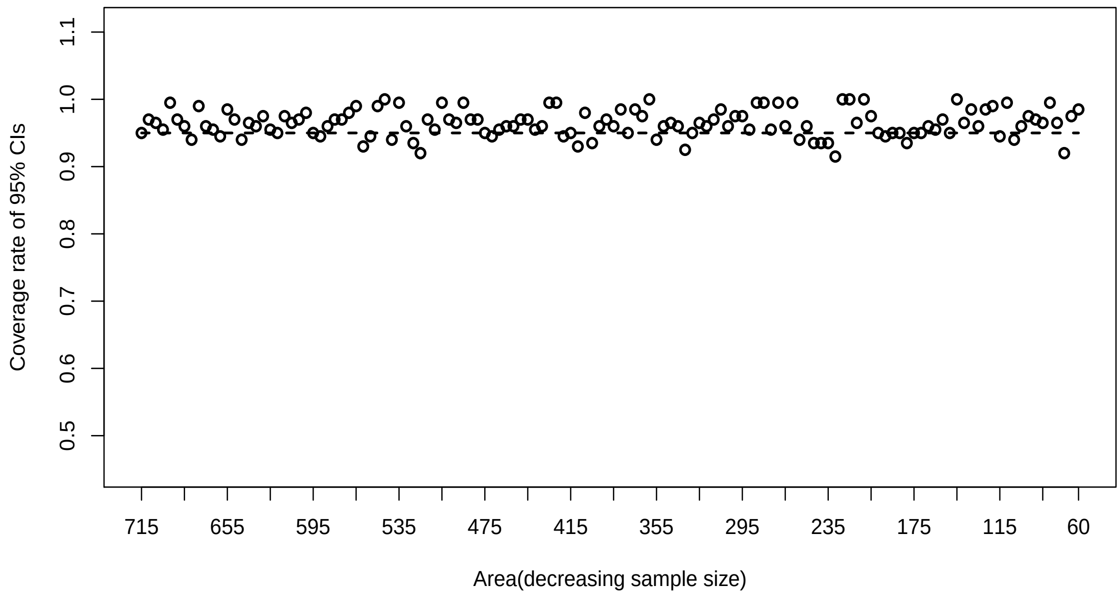

Figure 7: Design-based coverage rates of 95% normality-based CIs based on the true design MSE. Districts sorted by decreasing sample sizes.

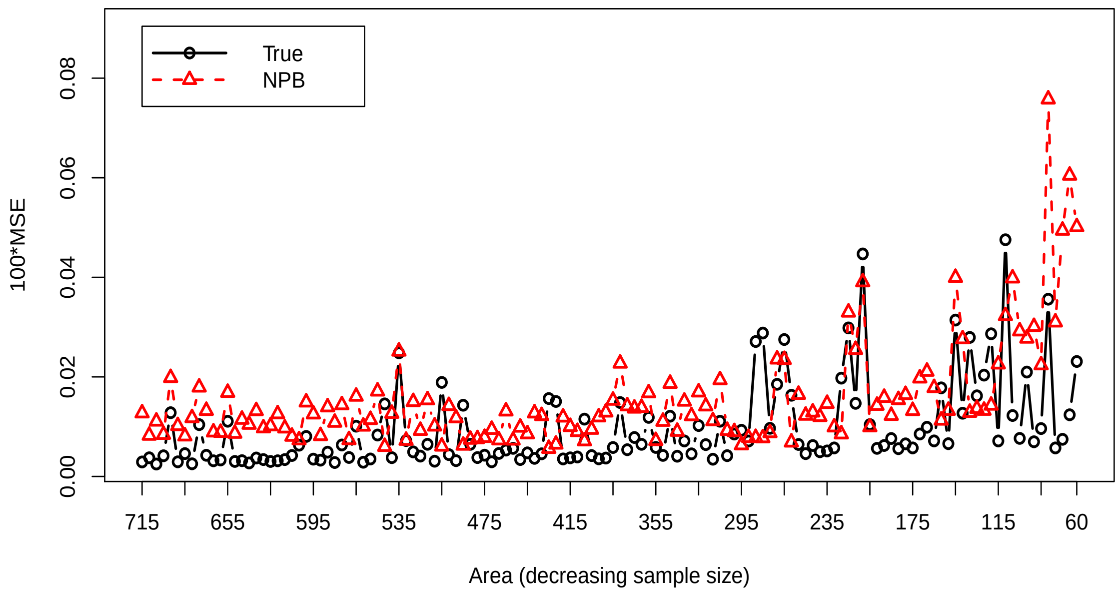

Figure 8: True design MSE (labeled True) of the benchmarked EBLUP based on the LMM and NPB estimator (labeled NPB). Districts sorted by decreasing sample sizes.

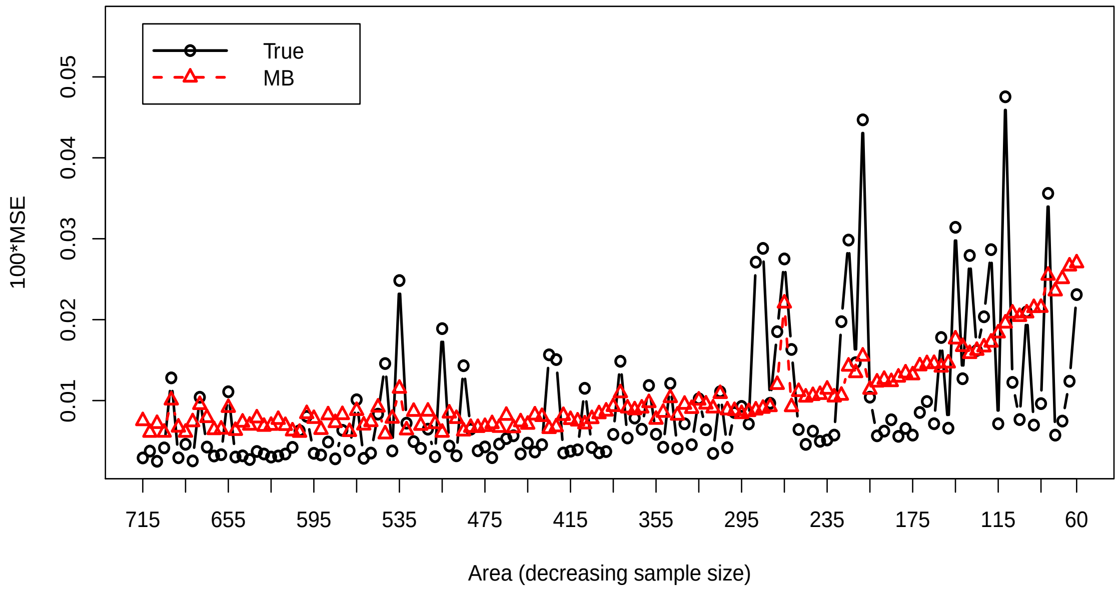

Figure 9: True design MSE (labeled True) of the benchmarked EBLUP based on the LMM and MB estimator (MB). Districts sorted by decreasing sample sizes.

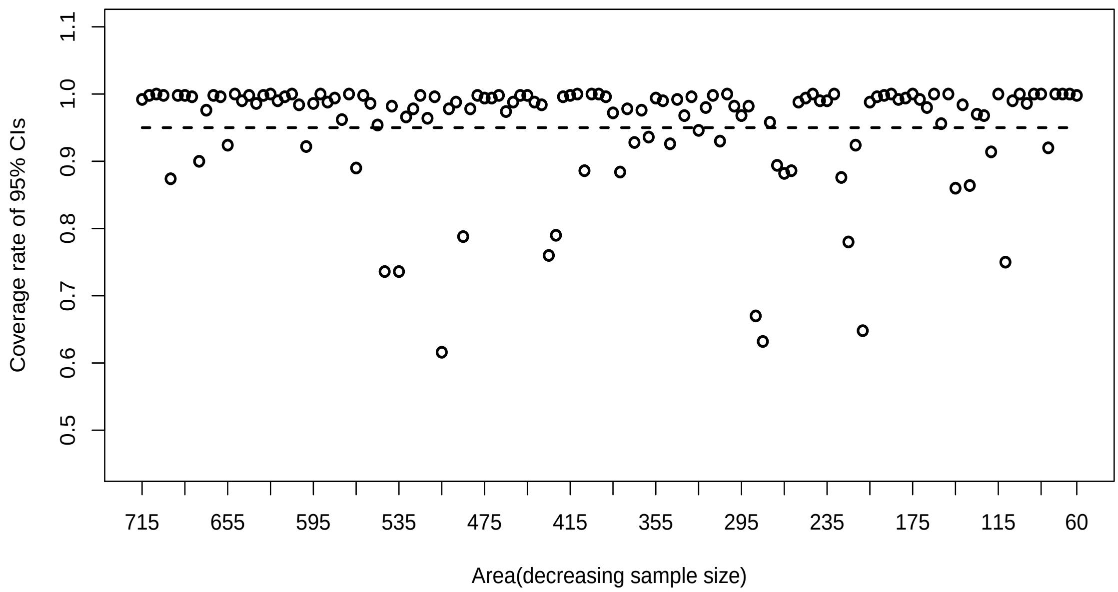

Figure 10: Design-based coverage rates of 95% normality-based CIs using the MB MSE estimator (Average: 0.953). Nominal level 0.95 indicated by the dashed line. Districts sorted by decreasing sample sizes.

$\hat{P}_d^{FIX}$. The MB estimator is slightly more biased but much less unstable, so it can represent a good compromise between all the estimators. The PB estimator performs acceptably well in average but not for each district, as we have seen in the more detailed plots.

Table 1: Averages across areas of ARB and of CV of PB, NPB, MB and PDB estimators of the MSE of the benchmarked estimators $\hat{P}_d^{BM}$, average CR and EL of corresponding 95% confidence intervals, in percentage.

MSE estimator	$\overline{\text{ARB}}(\overline{\text{PRB}})$ (%)	$\overline{\text{CV}}$ (%)	$\overline{\text{CR}}$ (%)	$\overline{\text{EL}}$ (%)
PB	62.1 (49.7)	16.1	94.5	3.7
NPB	136.7 (129.9)	53.4	94.6	4.5
MB	76.6 (67.5)	24.8	95.3	3.9
PDB	62.0 (60.9)	103.9	88.2	3.8

8 MSE and confidence intervals using GREG estimators

GREG weights w_{di} are obtained by calibration and then typically adjusted for non response. This means that GREG weights are random and induce some uncertainty in the final GREG estimator. Here we put ourselves in an ideal situation in which GREG weights are fixed. This means that the true variances of GREG estimators will be underestimated to some extent, and coverage rates will be approximated with much better precision than they will be in practice, where weights are actually random. To calculate the MSE of GREG estimators with fixed weights in our simulations, first note that the considered GREG estimator is a ratio estimator of the form $\hat{P}_d = \hat{Y}_d/\hat{N}_d$, where

$$\hat{Y}_d = \sum_{i\in s_d} w_{di}Y_{di}, \quad \hat{N}_d = \sum_{i\in s_d} w_{di}.$$

Then, by the Taylor linearization method, an approximation to the MSE of the above GREG estimator $\hat{P}_d$ is given by

$$\text{mse}_\pi(\hat{P}_d) = \frac{1}{\hat{N}_d^2}\left[\hat{P}_d^2 v_\pi(\hat{N}_d) + v_\pi(\hat{Y}_d) - 2\hat{P}_d \text{cov}_\pi(\hat{N}_d, \hat{Y}_d)\right], \tag{9}$$

where $v_\pi(\hat{N}_d)$ and $v_\pi(\hat{Y}_d)$ are the estimated design variances of $\hat{N}_d$ and $\hat{Y}_d$ respectively, and $\text{cov}_\pi(\hat{N}_d, \hat{Y}_d)$ is the estimated design covariance between $\hat{N}_d$ and $\hat{Y}_d$. In our simulation studies, we have considered independent simple random samples within each district. In that case, the true inclusion probabilities are given by $\pi_{di} = n_d/N_d$. Applying the approximation $\pi_{di,dj} = \pi_{di}\pi_{dj}$ for the second-order inclusion probabilities, an approximation to the estimated design variances of $\hat{N}_d$ and $\hat{Y}_d$ are respectively given by

$$v_\pi(\hat{N}_d) = \left(1 - \frac{n_d}{N_d}\right)\sum_{i\in s_d} w_{di}^2, \quad v_\pi(\hat{Y}_d) = \left(1 - \frac{n_d}{N_d}\right)\sum_{i\in s_d} w_{di}^2 Y_{di}^2.$$

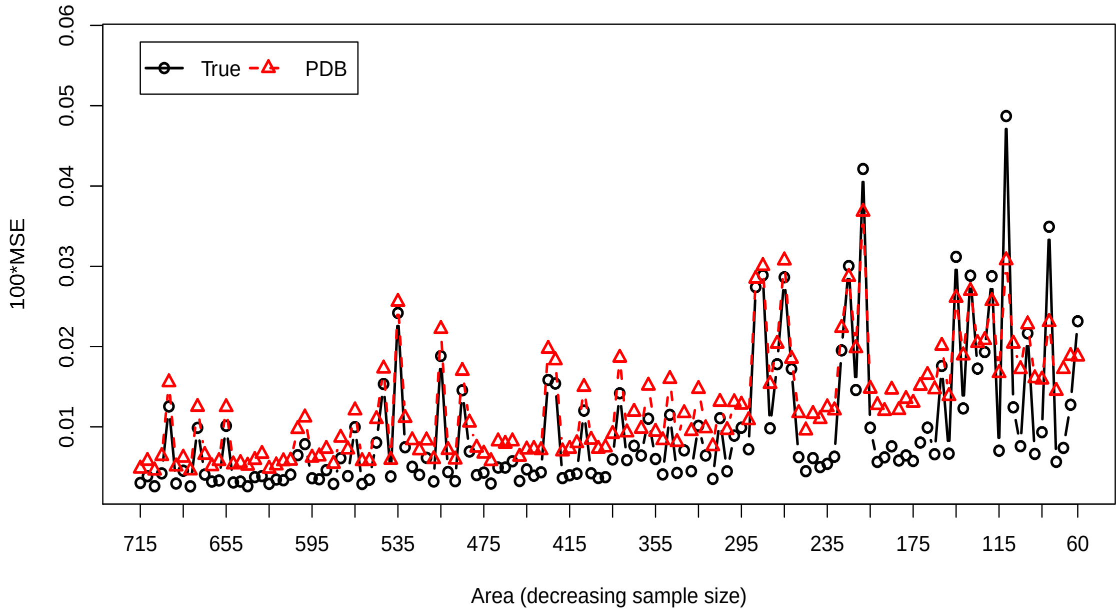

Figure 11: True design MSE (labeled True) of the benchmarked EBLUP based on the LMM and PDB estimator (labeled PDB). Districts sorted by decreasing sample sizes.

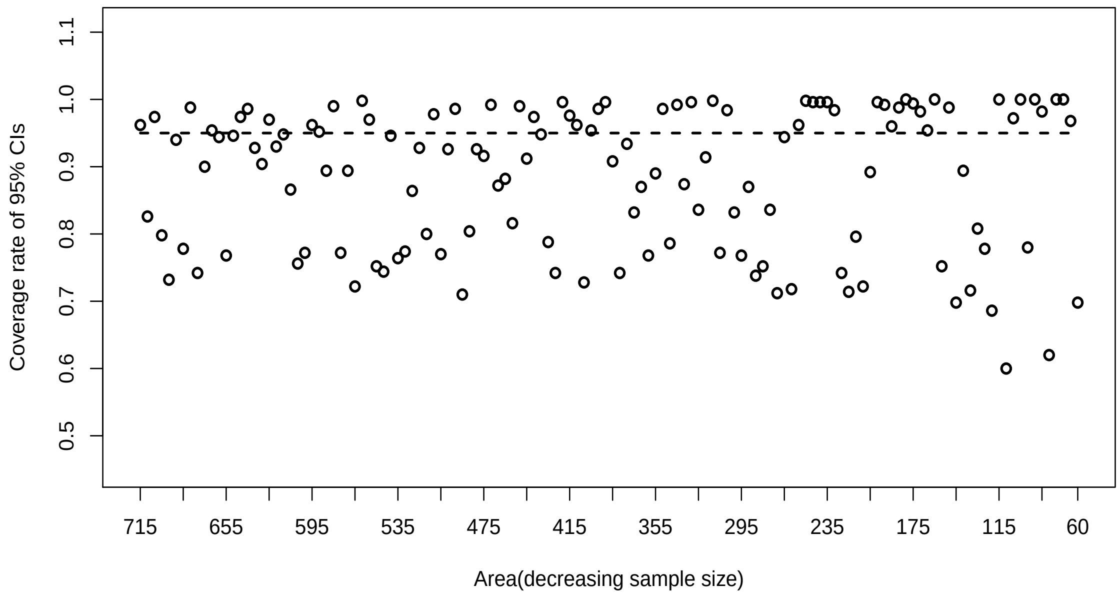

Figure 12: Design-based coverage rates of 95% normality-based CIs using the PDB MSE estimator (Average: 0.890). Nominal level 0.95 indicated by the dashed line. Districts sorted by decreasing sample sizes.

