Electronic Journal of Applied Statistical Analysis
EJASA, Electron. J. App. Stat. Anal.
http://siba-ese.unisalento.it/index.php/ejasa/index
e-ISSN: 2070-5948
DOI: 10.1285/i20705948v7n2p417

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Published: 14 October 2014

Electronic Journal of Applied Statistical Analysis
Vol. 07, Issue 02, 2014, 417-431
DOI: 10.1285/i20705948v7n2p417

Examining a weight reallocation method for small area estimation of poverty

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Published: 14 October 2014

Small area estimation methodologies used in poverty estimation usually entail significant data requirements and sophisticated modeling techniques. However, there is a growing need for simpler small area estimation tools which can be easily institutionalized by national statistical offices of developing countries. Using a survey reweighting method, the paper demonstrates a more straightforward approach of estimating poverty statistics at the sub-domain level.

keywords: small area estimation, survey reweighting, Lorenz curve estimation

1 Introduction

A great deal of socio-economic surveys conducted by national statistical offices are designed to provide reliable estimates only at the national and/or state/territory geographic levels. The level at which reliable estimates can be drawn is usually referred to as the survey domain. Analysis at the sub-domain level warrants caution on interpreting summary statistics at face value. In particular, researchers are encouraged to examine the behavior of sampling variance of direct survey estimators at the sub-domain level.

Statistical agencies especially from developing countries confront the challenge of securing both financial and administrative resources needed to implement surveys that would be able to yield reliable estimates at finer levels of disaggregation. Instead of implementing full-blown surveys with large sample sizes, small area estimation techniques

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ISSN: 2070-5948
http://siba-ese.unisalento.it/index.php/ejasa/index

provide an alternative approach in producing reliable estimates beyond the survey domain. Over the years, the literature on small area estimation strategies has flourished and among the list of popular techniques include Elbers, Lanjouw and Lanjouw methodology (Elbers et.al., 2003) which incorporates area-specific effects in the estimation of the model errors, the family of generalized regression (GREG) estimators (e.g., model-assisted design-based estimators) and estimated best linear unbiased prediction (e.g., model-dependent techniques) which are both useful in estimating means and totals for small areas (Estevao and Srndal, 2004, 1999; Srndal et.al, 1992). Although these approaches share a common advantage of allowing for local variation through complex error structures in the model (Rao, 2003), the use of these techniques often require a good grasp on advanced statistical modeling. In addition, these strategies require the availability of other data sources such as census data or administrative data which are not prone to sampling errors. However, these types of data are not always available. Furthermore, Martinez (2009) argues that national statistical agencies even among developed countries still avail of simpler techniques which are relatively easy to institutionalize and goes on to propose survey weight-reallocation method wherein sampled units from other neighboring sub-domains can be used to estimate characteristics for a particular sub-domain, thus "synthetically increasing" the sample size. Although Martinez (2009) has demonstrated the improvements in the reliability of survey estimates due to survey reweighting, the author did not examine the property of the reweighted estimator. This study contributes to this gap in the literature by examining the properties of the reweighted estimator.

The rest of the paper is structured following this outline - the second section discusses survey reweighting focused on a simple Poisson reallocation model proposed by Schirm and Zaslavsky (1997). The third section examines the statistical properties of the survey reweighted estimator and how it fairs against a simple random sample estimator. The fourth section draws most of the discussions from the work of Martinez (2009) by demonstrating how survey reweighting can be used in small area estimation of poverty-related indices. The last section draws conclusion and recommendations.

2 Survey Reweighting

In general, survey weight can be expressed as a product of three components: (i) basic weight, (ii) adjustments for non-response, and (iii) adjustments for non-coverage. Basic weight is fixed by the survey design since it refers to the inverse of the probability of selection of a particular unit (Martinez, 2009). Adjustments for non-response are implemented by using indicators that are related to the probability of response and key characteristics of interest in the survey (Kalton and Maligalig, 1991). Further, using raking ratio method, adjustments for non-coverage may be introduced to make the resulting survey weights sum up to known (control) totals. The following equation expresses the survey weight ω_i attached to the ith sampled unit, as a product of these three components:

