EVALUATING THE APPROACHES OF SMALL AREA ESTIMATION USING POVERTY MAPPING DATA

Abstract

Now-a-days estimation demand in statistics is increased worldwide to seek out an estimate, or approximation, which may be a value which will be used for various purpose, albeit the input data could also be incomplete, uncertain or unstable. The development of different estimation methods is trying to provide most accurate estimate and estimation theory deals with finding estimates with good properties. The demand of small area estimation (SAE) method has been increasing rapidly around the world because of its reliability compared to the traditional direct estimation methods especially in the case of small sample size. This paper mainly focuses on the comparison of several indirect small area estimation methods (post-stratified synthetic, SSD and EB estimates) with traditional direct estimator based on a renowned data set. Direct estimator is approximately unbiased but SSD and Post-stratified synthetic estimator is extreme biased. To cope up the problem we conduct another model based estimation procedure namely Empirical Bayes (EB) estimator which is unbiased and compare them using their coefficient of variation (CV). To check the model assumption, we used Q-Q plot as well as Histogram to confirm the normality, bivariate correlation, Akaike information criterion (AIC).

Keywords: Small Area Estimation, Direct Estimation, Indirect Estimation, Empirical Bayes Estimator, Poverty Mapping.

Introduction

Sample survey is a method of data collection with several advantages, such as saving time, money, and energy. Sample survey usually produced reliable estimated value usually direct estimate for mean or total of variable of interest for large areas or domain. Nevertheless, if there is a small area, i.e. if the sample is not large enough for some context, the result can be unacceptably large standard errors if it is based only on direct survey estimators and data from the sample field only. So to develop more reliable estimated value, it is important to use small area statistics. In recent years, interest from both the public and private sectors for accurate estimates for a specific region or area has grown.

The word "small area" generally refers to a population for which accurate statistics of interest cannot be produced, due to certain constraints of the available data. Small area comprises a geographic area such as states, counties, districts, or sub-districts and population community such as age, ethnicity, or gender (S Hariyanto, 2018). Some of the other words that are used as a synonym for a small area include ' small domain, ' ' minor domain, ' ' local area, ' ' small sub-domain ' (Rao 2003). Finally, it can be define that small area estimation (SAE) is a statistical technique to estimate the accurate approximation or estimate in the small geographical area where sample size is very small or even equal to zero.

In situations where direct estimates cannot be disseminated due to unsatisfactory accuracy, an ad hoc collection of methods, called methods for small area estimating (SAE), is necessary to overcome the problem. These methods are usually referred to as indirect estimators since they handle poor information from sample information belonging to other domains for each domain borrowing strength, resulting in an increase in the effective sample size for each small area.

The growing requirement for more timely and accurate information, along with the high cost of interviews frequently leads to comprehensive use of survey data. In fact, survey data is used many times to generate estimates in smaller domains or areas than those for which the survey was originally planned. A direct estimator, relying solely on the survey data coming from that area, may be very inefficient for a region with a low sample size. This sample size limitation prevents statistical figures from being produced at the demanded level and therefore limits the availability of statistical information to the public or the specific user. By comparison, through increasing the effective sample size, an indirect estimator for a region often uses external data from other areas to improve performance. Among indirect estimators, we consider the ones based on explicit models of regression, called model based estimators. These estimators are focused on the presumption of a constant link between the target variable and certain explanatory variables through areas. The common parameters of the model are estimated using the whole set of sample data, which often leads to small area estimators with significantly better efficiency than direct estimators as long because the assumptions of the model hold. Thus, these strategies include statistical figures at a much disaggregated level without raising the area-specific sample sizes and hence without raising the survey cost.

The key purposes of this research are to evaluate and comparison of various small area estimation approaches using poverty mapping data. In this paper, we use several table and figure to compare these methods.

Research methods define as the technique of strategy those are used for conduction of a research. All methods which are used by the researcher during the course of studying his research problem are termed as research method. In this paper, we will use the following methodologies:

1) Horvitz-Thompson (H-T) estimation use for direct estimation
2) Post-stratified synthetic indirect estimator use based on statistical approach on implicit models
3) Empirical Bayes (EB) method indirect estimator use based on statistical approach on explicit models
4) Mean square error (MSE)

For checking the model assumption, we use the following method

1. Q-Q plot as well as Histogram used to confirm the normality assumption.
2. Bivariate correlation.
3. Akaike information criterion (AIC)

Previous work on poverty mapping indicator

Poverty maps are an important source of information on the regional distribution of poverty and are currently used to support regional policy making and to allocate funds to local jurisdictions. Good examples are the poverty and inequality maps produced by the World Bank for many countries all over the world. Some previous work on poverty mapping using small area estimation are given below:

One paper (Novi Hidayat Pusponegoro, 2019) seeks to compare the SAE, Spatial SAE and Geo-additive model for calculating a sub-district average per capita income using data from the 2017 Bangka Belitung Province Poverty Survey. The paper's findings are the Geo-additive is the best fit model based on AIC, so the most important part of modelling is the form of relationship between response and covariate.

The research (Mai M. Kamal El Saied, 2019) is to study the SAE procedures for estimating the Egyptian provinces ' mean income and poverty indicators. They demonstrated the direct estimators for mean income and poverty indicators for all provinces. This research also applies the empirical best / Bayes (EB) and pseudo-empirical best / Bayes (PEB) approaches focused on unit level— nested error— models for estimating mean income and (FGT) deprivation indices for Egyptian border provinces with (2012-2013) data from the IECS. For comparative purposes, the (MSEs) and coefficient of variance (C. Vs) are determined.

Results (Hukum Chandra, 2018) in district-specific values suggest that the approximate assessments of the proportion of poor households in each district are unreliable, with CVs ranging from 13.33% to 64%, with an average of 24.69%. The CVs of the EBP estimates range from 12.96% to 37.27% with 21.19% on average. It also noted that the direct estimates CVs are greater than 20 percent (30 percent) in 22 (9) of the 38 districts. However, out of the 38 districts, the model-based estimates are greater than 20 per cent (30 per cent) in 20 (3).