Similarly, an approximation to the estimated design covariance between $\hat{N}_d$ and $\hat{Y}_d$ is given by

$$\mathrm{cov}_\pi(\hat{N}_d, \hat{Y}_d) = \left(1 - \frac{n_d}{N_d}\right) \sum_{i \in s_d} w_{di}^2 Y_{di}.$$

Using the above MSE estimator, a $1-\alpha$ confidence interval for P_d based on the GREG estimator is given by

$$\mathrm{CI}_{GREG,1-\alpha}^{(\ell)}(P_d) = \left[\hat{P}_d - z_{\alpha/2}\sqrt{\mathrm{mse}_\pi(\hat{P}_d)}, \hat{P}_d + z_{\alpha/2}\sqrt{\mathrm{mse}_\pi(\hat{P}_d)}\right],$$

Similarly as in the previous sections, a design-based simulation study was carried out to analyze the performance of the MSE estimator and the coverage rates of CIs based on the GREG with fixed weights. Then, for each Monte Carlo sample $\ell = 1, \ldots, L$, we computed the GREG estimates and the corresponding confidence intervals. Finally, the CRs were approximated as

$$\mathrm{CR}_{GREG} = L^{-1} \sum_{\ell=1}^{L} I\left\{P_d \in \mathrm{CI}_{GREG,1-\alpha}^{(\ell)}(P_d)\right\}.$$

Results are shown in Figures 13 and 14. See that the MSE estimator $\mathrm{mse}_\pi(\hat{P}_d)$ obtained with fixed weights performs very well and the coverage rates of the confidence intervals are very close to 0.95. On the other hand, the average length of those intervals is 9.3. This means that they are double as wider than the intervals obtained with the benchmarked LMM and any of our MSE estimators, see Table 1. The larger length of GREG-based CIs can be more clearly seen in the results with the true data shown in Figure 28 from Section 9.

9 Results for the STATPOP data set

The LMM that was selected in previous work for estimation of activity in Swiss districts contains all the auxiliary variables listed in Table 2 of Appendix 1. More concretely, the model contains random district effects and fixed effects for all the categories of all other variables in Table 2, leaving out the first of them as base reference and including an intercept. Fixed effects were also included for the interactions between `gender` and `age group`, and between `gender` and `civil status`. The estimated regression coefficients are listed in Table 2 of Appendix 2 and we can see that all of these variables are strongly significant and the signs of the coefficients are somehow intuitive. The selected LMM model was checked by simulation studies and also through model diagnostics, and results indicated that this model is relatively good in terms of predicting activity in the Swiss districts.

Table 3 in Appendix 3 lists, for each district within each stratum, the district sample sizes, the different estimates of the percentages of active people (GREGs, EBLUPs based on the LMM and benchmarked EBLUPs) with their estimated percent RRMSEs obtained using the PB, MB and PDB procedures. These results can be better analyzed with the aid of figures. Figure 15 plots the EBLUPs based on the LMM of the district percentages of active people (labeled LMM), together with the benchmarked EBLUPs (labeled LMM (BM)) for each district. See that the two sets of estimates are very close to each other, with

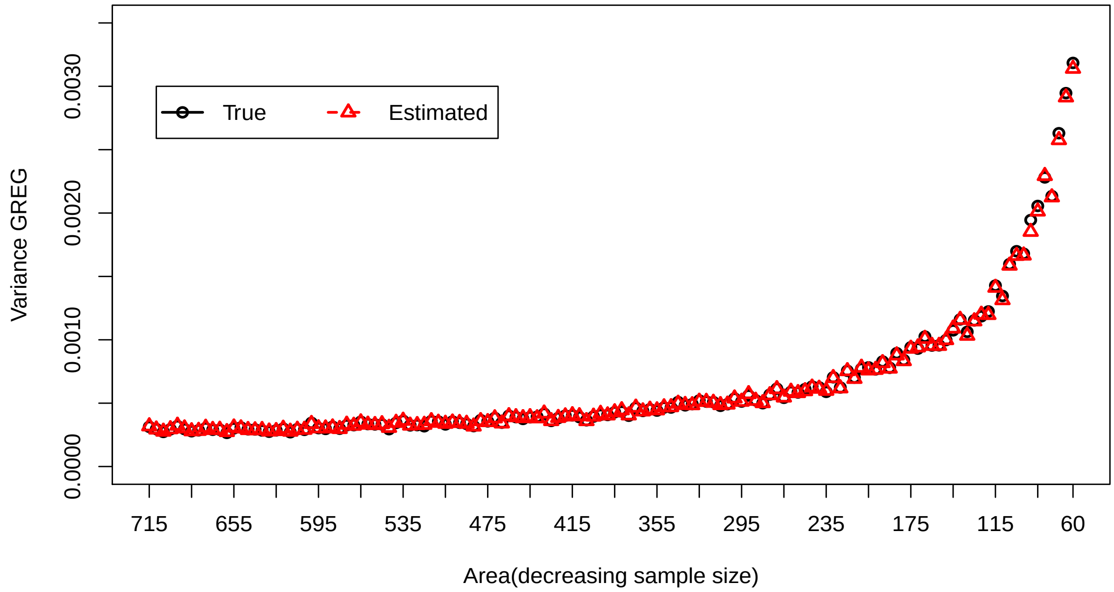

Figure 13: True design variance (labeled ”True”) of the GREG estimator and the variance estimator $\hat{V}_\pi(\hat{P}_d)$ (labeled ”Estimated”). Districts sorted by decreasing sample sizes.

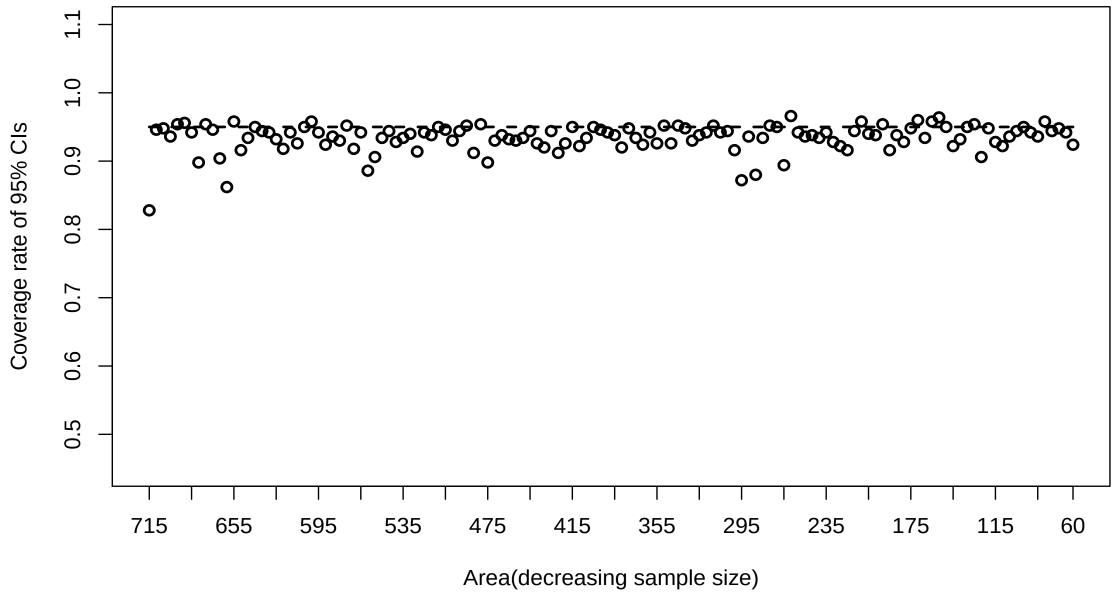

Figure 14: Coverage rates of 95% normality-based CIs of the GREG estimator. Average CR over all districts is 0.935. Nominal level 0.95 indicated by the dashed line. Districts sorted by decreasing sample sizes.

the benchmarked estimates just slightly larger than the unadjusted EBLUPs. In fact, the benchmarking adjustment turned out to be 1.0076, which means a very mild adjustment.

Figure 16 represents a line plot of the benchmarked EBLUPs against the GREG estimates. Since the GREG estimators are approximately design-unbiased, a cloud of points all above or below the line $y = x$ would suggest a systematic design bias of the EBLUPs. This does not seem to be the case because the points turn out to be around the line $y = x$, with points distributed at both sides. The group of points that appear below the line close to the top right corner indicate some deviation of the EBLUPs to the GREGs for those districts. But note that these points correspond to large GREG estimates of the proportions of active people. The points are a little further apart from the line because, according to the model, which is supposed to fit well the data, these districts should not have such large proportions of active people. Take into account that GREG estimates tend to vary more than they should due to the small district sample sizes. Thus, the model is smoothing those more extreme proportions and providing more reasonable estimates according to the model. In contrast, the points with large GREG estimates that appear close to the line correspond to districts in which the extreme GREG estimated proportions are explained by the considered auxiliary variables in the LMM model.

Figure 17 gives a different display of the two sets of estimates, for each district in the x axis. We can see that the estimates are practically the same for the large districts (on the left-hand side of the plot), but for the districts with smaller sample sizes (on the right-hand side), the two estimates present slight deviations. We know that for districts with small sample sizes, the GREG estimators can be inefficient as shown in Phase I of the project. Thus, here we consider the benchmarked EBLUPs as more reliable estimates.

Figure 18 plots the percent relative root MSE (RRMSE) estimates obtained by the proposed parametric bootstrap procedure with $B = 250$ replicates, for the unadjusted EBLUPs based on the LMM (labeled LMM) and the benchmarked EBLUPs (labeled LMM (BM)). See that the estimated RRMSE is about 0.5% larger for the benchmarked estimates in the districts with largest sample sizes, but the difference decreases with the district sample size. Still, 0.5% is not a stricking RRMSE increase. The decrease of the differences when decreasing the district sample size seems to be an artifact of estimating the RRMSE which is a ratio of the root MSE over the estimate. This decrease of the differences does not appear when looking at the (non-relative) estimated MSEs, see Figure 19. Concerning computation time, for the STATPOP data, the parametric bootstrap procedure with $B = 250$ replicates takes less than 22 hours in a 3.40-3.90 gHz PC with an Intel Core i7 processor.

Figure 20 plots the estimated model MSE using the parametric bootstrap (PB) method together with the estimated design MSE using the nonparametric bootstrap (NPB) procedure, for the benchmarked EBLUPs based on the LMM. Note that these two estimates have a different target parameter, which is the model MSE in the former and the design MSE in the latter. Thus, in principle they do not need to agree. However, if they were good estimates of their corresponding true MSEs and the model was correct, they should show a similar pattern because they will be similar when averaging across a large number of districts, see Appendix 1 in the report of Phase II of the previous contract. By the simulation studies performed in Section 6, we know that the PB procedure estimates correctly the model MSE for all districts and it also tracks acceptably well the design MSE for the districts with not so small sample sizes. In contrast, we have seen in the simulation study that the NPB method overestimates the true design MSE, especially for districts with sample sizes below $n_d = 300$. This was corrected to some extent by the new mixed bootstrap (MB) MSE estimates as shown in Figure 9 of Section 6. Figure 21 plots PB, MB and parametric design-bootstrap (PDB) MSE estimates, for the benchmarked EBLUPs based on the LMM. Comparing with the NPB MSE estimates from Figure 20, which reaches the value 0.20, these three estimates show much more reasonable results, with MSE values not overcoming the 0.08 level. We have seen in simulations that the PDB estimators track better the peaks of the true design MSEs. Thus, if one is very averse to underestimation of the error, the PDB estimates are recommended.

Figure 22 plots EBLUPs based on the LMM together with the 95% normality-based confidence intervals based on the PB MSE estimates. Figure 23 shows the analogous plot for the benchmarked EBLUPs. See that intervals are rather narrow for districts with larger sample sizes (on the left-hand side) but the length increases as long as district sample sizes decrease (on the right-hand side). Still, even for districts with small sample sizes, the lengths of intervals are not large and allow to discriminate with statistical significance between the proportions of active people in many districts. Point estimates together with lower limit (LL) and upper limit (UL) of 95% normality-based confidence intervals obtained using the EBLUPs as well as benchmarked EBLUPs are included for all districts in Table 4 of Appendix 4.

Similarly, Figure 24 plots EBLUPs based on the LMM together with the 95% normality-based confidence intervals using the new MB MSE estimates. Figure 25 shows the analogous plot for the benchmarked EBLUPs. As before, the intervals are rather narrow for districts with larger sample sizes (on the left-hand side) but the length increases as long as district sample sizes decrease (on the right-hand side). These intervals are just slightly wider than those obtained using the PB procedure only for few of the smaller districts. The estimated RRMSE obtained using the two type of MSE estimates, PB and MB, can be compared in Table 3 of Appendix 3. Again, the point estimates together with lower limit (LL) and upper limit (UL) of 95% normality-based confidence intervals obtained from EBLUPs as well as benchmarked EBLUPs are included for all districts in Table 5 of Appendix 4.

Figures 26 and 27 show the analogous intervals obtained using the PDB MSE estimates. These intervals are clearly wider for some of the districts with smaller sample sizes. Thus, we expect these intervals to cover better the true values. Estimated RRMSEs based on PDB estimates are also included in Table 3 of Appendix 3, and confidence intervals are reported in Table 6 of Appendix 4.

Finally, Figure 28 shows GREG estimates together with 95% CIs. See that these intervals are much wider than the corresponding ones obtained using the EBLUPs based on the LMM shown in Figures 22 to 25. MSE estimates of GREG estimates are obtained using the Taylor linearization method and considering that the inclusion probabilities in the Structural Survey are equal to $\pi_{di} = 1/w_{di}$, that is, using (9) with estimated variances given by

$$v_\pi(\hat{N}_d) = \sum_{i \in s_d} w_{di}(w_{di} - 1), \quad v_\pi(\hat{Y}_d) = \sum_{i \in s_d} w_{di}(w_{di} - 1) Y_{di}^2$$

and estimated covariance given by

$$\mathrm{cov}_{\pi}(\hat{N}_d, \hat{Y}_d) = \sum_{i \in s_d} w_{di}(w_{di} - 1)Y_{di}.$$

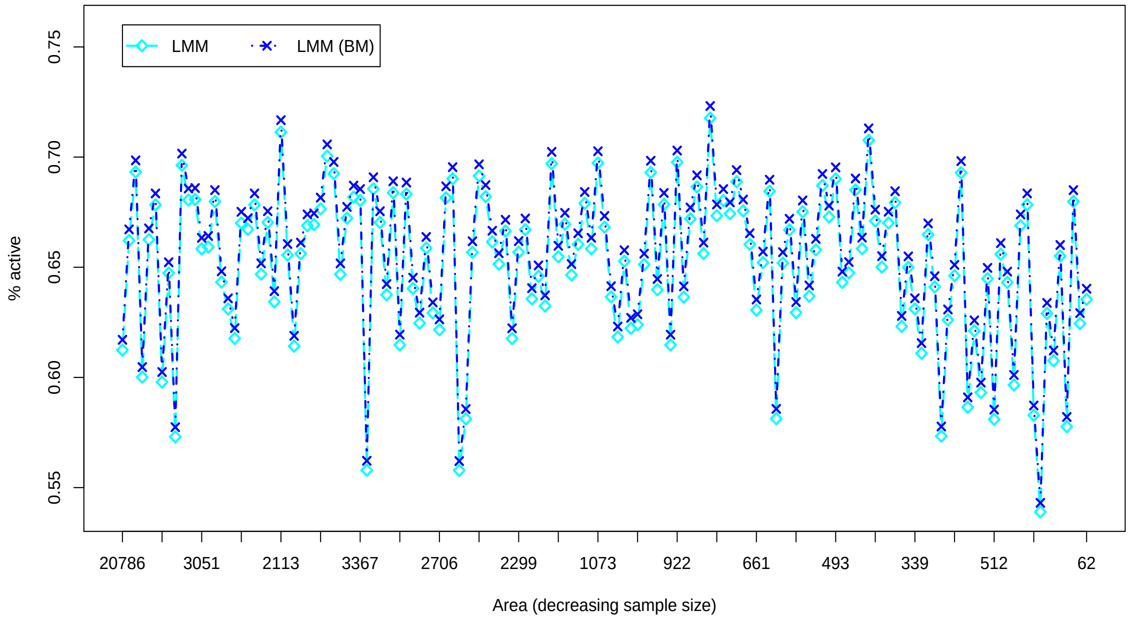

Figure 15: Estimated district percentages of active people using the EBLUPs and the benchmarked EBLUPs based on the LMM, with districts sorted by decreasing sample size.