$$\omega_i = \omega_i^b \omega_i^{nr} \omega_i^{nc} \tag{1}$$

where ω_i^b is the inverse of selection probability, $\omega_i^{nr}$is the adjustment for non-response and ω_i^{nc} is adjustment for non-coverage. To reallocate weights, it is arguably ideal to work only with ω_i^{nc} (Martinez, 2009). While there are myriad of ways to reallocate the survey weights, Schirm and Zaslavsky (1997) proposed a weight reallocation procedure following the Poisson model,

$$\ln w_{id} = \beta_d^i \underline{x_i} + \delta_i \tag{2}$$

where w_{id} is the allocated survey weight for the i^{th} sampled unit to be used in estimating characteristics of interest for sub-domain d within the neighborhood, where $\underline{X_d} = \sum_{i \in d} \underline{x}_i$is a p x 1 column vector of control totals for sub-domain d. Note that under this framework, it would not matter whether we reallocate ω_i or ω_i^{nc} since δ_i will just absorb the other components of (1). Schirm and Zaslavsky (1997) imposed two constraints in estimating β_d and δ_i:

Constraint 1: $\sum_d w_{id} = \omega_i$ for each i,
Constraint 2: $\sum_d w_{id} x_{il} = X_{dl}$

Consequently, weight reallocation alters the contribution of every sampled unit to sub-domain estimates but the first constraint assures that its corresponding contribution to the overall estimate for any characteristic of interest remains the same. The second constraint imposes that all sub-domain control totals are satisfied by the reallocated weights. Schirm and Zaslavsky (1997) also proposed an iterative Newton-Raphson procedure in estimating the Poisson model parameters that will satisfy the two constraints. Following similar notations as that of Schirm and Zaslavsky (1997), if βd(k) and δi(k) are the values for the unknown parameters of the reallocation model, the iterative approach consists of the following steps:

At the k^{th} iteration:
Step 1: $\delta_{h(k)} = \ln(\frac{\omega_i}{\sum \exp(\beta'_{d(k-1)} x_i})$
Step 2: $\beta_{d(k)} = \beta_{d(k-1)} + D_d^{-1} d_d$ for each d,
where, $D_d = \sum_i w_{id} x_i x_i'$, $d_d = X_d - \sum_i w_{id} x_i$

It is easy to show that the first step in the iterative procedure satisfies the constraint that the contribution of every sampled unit to the overall estimate for a particular characteristic of interest remains the same, by substituting the expression for $\delta_{h(k)}$ in (2). Similarly, Step 2 is geared to satisfy the second constraint that all sub-domain control totals are satisfied by the reallocated weights. Estimates converge if $d_d$is sufficiently small. Note that the procedure assumes some initial values, $\beta_{d(0)}$ and $\delta_{i(0)}$.

3 Evaluating Weight-reallocated Estimator

Without loss of generality, suppose the parameter of interest for the kth small area is a population proportion $\overline{V}_{(k)}$ such that

$$\overline{V}_{(k)} = \frac{\sum_{ij=1}^{N_{(k)}} V_{ij(k)}}{N_{(k)}}$$

$$V_{ij(k)} = \begin{cases} 1 \ if \ Y_{ij(k)} < z \\ 0, \ otherwise \end{cases}$$

where Y$_{ij}$ is the characteristic of interest for unit i in cluster j (belonging in the kth small area) and z is a pre-identified fixed threshold. Many of the existing model-based small area estimation techniques entail borrowing strength from other data sources that are less prone to large sampling error at finer levels of disaggregation. For example, consider the model depicted in the following equation.

$$Y_{ij(k)} = \ \beta X_{ij} + \ \varepsilon_{ij}$$
$$\varepsilon_{ij} = h_i + e_{ij}$$

where X$_{ij}$ is the corresponding correlate of the characteristic of interest and ε_{ij} is the stochastic error term. Note that the model specification above allows for a heterogeneous error variance structure to accommodate the possibility that the characteristics of interest are clustered, and hence, are not independent across space (Ghosh et.al., 1998). To estimate this model, it is often required for X$_{ij}$ to be free from sampling error. In this context, census is one of most commonly used data source to serve this purpose. However, there are limitations to using census data. First, it is not commonly available especially in many developing countries. On the other hand, if it is available, it is ideal for the time gap between the survey and census to be minimal. If this is not met, one has to assume that the covariates to be used are time-invariant for the conventional SAE model-based approaches to work (Martinez, 2009). Another limitation of the conventional model-based SAE strategies is that they depend on the parameter to be estimated. Such approach becomes very complicated when there are numerous characteristics of interest.