The paper (Mai M. Kamal El Saied, 2019) approximate mean income indicates that for all provinces, PEB and EB divided by regional sample sizes have no noticeable differences except for the third of sample size (Red Sea), the PEB therein is greater than the EB. The C.Vs for PEB are smaller than the C.Vs for EB in all selected provinces except the sec for PEB on it is greater than the C.V for EB. The estimated C.Vs are still under 15% for both methods in all selected provinces. EB estimates for poverty incidence and poverty gap are smaller than PEB for all se provinces. Additionally, that the differences are large in three provinces (Matruh, North Sinai and South Sinai), and are small in two of them (Red Sea and New Valley). Estimated poverty rate and poverty gap figures for C.Vs for EB, as predicted.

Paper (Molina, 2009) showed that the estimated CVs of direct estimators of poverty incidences exceeded the level of 10% for 78 (out of the 104) domains while those of the EB estimators exceeded this level for only 28 domains. If we increase the level to 20%, then the direct estimators have greater CV for 17 domains but the CV of EB estimators exceeded 20% only for the first domain.

In March 2017, the Province of Yogyakarta Special Region (DIY Province) has a poverty line above the national average of IDR 374,009, a proportion of poor people (13.03%) and Gini coefficient (0.432) (IDR 374,478; 10.64%; 0.393). The outcome of the 2017 happiness index indicates that DIY Province's position (72.93%) is higher than the national happiness index average (70.69%). For 2017, the dispersal between the index of satisfaction and the proportion of poor people for Indonesia indicates that DIY Province is on the first quadrant. It reflects the high level of happiness as well as the high percentage of the poor. To assess the spatial characteristics of deprivation and happiness profiles in DIY Province, a small area estimate approach developed by Elbers et al (known as the ELL method) is used. This study utilized data from the village census (Podes) 2018; Susenas March 2017 and SPTK 2017 as data from the survey. There are twenty-three variables for households and another five variables that are significant to urban and rural provincial models of poverty and happiness. Rural regency areas are dominated by a high profile of poverty (FGT0 0.0491–0.1076), low profile of happiness (FTG0 0.0087–0.0124), and inequality of happiness (Gini index 0.0847–0.0923). Low deprivation (FTG0 0.0082 – 0.0491), high satisfaction level (FTG0 0 – 0.0087), and total income equality (Gini index 0.3048 – 0.3604) and happiness levels (Gini index 0.0624 – 0.0847) dominate the urban regency regions. Yogyakarta City has the happiest and wealthiest profiles, while the urban regency area of Gunung Kidul has perfect income and happiness profile equality (Shafiera Rosa El-Yasha, 2019).

This paper (V Y Sundara, 2017) introduced an approach to the impact of the auxiliary variable on the clustering region by believing parallels occur between specific areas. All estimates were determined based on the relative bias and root mean error of the squares. The simulation result showed that the proposed approach can enhance model's ability to estimate non-sampled area. The suggested model was applied to estimate poverty measures in regency and city of Bogor, West Java, Indonesia at sub-districts level. The outcome of case study is smaller than the theoretical model relative root mean squares error estimation of empirical Bayes with knowledge cluster.

Sources of data

In this research our aim is to compare some techniques of small area estimation. Such that we use secondary data taken from R package “sae”. The name of the collected data set “incomedata” which was a Synthetic data on income and other related variables for Spanish 52 provinces. This is a data frame with 17199 observations with 21 variables. We also use three identifier such as “sizeprov” containing the population size for domains in data set incomedata, “sizeprovedu” population sizes by level of education for domains in data set incomedata and “Xoutsamp” containing the values of p auxiliary variables for out-of-sample units within domains of data set incomedata.

The data set incomedata contains synthetic unit-level data on income and other sociological variables in the Spanish provinces. These data have been obtained by simulation. Therefore, conclusions regarding the levels of poverty in the Spanish provinces obtained from these data are not realistic. We will use the following variables from the data set: province name (provlab), province code (prov), income (income), sampling weight (weight), education level (educ), labor status (labor), and finally the indicators of each of the categories of educ and labor.

Result and Discussion

In this study, we used poverty mapping data of Spanish provinces to analyze several simple estimates namely direct estimates, post-stratified synthetic estimates with education levels as post-strata, SSD estimates obtained from the com-position of direct and post-stratified synthetic estimates. Also we calculate the EB estimator considering the auxiliary variable from the out of sample. The poverty incidence for a province is the province mean of a binary variable taking value 1 when person's income is below a given poverty line and 0 otherwise. Binary variable could use for calculate the direct estimate easily applying usual theory. In this research, we used R, SPSS and Excel as the analysis tools. First, we read the **incomedata** data set which included the data for each individual and the data sets **sizeprov** the population sizes and **sizeprovedu** sizes by education level, respectively.

Considered poverty line Z = 6557.143

Table-1: Frequency distribution of poverty incidence

	Frequency	Percentage (%)
Poor (Income < Z)	3841	22.333
Not poor	13358	77.667
Total	17199	100

Maximum number of people about 13358 are not below the poverty line (Z) that is 77.667% people are not poor. And about 3841 people that is 22.333% people are below the poverty line i.e they are poor.

Table-2: Sorted Combination of Direct (DIR), Post-stratified synthetic and Sample size dependent (SSD) according to each province (Sorted by decreasing sample size)

Province	Sample Size	DIR×100	PSYN.educ×100	SSD×100
Barcelona	1420	29.81253	21.59556	29.81253
Madrid	944	18.21821	20.28249	18.25089
Murcia	885	17.70317	22.50054	17.72239
Oviedo	803	26.06401	22.00916	26.06401
Valencia	714	21.36068	21.32963	21.36054
Baleares	634	9.999792	21.71882	10.4024
Navarra	564	16.19077	20.92992	16.22866