10 Concluding remarks

Below we summarize the main achievements of all previous work together with those of Phase I of this project:

- A rich and powerful regression model has been found for the activity in Switzerland. This has an important economic value itself, since the model might help to understand the factors explaining the activity, and this might provide relevant information for the design of specific social policies or programs related with the labor force.
- Efficient estimators of the proportions of active people in the Swiss districts have been found. The selected model explains a large part of the between-district variability in the activity and therefore provides estimates of better quality than the current GREG estimates. The design-based simulation with true data carried out in Phase I of the previous project showed that the estimates (EBLUPs) obtained from the selected model

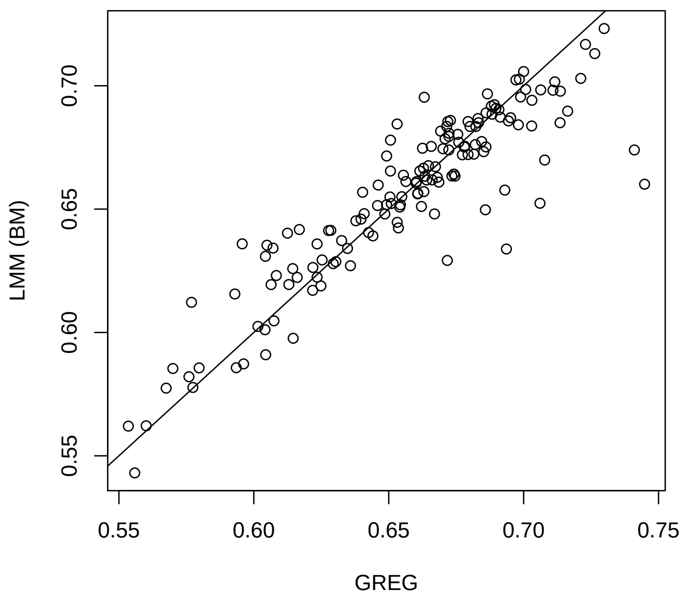

Figure 16: Estimated district percentages of actives using the benchmarked EBLUPs based on the LMM model against GREG estimates.

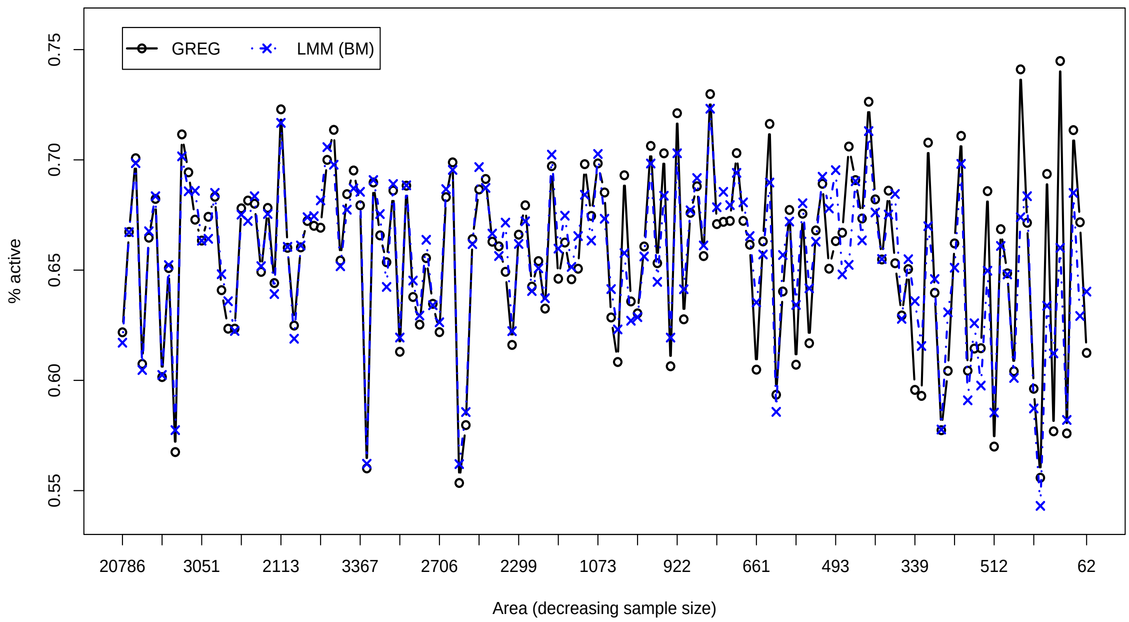

Figure 17: Estimated district percentages of actives using the GREG estimator and the benchmarked EBLUPs based on the LMM, with districts sorted by decreasing sample size.

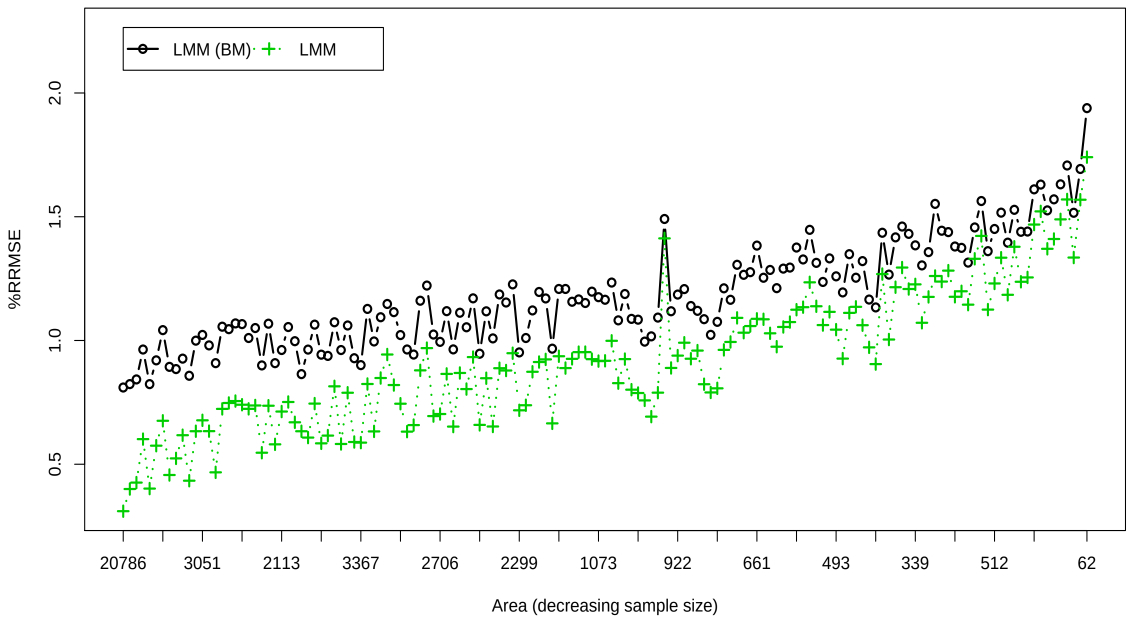

Figure 18: Estimated percent RRMSEs obtained by parametric bootstrap for the unadjusted EBLUPs (labeled LMM) and the benchmarked EBLUPs (labeled LMM(BM)) for each district, with districts sorted by decreasing sample size.

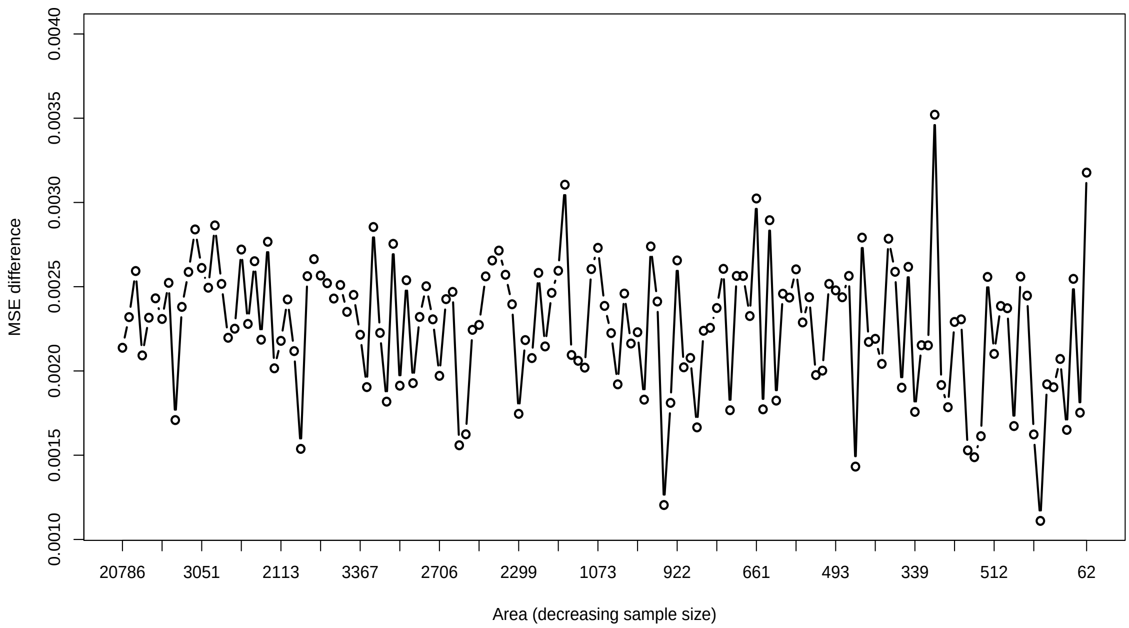

Figure 19: Difference between parametric bootstrap MSE estimates for the benchmarked EBLUPs and the unadjusted EBLUPs for each district, with districts sorted by decreasing sample size.

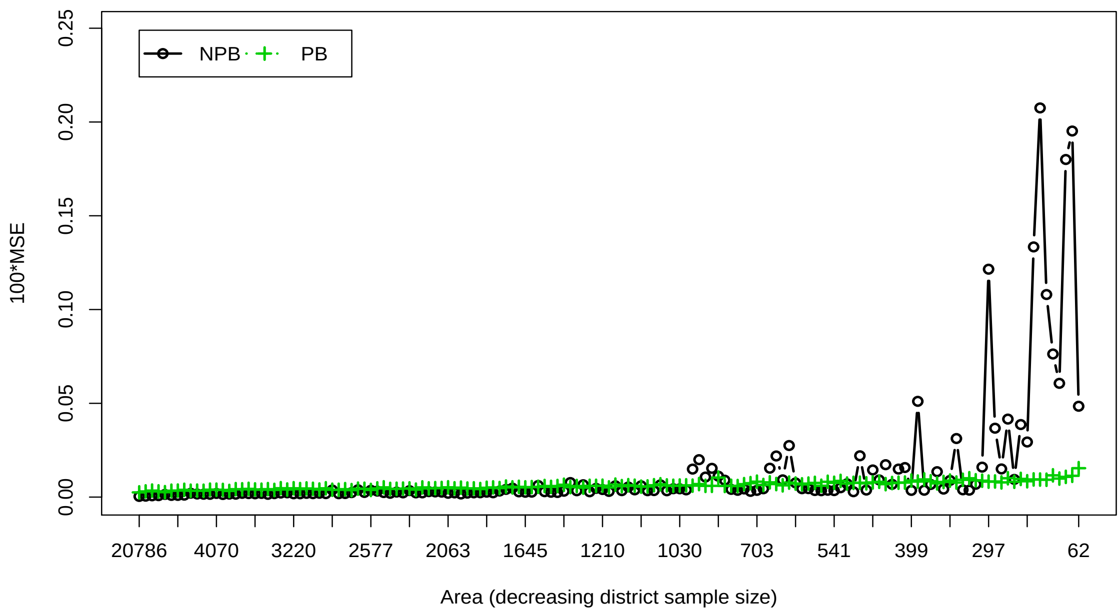

Figure 20: Estimated model MSEs using the parametric bootstrap (labeled "Model MSE") together with estimated design MSE using the nonparametric bootstrap (labeled "Design MSE"), for the benchmarked EBLUPs based on the LMM, with districts sorted by decreasing sample size.

(LMM) achieve a significant reduction in relative error in comparison with the GREG estimates for practically all districts, see Figure 57 of the report for Phase I of the previous project. In fact, when applying the new estimators to the read data, they achieve an average RRMSE reduction of 49% with respect to GREG estimators without increasing the district survey sample sizes. This is achieved thanks to a clever use of the available auxiliary information to establish relationships among all the districts, which helps to borrow strength from all districts when estimating in a particular one.

- Bootstrap procedures have been proposed for estimating both model MSE and design MSE. In Section 6, we have seen that the parametric bootstrap procedure estimates correctly the corresponding model MSE and it also gives acceptable estimates of the design MSE in average, but it is not showing the real design MSE for a particular district. The nonparametric bootstrap procedure for estimating the design MSE is not bad for the districts with larger sample sizes ($n_d \geq 300$) but is very unstable for districts with smaller sample sizes ($n_d < 300$). We have proposed two completely new bootstrap approaches for estimation of the design MSEs, namely MB and PDB, which compensate in an automatic way the lack of stability of the nonparametric bootstrap for the smallest districts and the overstability of the parametric bootstrap for the larger districts. These estimates give very reasonable results for estimation of the design

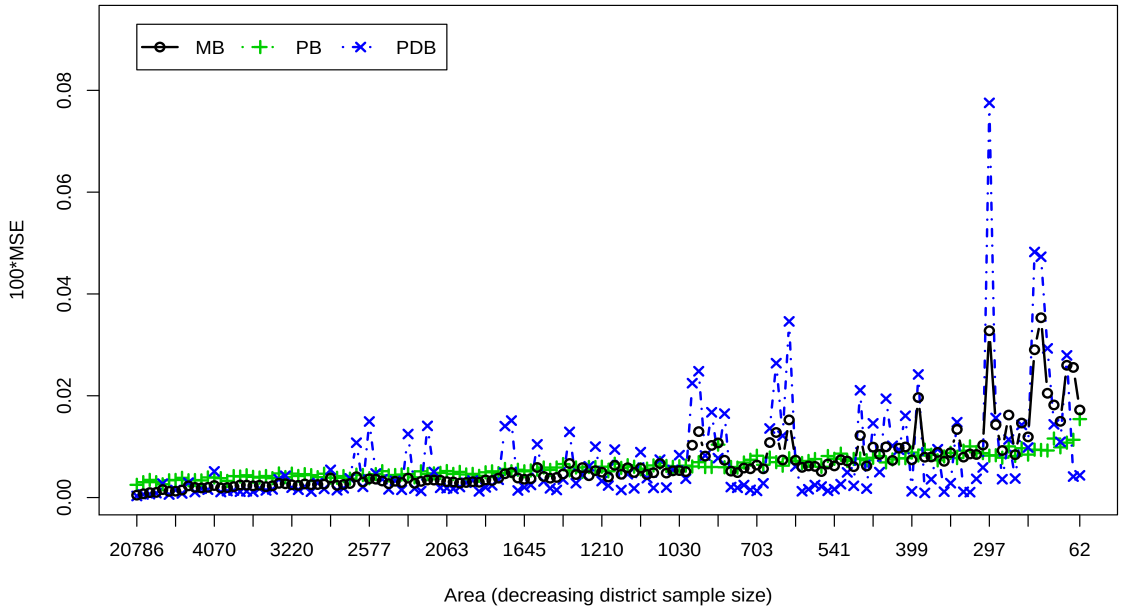

Figure 21: Estimated design MSEs using the parametric bootstrap (PB), the MB bootstrap with correction factor on NPB part (MB) and the parametric design-bootstrap (PDB), for the benchmarked EBLUPs based on the LMM, with districts sorted by decreasing sample size.

MSEs, as shown in the simulation studies of Section 7.

- Based on the proposed bootstrap MSE estimates, we have constructed normality-based confidence intervals. Despite of the limited number of simulations and bootstrap replicates, under the model confidence intervals have actual coverage of the target parameter rather close to the nominal level $1-\alpha$ for all districts. In the design-based simulations, coverage rates are not very accurate when considering the districts separately, but the averages of the coverage rates over groups of districts with similar sample sizes are also rather close to the nominal level.

- Using the whole STATPOP data and the Structural Survey data, we have computed the EBLUPs together with their benchmarked counterparts, for which the estimated district totals add up to the GREG estimate of the population total. The benchmarking adjustment turns out to be very mild in the true data, although this mild adjustment still leads to a small increase in RRMSE. Still, the estimated RRMSEs of the benchmarked estimates remain below 3.5% even for the smallest districts, see Table 3 in Appendix 3. Thus, the benchmarked EBLUPs represent more efficient alternatives to the current GREG district estimates, their MSEs can be estimated using the MB or PDB bootstrap methods described in Section 5 and normality-based confidence

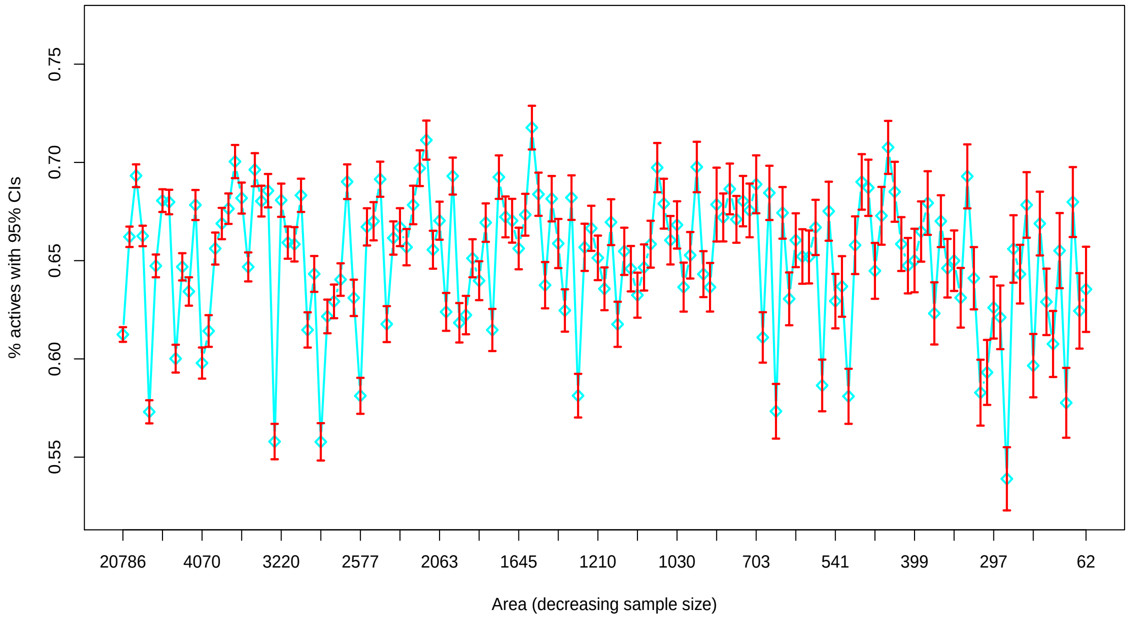

Figure 22: Estimated district percentages of active people using LMM model together with 95% CIs based on PB estimates of model MSE, with districts sorted by decreasing sample size.