Survey reweighting is an alternative to the conventional SAE model-based approach. In particular, consider the direct estimator for $\overline{V}_{(k)}$ denoted by $\overline{v}_k$ such that

$$\overline{v}_k = \frac{\sum_{ij(k)}^{n_k} w_{ij(k)} v_{ij(k)}}{n_k}$$

Because n_k is usually small, the estimator $\overline{v}_k$ usually have high sampling error. Nevertheless, as described in the previous section, we can re-estimate the survey weight to be able to synthetically increase the effective sample size. In other words, reweighting can be used as a small area estimation technique. Martinez (2009) points out that survey reweighting addresses the two limitations of conventional model-based procedure. First, reweighting is not heavily dependent on the characteristic of interest $Y_{ij(k)}$ unlike most of the other sophisticated modelling approaches in SAE.

Hence, reweighting's key advantage over other conventional SAE techniques is its weak reliance on which population parameter will be estimated. In addition, aside from the control totals, there is no need for covariates that will explain the variation of the underlying characteristic of interest. The application of reweighting is particularly attractive during intercensal years wherein there are limited covariates that have time invariant distribution commonly required by traditional small area estimation (SAE) approaches.

On the other hand, a disadvantage of this procedure is the potential bias that it may induce especially when the characteristic of interest is very different among the defined neighbors. Since reweighting borrows strength from pre-defined neighbors, when the true value of the characteristic of interest for a specific sub-domain is very different from the values of its pre-defined neighbors, then the reweighted estimator may be biased. Thus, it is important to identify on which instances would the reweighted estimator perform satisfactorily or not. To investigate this issue, we turn to a simple simulation experiment. In particular, we examine the properties of the survey reweighted estimator under different scenarios.

First, consider a population consisting of 10,000 units distributed among four sub-domains A, B, C and D. Without loss of generality, our parameter of interest is a population proportion (of a characteristic of interest). To estimate this proportion, a simple random sample (SRS) of size 382 is expected to yield an estimator satisfying $\alpha =$ 0.05 and 0.05 margin of error at the domain level. To provide a snapshot of the behavior of Poisson- reweighted estimators, we can do sampling iteratively.

The table below characterizes the behavior of Poisson-reweighted survey estimators under different scenarios. To serve as a point of comparison, the behavior of an SRS estimator is also summarized. The motivation for comparing the results from the Poisson-reweighting approach with that of SRS is that the latter usually provides the lowest standard error for a fixed sample size. The first scenario depicts estimation of a population proportion that is uniformly sparse across all sub-domains (considering three cases *P= 0.01, 0.05 and 0.1).* In terms of the deviation from the sub-domain population proportions, both SRS and Poisson- reweighted estimator seem to provide satisfactory results in terms of the difference between the actual population proportion and the mean of the survey estimates, although there may be a minimal advantage for Poisson-reweighted estimator for very sparse characteristics of interest (i.e., *P=0.01*). In terms of the variability of the estimator, the Poisson-reweighted estimator outperforms the SRS estimator. This observation is generally true for all other scenarios explored in this simple experiment and is intuitive in the sense that the Poisson reweighted estimator borrows strength from neighboring sub-domains, thus increasing its "effective sample size." Similarly, if the characteristic of interest is uniformly prevalent across all sub-domains, the Poisson-reweighted estimator notes a relative advantage compared to SRS only in terms of variability.