Zaragoza	564	10.03458	21.17064	10.03458
Alicante	539	20.7851	21.26954	20.7851
Vizcaya	524	21.69447	20.44194	21.69447
RiojaLa	510	25.81181	22.40296	25.78924
CorunaLa	495	25.34755	21.76006	25.23624
Badajoz	494	21.55389	22.35924	21.55389
Sevilla	482	20.50304	21.74189	20.58245
PalmasLas	472	16.65184	21.809	16.65184
Pontevedra	448	18.54907	21.86237	18.54907
Santander	434	34.24443	21.56598	34.07708
Cadiz	398	14.88735	22.51448	14.88735
Tenerife	381	18.42962	21.96155	19.17768
Malaga	379	22.91846	22.51928	22.90551
Valladolid	299	19.29233	20.98068	19.29233
Guipuzcoa	285	23.69055	20.76857	23.66709
Caceres	282	27.03132	22.23249	26.44514
Toledo	275	12.55338	23.14442	12.57643
CiudadReal	250	20.92153	23.23302	20.92153
Ceuta	235	19.7248	22.81006	19.7248
Jaen	232	31.2942	22.93972	31.2942
Cordoba	224	29.97571	22.91798	29.51045
Leon	218	18.80157	22.93115	19.22223
Granada	208	31.72734	22.39243	30.97619
Almeria	198	26.76398	23.02936	26.76398
Melilla	180	19.10912	22.00697	19.43014
Albacete	173	14.05924	22.67562	14.30411
Lugo	173	37.71872	23.94922	37.58235
Burgos	168	21.41315	22.35331	21.41315
Salamanca	164	16.10451	21.9324	16.76284
Gerona	142	18.33742	21.596	18.85399
Tarragona	134	32.03544	22.51761	29.51279
Lerida	130	15.55959	23.89632	15.55959

Orense	129	22.79961	23.58691	22.96765
Huelva	122	12.58345	22.35069	13.442
Castellon	118	17.5982	21.91192	18.73778
Huesca	115	24.10761	23.10616	23.98812
Zamora	104	30.02744	26.17055	30.02744
Alava	96	25.50373	20.7788	24.08931
Cuenca	92	26.33406	24.83639	26.13496
Guadalajara	89	17.90818	22.59389	18.78456
Palencia	72	30.16607	23.63212	29.39216
Teruel	72	27.36424	22.89205	26.70145
Avila	58	5.5122	22.8933	10.28835
Segovia	58	22.262	22.67927	22.33761
Soria	20	2.541207	23.10395	13.14019

For simplification, the estimated values of each estimator in table-2 is multiplied by 100. This table shows that direct estimates and SSD estimates are very similar. The estimated value of these two methods are fluctuate decreases as sample size decreases and they are more slightly more unstable. It is noticeable that when sample size is large the SSD estimator treated as a direct estimator, but it is increases when sample size was small such as table-2 shows that in "Soria" province (sample size = 20) direct estimated value was 2.541207 which increases to 13.14019 in SSD estimate, in "Avila" province 5.5122 (direct) tern in to 10.28835 (SSD) and others values are approximately similar in both direct and SSD estimates. Otherwise the synthetic estimator has a bigger contribution. However, the post-stratified synthetic estimates appear to be too stable, giving practically the same values for all provinces. It can be showed more clearly in the following Figure-1.

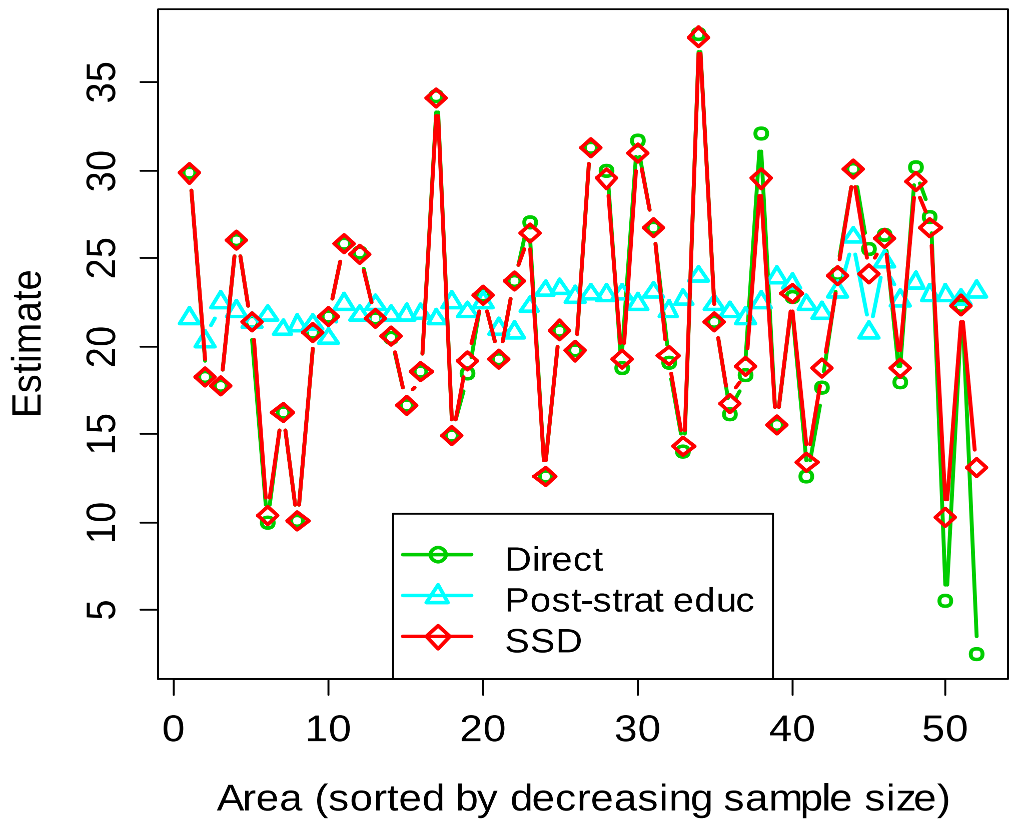


Figure-1: Sorted Combination of Direct (DIR), Post-stratified synthetic and Sample size dependent (SSD) according to each province

These estimates are plotted in the Figure for each province (area), with provinces sorted by decreasing sample size. This shows that direct estimates and SSD estimates are very similar. The estimated value of these two methods are fluctuately decreases as sample size decreases and they are slightly more unstable. It is noticeable that when sample size is large the SSD estimator treated as a direct estimator, but it is increases when sample size was small. However, the post-stratified synthetic estimates appear to be too stable, giving practically the same values for all provinces. From the result it can be conclude that Direct estimator and SSD estimator have a similar impact on estimation procedure and Post-stratified Synthetic estimator is the best estimator than Direct and SSD estimator.