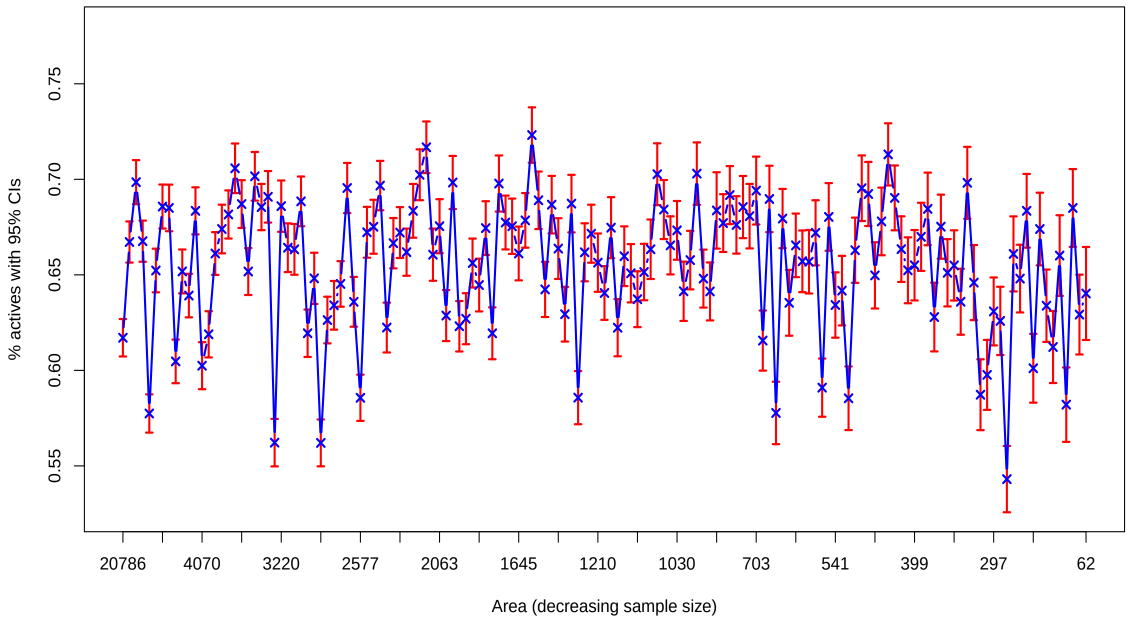

Figure 23: Estimated district percentages of active people using benchmarked LMM model together with 95% CIs based on PB estimates of model MSE, with districts sorted by decreasing sample size.

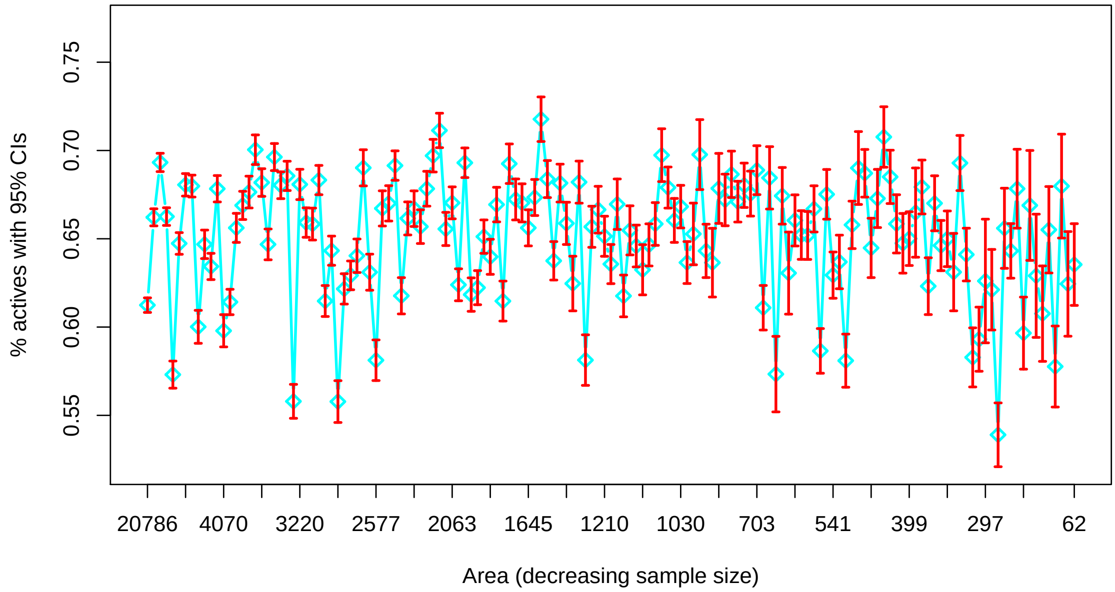

Figure 24: Estimated district percentages of active people using LMM model together with 95% CIs based on MB estimates of design MSE (with the new correction factor on NPB). Districts sorted by decreasing sample size.

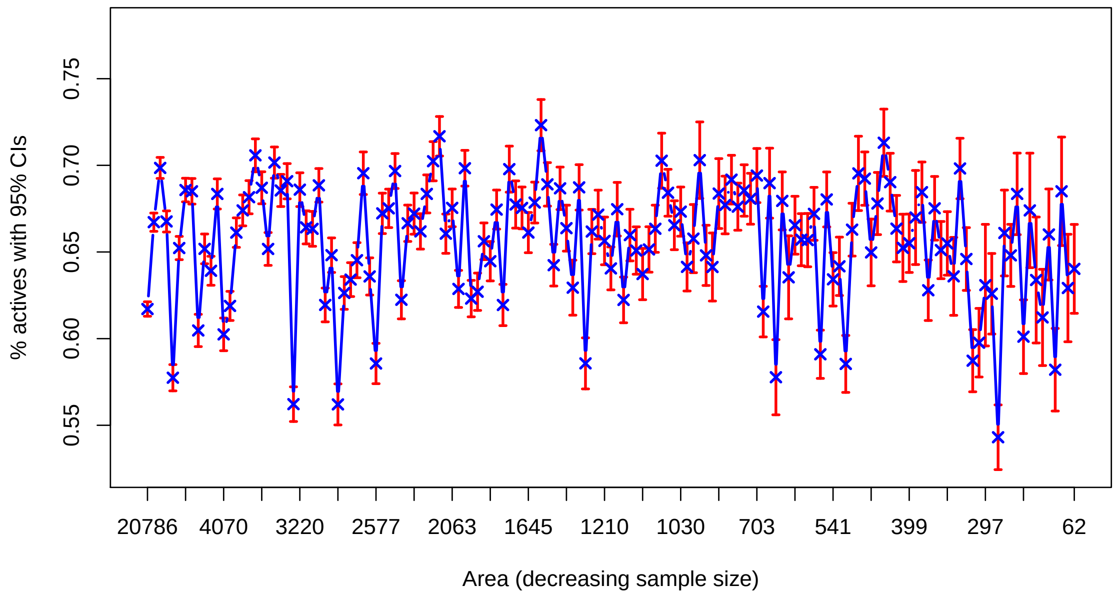

Figure 25: Estimated district percentages of active people using benchmarked LMM model together with 95% CIs based on MB estimates of design MSE (with the new correction factor on NPB). Districts sorted by decreasing sample size.

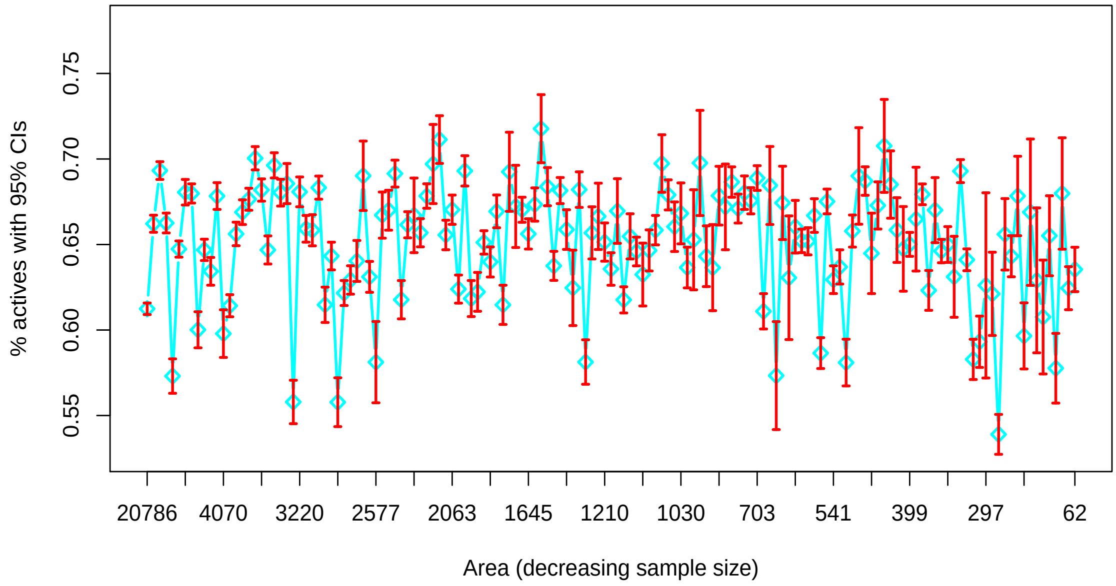

Figure 26: Estimated district percentages of active people using LMM model together with 95% CIs based on PDB estimates of design MSE. Districts sorted by decreasing sample size.

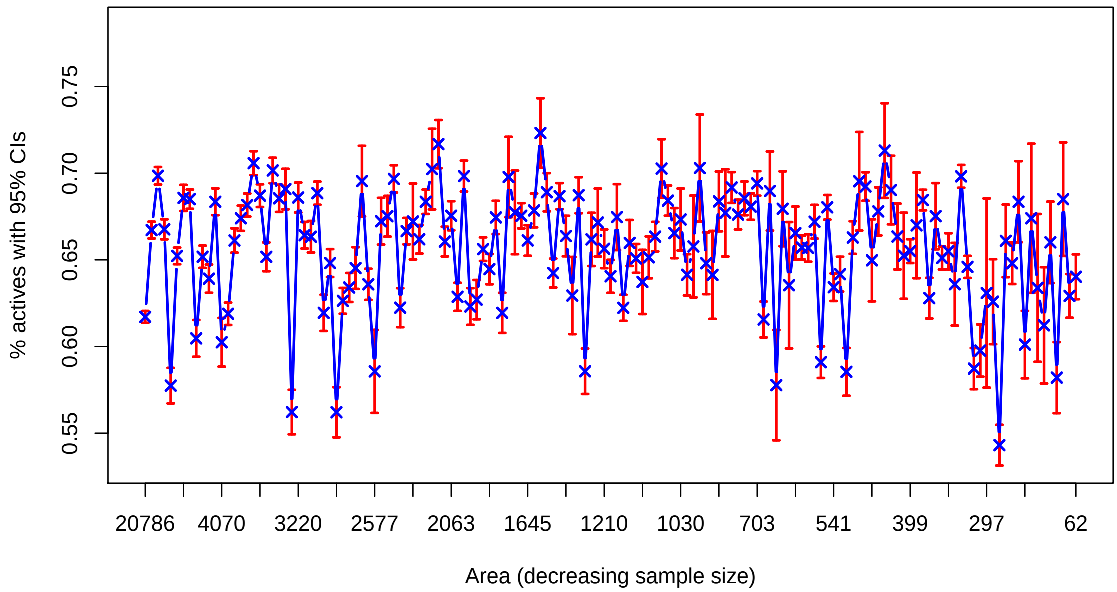

Figure 27: Estimated district percentages of active people using benchmarked LMM model together with 95% CIs based on PDB estimates of design MSE. Districts sorted by decreasing sample size.

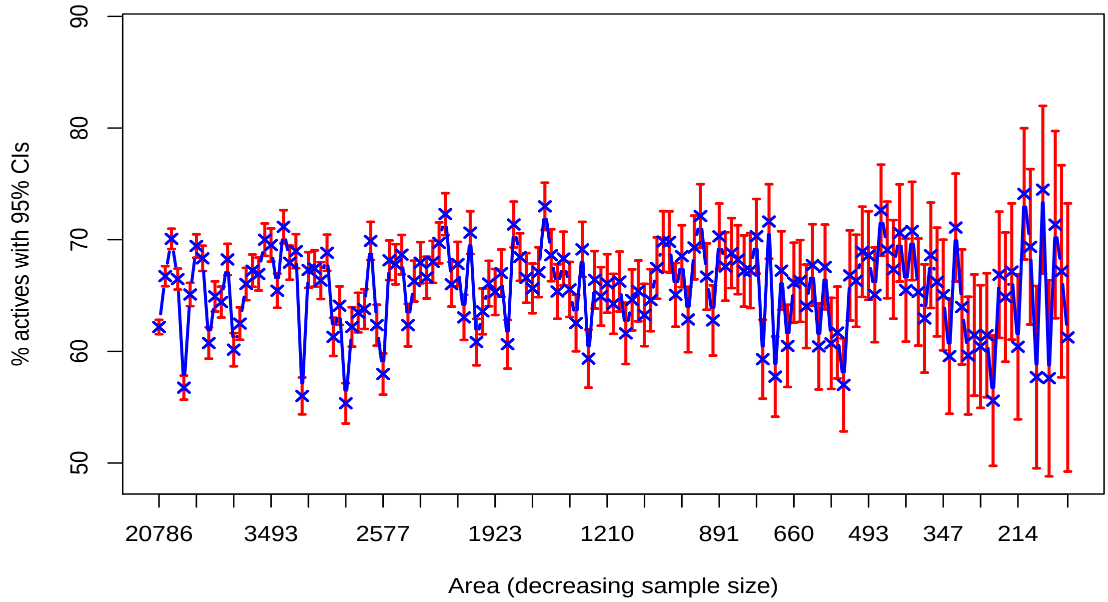

Figure 28: Estimated district percentages of active people using GREG together with 95% CIs. Districts sorted by decreasing sample size.

intervals can be constructed using those estimated MSEs.

- Additionally, we have presented the results of a simulation study for the estimated MSE of GREG estimator and the coverage rates of confidence intervals obtained from GREG estimates. We have seen that the Taylor linearization MSE estimator performs well and the coverage rate of the confidence intervals is around the nominal value 0.95. Nevertheless, as we have already seen, GREG estimators are less efficient than the proposed EBLUP based on LMM. Moreover, the CIs obtained using the GREG estimates are at least double wider than those obtained from the EBLUPs based on LMM model. This is more explicitly seen in Figure 28 showing the CIs obtained from GREG estimates using the Structural survey data.