Table 1: Simple Random Sampling vs. Poisson Reweighted Estimators under Iterative Sampling

Population characteristic of interest is sparse

			SRS		Poisson-Reweighting Approach	
Pop'n Prop.(%)	Sub-domain	Proportion by sub-domain(%)	Average(%)	Std.dev.	Average(%)	Std.dev.
	A	0.9000	0.7121	1.3220	1.0610	0.5073
P = 1.0	B	1.4500	1.7054	1.4679	1.0775	0.5168
	C	1.6670	1.3537	1.0056	1.0811	0.5144
	D	1.0000	0.6662	0.4739	1.0819	0.5166
	A	4.7000	4.6877	3.2404	5.1849	1.0188
P = 5.0	B	4.6000	4.8748	1.9645	5.2134	1.0231
	C	5.1667	4.9457	2.3358	5.2287	1.0319
	D	5.2500	5.7271	1.8816	5.2358	1.0423
	A	9.6000	8.0452	3.9275	9.7173	2.7014
P = 10.0	B	10.1500	9.7895	3.2892	9.6985	2.6079
	C	9.9667	10.1346	3.3876	9.6925	2.5460
	D	10.0000	9.8038	3.0423	9.6747	2.5173

Population characteristic of interest is frequent						
			SRS		Poisson-Reweighting Approach	
Pop'n Prop.(%)	Sub-domain	Proportion by sub-domain (%)	Average(%)	Std.dev.	Average(%)	Std.dev.
	A	90.4000	89.9685	5.4250	89.5962	1.1848
P = 90.0	B	90.1000	89.6953	2.9492	89.5454	1.1395
	C	90.0000	89.3780	2.5296	89.5252	1.1366
	D	89.7000	89.3614	2.1777	89.4877	1.1502
	A	95.1000	95.7092	3.0166	94.6407	1.1368
P = 95.0	B	94.7500	94.4997	3.3918	94.6136	1.1475
	C	94.4000	94.8624	1.7371	94.6023	1.1681
	D	94.2750	94.0552	2.2620	94.5937	1.1841
	A	99.1000	99.3283	1.0853	98.9223	0.4995
P = 99.0	B	99.0500	99.1108	1.2115	98.9248	0.4902
	C	98.8330	98.6418	1.0087	98.9355	0.4832
	D	99.0500	98.9315	0.7397	98.9374	0.4845
Population characteristic of interest not uniform across sub-domains						
			SRS		Poisson-Reweighting Approach	
Correl.	Sub-domain	Proportion by sub-domain (%)	Average (%)	Std.dev.	Average (%)	Std.dev.
	A	79.8000	80.9852	5.1523	67.8014	2.3327
-0.5128	B	70.0500	74.4596	3.1892	64.6520	2.3454
-0.3569	C	9.8667	10.4046	1.5673	18.4903	1.9161
0.3768	D	14.7000	14.6369	2.7241	19.9219	2.3913
	A	77.6000	80.8375	2.9664	33.8055	1.9447
0.1959	B	10.3000	8.6052	2.6329	31.9078	2.5307
0.0841	C	70.0000	65.8824	3.9541	38.5919	3.7896
0.0634	D	15.2250	15.7823	2.3781	36.6278	3.2187

Next, we turn our attention when the characteristic of interest significantly varies from one sub-domain to another (within the same neighborhood / domain). Recall the framework described in Equation 2. The weight reallocation is explicitly dependent on explanatory factors $\mathbf{X}$ which serve as control totals that must be satisfied. In all cases, the comparative advantage of SRS in terms of deviation from the population proportions far outweighs the benefit of using Poisson weight reallocation with respect to the variability of estimators. But, SRS's advantage over Poisson weight reallocation becomes smaller as the correlation of $\mathbf{X}$ with the population characteristic of interest becomes higher. For example, in the last four rows of the preceding table, practically, $\mathbf{X}$ cannot contribute significantly in the estimation process. Consequently, reweighting will just tend to the overall mean within the domain.

Although this simple experiment does not provide conclusive results to facilitate statistical inference for the estimator derived using the proposed reweighting approach, it still validates its feasibility as a statistical tool in small area estimation. The results also provide directions for future work with respect to improving the estimation procedure.

