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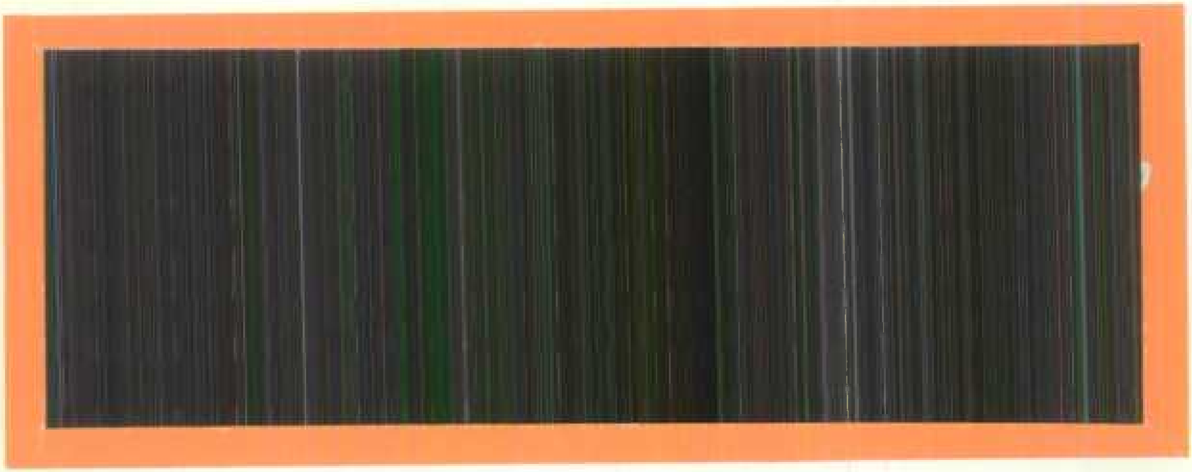

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SAMPLE SIZE DEPENDENT ESTIMATORS FOR SMALL AREAS

by
K.P. Srinath and M.A. Hidiroglou

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SAMPLE SIZE DEPENDENT ESTIMATORS FOR SMALL AREAS

K.P. Srinath and M.A. Hidiroglou

ABSTRACT

There are several estimation procedures available for producing small area data. These procedures include domain estimation, poststratified estimation and synthetic estimation. Recently, methods incorporating a linear combination of synthetic estimates or model based estimates and poststratified estimates have been proposed by Fay and Herriot (1979), Sarndal (1984) and Battese and Fuller (1984); these methods are based on regression procedures and some require the estimation of variances at the small area level. In this paper, some simple estimators which are a weighted combination of the poststratified estimator and the synthetic or model based estimator are proposed. The weights are simple functions of either the actual and the expected sample sizes or the actual sample total of the auxiliary variable and its expected value in the small areas of interest. The properties of these estimators are investigated through a Monte Carlo simulation based on business tax data.

ESTIMATEURS À BASE DE LA TAILLE RÉALISÉE DANS LES PETITES RÉGIONS

K.P. Srinath and M.A. Hidiroglou

Il existe plusieurs méthodes d'estimation pour les données des petites régions. Ces méthodes comprennent l'estimation par domaine, l'estimation post-stratifié et l'estimation synthétique. Récemment des méthodes incorporant une combinaison linéaire des estimations synthétiques ou estimation à base de modèles linéaires et l'estimation post-stratifié ont été proposé par Fay et Herriot (1979), Sarndal (1984), et Battese et Fuller (1984); ces méthodes sont basées sur des procédures de régression et quelques unes ont besoin de l'estimation de variances au niveau de la petite région. Dans cette article, nous proposons des estimateurs simples qui sont en fonction d'une combinaison pondérée de l'estimation post-stratifié et de l'estimation synthétique. Les poids sont de simples fonctions de la taille réelle ou espérée de l'échantillon ou du total réel d'une variable auxilliaire ou de son espérance mathématique pour les petites régions étudiées. Les characteristiques de ces estimations sont étudiées en se servant d'une étude Monté-Carlo basée sur des données d'entreprises.

SAMPLE SIZE DEPENDENT ESTIMATORS FOR SMALL AREAS

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1. INTRODUCTION

Large scale nationwide surveys are often designed to provide estimates at the national and provincial levels with a prespecified reliability. These surveys are not and sometimes cannot be designed to provide estimates with reasonable reliability for every subprovincial area or other small areas even when the survey is based on large samples. The publication of the estimates at the national and provincial levels always triggers a demand for similar data at other levels for purposes of administering social and fiscal programs at these levels. Therefore, it is of importance to investigate the problem of producing estimates with reasonable accuracy for small areas using survey information and other available auxiliary information.