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Appendix 1: Variables included in the selected LMM

Table 2: Variables included in selected LMM

active	1=active 0=inactive
district	there are 147 of them
Strata1	0=Strata with large sampling weight median, 1=otherwise
District1724	1=District nr 1724 / 0=otherwise
age group	$15,\ [16,20),\ [20,60),\ [60,64),\ 64,\ \geq 65$
gender	male (1) / female (2)
civil status	1 = single, unmarried, 2 = married, in a registered partnership,
	3 = widow/er, 4 = divorced, partnership dissolved
nationality	Not swiss (1) / Swiss (2)
secondary residence	no (1) / yes (2)
Household Size	1, 2, [3,5], [6,10] $>$10
Income	unknown (In OASI = no), $(0,12000]$, $(12000,24000]$, $(24000,48000]$,
	$(48000,72000]$, $(72000,96000]$, $(96000,120000]$, >120000
OASItri	1 = in OASI only Jan-March, 0 = otherwise

Appendix 2: Fitted regression for Structural Survey

Table 2: Model fitting results for LMM

Variable	Value	Std.Error	DF	t-value	p-value
(Intercept)	0.1442500	0.0070170	285837	20.55713	0.0000***
Strata1=1	-0.0070059	0.0019959	144	-3.51006	0.0006***
District1724=1	0.0789174	0.0128619	144	6.13575	0.0000***
age∈[16,20)	0.3487278	0.0073290	285837	47.58162	0.0000***
age∈[20,60]	0.2908208	0.0069008	285837	42.14277	0.0000***
age∈[60,64]	0.1302745	0.0076731	285837	16.97796	0.0000***
age=64	-0.0015075	0.0095230	285837	-0.15830	0.8742
age≥65	-0.1158139	0.0071840	285837	-16.12112	0.0000***
gender=F	-0.0128278	0.0094166	285837	-1.36224	0.1731
civil status=married	0.0165010	0.0020274	285837	8.13905	0.0000***
civil status=widow/er	0.0019708	0.0057550	285837	0.34246	0.7320
civil status=divorced	0.0073863	0.0031928	285837	2.31341	0.0207*
nationality=Swiss	-0.0184364	0.0013458	285837	-13.69904	0.0000***
secresid=yes	-0.0704905	0.0046144	285837	-15.27629	0.0000***
housesize=2	-0.0022829	0.0017894	285837	-1.27580	0.2020
housesize∈[3,5]	-0.0159658	0.0018651	285837	-8.56049	0.0000***
housesize∈[6,10]	-0.0326060	0.0032409	285837	-10.06066	0.0000***
housesize>10	0.0131268	0.0161541	285837	0.81260	0.4164
Income∈(0,12000]	0.3519415	0.0024847	285837	141.64245	0.0000***
Income∈(12000,24000]	0.4849786	0.0024818	285837	195.41596	0.0000***
Income∈(24000,48000]	0.5570826	0.0020546	285837	271.14377	0.0000***
Income∈(48000,72000]	0.5771984	0.0020013	285837	288.41058	0.0000***
Income∈(72000,96000]	0.5823435	0.0021831	285837	266.74995	0.0000***
Income∈(96000,120000]	0.5862130	0.0021795	285837	268.97042	0.0000***
Income> 120000	0.6061222	0.0059727	285837	101.48181	0.0000***
OASItri=1	-0.1852942	0.0085840	285837	-21.58584	0.0000***
age∈[16,20):gender=F	-0.0137442	0.0104941	285837	-1.30971	0.1903
age∈[20,60):gender=F	0.0133350	0.0096555	285837	1.38108	0.1673
age∈[60,64):gender=F	-0.0047423	0.0106959	285837	-0.44337	0.6575
age=64:gender=F	-0.1469525	0.0131640	285837	-11.16318	0.0000***
age≥ 65:gender=F	0.0595271	0.0100597	285837	5.91739	0.0000***
gender=F:civil status=married	-0.0515040	0.0027248	285837	-18.90159	0.0000***
gender=F:civil status=widow/er	-0.0440050	0.0066260	285837	-6.64127	0.0000***
gender=F:civil status=divorced	-0.0130737	0.0042418	285837	-3.08211	0.0021**

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Appendix 3: Estimates of district proportions

Table 3: Estimated district proportions of active people and estimated percent RRMSE in parenthesis, where rrmse, rrmseMB and rrmsePDB are obtained respectively with the PB, MB and PDB estimates of MSE.

	ZH00											
Nr	101	102	103	104	105	106	107	108	109	110	111	112
size	1309	807	3455	2113	2294	3088	2600	1488	3220	4075	2063	9510
GREG	0.6913	0.6719	0.7115	0.7229	0.6801	0.6742	0.6234	0.6861	0.6729	0.6823	0.6782	0.7008
%CV(GREG)	(1.817)	(2.421)	(1.069)	(1.325)	(1.412)	(1.233)	(1.502)	(1.729)	(1.212)	(1.047)	(1.49)	(0.661)
LMM	0.6821	0.6803	0.6963	0.7113	0.6783	0.6592	0.6311	0.6838	0.6808	0.6783	0.6703	0.6932
%rrmse	(0.847)	(0.962)	(0.617)	(0.713)	(0.737)	(0.634)	(0.747)	(0.82)	(0.633)	(0.575)	(0.736)	(0.426)
%rrmseMB	(0.891)	(0.942)	(0.562)	(0.7)	(0.742)	(0.646)	(0.826)	(0.783)	(0.643)	(0.562)	(0.688)	(0.382)
%rrmsePDB	(0.777)	(0.734)	(0.54)	(1)	(0.538)	(0.604)	(0.73)	(0.832)	(0.654)	(0.589)	(0.652)	(0.383)
BM	0.6873	0.6855	0.7016	0.7168	0.6835	0.6642	0.6359	0.6890	0.6860	0.6835	0.6755	0.6985
%rrmse	(1.118)	(1.211)	(0.927)	(0.962)	(1.05)	(0.98)	(1.046)	(1.115)	(0.999)	(0.92)	(1.068)	(0.843)
%rrmseMB	(0.972)	(1.105)	(0.654)	(0.811)	(0.819)	(0.733)	(0.861)	(0.929)	(0.724)	(0.649)	(0.822)	(0.442)
%rrmsePDB	(0.772)	(0.723)	(0.534)	(0.99)	(0.524)	(0.589)	(0.721)	(0.817)	(0.642)	(0.576)	(0.634)	(0.37)

	BE02	BE00									LU00	
Nr	241	242	243	244	245	246	247	248	249	250	301	302
size	2706	2420	1800	2079	2556	10294	2870	404	1013	1210	909	3493
GREG	0.6219	0.6234	0.7136	0.6601	0.6815	0.6673	0.6409	0.7061	0.6285	0.6608	0.667	0.6952
%CV(GREG)	(1.449)	(1.558)	(1.466)	(1.549)	(1.33)	(0.687)	(1.374)	(3.144)	(2.374)	(2.025)	(2.273)	(1.09)
LMM	0.6216	0.6177	0.6925	0.6556	0.6672	0.6621	0.6433	0.6474	0.6365	0.6514	0.6431	0.6819
%rrmse	(0.703)	(0.755)	(0.815)	(0.751)	(0.724)	(0.4)	(0.724)	(1.111)	(0.999)	(0.888)	(0.927)	(0.59)
%rrmseMB	(0.705)	(0.849)	(0.824)	(0.731)	(0.762)	(0.373)	(0.656)	(1.332)	(0.952)	(0.889)	(1.199)	(0.586)
%rrmsePDB	(0.6)	(0.925)	(1.704)	(0.672)	(1.031)	(0.385)	(0.642)	(1.949)	(0.955)	(0.875)	(1.409)	(0.487)
BM	0.6263	0.6224	0.6978	0.6606	0.6723	0.6672	0.6482	0.6524	0.6414	0.6564	0.6480	0.6870
%rrmse	(0.995)	(1.069)	(1.074)	(1.054)	(1.01)	(0.824)	(1.056)	(1.349)	(1.234)	(1.186)	(1.194)	(0.928)
%rrmseMB	(0.769)	(0.902)	(0.971)	(0.876)	(0.885)	(0.404)	(0.784)	(1.518)	(1.107)	(1.069)	(1.367)	(0.686)
%rrmsePDB	(0.606)	(0.921)	(1.698)	(0.662)	(1.024)	(0.371)	(0.635)	(1.943)	(0.947)	(0.867)	(1.402)	(0.487)

	LU00			UR00	SZ00						OW00	NW00
Nr	303	304	305	400	501	502	503	504	505	506	600	700
size	9168	3634	2503	895	371	62	703	333	1073	1405	922	1183
GREG	0.6647	0.7	0.6866	0.6277	0.6531	0.6125	0.7031	0.7109	0.6984	0.6831	0.7212	0.6625
%CV(GREG)	(0.721)	(1.058)	(1.313)	(2.555)	(3.747)	(10.001)	(2.425)	(3.469)	(1.986)	(1.799)	(2.018)	(2.065)
LMM	0.6626	0.7004	0.6914	0.6365	0.6793	0.6354	0.6889	0.6929	0.6973	0.6815	0.6977	0.6696
%rrmse	(0.402)	(0.616)	(0.659)	(0.991)	(1.215)	(1.741)	(1.091)	(1.199)	(0.917)	(0.865)	(0.939)	(0.888)
%rrmseMB	(0.385)	(0.611)	(0.615)	(1.559)	(1.146)	(1.858)	(1.026)	(1.149)	(1.094)	(0.803)	(1.449)	(1.089)
%rrmsePDB	(0.447)	(0.497)	(0.581)	(2.018)	(0.457)	(1.043)	(0.535)	(0.495)	(1.23)	(0.571)	(2.25)	(1.44)
BM	0.6676	0.7058	0.6967	0.6413	0.6845	0.6403	0.6941	0.6982	0.7027	0.6867	0.7030	0.6747
%rrmse	(0.824)	(0.938)	(0.947)	(1.208)	(1.417)	(1.939)	(1.306)	(1.374)	(1.175)	(1.119)	(1.186)	(1.208)
%rrmseMB	(0.466)	(0.688)	(0.738)	(1.562)	(1.298)	(2.044)	(1.148)	(1.274)	(1.154)	(0.91)	(1.602)	(1.169)

%rrmsePDB	(0.441)	(0.498)	(0.576)	(2.018)	(0.442)	(1.032)	(0.521)	(0.481)	(1.228)	(0.561)	(2.241)	(1.439)

	GL00	ZG00	FR00							SO00		
Nr	800	900	1001	1002	1003	1004	1005	1006	1007	1101	1102	1103
size	1030	6086	730	571	1238	2509	816	1050	448	493	347	221
GREG	0.6852	0.6833	0.6723	0.6756	0.6492	0.678	0.688	0.6981	0.7263	0.6632	0.6505	0.6715
%CV(GREG)	(2.062)	(0.845)	(2.546)	(2.865)	(2.062)	(1.354)	(2.323)	(1.999)	(2.869)	(3.175)	(3.886)	(4.635)
LMM	0.6682	0.6798	0.6756	0.6752	0.6665	0.6701	0.6865	0.6790	0.7076	0.6901	0.6500	0.6784
%rrmse	(0.918)	(0.467)	(1.031)	(1.135)	(0.879)	(0.74)	(0.959)	(0.953)	(0.972)	(1.044)	(1.208)	(1.255)
%rrmseMB	(0.921)	(0.466)	(0.961)	(1.064)	(1.014)	(0.762)	(0.976)	(0.874)	(1.235)	(1.526)	(1.237)	(1.68)
%rrmsePDB	(1.36)	(0.42)	(0.578)	(0.546)	(1.485)	(0.889)	(0.66)	(0.661)	(1.96)	(2.087)	(0.821)	(1.747)
BM	0.6733	0.6850	0.6807	0.6803	0.6715	0.6752	0.6917	0.6842	0.713	0.6953	0.6549	0.6835
%rrmse	(1.165)	(0.908)	(1.265)	(1.327)	(1.153)	(1.066)	(1.12)	(1.152)	(1.165)	(1.259)	(1.431)	(1.44)
%rrmseMB	(1.075)	(0.549)	(1.101)	(1.189)	(1.074)	(0.838)	(1.036)	(1.009)	(1.388)	(1.574)	(1.428)	(1.756)
%rrmsePDB	(1.355)	(0.414)	(0.571)	(0.533)	(1.49)	(0.888)	(0.656)	(0.648)	(1.954)	(2.088)	(0.811)	(1.748)

	SO00							BS00	BL00			
Nr	1104	1105	1106	1107	1108	1109	1110	1200	1301	1302	1303	1304
size	523	619	1261	1195	1396	428	339	4609	4070	509	1431	873
GREG	0.6169	0.6403	0.6641	0.6425	0.6554	0.6908	0.5957	0.6075	0.6015	0.668	0.6536	0.676
%CV(GREG)	(3.399)	(2.978)	(1.978)	(2.133)	(1.92)	(3.195)	(4.418)	(1.178)	(1.261)	(3.082)	(1.902)	(2.311)
LMM	0.6369	0.6519	0.6568	0.6357	0.6587	0.6851	0.6311	0.6001	0.5979	0.6579	0.6375	0.6720
%rrmse	(1.235)	(1.055)	(0.933)	(0.874)	(0.969)	(1.136)	(1.227)	(0.601)	(0.676)	(1.138)	(0.943)	(0.926)
%rrmseMB	(1.216)	(1.063)	(0.904)	(0.89)	(0.927)	(1.125)	(1.773)	(0.794)	(0.779)	(1.042)	(0.871)	(1.109)
%rrmsePDB	(0.801)	(0.622)	(1.184)	(0.762)	(0.898)	(1.466)	(1.913)	(0.897)	(1.189)	(0.727)	(0.68)	(1.902)
BM	0.6417	0.6568	0.6618	0.6405	0.6637	0.6903	0.6359	0.6047	0.6024	0.6629	0.6424	0.6771
%rrmse	(1.447)	(1.29)	(1.17)	(1.121)	(1.222)	(1.254)	(1.384)	(0.964)	(1.042)	(1.314)	(1.148)	(1.139)
%rrmseMB	(1.339)	(1.195)	(0.985)	(0.986)	(1.019)	(1.233)	(1.804)	(0.785)	(0.799)	(1.172)	(0.955)	(1.254)
%rrmsePDB	(0.8)	(0.616)	(1.184)	(0.759)	(0.897)	(1.461)	(1.913)	(0.895)	(1.19)	(0.725)	(0.663)	(1.896)

	BL00	SH00						AR00			AI00	SG00
Nr	1305	1401	1402	1403	1404	1405	1406	1501	1502	1503	1600	1721
size	399	106	202	1368	90	162	122	600	413	389	362	3051
GREG	0.6548	0.7135	0.741	0.6253	0.6717	0.6936	0.7448	0.6773	0.6734	0.7078	0.686	0.6634
%CV(GREG)	(3.592)	(5.994)	(4.049)	(2.059)	(7.213)	(5.12)	(5.14)	(2.755)	(3.347)	(3.172)	(3.511)	(1.272)
LMM	0.6501	0.6798	0.6689	0.6246	0.6244	0.629	0.6551	0.6669	0.6584	0.6648	0.6701	0.6583
%rrmse	(1.268)	(1.335)	(1.237)	(0.879)	(1.569)	(1.37)	(1.489)	(1.074)	(1.062)	(1.176)	(1.004)	(0.677)
%rrmseMB	(1.195)	(2.208)	(2.374)	(1.264)	(2.421)	(2.831)	(1.906)	(1.001)	(1.279)	(1.939)	(1.186)	(0.701)
%rrmsePDB	(0.549)	(2.444)	(3.265)	(1.802)	(1.028)	(3.436)	(1.821)	(0.751)	(1.467)	(2.328)	(1.448)	(0.705)
BM	0.655	0.685	0.674	0.6294	0.6292	0.6338	0.6601	0.672	0.6635	0.6699	0.6752	0.6633
%rrmse	(1.435)	(1.516)	(1.439)	(1.161)	(1.693)	(1.526)	(1.631)	(1.295)	(1.321)	(1.357)	(1.266)	(1.022)
%rrmseMB	(1.312)	(2.332)	(2.502)	(1.287)	(2.514)	(2.925)	(2.03)	(1.16)	(1.475)	(2.067)	(1.388)	(0.773)
%rrmsePDB	(0.535)	(2.44)	(3.259)	(1.805)	(1.02)	(3.431)	(1.817)	(0.738)	(1.461)	(2.321)	(1.443)	(0.7)

	SG00							GR00				

Nr	1722	1723	1724	1725	1726	1727	1728	1821	1822	1823	1824	1825
size	1039	1767	891	966	1678	1136	1841	256	120	326	477	261
GREG	0.6506	0.6845	0.703	0.693	0.6658	0.6541	0.6701	0.6486	0.576	0.6397	0.6507	0.6686
%CV(GREG)	(2.239)	(1.589)	(2.132)	(2.099)	(1.703)	(2.124)	(1.609)	(4.552)	(7.78)	(4.109)	(3.327)	(4.317)
LMM	0.6604	0.6723	0.6785	0.6527	0.6703	0.6459	0.6694	0.6431	0.5776	0.6411	0.6728	0.6560
%rrmse	(0.953)	(0.789)	(1.413)	(0.925)	(0.848)	(0.913)	(0.745)	(1.185)	(1.57)	(1.26)	(1.116)	(1.334)
%rrmseMB	(0.961)	(0.882)	(1.49)	(1.365)	(0.823)	(0.936)	(0.746)	(1.226)	(2.026)	(1.189)	(1.25)	(1.765)
%rrmsePDB	(1.119)	(1.824)	(1.29)	(2.287)	(0.558)	(0.663)	(0.73)	(0.954)	(1.8)	(0.508)	(1.046)	(1.624)
BM	0.6654	0.6774	0.6837	0.6577	0.6754	0.6508	0.6745	0.6480	0.5821	0.6459	0.678	0.6610
%rrmse	(1.166)	(1.061)	(1.491)	(1.188)	(1.094)	(1.196)	(1.064)	(1.395)	(1.707)	(1.552)	(1.332)	(1.517)
%rrmseMB	(1.083)	(1.027)	(1.505)	(1.526)	(0.911)	(1.072)	(0.853)	(1.41)	(2.089)	(1.431)	(1.35)	(1.911)
%rrmsePDB	(1.108)	(1.816)	(1.287)	(2.279)	(0.551)	(0.652)	(0.726)	(0.943)	(1.797)	(0.503)	(1.043)	(1.616)