When there is sufficient reason to believe that the characteristic of interest significantly varies across the sub-domains, there are two possible options which we may consider. First, like other SAE techniques, we can borrow strength from variables that are not prone to large sampling error and are significantly correlated with the characteristic of interest. But, if there are numerous characteristics of interest, the performance of $\mathbf{X}$ may vary from one to the other, unless we use different sets of $\mathbf{X}$ per characteristic of interest (perhaps not the ideal case). Alternatively, as Martinez (2009) proposed, we can ensure the efficiency of constructing a neighborhood system by using prior information to minimize the variability of the unknown population characteristic of interest among defined neighbors. Operationally, we can adopt restrictive borrowing where neighbors are defined with respect to spatial distance functions so that more strength will be borrowed from "nearer" neighbors.

In the next section, we turn for an empirical example of how the methodology can be used for small area estimation of poverty-related indices. Most of the discussions are extension from the work of Martinez (2009).

4 Empirical Application

The multidimensionality of the economic paradigm eludes many in the sense that both development miracles altering the economic landscape of some countries that were once considered among the very poor co-exist with development mirages in which despite economic growth, other indicators of development suggest otherwise. This prompted to the rise of the concept of pro-poor growth. Martinez (2009) briefly surveyed the existing literature which discussed the different methodologies in assessing pro-poorness of growth – (Kakwani and Pernia, 2000; Lopez, 2004; McCulloch and Baulch, 1999; Ravallion, 2004; White and Anderson, 2000). Among these are two schools of thought; Kakwani and Pernia (2000) characterized pro-poor growth corresponds to the type which produces greater poverty reduction than it would have been if all incomes had grown at the same rate, while Ravallion and Chen (2003) referred pro-poor growth to growth that reduces poverty. This paper adopts the measure developed by Kakwani et.al. (2004). The poverty equivalent growth rate is an index to measure the degree to which the poor benefit from growth. Kakwani et.al. (2004) expressed the elasticity of a poverty measure measure K(.) with respect to mean income (or expenditure). We use a subset of the Family Income and Expenditure Survey conducted triennially by the Philippine National Statistics Office. The survey collects detailed data on household demographics, income sources and consumption. Starting 2003, FIES has been designed to provide reliable estimates at the regional level.

Consisting the provinces of Basilan, Lanao del Sur, Maguindanao, Sulu and Tawi- tawi, the Autonomous Region of Muslim Mindanao is among the less developed regions in the Philippines. Its per capita gross regional domestic product at Php 18,924 (at constant 1985 prices) based from 2009 official estimates of the National Statistical Coordination Board (NSCB)[1]. This is equivalent to 0.90 percent contribution to total national output for the same year. More than half of its 4.1 million population are living below the poverty line and 0.8 million are subsistence / food poor based from NSCB estimates. In addition, approximately two thirds of the poorest 40 percent of its population has little education (Schelzig, 2005).

Treating the geographic provinces as small areas, Martinez (2009) used Poisson reweighting and estimated parametric Lorenz curves to reduce the high coefficient of variation associated to the direct survey estimates for FGT measures[2]. After computing poverty equivalent growth rates, Martinez (2009) hinted that while the poor, in general, did not suffer more than their counterparts living above the poverty line during this period (2000-2006) of decreasing average real income as is indicated by the higher PEGRs for the percentage of poor, the ultra-poor in Lanao del Sur, Sulu and Tawi-tawi appeared to be more disadvantaged as indicated by lower PEGRs with respect to the poverty gap ratio[3].

This section extends the illustration of the estimation procedure by computing food poverty using a constant food poverty line of Php 8,313. In other words, relative to the

[1]The National Statistical Coordination Board is the government agency mandated to compute official economic (e.g., national accounts) and poverty statistics in the Philippines.

[2]For convenience, Martinez (2009) used a simple definition of neighborhood system (i.e., provinces within the same region are considered neighbors) in the reallocation of survey weights. In particular, the following variables were used as control totals: (i) population size, (ii) total number of male-headed households, (iii) total number of households whose head finished at most primary education, (iv) total number of households whose head finished at most secondary education, and (v) total number of households whose head finished college education.