Table-3: Descriptive statistics of Direct, Post-stratified synthetic and SSD estimate

Descriptive statistics			
Estimator	Direct	Post-stratified synthetic	SSD
Minimum	2.54	20.28	10.03
Maximum	37.72	26.17	37.58
Mean	21.3766	22.3575	21.6464
Standard Error (SE)	.98729	.14871	.86618
Standard deviation	7.11945	1.07233	6.24609

Above Table-3 depicted a descriptive comparison among the three estimator namely Direct estimator, Post-stratified Synthetic estimator and Sample Size Dependent (SSD) estimator. The Direct estimated values ranging from 2.54 to 37.72, which is approximately similar to the SSD estimated value ranging from 10.03 to 37.03. But in SSD the minimum estimated value (10.03) is greater than the Direct estimated value (2.54), in this sense SSD estimator have a great impact in small area estimation. The Post-stratified Synthetic estimates are ranging from 20.28 to 26.17. The mean value of these three estimators are approximately similar to each other. The standard deviation (SD) of Direct estimates (sd=7.11945) and SSD estimates (sd=6.24609) are approximately similar, but they are greater than the standard deviation (SD) of Post-stratified Synthetic estimates (sd=1.07233). Therefore, from the table-3 it can be conclude that among these three estimator Post-stratified Synthetic estimator is the best estimator than Direct and SSD estimator.

The estimation of nonlinear parameters of EB estimators based on BHF model provided by Battese et al. (1988). The values of the auxiliary variables in the model are needed for each out-of-sample unit. We use the sample data from all the provinces to fit the model and compute EB estimates and corresponding MSE estimates for all the provinces. For these selected provinces, the data set **Xoutsamp** contains the values for each out-of-sample individual of the considered auxiliary variables, which are the categories of education level and of labor status, defined exactly as in the data set **incomedata**. MSE estimates of the EB estimators under BHF model can be obtained using the parametric bootstrap method for finite populations introduced by González-Manteiga et al. (2008). Again, these data have been obtained by simulation.

To calculate EB estimates of the poverty incidences under BHF model for log (income + constant) for all provinces to fulfill the normality assumption. The list fit of the output gives information about the fitting process. The resulted linear mixed effects model fit by REAL method are depicted below, whether we find that all the auxiliary variables are significant (see Fixed effect table) and the correlation among the variables are independent (Fixed effects correlation table).

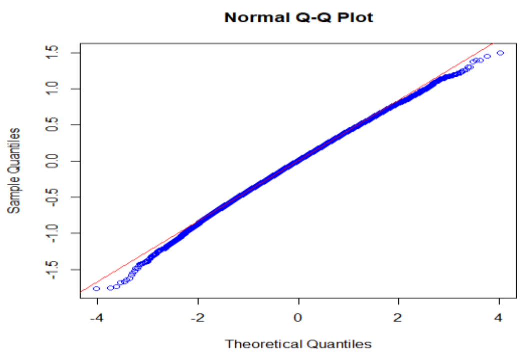
REML criterion at convergence: 18966.7

Random effects		
Groups	Variance	Standard Dev.
Dom (intercept)	0.008904	0.09436
Residual	0.174676	0.41794
Number of observation: 17199 Number of domain : 52		

Fixed effects				
	Estimate	Std. Error	t value	p-value
Xs(Intercept	9.505176	0.014385	660.8	0.00
Xseduc1	-0.124043	0.007281	-17.0	0.00
Xseduc3	0.291927	0.010366	28.2	0.00
Xslabor1	0.145985	0.006916	21.1	0.00
Xslabor2	-0.081624	0.017083	-4.8	0.00

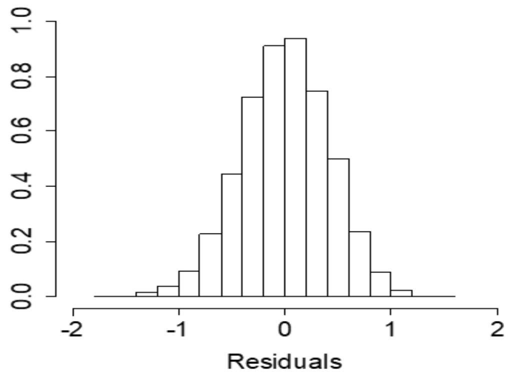
Correlation of fixed effects				
	Xs(In)	Xsedc1	Xsedc3	Xslabor1
Xseduc1	-0.212			
Xseduc1	-0.070	0.206		
Xslabor1	-0.199	0.128	-0.228	
Xslabor2	-0.079	0.039	-0.039	0.168

Checking model assumptions is crucial since the optimality properties of the EB estimates depend on the extent to which those assumptions are true. We draw the usual residual plots to detect departures from BHF model for the transformed income. An index plot of residuals and a histogram are given below:



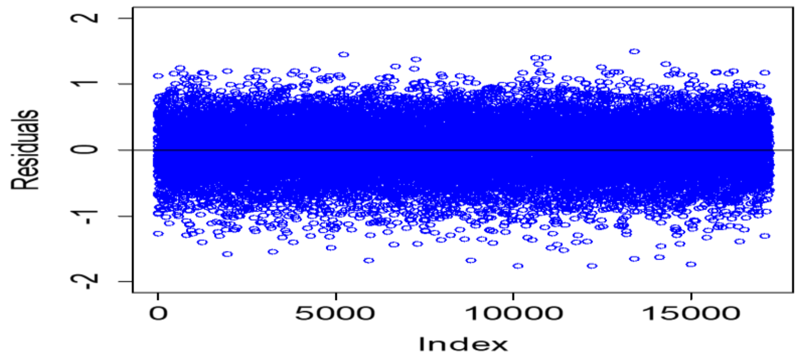
Normal Q-Q plot of EB predicted province effects

From the above graph, we can see that the data set is going through the origin. So we can say that our observe data is normally distributed.



Histogram of residuals from the fitting of BHF model to log (income + constant)

We see that it is approximately bell- shaped. That means data are normally distributed.



Index plot of residuals from the fitting of BHF model to log (income + constant)

Above scatter plot indicates that the data are very closer to each other that means variance are constant.