	GR00						AG00					
Nr	1826	1827	1828	1829	1830	1831	1901	1902	1903	1904	1905	1906
size	690	493	214	1096	660	541	3805	6956	3683	2409	1954	1594
GREG	0.7163	0.6892	0.6042	0.6746	0.6615	0.6071	0.6723	0.6944	0.6692	0.6629	0.6607	0.6709
%CV(GREG)	(2.377)	(2.993)	(5.493)	(2.079)	(2.758)	(3.429)	(1.096)	(0.77)	(1.123)	(1.409)	(1.569)	(1.695)
LMM	0.6845	0.6871	0.5966	0.6584	0.6604	0.6294	0.6689	0.6806	0.6765	0.6615	0.6512	0.6734
%rrmse	(1.029)	(1.062)	(1.379)	(0.924)	(1.058)	(1.124)	(0.608)	(0.433)	(0.584)	(0.653)	(0.758)	(0.807)
%rrmseMB	(1.317)	(1.002)	(1.745)	(0.938)	(1.119)	(1.061)	(0.609)	(0.477)	(0.679)	(0.722)	(0.741)	(0.774)
%rrmsePDB	(1.699)	(0.619)	(1.652)	(0.667)	(1.189)	(0.657)	(0.551)	(0.56)	(0.486)	(0.589)	(0.535)	(0.736)
BM	0.6897	0.6923	0.6011	0.6634	0.6654	0.6342	0.674	0.6857	0.6816	0.6666	0.6562	0.6785
%rrmse	(1.285)	(1.237)	(1.528)	(1.197)	(1.276)	(1.376)	(0.963)	(0.857)	(0.943)	(1.008)	(0.995)	(1.075)
%rrmseMB	(1.493)	(1.134)	(1.805)	(1.047)	(1.281)	(1.24)	(0.675)	(0.506)	(0.716)	(0.803)	(0.823)	(0.887)
%rrmsePDB	(1.689)	(0.604)	(1.649)	(0.655)	(1.175)	(0.639)	(0.551)	(0.561)	(0.498)	(0.584)	(0.53)	(0.733)

	AG00					TG00					TI00	
Nr	1907	1908	1909	1910	1911	2011	2012	2013	2014	2015	2101	2102
size	2941	1575	2299	3367	1645	2656	3324	2316	2276	2603	2577	262
GREG	0.6883	0.7298	0.6661	0.6794	0.6564	0.6378	0.6897	0.6794	0.6971	0.6989	0.5797	0.5559
%CV(GREG)	(1.202)	(1.481)	(1.431)	(1.146)	(1.728)	(1.422)	(1.129)	(1.386)	(1.337)	(1.248)	(1.628)	(5.36)
LMM	0.6833	0.7177	0.6569	0.6803	0.6562	0.6404	0.6856	0.6670	0.6971	0.6902	0.5812	0.5390
%rrmse	(0.632)	(0.79)	(0.718)	(0.587)	(0.823)	(0.658)	(0.633)	(0.738)	(0.665)	(0.652)	(0.804)	(1.522)
%rrmseMB	(0.619)	(0.897)	(0.741)	(0.569)	(0.794)	(0.756)	(0.618)	(0.771)	(0.677)	(0.757)	(1.01)	(1.71)
%rrmsePDB	(0.504)	(1.415)	(0.641)	(0.587)	(0.687)	(0.953)	(0.873)	(1.669)	(1.694)	(1.501)	(2.086)	(1.104)
BM	0.6885	0.7232	0.6619	0.6855	0.6612	0.6453	0.6908	0.6721	0.7024	0.6954	0.5856	0.5431
%rrmse	(0.964)	(1.023)	(0.952)	(0.901)	(1.086)	(0.943)	(0.996)	(1.01)	(0.967)	(0.964)	(1.053)	(1.630)
%rrmseMB	(0.717)	(1.043)	(0.787)	(0.69)	(0.896)	(0.8)	(0.751)	(0.902)	(0.821)	(0.901)	(1.014)	(1.755)
%rrmsePDB	(0.494)	(1.414)	(0.635)	(0.584)	(0.68)	(0.951)	(0.864)	(1.662)	(1.689)	(1.492)	(2.087)	(1.105)

	TI00						VD00					
Nr	2103	2104	2105	2106	2107	2108	2221	2222	2223	2224	2225	2226
size	512	3271	7664	2739	685	314	1986	1923	2029	4325	7617	2915

GREG	0.57	0.5601	0.5675	0.5535	0.5774	0.5962	0.6083	0.6531	0.7063	0.6441	0.6509	0.613
%CV(GREG)	(3.728)	(1.504)	(0.969)	(1.667)	(3.172)	(4.508)	(1.746)	(1.609)	(1.381)	(1.094)	(0.816)	(1.427)
LMM	0.5810	0.5579	0.5731	0.5578	0.5733	0.5828	0.6184	0.6398	0.6930	0.6343	0.6473	0.6147
%rrmse	(1.23)	(0.824)	(0.524)	(0.869)	(1.238)	(1.468)	(0.828)	(0.789)	(0.692)	(0.58)	(0.457)	(0.744)
%rrmseMB	(1.321)	(0.879)	(0.684)	(1.083)	(1.903)	(1.465)	(0.781)	(0.791)	(0.618)	(0.598)	(0.484)	(0.728)
%rrmsePDB	(1.2)	(1.162)	(0.896)	(1.306)	(2.81)	(1.031)	(0.869)	(0.702)	(0.652)	(0.652)	(0.373)	(0.858)
BM	0.5854	0.5622	0.5774	0.562	0.5777	0.5873	0.6231	0.6447	0.6983	0.6391	0.6523	0.6194
%rrmse	(1.451)	(1.128)	(0.885)	(1.112)	(1.444)	(1.611)	(1.081)	(1.093)	(1.017)	(0.908)	(0.893)	(1.022)
%rrmseMB	(1.433)	(0.908)	(0.669)	(1.075)	(1.915)	(1.558)	(0.862)	(0.899)	(0.753)	(0.667)	(0.525)	(0.803)
%rrmsePDB	(1.202)	(1.164)	(0.905)	(1.313)	(2.812)	(1.032)	(0.867)	(0.694)	(0.651)	(0.65)	(0.374)	(0.861)

	VD00				VS00							
Nr	2227	2228	2229	2230	2301	2302	2303	2304	2305	2306	2307	2308
size	3861	4498	3468	3993	661	625	371	138	301	297	1152	1110
GREG	0.6603	0.6492	0.6543	0.6249	0.6049	0.663	0.6294	0.5769	0.6146	0.6043	0.6461	0.6459
%CV(GREG)	(1.117)	(1.063)	(1.196)	(1.188)	(3.104)	(2.821)	(3.93)	(7.219)	(4.507)	(4.638)	(2.157)	(2.195)
LMM	0.6562	0.6469	0.6468	0.6142	0.6306	0.6521	0.6232	0.6076	0.5931	0.6261	0.6548	0.6465
%rrmse	(0.633)	(0.547)	(0.582)	(0.669)	(1.088)	(1.086)	(1.295)	(1.41)	(1.422)	(1.282)	(0.936)	(0.926)
%rrmseMB	(0.64)	(0.637)	(0.688)	(0.597)	(1.881)	(1.078)	(1.318)	(2.269)	(1.562)	(2.854)	(1.084)	(0.941)
%rrmsePDB	(0.535)	(0.493)	(0.648)	(0.537)	(2.926)	(0.537)	(0.954)	(2.796)	(1.291)	(4.413)	(1.029)	(0.948)
BM	0.6612	0.6518	0.6517	0.6189	0.6354	0.6571	0.6279	0.6122	0.5976	0.6309	0.6597	0.6515
%rrmse	(0.864)	(0.899)	(0.961)	(0.997)	(1.383)	(1.254)	(1.461)	(1.57)	(1.564)	(1.438)	(1.208)	(1.157)
%rrmseMB	(0.657)	(0.671)	(0.741)	(0.693)	(1.924)	(1.168)	(1.418)	(2.314)	(1.69)	(2.837)	(1.151)	(1.027)
%rrmsePDB	(0.54)	(0.503)	(0.65)	(0.532)	(2.928)	(0.536)	(0.954)	(2.796)	(1.286)	(4.414)	(1.026)	(0.947)

	VS00					NE00						GE00
Nr	2309	2310	2311	2312	2313	2401	2402	2403	2404	2405	2406	2500
size	287	355	1177	1124	663	2052	1980	696	2665	814	581	20786
GREG	0.6144	0.6621	0.6161	0.6325	0.6723	0.6304	0.6358	0.593	0.6347	0.6821	0.6044	0.6218
%CV(GREG)	(4.612)	(3.749)	(2.273)	(2.251)	(2.672)	(1.636)	(1.646)	(3.04)	(1.421)	(2.308)	(3.248)	(0.525)
LMM	0.6211	0.6462	0.6176	0.6324	0.6743	0.6239	0.6223	0.6109	0.6293	0.6710	0.5865	0.6124
%rrmse	(1.33)	(1.177)	(0.949)	(0.924)	(0.994)	(0.788)	(0.801)	(1.072)	(0.695)	(0.905)	(1.145)	(0.31)
%rrmseMB	(1.874)	(1.122)	(0.978)	(1.146)	(1.214)	(0.74)	(0.792)	(1.053)	(0.661)	(0.878)	(1.1)	(0.345)
%rrmsePDB	(2)	(0.54)	(0.631)	(1.483)	(1.622)	(0.671)	(0.931)	(0.863)	(0.673)	(0.644)	(0.785)	(0.282)
BM	0.6259	0.6511	0.6223	0.6373	0.6795	0.6287	0.6270	0.6156	0.6341	0.6761	0.5910	0.6171
%rrmse	(1.457)	(1.38)	(1.227)	(1.17)	(1.164)	(1.084)	(1.087)	(1.303)	(1.024)	(1.134)	(1.315)	(0.81)
%rrmseMB	(1.895)	(1.293)	(1.08)	(1.185)	(1.256)	(0.867)	(0.877)	(1.21)	(0.786)	(1.026)	(1.202)	(0.346)
%rrmsePDB	(1.998)	(0.52)	(0.617)	(1.482)	(1.622)	(0.658)	(0.922)	(0.859)	(0.674)	(0.647)	(0.787)	(0.284)

	JU00		
Nr	2601	2602	2603
size	1817	493	1292
GREG	0.6064	0.6858	0.5935
%CV(GREG)	(1.836)	(2.948)	(2.233)

LMM	0.6147	0.6448	0.5813
%rrmse	(0.889)	(1.125)	(0.975)
%rrmseMB	(0.94)	(1.33)	(1.257)
%rrmsePDB	(0.952)	(1.861)	(1.141)
BM	0.6194	0.6497	0.5857
%rrmse	(1.118)	(1.361)	(1.211)
%rrmseMB	(0.981)	(1.511)	(1.284)
%rrmsePDB	(0.954)	(1.858)	(1.141)

Appendix 4: Estimates of district proportions with 95% CIs

Table 4: Estimated district proportions of active people together with a 95% confidence intervals based on parametric bootstrap MSE estimates.

	ZH00											
Nr	101	102	103	104	105	106	107	108	109	110	111	112
size	1309	807	3455	2113	2294	3088	2600	1488	3220	4075	2063	9510
LMM	0.6821	0.6803	0.6963	0.7113	0.6783	0.6592	0.6311	0.6838	0.6808	0.6783	0.6703	0.6932
UL	0.6934	0.6931	0.7047	0.7213	0.6881	0.6674	0.6403	0.6948	0.6892	0.6860	0.6800	0.6990
LL	0.6708	0.6675	0.6879	0.7014	0.6685	0.651	0.6218	0.6728	0.6723	0.6707	0.6607	0.6874
BM	0.6873	0.6855	0.7016	0.7168	0.6835	0.6642	0.6359	0.6890	0.6860	0.6835	0.6755	0.6985
UL	0.7023	0.7018	0.7143	0.7303	0.6976	0.6770	0.6489	0.7041	0.6994	0.6958	0.6896	0.7100
LL	0.6722	0.6692	0.6888	0.7033	0.6694	0.6514	0.6229	0.674	0.6725	0.6712	0.6613	0.6870

	BE02	BE00									LU00	
Nr	241	242	243	244	245	246	247	248	249	250	301	302
size	2706	2420	1800	2079	2556	10294	2870	404	1013	1210	909	3493
LMM	0.6216	0.6177	0.6925	0.6556	0.6672	0.6621	0.6433	0.6474	0.6365	0.6514	0.6431	0.6819
UL	0.6302	0.6268	0.7036	0.6652	0.6767	0.6673	0.6524	0.6615	0.649	0.6628	0.6548	0.6897
LL	0.6130	0.6086	0.6815	0.6459	0.6577	0.6569	0.6341	0.6333	0.6241	0.6401	0.6315	0.674
BM	0.6263	0.6224	0.6978	0.6606	0.6723	0.6672	0.6482	0.6524	0.6414	0.6564	0.6480	0.6870
UL	0.6386	0.6355	0.7125	0.6742	0.6856	0.6780	0.6616	0.6696	0.6569	0.6716	0.6632	0.6996
LL	0.6141	0.6094	0.6831	0.6469	0.6590	0.6564	0.6347	0.6351	0.6259	0.6411	0.6329	0.6745

	LU00			UR00	SZ00						OW00	NW00
Nr	303	304	305	400	501	502	503	504	505	506	600	700
size	9168	3634	2503	895	371	62	703	333	1073	1405	922	1183
LMM	0.6626	0.7004	0.6914	0.6365	0.6793	0.6354	0.6889	0.6929	0.6973	0.6815	0.6977	0.6696
UL	0.6678	0.7089	0.7004	0.6488	0.6955	0.6571	0.7036	0.7092	0.7099	0.6931	0.7105	0.6812
LL	0.6574	0.6920	0.6825	0.6241	0.6631	0.6137	0.6741	0.6766	0.6848	0.6700	0.6848	0.6579
BM	0.6676	0.7058	0.6967	0.6413	0.6845	0.6403	0.6941	0.6982	0.7027	0.6867	0.7030	0.6747
UL	0.6784	0.7187	0.7096	0.6565	0.7035	0.6646	0.7119	0.7170	0.7188	0.7018	0.7193	0.6907
LL	0.6568	0.6928	0.6838	0.6261	0.6655	0.6159	0.6763	0.6794	0.6865	0.6717	0.6867	0.6587

	GL00	ZG00	FR00							SO00		
Nr	800	900	1001	1002	1003	1004	1005	1006	1007	1101	1102	1103
size	1030	6086	730	571	1238	2509	816	1050	448	493	347	221
LMM	0.6682	0.6798	0.6756	0.6752	0.6665	0.6701	0.6865	0.679	0.7076	0.6901	0.65	0.6784
UL	0.6802	0.6861	0.6892	0.6902	0.6779	0.6798	0.6994	0.6917	0.7211	0.7042	0.6654	0.6950
LL	0.6562	0.6736	0.6619	0.6602	0.6550	0.6603	0.6736	0.6663	0.6942	0.6760	0.6346	0.6617
BM	0.6733	0.6850	0.6807	0.6803	0.6715	0.6752	0.6917	0.6842	0.713	0.6953	0.6549	0.6835
UL	0.6887	0.6972	0.6976	0.698	0.6867	0.6893	0.7069	0.6996	0.7293	0.7125	0.6733	0.7028
LL	0.6579	0.6728	0.6638	0.6626	0.6564	0.6611	0.6766	0.6687	0.6968	0.6782	0.6366	0.6642

	SO00							BS00	BL00			
Nr	1104	1105	1106	1107	1108	1109	1110	1200	1301	1302	1303	1304
size	523	619	1261	1195	1396	428	339	4609	4070	509	1431	873
LMM	0.6369	0.6519	0.6568	0.6357	0.6587	0.6851	0.6311	0.6001	0.5979	0.6579	0.6375	0.672
UL	0.6523	0.6654	0.6688	0.6466	0.6712	0.7003	0.6463	0.6072	0.6058	0.6725	0.6493	0.6842
LL	0.6215	0.6384	0.6448	0.6248	0.6462	0.6698	0.6159	0.5931	0.59	0.6432	0.6257	0.6598
BM	0.6417	0.6568	0.6618	0.6405	0.6637	0.6903	0.6359	0.6047	0.6024	0.6629	0.6424	0.6771
UL	0.6599	0.6735	0.6770	0.6546	0.6796	0.7072	0.6532	0.6161	0.6148	0.6799	0.6568	0.6922
LL	0.6235	0.6402	0.6466	0.6264	0.6478	0.6733	0.6187	0.5933	0.5901	0.6458	0.6279	0.662

	BL00	SH00						AR00			AI00	SG00
Nr	1305	1401	1402	1403	1404	1405	1406	1501	1502	1503	1600	1721
size	399	106	202	1368	90	162	122	600	413	389	362	3051
LMM	0.6501	0.6798	0.6689	0.6246	0.6244	0.629	0.6551	0.6669	0.6584	0.6648	0.6701	0.6583
UL	0.6662	0.6976	0.6851	0.6354	0.6436	0.6459	0.6742	0.6810	0.6721	0.6802	0.6833	0.6671
LL	0.6339	0.6620	0.6527	0.6139	0.6052	0.6121	0.6360	0.6529	0.6447	0.6495	0.6569	0.6496
BM	0.655	0.685	0.674	0.6294	0.6292	0.6338	0.6601	0.672	0.6635	0.6699	0.6752	0.6633
UL	0.6735	0.7054	0.693	0.6437	0.6501	0.6528	0.6812	0.6891	0.6806	0.6877	0.6920	0.6766
LL	0.6366	0.6647	0.6550	0.6151	0.6083	0.6149	0.6390	0.655	0.6463	0.6521	0.6584	0.6501