[3]Martinez (2009) used a constant poverty line of Php 11,375 in computing provincial poverty indices for the years 2000, 2003 and 2006. The value Php 11,375 is the regional poverty threshold computed by NSCB for the year 2000. In particular, this is the weighted mean of the provincial poverty thresholds used in the computation of official provincial poverty statistics in the Philippines. Moreover, these menu-based provincial poverty thresholds are updated annually. During FIES years, the nominal income from the survey data is compared with the updated provincial poverty thresholds to derive the official poverty estimates. Per capita household real income was computed at 2000 prices using provincial consumer price index. Similar approach was implemented in this paper, the only difference is here, food poverty is the characteristic of interest

Martinez (2009) study, this study estimates subsistence poverty, a more extreme form of economic deprivation.

The following table provides the provincial average per capita (nominal) income as computed from the FIES data. In particular, the numerical figures were computed using the original and the allocated survey weights. The overlapping confidence intervals for the estimated mean per capita household income using the original survey weights suggest that up to some extent, the provincial population means tend are more or less the same among the five provinces. As noted in Section 3, when the characteristics of interest are uniform within the domain, estimates using reallocated weights perform satisfactorily (over SRS) with respect to bias and sampling error. This is validated in the following table.

Table 2: Provincial Mean Per Capita Household Income and its Coefficient of Variations (CVs)

Province	(Using Original Survey Weights)					
	2000		2003		2006	
	Ave. Inc.	CV	Ave. Inc.	CV	Ave. Inc.	CV
Basilan	13,391.46	9.33	15,931.85	9.82	23,678.28	14.58
Lanao del Sur	16,684.17	3.04	23,552.07	11.12	19,937.52	8.11
Maguindanao	17,759.85	25.72	14,947.53	8.17	16,922.50	6.47
Sulu	13,104.66	9.05	16,276.10	6.70	17,863.20	4.49
Tawi-tawi	15,421.29	11.39	16,573.07	7.96	12,783.44	13.22
Basilan	13,391.46	9.33	15,931.85	9.82	23,678.28	14.58

Province	(using Poisson-allocated survey weights)					
	2000		2003		2006	
	Ave. Income	CV	Ave. Inc.	CV	Ave. Inc.	CV
Basilan	15,706.96	8.73	18,631.42	4.75	19,427.46	4.24
Lanao del Sur	17,295.60	9.63	19,502.76	5.58	18,713.28	4.24
Maguindanao	16,302.59	9.27	17,235.18	4.43	18,621.97	4.40
Sulu	13,908.28	8.32	15,888.50	4.13	16,614.18	3.68
Tawi-tawi	15,404.33	8.89	17,618.17	4.78	16,632.46	4.09

Source: Author's computations using FIES data.

Using the reallocated survey weights, real per capita income quintiles were computed.

In turn, these were used to fit Beta Lorenz curves[4]. Martinez (2009) noted that except for the province of Basilan between 2000 and 2003, real income seemed to decline in the region over the recent years. Consequently, sharp increase both in terms of poverty and inequality were observed for the provinces of Sulu and Tawi-tawi. Santos (2008) identified high inflation of food and non-food basic needs and oil prices to be among the reasons for the worsened poverty situation. On the other hand, Table 3 shows the estimates for the parametric poverty indices and inequality with respect to food poverty threshold.

Table 3: Indices of Poverty and Inequality

Province	2000			2003			2006		
	Share of food poor	Food poverty gap ratio	Gini	Share of food poor	Food poverty gap ratio	Gini	Share of food poor	Food poverty gap ratio	Gini
Basilan	25.66	4.89	27.74	27.38	5.16	29.89	35.83	7.6	27.28
Lanao del Sur	25.43	4.66	29.35	30.24	6.19	32.56	40.85	8.89	26.98
Maguindanao	25.68	4.8	27.98	32.17	6.51	29.46	38.09	8.04	26.15
Sulu	33.18	6.63	25.63	37.36	7.95	28.19	44.18	9.79	24.54
Tawi-tawi	28.16	5.36	27	33.03	6.9	30.29	48.88	11.27	25.31

Source: Author's computations using FIES data; all estimates are based from Beta parameterization.

Between 2000 and 2003, the poverty equivalent growth rates (PEGRs) for percentage of food poor and food poverty gap ratio provide diverging observations. While the poor, in general, did not suffer more than their counterparts living above the poverty line during this period of decreasing average real income as is indicated by the higher PEGRs for the percentage of food poor, the ultra-poor in Basilan, Lanao del Sur, Sulu and Tawi-tawi appeared to be more disadvantaged as indicated by lower PEGRs with respect to the food poverty gap ratio between 2000 and 2003.