Currently, there are several estimation techniques available for producing small area data and the list of such techniques is growing due to increased importance and the need for such data. The procedures include domain estimation, poststratified estimation and synthetic estimation. Recently, methods involving a linear combination of synthetic estimators and poststratified estimators have been proposed by Fay and Herriot (1979), Sarndal (1984), Battese and Fuller (1984), Drew, Singh and Choudhry (1982) and Sarndal and Hidiroglou (1985). A comprehensive bibliography on small area estimation has also been published (Statistics Canada; 1983). From the available literature, it seems that there is no single best solution to the problem of producing accurate small area estimates even when the availability of auxiliary information is assured. The efficiency of an estimation procedure to produce small area estimates depends on several factors which include the size of the small area, the strength of the relationship between auxiliary variables and the variable of interest, the overall sample size and the sample size within each small area.

In this paper, some simple estimators which are a weighted combination of the poststratified estimator and a model based estimator are proposed. The weights are simple functions of either the actual and the expected sample sizes or the actual sample total of the auxiliary variable and its expected value in the small areas of interest. If the number of sampled units falling in the small area is close to or more than the expected sample size, then the proposed estimators tend more towards the poststratified estimator than the model based estimator. Otherwise, they tend more towards the model based estimator. Similarly, if the actual sample total of the auxiliary variable is close to or more than its expected value, then the estimators based on auxiliary variables tend more towards the poststratified ratio estimator. The weights used in the above estimators do not involve estimated variances or other complex relationships between the auxiliary variable and the variable of interest. The emphasis, here, is on weights rather than the estimators used to form the combination. The weights suggested in this paper provide a procedure for combining an estimator based solely on the sample size and auxiliary information within the small area with an estimator based on samples in other areas.

The paper is structured as follows. In section 2, the estimators are defined and their properties stated. In section 3, the proposed estimators are compared with some of the estimators available in the literature. The comparison of the efficiencies is undertaken through a Monte Carlo simulation assuming simple random sampling and using business tax data. Finally, section 4 gives some general conclusions.

2. ESTIMATORS

Suppose that a finite population of size N units is divided into 'A' mutually exclusive and exhaustive small areas. These can be considered 'A' nonoverlapping domains for which estimates of the characteristics of interest are required. Assume that the population of N units can also be divided into a small number of groups G. This means, that units within each small area are classified into G groups giving a total of AG cross classified cells.

The small area as defined above need not necessarily be just a geographical area. For example, estimates may be needed for a small area by categories of a certain other variable, then a small area by category is the domain of interest and therefore will be defined as 'small area' for our purpose. For example, the population of interest could be businesses. The variable by which the small area is categorized could be industry and the groups could be earnings of businesses. Here, it is of interest to obtain estimates for small areas by industry.

Let N_{ag} represent the number of units in the population in the a^{th} small area and g^{th} group; a = 1, 2, ..., A, g = 1, 2, ..., G. Let $N_{a.} = \sum_{g=1}^{G} N_{ag}$ denote the number of units in the population in the a^{th} small area.

Let n_{ag} denote the number of units falling into the ag^{th} cell when a simple random sample of n units is drawn from N. $n_{a.} = \sum_{g} n_{ag}$ denotes the number of units in the sample in the a^{th} small area. Let y denote the variable of interest and x the auxiliary variable.

Let Y_a denote the population total of the characteristic of interest y in the a^{th} small area.

First, some usual estimators of the population total will be stated. The direct estimator of Y_a is given by

$$T_a(1) = \sum_{g} \frac{N}{n} n_{ag} \bar{y}_{ag},$$

where $\bar{y}_{ag}$ is the sample mean in the ag^{th} cell based on n_{ag} units. The post-stratified estimator is given by

$$T_a(2) = \sum_g N_{ag} \; \bar{y}_{ag}.$$

The poststratified ratio estimator is

$$T_a(3) = \sum_g X_{ag} \frac{\bar{y}_{ag}}{\bar{x}_{ag}}$$

where X_{ag} is the population total of the auxiliary variable in the ag^{th} cell and $\bar{x}_{ag}$ is the sample mean based on n_{ag} units.

The count synthetic and the ratio synthetic estimators are given by

$$T_a(4) = \sum_g \; N_{ag} \; \bar{y}_{.g}$$

and

$$T_a(5) = \sum_g \; X_{ag} \; \frac{\bar{y}_{.g}}{\bar{x}_{.g}}$$

where $\bar{y}_{.g}$ and $\bar{x}_{.g}$ are the sample means for the g^{th} group based on $n_{.g}$ units.

$$n_{.g} = \sum_{a=1}^{A} \; n_{ag}.$$

The weights to be used in the proposed estimators are defined as follows for $n_{ag} \geq 1$ or $x_{ag} > 0$.