	SG00							GR00				
Nr	1722	1723	1724	1725	1726	1727	1728	1821	1822	1823	1824	1825
size	1039	1767	891	966	1678	1136	1841	256	120	326	477	261
LMM	0.6604	0.6723	0.6785	0.6527	0.6703	0.6459	0.6694	0.6431	0.5776	0.6411	0.6728	0.656
UL	0.6727	0.6827	0.6973	0.6646	0.6815	0.6575	0.6791	0.6581	0.5954	0.6569	0.6875	0.6731
LL	0.6481	0.6619	0.6598	0.6409	0.6592	0.6343	0.6596	0.6282	0.5599	0.6252	0.6581	0.6388
BM	0.6654	0.6774	0.6837	0.6577	0.6754	0.6508	0.6745	0.6480	0.5821	0.6459	0.6780	0.6610
UL	00.6806	0.6915	0.7037	0.673	0.6899	0.6661	0.6885	0.6658	0.6015	0.6656	0.6957	0.6806
LL	0.6502	0.6633	0.6637	0.6424	0.6609	0.6356	0.6604	0.6303	0.5626	0.6263	0.6603	0.6413

	GR00						AG00					
Nr	1826	1827	1828	1829	1830	1831	1901	1902	1903	1904	1905	1906
size	690	493	214	1096	660	541	3805	6956	3683	2409	1954	1594
LMM	0.6845	0.6871	0.5966	0.6584	0.6604	0.6294	0.6689	0.6806	0.6765	0.6615	0.6512	0.6734
UL	0.6983	0.7014	0.6127	0.6703	0.6741	0.6433	0.6769	0.6863	0.6842	0.6700	0.6609	0.6840
LL	0.6707	0.6728	0.5804	0.6464	0.6467	0.6155	0.6609	0.6748	0.6687	0.6531	0.6415	0.6627
BM	0.6897	0.6923	0.6011	0.6634	0.6654	0.6342	0.674	0.6857	0.6816	0.6666	0.6562	0.6785
UL	0.7071	0.7091	0.6191	0.679	0.6821	0.6513	0.6867	0.6973	0.6942	0.6797	0.6690	0.6928
LL	0.6723	0.6755	0.5831	0.6478	0.6488	0.6171	0.6613	0.6742	0.6690	0.6534	0.6434	0.6642

	AG00					TG00					TI00	
Nr	1907	1908	1909	1910	1911	2011	2012	2013	2014	2015	2101	2102
size	2941	1575	2299	3367	1645	2656	3324	2316	2276	2603	2577	262
LMM	0.6833	0.7177	0.6569	0.6803	0.6562	0.6404	0.6856	0.667	0.6971	0.6902	0.5812	0.539

UL	0.6917	0.7288	0.6661	0.6881	0.6668	0.6486	0.6941	0.6767	0.7061	0.6990	0.5904	0.5550
LL	0.6748	0.7066	0.6476	0.6725	0.6456	0.6321	0.6771	0.6574	0.688	0.6814	0.5721	0.5229
BM	0.6885	0.7232	0.6619	0.6855	0.6612	0.6453	0.6908	0.6721	0.7024	0.6954	0.5856	0.5431
UL	0.7015	0.7377	0.6742	0.6976	0.6753	0.6572	0.7043	0.6854	0.7157	0.7086	0.5977	0.5604
LL	0.6755	0.7087	0.6495	0.6734	0.6471	0.6333	0.6774	0.6588	0.6891	0.6823	0.5735	0.5257
	TI00						VD00					
Nr	2103	2104	2105	2106	2107	2108	2221	2222	2223	2224	2225	2226
size	512	3271	7664	2739	685	314	1986	1923	2029	4325	7617	2915
LMM	0.581	0.5579	0.5731	0.5578	0.5733	0.5828	0.6184	0.6398	0.693	0.6343	0.6473	0.6147
UL	0.5950	0.5669	0.5789	0.5673	0.5873	0.5996	0.6284	0.6497	0.7024	0.6415	0.6531	0.6237
LL	0.5670	0.5489	0.5672	0.5483	0.5594	0.566	0.6084	0.6299	0.6836	0.6271	0.6415	0.6058
BM	0.5854	0.5622	0.5774	0.562	0.5777	0.5873	0.6231	0.6447	0.6983	0.6391	0.6523	0.6194
UL	0.6020	0.5746	0.5874	0.5743	0.5941	0.6058	0.6363	0.6585	0.7122	0.6505	0.6637	0.6318
LL	0.5688	0.5498	0.5674	0.5498	0.5614	0.5687	0.6099	0.6309	0.6844	0.6278	0.6409	0.6070
	VD00				VS00							
Nr	2227	2228	2229	2230	2301	2302	2303	2304	2305	2306	2307	2308
size	3861	4498	3468	3993	661	625	371	138	301	297	1152	1110
LMM	0.6562	0.6469	0.6468	0.6142	0.6306	0.6521	0.6232	0.6076	0.5931	0.6261	0.6548	0.6465
UL	0.6643	0.6538	0.6542	0.6223	0.6440	0.666	0.6390	0.6244	0.6097	0.6418	0.6668	0.6583
LL	0.6480	0.6399	0.6394	0.6061	0.6171	0.6382	0.6073	0.5908	0.5766	0.6104	0.6427	0.6348
BM	0.6612	0.6518	0.6517	0.6189	0.6354	0.6571	0.6279	0.6122	0.5976	0.6309	0.6597	0.6515
UL	0.6724	0.6633	0.664	0.631	0.6526	0.6732	0.6459	0.6311	0.6160	0.6486	0.6754	0.6662
LL	0.6500	0.6403	0.6395	0.6068	0.6181	0.6409	0.6099	0.5934	0.5793	0.6131	0.6441	0.6367
	VS00					NE00						GE00
Nr	2309	2310	2311	2312	2313	2401	2402	2403	2404	2405	2406	2500
size	287	355	1177	1124	663	2052	1980	696	2665	814	581	20786
LMM	0.6211	0.6462	0.6176	0.6324	0.6743	0.6239	0.6223	0.6109	0.6293	0.6710	0.5865	0.6124
UL	0.6373	0.6611	0.6291	0.6439	0.6875	0.6336	0.6321	0.6238	0.6378	0.6829	0.5996	0.6161
LL	0.6050	0.6313	0.6061	0.621	0.6612	0.6143	0.6125	0.5981	0.6207	0.6591	0.5733	0.6087
BM	0.6259	0.6511	0.6223	0.6373	0.6795	0.6287	0.6270	0.6156	0.6341	0.6761	0.5910	0.6171
UL	0.6438	0.6687	0.6373	0.6519	0.6950	0.6420	0.6404	0.6313	0.6468	0.6912	0.6062	0.6269
LL	0.6080	0.6335	0.6074	0.6226	0.664	0.6153	0.6137	0.5999	0.6213	0.6611	0.5757	0.6073
	JU00											
Nr	2601	2602	2603									
size	1817	493	1292									
LMM	0.6147	0.6448	0.5813									
UL	0.6254	0.659	0.5924									
LL	0.6040	0.6306	0.5702									
BM	0.6194	0.6497	0.5857									
UL	0.633	0.6671	0.5996									

LL	0.6058	0.6324	0.5718

Table 5: Estimated district proportions of active people together with a 95% confidence intervals based on MB MSE estimates.

	ZH00											
Nr	101	102	103	104	105	106	107	108	109	110	111	112
size	1309	807	3455	2113	2294	3088	2600	1488	3220	4075	2063	9510
LMM	0.6821	0.6803	0.6963	0.7113	0.6783	0.6592	0.6311	0.6838	0.6808	0.6783	0.6703	0.6932
UL	0.694	0.6929	0.704	0.7211	0.6882	0.6675	0.6413	0.6943	0.6893	0.6858	0.6794	0.6984
LL	0.6702	0.6677	0.6886	0.7016	0.6685	0.6508	0.6209	0.6733	0.6722	0.6709	0.6613	0.688
BM	0.6873	0.6855	0.7016	0.7168	0.6835	0.6642	0.6359	0.6890	0.6860	0.6835	0.6755	0.6985
UL	0.7004	0.7003	0.7106	0.7282	0.6945	0.6737	0.6466	0.7016	0.6957	0.6922	0.6863	0.7046
LL	0.6742	0.6706	0.6926	0.7054	0.6725	0.6547	0.6252	0.6765	0.6762	0.6748	0.6646	0.6925
	BE02	BE00									LU00	
Nr	241	242	243	244	245	246	247	248	249	250	301	302
size	2706	2420	1800	2079	2556	10294	2870	404	1013	1210	909	3493
LMM	0.6216	0.6177	0.6925	0.6556	0.6672	0.6621	0.6433	0.6474	0.6365	0.6514	0.6431	0.6819
UL	0.6302	0.628	0.7037	0.665	0.6772	0.667	0.6515	0.6643	0.6484	0.6628	0.6582	0.6897
LL	0.613	0.6074	0.6813	0.6462	0.6572	0.6573	0.635	0.6305	0.6247	0.6401	0.628	0.674
BM	0.6263	0.6224	0.6978	0.6606	0.6723	0.6672	0.6482	0.6524	0.6414	0.6564	0.6480	0.6870
UL	0.6358	0.6334	0.7111	0.6719	0.6839	0.6725	0.6581	0.6718	0.6553	0.6701	0.6654	0.6963
LL	0.6169	0.6114	0.6845	0.6492	0.6606	0.6619	0.6382	0.633	0.6275	0.6426	0.6307	0.6778
	LU00			UR00	SZ00						OW00	NW00
Nr	303	304	305	400	501	502	503	504	505	506	600	700
size	9168	3634	2503	895	371	62	703	333	1073	1405	922	1183
LMM	0.6626	0.7004	0.6914	0.6365	0.6793	0.6354	0.6889	0.6929	0.6973	0.6815	0.6977	0.6696
UL	0.6676	0.7088	0.6998	0.6559	0.6946	0.6585	0.7027	0.7085	0.7123	0.6923	0.7175	0.6839
LL	0.6576	0.692	0.6831	0.617	0.6641	0.6123	0.675	0.6773	0.6824	0.6708	0.6779	0.6553
BM	0.6676	0.7058	0.6967	0.6413	0.6845	0.6403	0.6941	0.6982	0.7027	0.6867	0.7030	0.6747
UL	0.6737	0.7153	0.7068	0.661	0.7019	0.6659	0.7097	0.7156	0.7186	0.699	0.7251	0.6901
LL	0.6615	0.6963	0.6866	0.6217	0.6671	0.6146	0.6785	0.6807	0.6868	0.6745	0.6809	0.6592
	GL00	ZG00	FR00							SO00		
Nr	800	900	1001	1002	1003	1004	1005	1006	1007	1101	1102	1103
size	1030	6086	730	571	1238	2509	816	1050	448	493	347	221
LMM	0.6682	0.6798	0.6756	0.6752	0.6665	0.6701	0.6865	0.679	0.7076	0.6901	0.65	0.6784
UL	0.6803	0.686	0.6883	0.6892	0.6797	0.6801	0.6996	0.6906	0.7248	0.7107	0.6657	0.7007
LL	0.6561	0.6736	0.6628	0.6611	0.6532	0.66	0.6734	0.6674	0.6905	0.6694	0.6342	0.656
BM	0.6733	0.6850	0.6807	0.6803	0.6715	0.6752	0.6917	0.6842	0.713	0.6953	0.6549	0.6835
UL	0.6875	0.6924	0.6954	0.6962	0.6857	0.6863	0.7058	0.6977	0.7324	0.7168	0.6733	0.7071
LL	0.6591	0.6776	0.666	0.6645	0.6574	0.6641	0.6777	0.6707	0.6936	0.6739	0.6366	0.66
	SO00							BS00	BL00			
Nr	1104	1105	1106	1107	1108	1109	1110	1200	1301	1302	1303	1304

size	523	619	1261	1195	1396	428	339	4609	4070	509	1431	873
LMM	0.6369	0.6519	0.6568	0.6357	0.6587	0.6851	0.6311	0.6001	0.5979	0.6579	0.6375	0.672
UL	0.6521	0.6655	0.6684	0.6468	0.6707	0.7002	0.653	0.6095	0.607	0.6713	0.6484	0.6866
LL	0.6217	0.6383	0.6452	0.6246	0.6468	0.67	0.6092	0.5908	0.5888	0.6444	0.6266	0.6574
BM	0.6417	0.6568	0.6618	0.6405	0.6637	0.6903	0.6359	0.6047	0.6024	0.6629	0.6424	0.6771
UL	0.6586	0.6722	0.6746	0.6529	0.677	0.707	0.6584	0.614	0.6119	0.6781	0.6544	0.6937
LL	0.6249	0.6415	0.649	0.6281	0.6505	0.6736	0.6134	0.5954	0.593	0.6476	0.6304	0.6605

	BL00	SH00						AR00			AI00	SG00
Nr	1305	1401	1402	1403	1404	1405	1406	1501	1502	1503	1600	1721
size	399	106	202	1368	90	162	122	600	413	389	362	3051
LMM	0.6501	0.6798	0.6689	0.6246	0.6244	0.629	0.6551	0.6669	0.6584	0.6648	0.6701	0.6583
UL	0.6653	0.7093	0.7	0.6401	0.6541	0.6639	0.6796	0.68	0.6749	0.6901	0.6857	0.6674
LL	0.6349	0.6504	0.6378	0.6092	0.5948	0.5941	0.6306	0.6538	0.6419	0.6396	0.6545	0.6493
BM	0.6719	0.7166	0.7074	0.6454	0.6605	0.6707	0.6865	0.6873	0.6828	0.6974	0.6937	0.6735
UL	0.6719	0.7163	0.707	0.6453	0.6602	0.6702	0.6864	0.6873	0.6826	0.697	0.6936	0.6734
LL	0.6382	0.6537	0.6409	0.6135	0.5982	0.5975	0.6338	0.6567	0.6443	0.6428	0.6568	0.6533

	SG00							GR00				
Nr	1722	1723	1724	1725	1726	1727	1728	1821	1822	1823	1824	1825
size	1039	1767	891	966	1678	1136	1841	256	120	326	477	261
LMM	0.6604	0.6723	0.6785	0.6527	0.6703	0.6459	0.6694	0.6431	0.5776	0.6411	0.6728	0.656
UL	0.6728	0.6839	0.6984	0.6702	0.6811	0.6578	0.6791	0.6586	0.6006	0.656	0.6893	0.6786
LL	0.648	0.6607	0.6587	0.6353	0.6595	0.6341	0.6596	0.6277	0.5547	0.6261	0.6563	0.6333
BM	0.6654	0.6774	0.6837	0.6577	0.6754	0.6508	0.6745	0.6480	0.5821	0.6459	0.6780	0.6610
UL	0.6796	0.691	0.7039	0.6774	0.6875	0.6645	0.6857	0.666	0.6059	0.6641	0.6959	0.6857
LL	0.6513	0.6638	0.6635	0.638	0.6634	0.6372	0.6632	0.6301	0.5582	0.6278	0.66	0.6362

	GR00						AG00					
Nr	1826	1827	1828	1829	1830	1831	1901	1902	1903	1904	1905	1906
size	690	493	214	1096	660	541	3805	6956	3683	2409	1954	1594
LMM	0.6845	0.6871	0.5966	0.6584	0.6604	0.6294	0.6689	0.6806	0.6765	0.6615	0.6512	0.6734
UL	0.7022	0.7006	0.617	0.6705	0.6749	0.6425	0.6769	0.6869	0.6855	0.6709	0.6607	0.6836
LL	0.6668	0.6736	0.5762	0.6463	0.6459	0.6163	0.6609	0.6742	0.6674	0.6522	0.6418	0.6632
BM	0.6897	0.6923	0.6011	0.6634	0.6654	0.6342	0.674	0.6857	0.6816	0.6666	0.6562	0.6785
UL	0.7099	0.7077	0.6224	0.677	0.6821	0.6496	0.6829	0.6926	0.6912	0.6771	0.6668	0.6903
LL	0.6695	0.6769	0.5798	0.6498	0.6487	0.6188	0.6651	0.6789	0.672	0.6561	0.6456	0.6667

	AG00					TG00					TI00	
Nr	1907	1908	1909	1910	1911	2011	2012	2013	2014	2015	2101	2102
size	2941	1575	2299	3367	1645	2656	3324	2316	2276	2603	2577	262
LMM	0.6833	0.7177	0.6569	0.6803	0.6562	0.6404	0.6856	0.667	0.6971	0.6902	0.5812	0.539
UL	0.6915	0.7303	0.6664	0.6879	0.6664	0.6499	0.6939	0.6771	0.7063	0.7004	0.5927	0.557
LL	0.675	0.7051	0.6473	0.6727	0.646	0.6309	0.6773	0.657	0.6878	0.6799	0.5697	0.5209

BM	0.6885	0.7232	0.6619	0.6855	0.6612	0.6453	0.6908	0.6721	0.7024	0.6954	0.5856	0.5431
UL	0.6981	0.738	0.6721	0.6948	0.6728	0.6554	0.701	0.684	0.7137	0.7077	0.5973	0.5618
LL	0.6788	0.7084	0.6517	0.6762	0.6496	0.6351	0.6807	0.6602	0.6911	0.6832	0.574	0.5244