Figure-2: Checking model assumption

Table-4: Comparison of Direct and Empirical Bayes (EB) estimates and their respective coefficient of variation

Province Index	Province Name	Sample Size	Direct	CV. DIR	EB	CV. EB
1	Alava	96	0.255037	19.00367	0.335	7.226619
2	Albacete	173	0.140592	21.6384	0.159711	12.93839
3	Alicante	539	0.207851	10.48198	0.210909	5.402373
4	Almeria	198	0.26764	15.28299	0.24101	7.834946
5	Avila*	58	0.055122	46.35946	0.123793	24.96203
6	Badajoz	494	0.215539	10.93958	0.201012	5.96569
7	Baleares	634	0.099998	15.36549	0.11511	8.837025
8	Barcelona	1420	0.298125	5.428952	0.289218	2.307215
9	Burgos	168	0.214132	20.89156	0.188929	8.973926
10	Caceres	282	0.270313	11.56369	0.331773	4.358747
11	Cadiz	398	0.148874	14.7039	0.135251	8.6262
12	Castellon	118	0.175982	20.37073	0.255	8.938094
13	CiudadReal	250	0.209215	15.67395	0.20264	8.696991
14	Cordoba	224	0.299757	13.12423	0.311161	5.926287
15	CorunaLa	495	0.253475	9.73552	0.268444	3.99551
16	Cuenca	92	0.263341	22.45527	0.247717	9.927219
17	Gerona	142	0.183374	20.23291	0.222254	8.419048
18	Granada	208	0.317273	12.74599	0.335529	5.548515
19	Guadalajara	89	0.179082	23.64297	0.254157	9.667373
20	Guipuzcoa	285	0.236905	13.48546	0.245158	6.101039
21	Huelva	122	0.125834	25.45047	0.139508	16.48341
22	Huesca	115	0.241076	20.14448	0.278	8.05499
23	Jaen	232	0.312942	13.17392	0.284138	5.585637
24	Leon	218	0.188016	15.97012	0.249541	6.945103
25	Lerida	130	0.155596	24.88785	0.168231	12.96007
26	RiojaLa	510	0.258118	9.527405	0.265843	3.809543
27	Lugo	173	0.377187	15.10213	0.341387	5.242763
28	Madrid	944	0.182182	8.996593	0.191716	3.688254

29	Malaga	379	0.229185	11.93636	0.244908	5.155946
30	Murcia	885	0.177032	9.31421	0.186565	4.323254
31	Navarra	564	0.161908	11.37696	0.174574	5.835955
32	Orense	129	0.227996	18.41902	0.306667	7.349597
33	Oviedo	803	0.26064	8.03322	0.268319	3.274346
34	Palencia*	72	0.301661	23.80085	0.274306	11.25716
35	PalmasLas	472	0.166518	13.85587	0.150212	7.020753
36	Pontevedra	448	0.185491	13.04047	0.161652	7.475342
37	Salamanca	164	0.161045	18.61741	0.199634	10.25905
38	Tenerife	381	0.184296	11.14808	0.249711	4.648279
39	Santander	434	0.342444	9.487491	0.351866	3.26399
40	Segovia*	58	0.22262	25.33449	0.283448	10.66742
41	Sevilla	482	0.20503	10.35226	0.231784	4.650448
42	Soria*	20	0.025412	99.97815	0.1175	42.7319
43	Tarragona	134	0.320354	15.40193	0.414328	5.333037
44	Teruel*	72	0.273642	24.57017	0.315556	9.257185
45	Toledo	275	0.125534	16.98341	0.149673	9.837353
46	Valencia	714	0.213607	9.693081	0.228852	3.890675
47	Valladolid	299	0.192923	16.64643	0.157492	9.689178
48	Vizcaya	524	0.216945	10.21295	0.22063	5.150919
49	Zamora	104	0.300274	20.06599	0.274712	8.936914
50	Zaragoza	564	0.100346	15.63731	0.112996	8.187835
51	Ceuta	235	0.197248	16.93905	0.189915	8.724863
52	Melilla	180	0.191091	18.00719	0.216833	7.904507

Above table shows that most of the estimated value of Direct estimation for each province less than the estimated value obtain by EB estimation. Coefficient of variation in each province for direct estimate is greater than the coefficient of variation (CV) of EB estimate. It can be visually shown in Figure-3 and Figure-4.

*indicate 5 selected province with small sample size. The table shows that the estimated value of Direct (DIR) estimators for four provinces with small sample size namely Avila, Segovia, Soria, Teruel poverty incidence lie under EB estimates. Additionally that the differences are large in three provinces (Avila, Segovia, Soria), and are small in one of them (palencia). The above table also shows that the estimated C.Vs of Direct (DIR) for poverty incidence estimators are noticeably larger than those of Empirical Bayes (EB) estimators in all provinces. Such that we can say that EB estimate is better than direct estimation.

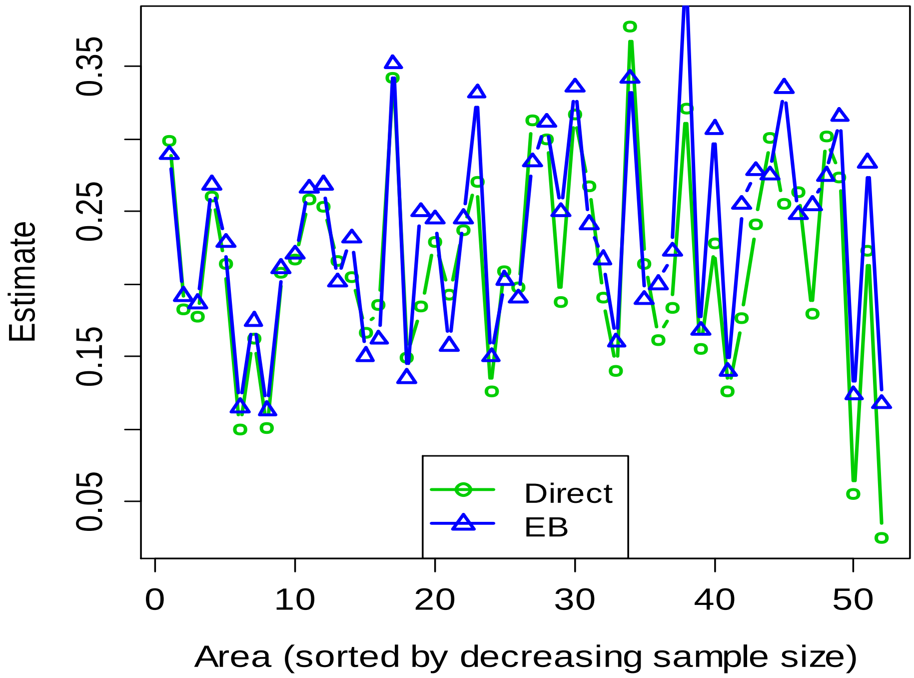


Figure-3: The estimated poverty incidence for Direct (DIR) and EB estimates

The figures showed that most of the direct estimates for poverty incidence lie under Empirical Bayes (EB) estimator for all selected provinces.