On the other hand, between 2003 and 2006, the computed PEGRs for both percentage of food poor and food poverty gap ratio are both higher than the actual rate of decline in per capita household real income. This is similar to what Martinez (forthcoming) has observed, suggesting some degree of pro-poorness such that for the same proportional poverty increase, the real income should have contracted at a slower rate if there had been no change in inequality. In other words, fixing the share of each individual to total

[4]Estimation of Beta or GQ parameterization may yield invalid Lorenz curves. In this case, GQ Lorenz curves were invalid for the income data. In general, when both Beta and GQ parameterization produced invalid Lorenz curves, different parameterization such as Log Normal, Gupta or Pareto Lorenz functions may be considered.

Table 4: Poverty Equivalent Growth Rates

Province	2000-2003			2003-2006		
	Actual Growth Rate	Poverty Equiv. Growth Rate		Actual Growth Rate	Poverty Equiv. Growth Rate	
		Percentage of Food Poor	Food Pov. Gap Ratio		Percentage of Food Poor	Food Pov. Gap Ratio
Basilan	3.33	3.97	2.02	-17.57	-13.78	-15.19
Lanao del Sur	-1.82	-1.7	-4.09	-26.16	-14.75	-14.58
Maguindanao	-8.2	-2.28	-4.81	-14.16	-9.8	-10.01
Sulu	-0.49	-0.89	-3.07	-17.6	-9.91	-9.36
Tawi-tawi	-0.37	-1.28	-3.96	-28.11	-19.82	-17.84

income, a smaller contraction of average income would have caused the same increase in poverty as that of what was actually observed.

On the whole, the entire region of ARMM has remained among the poorest in the country both with respect to official poverty and food thresholds. During the episodes of decreasing real income, there were some indications that the ultra food poor were bearing the grunt of the episode of decreasing real income especially between 2000 and 2003. In particular, more than half of the food poor in 2003 were still poor in 2006. Although there were hints that the food poor did not suffer more than those above the food poverty line from 2003 to 2006, whether poverty situation in ARMM will experience significant improvement in the coming years is still open to question.

5 Conclusion and Recommendation

The use of the proposed reweighting procedure is attractive in the sense that it provides a simpler methodology in improving the reliability of direct survey estimators compared to existing SAE techniques. In particular, unlike the usual SAE techniques which entail sophisticated modeling procedures, survey reweighting is relatively simpler; requiring only a set of indicators which can be used to group the observations under different neighborhoods. To be able to maximize the performance of this type of estimator, it is operationally useful to examine its statistical properties. Using a simple simulation experiment, this paper briefly investigates the properties of reweighted survey estimators under different scenarios. Our findings suggest that the simplicity of the reweighting as a small area estimation tool has a potential trade-off. When the characteristics of interest tend to be uniform across the sub-domains, it performs satisfactorily compared to SRS. Otherwise, when the characteristic of interest significantly differ from one sub-domain to another; and the indicators used as control totals are weakly related with the characteristic of interest, a restrictive borrowing may be adopted such that more strength will be borrowed from "nearer" neighbors (with respect to some defined spatial distance functions). Although the paper only provided a snapshot on the estimator's behavior under different scenarios and its relative performance over SRS, the results may be used to provide direction for future work. In addition, future studies must also take into account how issues of missing values and outliers could affect the accuracy of reweighted survey estimators. Furthermore, another important task that remains for future research is to provide a quantitative assessment comparing the Poisson-weight reallocation method with more conventional SAE approaches in terms of accuracy of parameter estimates.

To demonstrate the feasibility of survey reweighting as an SAE technique using empirical data, the study extended the illustration of Martinez (2009) with respect to the practical applications of the proposed procedure. In particular, the concepts of Poisson reweighting and Lorenz curve parameterization may be combined to come up with an alternative tool for small area food poverty estimation. Although, it would have been instructive to compare the reweighted estimators with the performance of other conventional model-based estimators, this has not been implemented in this study due to the lack of access to appropriate census data. This is reserved for future research.

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