Let $$W_{1ag} = \hat{N}_{ag} \left(\frac{n_{ag}}{En_{ag}} \right)$$

and $$W_{2ag} = (N_{ag} - \hat{N}_{ag}) \left(\frac{En_{ag}}{n_{ag}} - 1 \right)$$

where $$\hat{N}_{ag} = \frac{N}{n} (n_{ag}) \quad \text{and} \quad En_{ag} = \frac{n}{N} N_{ag}.$$

Also, let $$W'_{1ag} = \hat{X}_{ag} \left(\frac{x_{ag}}{Ex_{ag}} \right)$$

and $$W'_{2ag} = (X_{ag} - \hat{X}_{ag}) \left(\frac{Ex_{ag}}{x_{ag}} - 1 \right),$$

where $$\hat{X}_{ag} = \frac{X}{x} (x_{ag}) \quad \text{and} \quad Ex_{ag} = \frac{x}{X} (X_{ag})$$

X is the population total of the auxiliary variable, x the sample total, and x_{ag} the sample total in the ag^{th} cell. If $n_{ag} = 0$, then, set $W_{1ag} = 0$ and $W_{2ag} = 1$. Similarly, if $x_{ag} = 0$, then $W'_{1ag} = 0$ and $W'_{2ag} = 1$.

We now propose the following estimators

$$T_a(6) = \sum_g N_{ag} \left(\frac{W_{1ag} \bar{y}_{ag} + W_{2ag} \bar{y}_{.g}}{W_{1ag} + W_{2ag}} \right)$$

$$T_a(7) = \sum_g X_{ag} \left(\frac{W'_{1ag} \bar{y}_{ag} + W'_{2ag} \bar{y}_{.g}}{W'_{1ag} \bar{x}_{ag} + W'_{2ag} \bar{x}_{.g}} \right)$$

$$T_a(8) = \sum_g X_{ag} \left(\frac{W_{1ag}\,\bar{y}_{ag} + W_{2ag}\,\bar{y}_{.g}}{W_{1ag}\,\bar{x}_{ag} + W_{2ag}\,\bar{x}_{.g}} \right)$$

$$T_a(9) = \sum_g X_{ag} \frac{W'_{1ag}\left(\frac{\bar{y}_{ag}}{\bar{x}_{ag}}\right) + W'_{2ag}\left(\frac{\bar{y}_{.g}}{\bar{x}_{.g}}\right)}{W'_{1ag} + W'_{2ag}}$$

$$T_a(10) = \sum_g X_{ag} \frac{W_{1ag}\left(\frac{\bar{y}_{ag}}{\bar{x}_{ag}}\right) + W_{2ag}\left(\frac{\bar{y}_{.g}}{\bar{x}_{.g}}\right)}{W_{1ag} + W_{2ag}}$$

It is seen from an examination of the weights that they are always positive. If $N_{ag} = \hat{N}_{ag}$ then $T_a(6)$ reduces to the poststratified estimator $T_a(2)$. If $n_{ag} = 0$, then $T_a(6)$ is the same as the synthetic estimator $T_a(4)$. As n_{ag} approaches En_{ag} the estimator tends more towards the poststratified estimator. Similarly, if $X_{ag} = \hat{X}_{ag}$, then $T_a(7)$ is same as $T_a(3)$ and if $n_{ag} = 0$ then $T_a(7)$ is same as $T_a(5)$.

Other estimators also reduce to either the poststratified ratio estimator or the ratio synthetic estimator depending on whether $W_{2ag} = 0$ or $W_{1ag} = 0$ and $W'_{1ag} = 0$ or $W'_{2ag} = 0$.

All the estimators are biased, though the biases tend to be small when $n_{ag} > En_{ag}$ and $x_{ag} > Ex_{ag}$. The conditional bias of $T_a(6)$ can easily be derived and is equal to

$$B[T_a(6)] = \frac{W_{2ag} N_{ag}}{W_{1ag} + W_{2ag}} (1 - \frac{N_{ag}}{N_{.g}}) (\bar{Y}^{(a)}_{.g} - \bar{Y}_{ag})$$

where $\bar{Y}^{(a)}_{.g}$ is the population mean for the g^{th} group excluding small area a. $\bar{Y}_{ag}$ is the population mean of the ag^{th} cell.