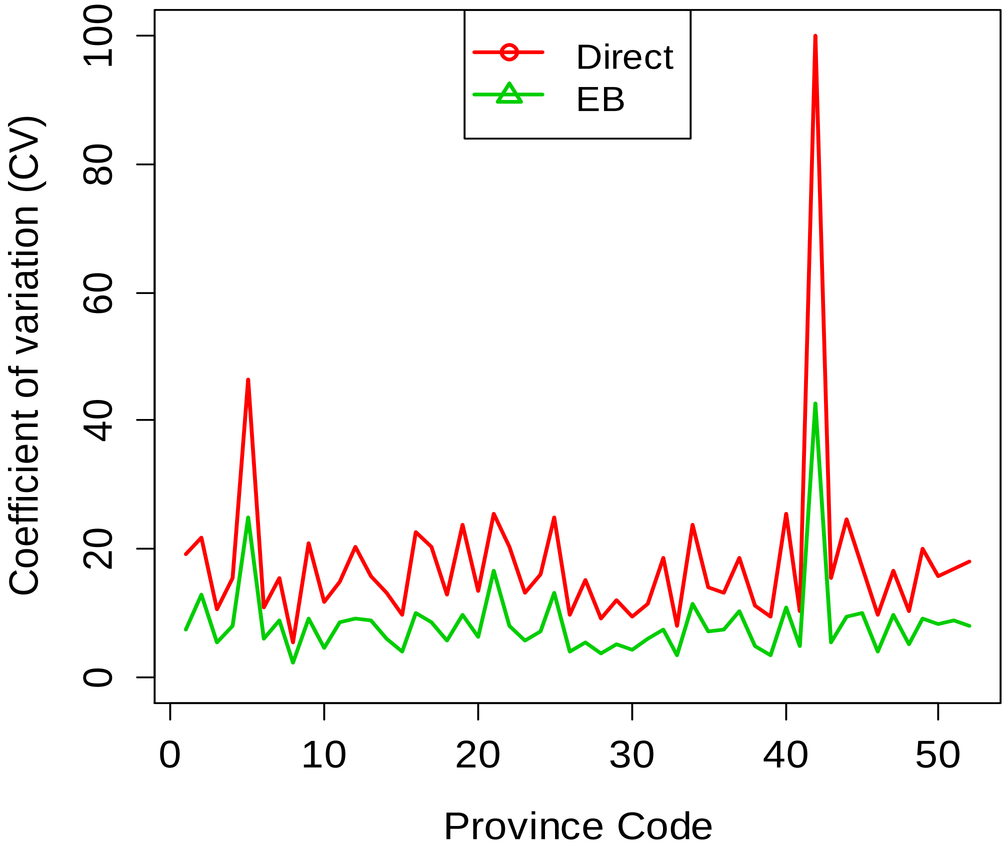
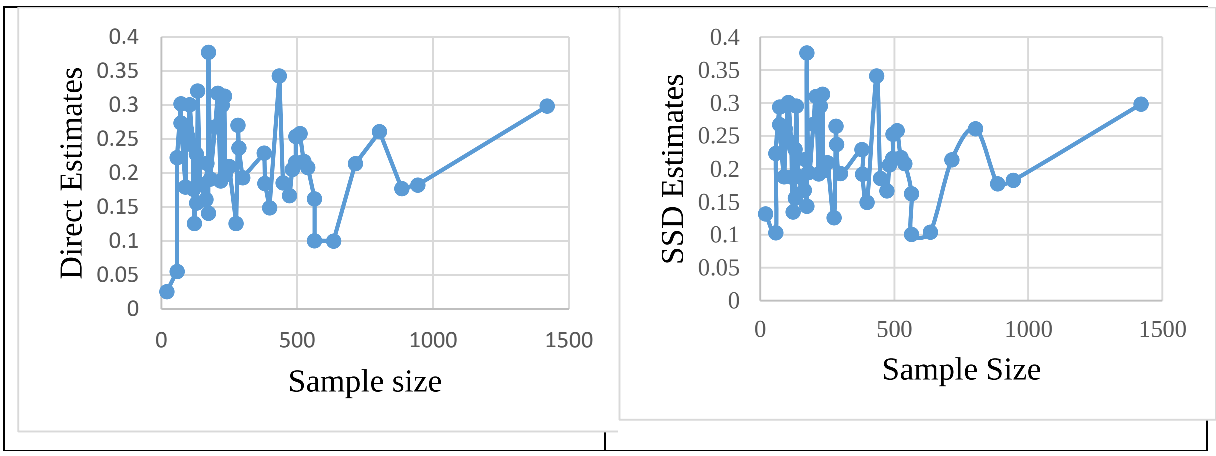


Figure-4: Estimated C.Vs of Direct (DIR) and EB for each area

The above graph shows that the estimated C.Vs of Direct (DIR) estimators are noticeably larger than those of Empirical Bayes (EB) estimators in all provinces. From figure-3 and figure-4, it is clear that model based estimator such as Empirical Bayes (EB) estimator is one of the most efficient estimator than direct estimator in the case of small area estimation.