	TI00						VD00					
Nr	2103	2104	2105	2106	2107	2108	2221	2222	2223	2224	2225	2226
size	512	3271	7664	2739	685	314	1986	1923	2029	4325	7617	2915
LMM	0.581	0.5579	0.5731	0.5578	0.5733	0.5828	0.6184	0.6398	0.693	0.6343	0.6473	0.6147
UL	0.596	0.5675	0.5807	0.5696	0.5947	0.5996	0.6279	0.6497	0.7014	0.6417	0.6535	0.6235
LL	0.5659	0.5483	0.5654	0.546	0.552	0.5661	0.6089	0.6299	0.6847	0.6269	0.6412	0.606
BM	0.5854	0.5622	0.5774	0.562	0.5777	0.5873	0.6231	0.6447	0.6983	0.6391	0.6523	0.6194
UL	0.6018	0.5722	0.585	0.5739	0.5994	0.6052	0.6336	0.656	0.7086	0.6475	0.659	0.6292
LL	0.569	0.5522	0.5699	0.5502	0.556	0.5693	0.6126	0.6333	0.688	0.6308	0.6456	0.6097

	VD00				VS00							
Nr	2227	2228	2229	2230	2301	2302	2303	2304	2305	2306	2307	2308
size	3861	4498	3468	3993	661	625	371	138	301	297	1152	1110
LMM	0.6562	0.6469	0.6468	0.6142	0.6306	0.6521	0.6232	0.6076	0.5931	0.6261	0.6548	0.6465
UL	0.6644	0.6549	0.6555	0.6214	0.6538	0.6659	0.6392	0.6346	0.6113	0.6611	0.6687	0.6585
LL	0.6479	0.6388	0.6381	0.607	0.6073	0.6383	0.6071	0.5806	0.575	0.5911	0.6408	0.6346
BM	0.6612	0.6518	0.6517	0.6189	0.6354	0.6571	0.6279	0.6122	0.5976	0.6309	0.6597	0.6515
UL	0.6697	0.6604	0.6612	0.6273	0.6593	0.6721	0.6454	0.64	0.6174	0.6659	0.6746	0.6646
LL	0.6527	0.6432	0.6423	0.6105	0.6114	0.6421	0.6105	0.5845	0.5779	0.5958	0.6449	0.6383

	VS00					NE00						GE00
Nr	2309	2310	2311	2312	2313	2401	2402	2403	2404	2405	2406	2500
size	287	355	1177	1124	663	2052	1980	696	2665	814	581	20786
LMM	0.6211	0.6462	0.6176	0.6324	0.6743	0.6239	0.6223	0.6109	0.6293	0.6710	0.5865	0.6124
UL	0.644	0.6604	0.6295	0.6466	0.6904	0.633	0.632	0.6235	0.6374	0.6826	0.5991	0.6165
LL	0.5983	0.6319	0.6058	0.6182	0.6583	0.6149	0.6127	0.5983	0.6211	0.6595	0.5738	0.6083
BM	0.6259	0.6511	0.6223	0.6373	0.6795	0.6287	0.6270	0.6156	0.6341	0.6761	0.5910	0.6171
UL	0.6491	0.6676	0.6355	0.6521	0.6962	0.6394	0.6378	0.6302	0.6438	0.6897	0.6049	0.6213
LL	0.6026	0.6346	0.6091	0.6225	0.6627	0.618	0.6163	0.601	0.6243	0.6625	0.577	0.6129

	JU00		
Nr	2601	2602	2603
size	1817	493	1292
LMM	0.6147	0.6448	0.5813
UL	0.626	0.6616	0.5956
LL	0.6034	0.628	0.567
BM	0.6194	0.6497	0.5857
UL	0.6313	0.669	0.6005
LL	0.6075	0.6305	0.571

Table 6: Estimated district proportions of active people together with a 95% confidence intervals based on PDB MSE estimates.

	ZH00											
Nr	101	102	103	104	105	106	107	108	109	110	111	112
size	1309	807	3455	2113	2294	3088	2600	1488	3220	4075	2063	9510
LMM	0.6821	0.6803	0.6963	0.7113	0.6783	0.6592	0.6311	0.6838	0.6808	0.6783	0.6703	0.6932
UL	0.6925	0.6901	0.7036	0.7253	0.6855	0.667	0.6401	0.695	0.6895	0.6862	0.6789	0.6984
LL	0.6717	0.6705	0.6889	0.6974	0.6712	0.6514	0.622	0.6727	0.672	0.6705	0.6618	0.688
BM	0.6873	0.6855	0.7016	0.7168	0.6835	0.6642	0.6359	0.6890	0.6860	0.6835	0.6755	0.6985
UL	0.6977	0.6952	0.7089	0.7307	0.6905	0.6719	0.6449	0.7001	0.6946	0.6912	0.6838	0.7036
LL	0.6769	0.6758	0.6942	0.7029	0.6765	0.6565	0.6269	0.678	0.6773	0.6758	0.6671	0.6934

	BE02	BE00									LU00	
Nr	241	242	243	244	245	246	247	248	249	250	301	302
size	2706	2420	1800	2079	2556	10294	2870	404	1013	1210	909	3493
LMM	0.6216	0.6177	0.6925	0.6556	0.6672	0.6621	0.6433	0.6474	0.6365	0.6514	0.6431	0.6819
UL	0.6289	0.6289	0.7156	0.6642	0.6807	0.6671	0.6514	0.6722	0.6485	0.6626	0.6609	0.6884
LL	0.6143	0.6065	0.6694	0.6469	0.6537	0.6571	0.6352	0.6227	0.6246	0.6402	0.6254	0.6753
BM	0.6263	0.6224	0.6978	0.6606	0.6723	0.6672	0.6482	0.6524	0.6414	0.6564	0.6480	0.6870
UL	0.6338	0.6337	0.721	0.6691	0.6858	0.672	0.6562	0.6772	0.6533	0.6675	0.6659	0.6936
LL	0.6189	0.6112	0.6746	0.652	0.6588	0.6623	0.6401	0.6275	0.6295	0.6452	0.6302	0.6805

	LU00			UR00	SZ00						OW00	NW00
Nr	303	304	305	400	501	502	503	504	505	506	600	700
size	9168	3634	2503	895	371	62	703	333	1073	1405	922	1183
LMM	0.6626	0.7004	0.6914	0.6365	0.6793	0.6354	0.6889	0.6929	0.6973	0.6815	0.6977	0.6696
UL	0.6684	0.7072	0.6993	0.6616	0.6854	0.6484	0.6961	0.6996	0.7142	0.6892	0.7284	0.6885
LL	0.6568	0.6936	0.6836	0.6113	0.6732	0.6224	0.6816	0.6862	0.6805	0.6739	0.6669	0.6507
BM	0.6676	0.7058	0.6967	0.6413	0.6845	0.6403	0.6941	0.6982	0.7027	0.6867	0.7030	0.6747
UL	0.6734	0.7127	0.7046	0.6667	0.6904	0.6532	0.7012	0.7048	0.7196	0.6943	0.7339	0.6937
LL	0.6618	0.6989	0.6889	0.616	0.6786	0.6273	0.687	0.6916	0.6857	0.6792	0.6721	0.6557

	GL00	ZG00	FR00							SO00		
Nr	800	900	1001	1002	1003	1004	1005	1006	1007	1101	1102	1103
size	1030	6086	730	571	1238	2509	816	1050	448	493	347	221
LMM	0.6682	0.6798	0.6756	0.6752	0.6665	0.6701	0.6865	0.679	0.7076	0.6901	0.65	0.6784
UL	0.686	0.6854	0.6832	0.6824	0.6859	0.6817	0.6954	0.6878	0.7348	0.7183	0.6604	0.7016
LL	0.6504	0.6742	0.6679	0.6679	0.6471	0.6584	0.6776	0.6702	0.6805	0.6619	0.6395	0.6551
BM	0.6733	0.6850	0.6807	0.6803	0.6715	0.6752	0.6917	0.6842	0.713	0.6953	0.6549	0.6835
UL	0.6912	0.6906	0.6883	0.6874	0.6911	0.6869	0.7006	0.6929	0.7404	0.7238	0.6653	0.7069
LL	0.6554	0.6795	0.6731	0.6732	0.6519	0.6634	0.6828	0.6755	0.6857	0.6669	0.6445	0.6601

	SO00							BS00	BL00			
Nr	1104	1105	1106	1107	1108	1109	1110	1200	1301	1302	1303	1304

size	523	619	1261	1195	1396	428	339	4609	4070	509	1431	873
LMM	0.6369	0.6519	0.6568	0.6357	0.6587	0.6851	0.6311	0.6001	0.5979	0.6579	0.6375	0.672
UL	0.6469	0.6598	0.672	0.6452	0.6703	0.7047	0.6548	0.6107	0.6118	0.6672	0.646	0.697
LL	0.6269	0.6439	0.6416	0.6262	0.6471	0.6654	0.6074	0.5896	0.584	0.6485	0.629	0.6469
BM	0.6417	0.6568	0.6618	0.6405	0.6637	0.6903	0.6359	0.6047	0.6024	0.6629	0.6424	0.6771
UL	0.6518	0.6648	0.6772	0.65	0.6754	0.71	0.6598	0.6153	0.6165	0.6723	0.6507	0.7023
LL	0.6317	0.6489	0.6464	0.631	0.6521	0.6705	0.6121	0.5941	0.5884	0.6535	0.634	0.6519
	BL00	SH00						AR00			AI00	SG00
Nr	1305	1401	1402	1403	1404	1405	1406	1501	1502	1503	1600	1721
size	399	106	202	1368	90	162	122	600	413	389	362	3051
LMM	0.6501	0.6798	0.6689	0.6246	0.6244	0.629	0.6551	0.6669	0.6584	0.6648	0.6701	0.6583
UL	0.6571	0.7124	0.7117	0.6467	0.637	0.6714	0.6785	0.6767	0.6774	0.6952	0.6891	0.6674
LL	0.6431	0.6473	0.6261	0.6026	0.6119	0.5867	0.6317	0.6571	0.6395	0.6345	0.6511	0.6492
BM	0.6719	0.7166	0.7074	0.6454	0.6605	0.6707	0.6865	0.6873	0.6828	0.6974	0.6937	0.6735
UL	0.6619	0.7178	0.717	0.6517	0.6418	0.6765	0.6836	0.6817	0.6825	0.7004	0.6943	0.6724
LL	0.6482	0.6523	0.6309	0.6071	0.6166	0.5912	0.6366	0.6623	0.6445	0.6394	0.6561	0.6542
	SG00							GR00				
Nr	1722	1723	1724	1725	1726	1727	1728	1821	1822	1823	1824	1825
size	1039	1767	891	966	1678	1136	1841	256	120	326	477	261
LMM	0.6604	0.6723	0.6785	0.6527	0.6703	0.6459	0.6694	0.6431	0.5776	0.6411	0.6728	0.656
UL	0.6749	0.6963	0.6957	0.682	0.6776	0.6543	0.6789	0.6552	0.598	0.6474	0.6866	0.6768
LL	0.6459	0.6482	0.6614	0.6235	0.663	0.6375	0.6598	0.6311	0.5573	0.6347	0.659	0.6351
BM	0.6654	0.6774	0.6837	0.6577	0.6754	0.6508	0.6745	0.6480	0.5821	0.6459	0.6780	0.6610
UL	0.6799	0.7015	0.701	0.6871	0.6827	0.6591	0.6841	0.66	0.6026	0.6523	0.6918	0.6819
LL	0.651	0.6533	0.6665	0.6283	0.6681	0.6425	0.6649	0.6361	0.5616	0.6396	0.6641	0.64
	GR00						AG00					
Nr	1826	1827	1828	1829	1830	1831	1901	1902	1903	1904	1905	1906
size	690	493	214	1096	660	541	3805	6956	3683	2409	1954	1594
LMM	0.6845	0.6871	0.5966	0.6584	0.6604	0.6294	0.6689	0.6806	0.6765	0.6615	0.6512	0.6734
UL	0.7073	0.6954	0.6159	0.667	0.6758	0.6375	0.6761	0.688	0.6829	0.6692	0.658	0.6831
LL	0.6617	0.6788	0.5772	0.6498	0.645	0.6213	0.6617	0.6731	0.67	0.6539	0.6444	0.6637
BM	0.6897	0.6923	0.6011	0.6634	0.6654	0.6342	0.674	0.6857	0.6816	0.6666	0.6562	0.6785
UL	0.7125	0.7005	0.6205	0.6719	0.6808	0.6422	0.6813	0.6933	0.6883	0.6742	0.663	0.6883
LL	0.6669	0.6841	0.5817	0.6549	0.6501	0.6263	0.6667	0.6782	0.675	0.6589	0.6494	0.6688
	AG00					TG00					TI00	
Nr	1907	1908	1909	1910	1911	2011	2012	2013	2014	2015	2101	2102
size	2941	1575	2299	3367	1645	2656	3324	2316	2276	2603	2577	262
LMM	0.6833	0.7177	0.6569	0.6803	0.6562	0.6404	0.6856	0.667	0.6971	0.6902	0.5812	0.539
UL	0.69	0.7376	0.6651	0.6881	0.665	0.6523	0.6973	0.6889	0.7202	0.7105	0.605	0.5506
LL	0.6765	0.6978	0.6486	0.6725	0.6473	0.6284	0.6739	0.6452	0.6739	0.6699	0.5574	0.5273

BM	0.6885	0.7232	0.6619	0.6855	0.6612	0.6453	0.6908	0.6721	0.7024	0.6954	0.5856	0.5431
UL	0.6951	0.7432	0.6701	0.6933	0.67	0.6573	0.7025	0.694	0.7256	0.7158	0.6096	0.5548
LL	0.6818	0.7031	0.6536	0.6776	0.6524	0.6332	0.6791	0.6502	0.6791	0.6751	0.5617	0.5313

	TI00						VD00					
Nr	2103	2104	2105	2106	2107	2108	2221	2222	2223	2224	2225	2226
size	512	3271	7664	2739	685	314	1986	1923	2029	4325	7617	2915
LMM	0.581	0.5579	0.5731	0.5578	0.5733	0.5828	0.6184	0.6398	0.693	0.6343	0.6473	0.6147
UL	0.5946	0.5706	0.5831	0.5721	0.6049	0.5946	0.6289	0.6486	0.7019	0.6424	0.6521	0.6251
LL	0.5673	0.5452	0.563	0.5435	0.5418	0.571	0.6078	0.631	0.6842	0.6262	0.6426	0.6044
BM	0.5854	0.5622	0.5774	0.562	0.5777	0.5873	0.6231	0.6447	0.6983	0.6391	0.6523	0.6194
UL	0.5992	0.575	0.5877	0.5765	0.6096	0.5991	0.6337	0.6534	0.7072	0.6473	0.657	0.6299
LL	0.5716	0.5494	0.5672	0.5476	0.5459	0.5754	0.6125	0.6359	0.6894	0.631	0.6475	0.609

	VD00				VS00							
Nr	2227	2228	2229	2230	2301	2302	2303	2304	2305	2306	2307	2308
size	3861	4498	3468	3993	661	625	371	138	301	297	1152	1110
LMM	0.6562	0.6469	0.6468	0.6142	0.6306	0.6521	0.6232	0.6076	0.5931	0.6261	0.6548	0.6465
UL	0.6631	0.6531	0.655	0.6207	0.6667	0.659	0.6348	0.6409	0.6081	0.6802	0.668	0.6585
LL	0.6493	0.6406	0.6386	0.6077	0.5944	0.6452	0.6115	0.5743	0.5781	0.5719	0.6416	0.6345
BM	0.6612	0.6518	0.6517	0.6189	0.6354	0.6571	0.6279	0.6122	0.5976	0.6309	0.6597	0.6515
UL	0.6682	0.6582	0.66	0.6253	0.6718	0.664	0.6396	0.6458	0.6127	0.6854	0.673	0.6636
LL	0.6542	0.6454	0.6434	0.6124	0.5989	0.6502	0.6162	0.5787	0.5826	0.5763	0.6465	0.6394

	VS00					NE00						GE00
Nr	2309	2310	2311	2312	2313	2401	2402	2403	2404	2405	2406	2500
size	287	355	1177	1124	663	2052	1980	696	2665	814	581	20786
LMM	0.6211	0.6462	0.6176	0.6324	0.6743	0.6239	0.6223	0.6109	0.6293	0.6710	0.5865	0.6124
UL	0.6455	0.653	0.6253	0.6508	0.6958	0.6321	0.6337	0.6213	0.6376	0.6795	0.5955	0.6158
LL	0.5968	0.6393	0.61	0.6141	0.6529	0.6157	0.611	0.6006	0.621	0.6626	0.5775	0.609
BM	0.6259	0.6511	0.6223	0.6373	0.6795	0.6287	0.6270	0.6156	0.6341	0.6761	0.5910	0.6171
UL	0.6504	0.6577	0.6299	0.6558	0.7011	0.6368	0.6384	0.626	0.6424	0.6847	0.6001	0.6205
LL	0.6014	0.6444	0.6148	0.6187	0.6579	0.6206	0.6157	0.6052	0.6257	0.6676	0.5818	0.6136

	JU00		
Nr	2601	2602	2603
size	1817	493	1292
LMM	0.6147	0.6448	0.5813
UL	0.6262	0.6683	0.5943
LL	.6032	0.6213	0.5683
BM	0.6194	0.6497	0.5857
UL	0.631	0.6734	0.5988
LL	0.6078	0.6261	0.5726