The estimators attempt to achieve some kind of a balance between their variances and biases, thus keeping the mean square error under control as can be seen from the simulation studies.

Some variations of the estimators proposed above are possible. For example, if estimates are obtained only for non-sampled portion since the sample total is known, (Royall, 1978) then $T_a(7)$, for example can be written as

$$T_a(7A) = \sum_g y_{ag} + (X_{ag} - x_{ag}) \frac{W'_{1ag} \bar{y}_{ag} + W'_{2ag} \bar{y}_{.g}}{W'_{1ag} \bar{x}_{ag} + W'_{2ag} \bar{x}_{.g}}$$

In the following section all the proposed estimators are compared with the usual estimators T(1) to T(5) and other similar estimators proposed by Drew, Singh and Choudhry (1982).

3. RESULTS OF THE EMPIRICAL STUDY

In order to study the properties of the various estimators discussed in the previous section, a simulation was undertaken. The province of Nova Scotia was chosen as our population with N = 1,678 unincorporated tax filers. The small areas of interest were 18 Census divisions within that province. The major industrial groups studied within these areas were Retail (515 units in the population), Construction (496 units in the population), Accommodation (114 units in the population) and the remaining industries grouped into Others (533 units in the population). The variable of interest is Wages and Salaries (available on a sample basis) and the auxiliary variable are either counts of tax filers or Gross Business Income (available on a 100% basis). The overall correlation coefficients between Wages and Salaries and Gross Business Income were 0.42 for Retail, 0.64 for Construction, 0.78 for Accommodation and 0.61 for Others.

For the Monte Carlo simulation, 500 samples, each of size 419, were selected using simple random sampling without replacement from the target population of 1,678 unincorporated tax filers. The selected sample units were classified into type of industry and Census Division. The population could have been divided along a second dimension, say income groups. But for purposes of this study, all the taxfilers were considered as belonging to one income group (G = 1).

The findings of the empirical study are summarized in two parts. In the first part, the absolute relative bias of the estimates averaged over all Census divisions are compared with the corresponding values of the direct estimator. The relative efficiencies which are defined to be the ratio of the mean squared error of estimators to the mean squared error of the direct estimator are also given. In the second part, the mean squared error is computed for each sample realization within a census division and industry.

The average absolute relative bias is defined as

$$\overline{\text{ARB}}(T) = \frac{1}{A} \sum_{a=1}^{A} \left| \frac{1}{R} \sum_{r=1}^{R} \left(\frac{T_a^{(r)}}{Y_a} - 1 \right) \right|$$

where $T^{(r)}$ is the value for a particular estimator T based on the r^{th} Monte Carlo sample and a^{th} small area, Y is the known population total and R is the number of samples. The average mean squared error of the estimator is defined as

$$\overline{\text{MSE}}(T) = \frac{1}{A} \sum_{a=1}^{A} \frac{1}{R} \sum_{r=1}^{R} \left(T_a^{(r)} - Y_a \right)^2$$

The relative efficiency of an estimator T with respect to the direct or Expansion estimator (EXP) is defined as

$$\overline{\text{RE}}(T) = \left[\frac{\overline{\text{MSE}}(\text{EXP})}{\overline{\text{MSE}}(T)} \right]^{1/2}$$

Estimators requiring counts as auxiliary information are denoted as T/N, while those using gross business income are denoted by T/X. The estimators that are considered for the first part of the study are the expansion estimator T(1), the poststratified estimators T(2) and T(3), the synthetic estimators T(4) and T(5), the mixture estimators T(6), T(7), T(7A), T(8), T(9), T(10).

The mixture estimators known as k_o estimators given in Drew, Singh and Choudhry (1982) using counts as stated below are also included in the study with k_o = 0.5, 1.0, 1.5 and 2.0. They are denoted as T(11), T(12), T(13), and T(14).

$$Tk_o = \sum_g N_{ag} \left[W''_{ag} \bar{y}_{ag} + (1 - W''_{ag}) \bar{y}_{.g}\right]$$

where

$$W''_{ag} = 1 \quad \text{if} \quad \left(\frac{n_{ag}}{N_{ag}}\right) \left(\frac{N}{n}\right) \geq k_o$$

$$= \frac{1}{k_o} \left(\frac{n_{ag}}{N_{ag}}\right) \left(\frac{N}{n}\right) \quad \text{if} \quad \left(\frac{n_{ag}}{N_{ag}}\right) \left(\frac{N}{n}\right) < k_o$$

Tables 1 and 2 give the values of relative bias and relative efficiency of the various estimators for different industries. The values given in Table 1 are not surprising. In general, the expansion estimator has the least unconditional bias (which is due to Monte Carlo variance) and the synthetic estimators (both count and ratio) have the maximum bias. The mixture estimators have biases in betwen these two values. The bias in the estimator T(6) is close to the bias in the estimator T(12) which has a value of

$k_o = 1$. For the k_o estimators the bias increases as k_o increases from 0.5 to 2.0.