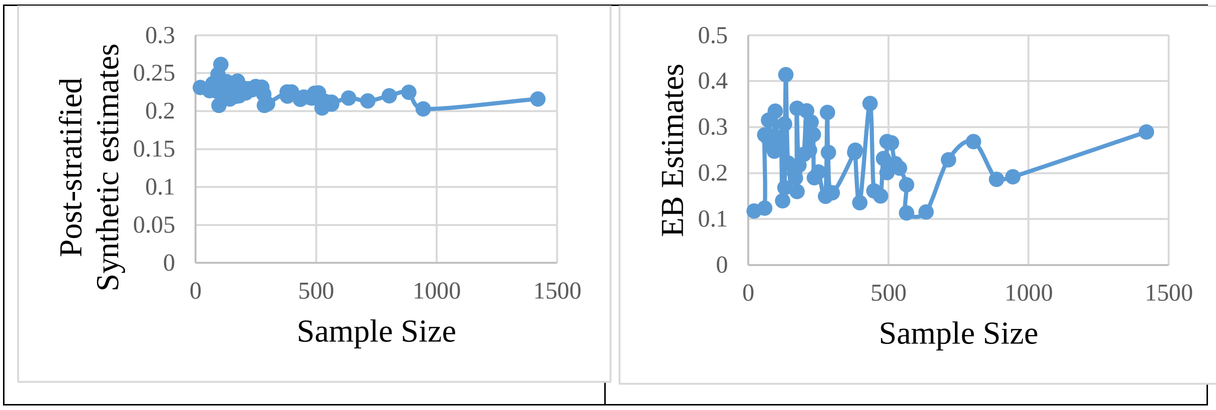
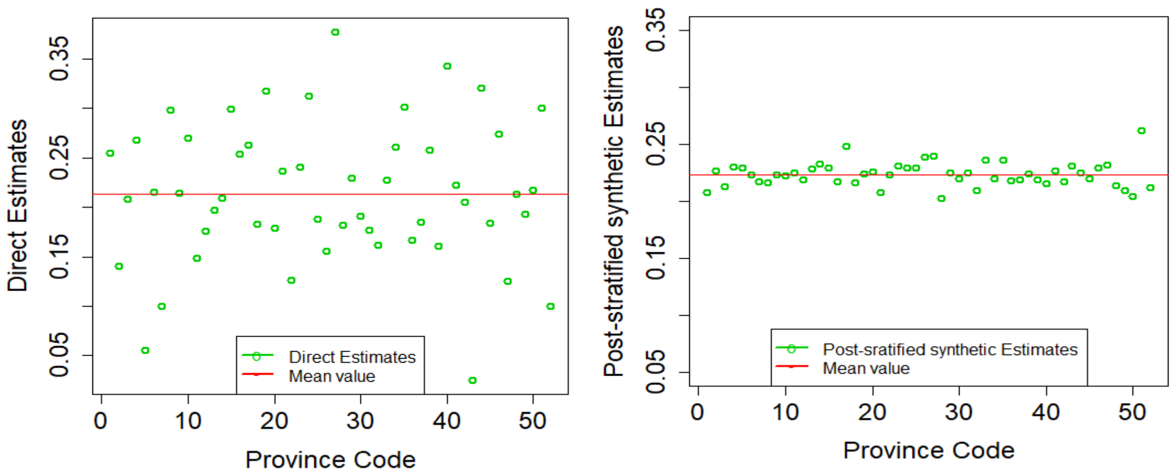


Figure-5: Scatter plot of Direct, SSD, Post-stratified synthetic and EB estimates according to sample size

From the figure-5 it can be seen that scatter plot of direct estimates (Range: 0.025412- 0.377187), SSD estimates (Range: .100346- .375823) and EB estimates (Range: 0.11299- 0.41432) according to the sample size estimated value are fluctuately increasing as sample size increases, they are unstable (Range: 0.025412- 0.377187) and they are approximately same. But in the case of post-stratified synthetic estimated values are stable (Range: 0.202825- 0.261705). Comparing to the direct estimates with indirect estimates (post- stratified synthetic, SSD, EB) it can be shown that the estimated value of indirect estimates are greater than direct estimated values as if there is small sample size.