It is seen from Table 2, the efficiencies of all estimators are better than the direct or expansion estimator T(1). Again, the estimator T(6) which depends on counts has the same efficiency as the k_o estimator with $k_o = 1$. The high efficiency of the synthetic estimator shows the peculiarity of the data set. The bias in the synthetic estimator is not large enough to offset the reduction in its variance compared to the poststratified estimator. This may be one of the reasons for the increasing efficiency of the k_o estimators as k_o increases. T(7) and T(9) which are ratio type estimators seem to be most efficient especially in industries where the correlation is high (Accommodation). The predictive version of T(7) given by T(7A) is not as efficient as T(7) though the loss of efficiency is marginal.

Table 3 relates to the second part of the study of efficiencies and give values of mean squared errors of T(6), T(12), T(7), T(7A) and T(3) for selected census divisions and industries conditional on the number of units falling into the census division and industry. It is seen from Table 3, that the proposed estimator T(7) does better than the poststratified ratio estimator for both the Retail and Accommodation industries. The predictive approach does not show any significant gains. It is interesting to compare T(6) and T(12) which is a k_o estimator with $k_o = 1$. T(6) seems to do better when the sample size is either large or small relative to the expected sample size. This may be due to the higher efficiency of the synthetic estimator relative to the poststratified estimator for this data set.

The graphs show the relative conditional bias and the square root of the conditional mean squared error of the expansion estimator T(1), poststratified ratio estimator T(3), ratio synthetic estimator T(5) and the proposed estimator T(7). It is interesting to see that the ratio synthetic estimator T(5) though has a slightly smaller mean squared error than T(7), in the case of Accommodation, has a high conditional bias which remains high even for large sample sizes. In Construction the bias is negative and the mean squared error for T(7) is much smaller than for the synthetic ratio estimator T(5). This is due to the bias of the synthetic estimator being high.

4. CONCLUSIONS

As expected, the expansion estimator is conditionally badly biased above and below the expected sample size within a small area and it also has the highest root mean squared error. The use of this estimator is obviously not recommended. The synthetic estimator performs best when biases are small. But in practice, it is hard to predict these biases.

The mixture estimators offer a good compromise for achieving a balance between bias and mean squared error. Amongst the proposed estimators, the estimator T(7) which involves the ratio of weighted averages using the weights proposed seems to do well especially if there is a high correlation between the auxiliary variable and the variable of interest. The biases tend to be low even when sample sizes within small areas are small. This may be due to the estimators taking into account the available information within the small area.

Acknowledgement

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TABLE 1: ABSOLUTE RELATIVE BIAS OF THE ESTIMATORS

Estimators			Industrial Group			
			Retail	Construction	Accommodation	Others
1.	EXP	T(1)	0.023	0.019	0.036	0.027
2.	POS/N	T(2)	0.085	0.054	0.264	0.043
3.	POS/X	T(3)	0.108	0.049	0.267	0.049
4.	SYN/N	T(4)	0.207	0.173	0.584	0.337
5.	SYN/X	T(5)	0.324	0.157	0.414	0.264
6.	W/N	T(6)	0.052	0.038	0.277	0.069
7.	RW'/X	T(7)	0.126	0.047	0.253	0.071
8.	PRW'/X	T(7A)	0.122	0.045	0.246	0.068
9.	RW/X	T(8)	0.145	0.043	0.246	0.062
10.	W'R/X	T(9)	0.132	0.047	0.253	0.070
11.	WR/X	T(10)	0.158	0.044	0.249	0.063
12.	K1/N	T(11)	0.025	0.020	0.241	0.027
13.	K2/N	T(12)	0.046	0.033	0.261	0.062
14.	K3/N	T(13)	0.079	0.065	0.307	0.123
15.	K4/N	T(14)	0.106	0.089	0.341	0.171

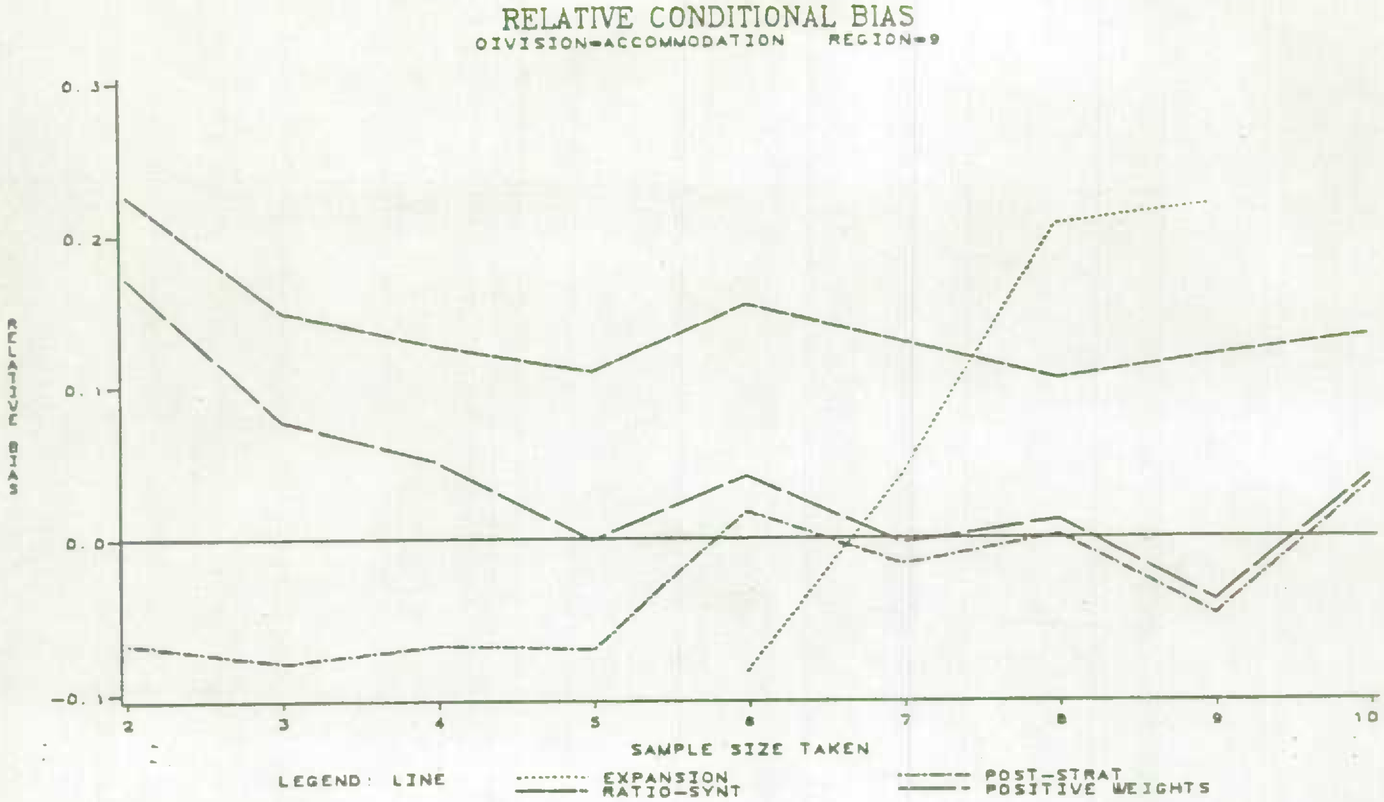
TABLE 2: EFFICIENCIES OF THE ESTIMATORS WITH RESPECT TO T(1)

Estimators			Industrial Group			
			Retail	Construction	Accommodation	Others
1.	POS/N	T(2)	1.345	1.352	1.293	1.177
2.	POS/X	T(3)	1.241	1.860	1.860	1.641
3.	SYN/N	T(4)	1.880	1.465	2.074	1.714
4.	SYN/X	T(5)	2.269	1.925	3.265	2.041
5.	W/N	T(6)	1.513	1.539	1.704	1.347
6.	RW'/X	T(7)	1.669	2.154	3.395	1.863
7.	PRW'/X	T(7A)	1.650	2.147	3.372	1.855
8.	RW/X	T(8)	1.520	2.105	3.083	1.833
9.	W'R/X	T(9)	1.653	2.150	3.392	1.865
10.	WR/X	T(10)	1.491	2.097	3.008	1.832
11.	K1/N	T(11)	1.381	1.397	1.468	1.221
12.	K2/N	T(12)	1.555	1.571	1.699	1.382
13.	K3/N	T(13)	1.913	1.855	1.984	1.722
14.	K4/N	T(14)	2.118	1.937	2.170	1.933