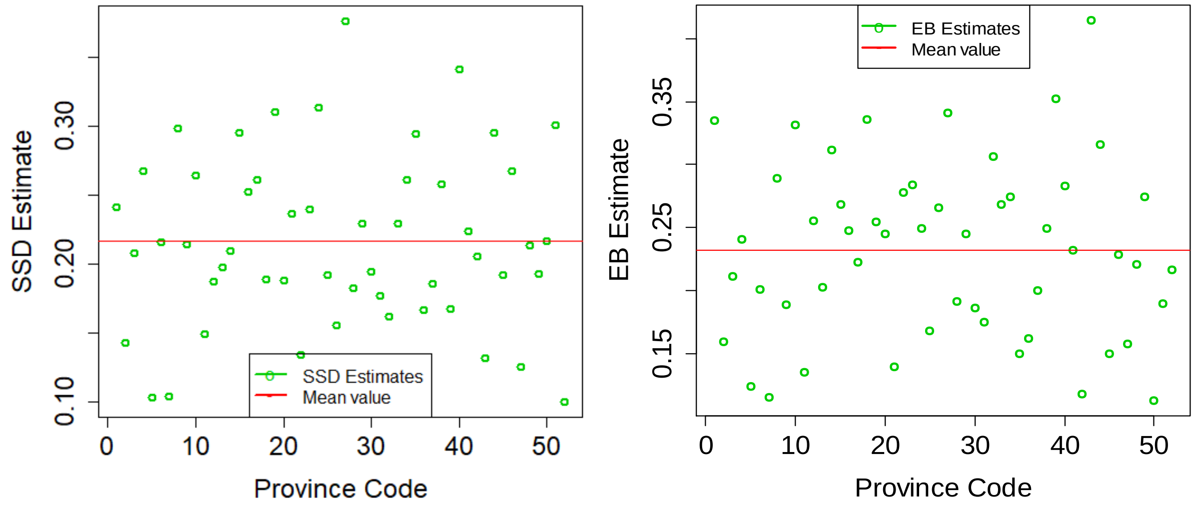
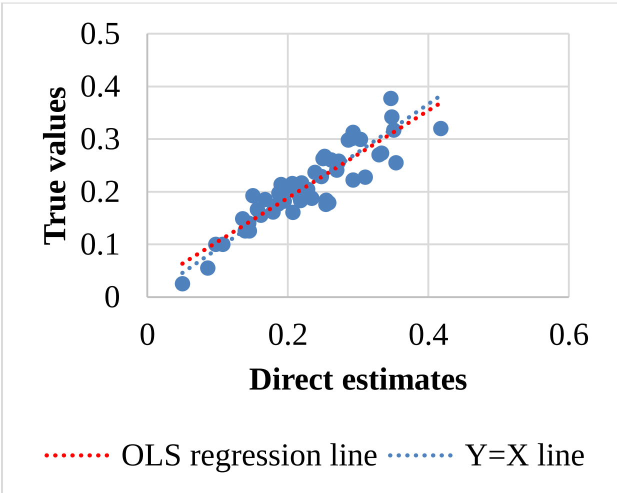
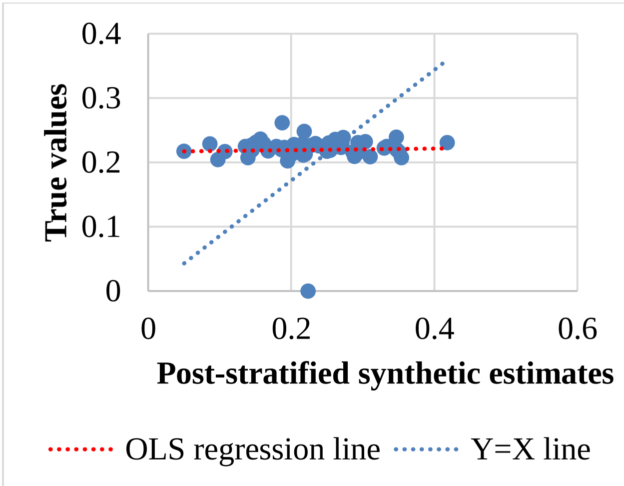
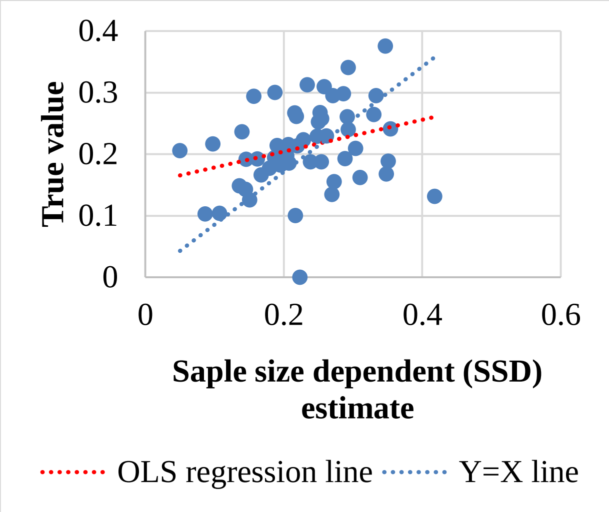


Figure-6: Scatter plot of Direct, post-stratified synthetic, SSD and EB estimates according to province code

Figure-6 indicates that the estimated value of Direct, SSD and EB estimator have a great distance from their mean value and the estimated value of Post-stratified Synthetic estimator are closer to their mean value and they are approximately stable.







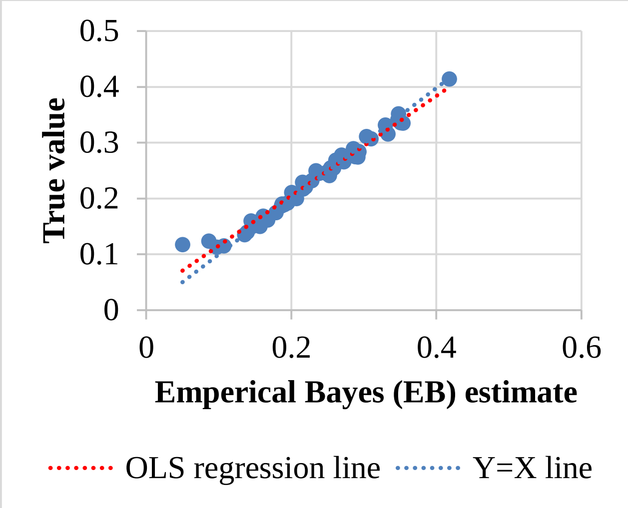


Figure-7: Bias scatter plot between True values and Direct, post-stratified synthetic and EB estimates

The scatter plot of true value (on the Y-axis) against direct estimates and EB estimates (on the X-axis) displayed a regression line close to the Y=X line. Here the slope coefficient estimate was near to 1 and intercept was not significantly differ from zero (0), indicating that there is no evidence to reject the hypothesis of lack bias for the direct estimate. That means, it can be conclude that Direct estimates and EB estimates are approximately unbiased. The main difference is that the value points in EB estimator are situated exactly in a straight line but the points of direct estimator have a significance distance from the straight line.

The scatter plot of true value (on the Y-axis) against post-stratified synthetic estimates and SSD estimates (on the X-axis) displayed a regression line that are not close to the Y=X line. Here the slope coefficient estimate was not near to 1 and intercept was significantly differ from zero (0), indicating that there is an evidence to reject the hypothesis of lack bias for the post-stratified synthetic estimate. That means, it can be conclude that post-stratified synthetic estimates and SSD estimates are extreme biased.

Conclusion

Our estimated results shown that direct estimates and sample size dependent (SSD) estimates are very similar. The estimated value of these two methods are fluctuately decreases as sample size decreases and they are slightly more unstable. It is noticeable that when sample size is large the SSD estimator treated as a direct estimator, but it is increases when sample size was small. However, the post-stratified synthetic estimates appear to be too stable, giving practically the same values for all provinces. But direct estimator is approximately unbiased but SSD and Post-stratified synthetic estimator is extreme biased. EB estimator depicted that most of the estimated value of Direct estimation for each province less than the estimated value obtain by EB estimation. Coefficient of variation in each province for direct estimate is greater than the coefficient of variation (CV) of EB estimate and it can also be shown that EB estimator is approximately unbiased. Such that we can say that EB (model based) estimate is better estimation method in the case of small area estimation. That's why, it is impossible to think any research work without knowing the SAE technique in the present world.

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