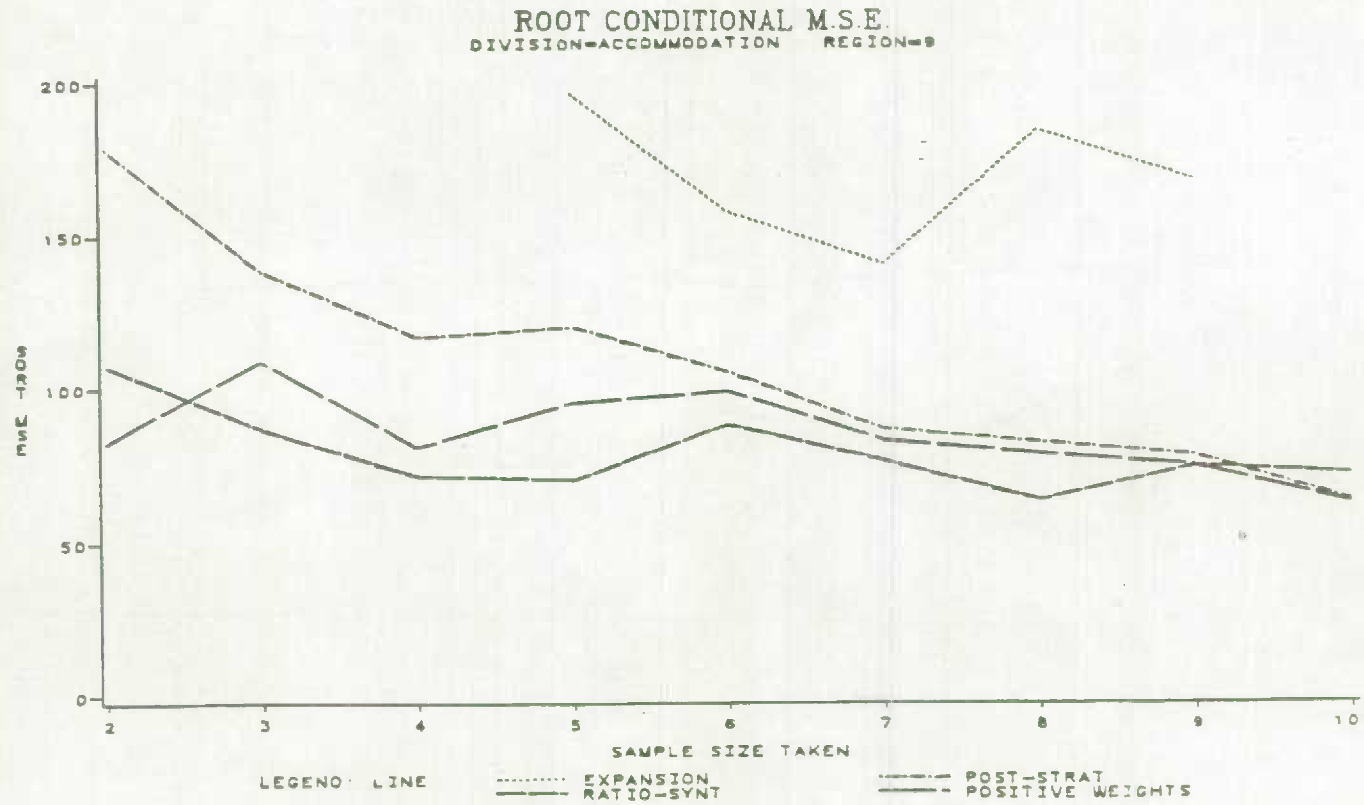
TABLE 3: MEAN SQUARED ERRORS FOR SELECTED INDUSTRIAL GROUPS

AND CENSUS DIVISIONS BY SAMPLE SIZE TAKE

Sample Size Take	Frequency (No. of Samples)	Estimators				
		W/N T(6)	K2/N T(12)	RW'/X T(7)	PRW'/X T(7A)	POS/X T(3)
		Retail, Region 2				
2	30	22,193	21,300	10,751	10,751	151,382
3	58	20,485	21,634	10,751	10,741	21,454
4	74	26,939	22,102	13,284	13,284	24,576
5	93	17,718	16,365	12,866	12,866	23,262
6	98	15,829	16,192	13,070	13,383	15,207
7	58	12,690	13,608	9,472	9,569	9,784
8	48	11,790	12,596	6,768	6,849	7,068
9	20	6,566	7,307	2,767	2,897	3,094
10	13	4,439	4,667	5,830	6,090	6,514
		Accommodation, Region 9				
2	6	15,958	31,962	6,791	6,791	32,077
3	24	10,541	14,876	11,889	11,889	19,183
4	42	18,324	19,873	6,555	6,555	13,644
5	69	29,719	24,283	9,038	9,038	14,333
6	73	29,128	25,426	9,770	9,770	11,017
7	98	17,888	17,924	6,862	6,935	7,465
8	77	17,617	18,175	6,156	6,259	6,760
9	49	10,978	11,885	5,577	5,717	6,098
10	30	11,788	12,885	3,930	3,983	4,057
11	14	11,459	12,677	1,734	1,744	1,764
		Accommodation, Region 2				
0	115	833	833	737	737	-
1	171	3,683	3,172	407	407	594
2	141	2,481	2,689	157	144	197
3	64	1,159	1,350	69	65	71
4	6	485	553	69	71	85



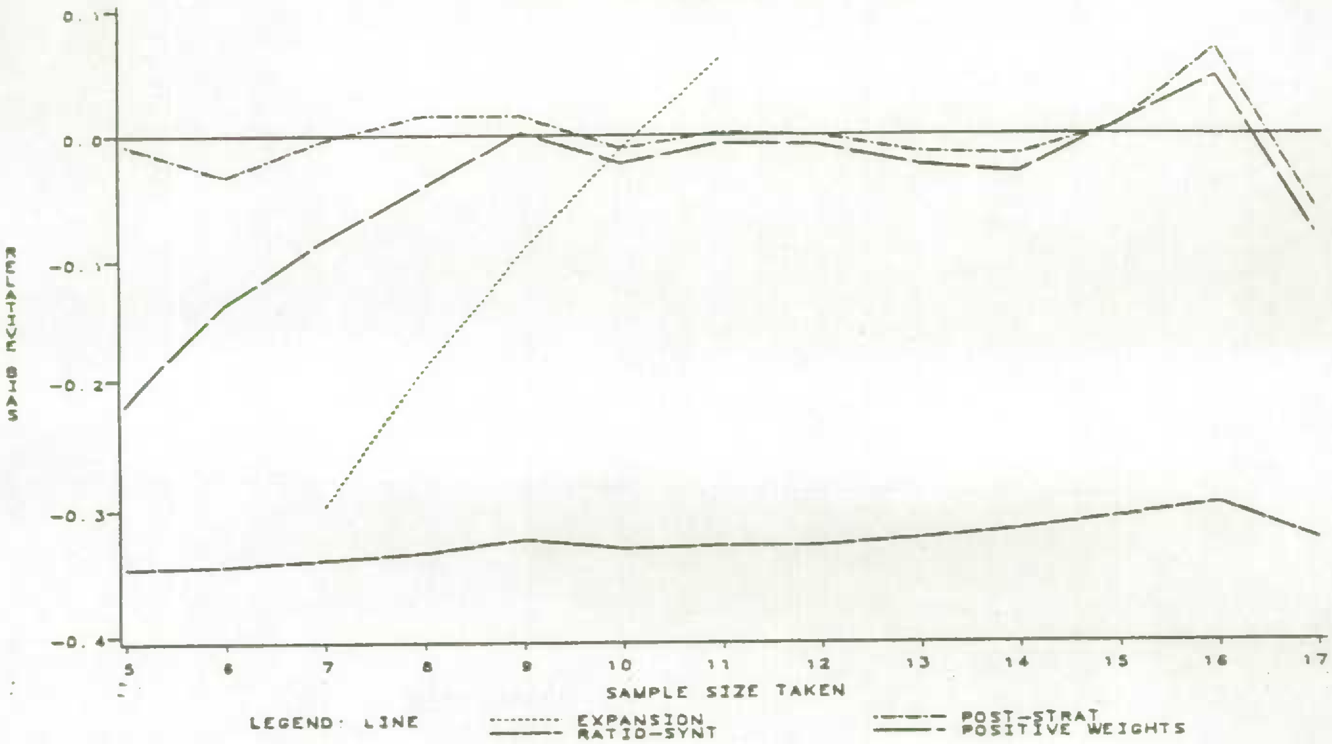
RELATIVE BIAS FOR REGRESSION ESTIMATORS



SQUARE ROOT MSE FOR REGRESSION ESTIMATORS

RELATIVE CONDITIONAL BIAS

DIVISION=CONSTRUCTION REGION=6



RELATIVE BIAS FOR REGRESSION ESTIMATORS

ROOT CONDITIONAL M.S.E.

DIVISION=CONSTRUCTION REGION=6

SQUARE ROOT MSE FOR REGRESSION ESTIMATORS

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