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A Modified Ratio-Correlation Method For Local Population Estimates

March, 1982

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Subcounty estimates of population have become, in recent years, the bane of existence for those demographers charged with their production. On the one hand, increasing numbers of federal and state programs are using such estimates for the allocation of monies to local governments, thus mandating the production of the estimates. On the other hand, demographers are becoming increasingly aware of the difficulty in producing quality estimates, especially for very small populations. Smith and Lewis (1980) indicate that average absolute errors of 20% or more are not uncommon for places with populations of 1,000 or less. A recent National Academy of Science panel concluded that estimation for places with very small populations is a lost cause and recommended preparing estimates only for larger jurisdictions. (NAS, 1981)

While much discussion can be made of the recommendations of the NAS panel, those of us demographers who find ourselves in the trenches of numeric warfare, being annually required to rush over the top to defend the faith against random error must still continue to explore alternative ways of improving estimates, even for very small places. The purpose of this paper is to present Minnesota's approach to producing more reliable subcounty population estimates, especially for places with very small populations.

Minnesota Situation and Objectives of the Method

Annual estimates of population are required by law for all of Minnesota's cities and townships. These estimates are used for the distribution of local government aid, for limiting local government taxing authority, and for a variety of other purposes.

Table 1 presents the distribution of minor civil divisions in Minnesota according to the 1980 Census. Of the 2,688 places in Minnesota, 61.1% are less than 500 population and 96% are less than 5,000 population. Cities range in size from 18 (Funkley) to 370,951 (Minneapolis). Intercensal growth rates for cities over 5,000 population range from an increase of 328% to a loss of 20%. Smaller places have an even wider range.

To meet the legislative requirement for producing annual estimates, a model is required which has the following characteristics:

1. A low median absolute error with a minimum of unacceptable errors (arbitrarily set at > 10%).

2. A minimal lag in the timing of estimates. For example, April 1981 estimates should be produced by April 1982.

3. An assured, relatively consistent, and low cost data source for population symptoms.

4. A method that requires a minimum of staff time.

5. A minimum of bias in errors for small places and those experiencing rapid increase or decline.

Data

After an examination of alternative data sources, only one appeared to meet our requirements: records of state income tax filers. From this source, for each minor civil division (MCD), we are able to obtain the total number of filers, the number of joint married returns and the number of other dependents claimed. Furthermore, we were able to obtain these data for both 1970 and 1980 and certain intervening years. As the tax forms are coded by MCD lived in during the tax year, the symptom data is for the year preceding the census or estimate year (1969 for 1970 census). The data are also available within approximately nine months of the April 15 filing date.

Each year before estimates are prepared, the data are cleaned and the population symptom is calculated. First, geographical coding errors are corrected. Thorough analysis of the geocodes showed that there were obvious patterns of typographical, spelling and reference area errors. For example, many filers gave a tax year residence of Minneapolis but listed the county of residence as a county other than Hennepin, in which Minneapolis is located. We constructed a program that transfers these filers from places with invalid geocodes to the valid ones; each year the individual records are processed through this program and any remaining invalid geocodes are hand edited if they fall into any of the identifiable patterns of error. After corrections have been made, the records are aggregated for each minor civil division. Second, annexations and boundary changes occurring after the benchmark year are handled by assigning the new geocode for all previous years. Third, the population symptom is calculated as the sum of the total numbers of filers, joint married returns, and dependents. Although other population symptoms are available on the tax records, extensive testing showed that the total individual symptom (TN) best captures variation in population size and change.

Specification of the Population Estimation Model

Given the data available, as well as past experience in Minnesota with different estimation techniques, the ratio-correlation method was considered a likely candidate for a basic model. Ratio-correlation methods do not require the static assumption that future population will always have the same relation to the observed symptom; instead, the population-symptom ratio is expected to change in the same proportion as in the parent population. Although the ratio-correlation method requires other assumptions about covariance of the local and parent population (Namboodiri, 1972), we feel that these assumptions are less stringent than the ones required by simple ratio models. However, after a considerable amount of experimentation, some modifications of the general format of the model were considered necessary.

The general form of the ratio-correlation method is:

$$[1]\quad \frac{\dfrac{P(t)}{CP(t)}}{\dfrac{P(t-n)}{CP(t-n)}} = a + b\,\frac{\dfrac{TN(t)}{CTN(t)}}{\dfrac{TN(t-n)}{CTN(t-n)}} + e$$

where

P(t) = household population of the place in year t
CP(t) = household population of the county in year t
TN(t) = total individuals indicated on tax files for the place
CTN(t) = total individuals indicated on tax files for the county
t-n = 1970 for census household population, 1969 for TN

When the dependent variable (a ratio) is transformed to determine the final estimate, however, the error term is also transformed to:

$$[2] \quad e^* = e \frac{CP(t)}{CP(t-n)} P(t-n),$$

an error proportional to the growth rate of the county and to the previous size of the place.

To correct for this proportional error problem, the basic model is transformed to the reduced form as follows:

$$[3] \quad Pt = a\,A + b\,AB + u$$

where $A = \frac{CP(t)}{CP(t-n)} P(t-n)$ and $B = \frac{TN(t)}{CTN(t)} \Big/ \frac{TN(t-n)}{CTN)t-n)}$

This model conforms to the basic ratio-correlation form where population of the place relative to the county changes proportionally to the relationship of the place symptom to the county symptom. Over time we expect this assumption to break down as population to symptom relationships are shifted within the county. As an alternative, we added a variable which explicitly recognizes this problem:

$$[4] \quad D = \left(\frac{P(t)}{TN(t)} \Big/ \frac{CP(t)}{CTN(t)}\right) \Big/ \left(\frac{P(t-n)}{TN(t-n)} \Big/ \frac{CP(t-n)}{CTN(t-n)}\right)$$

The functional form of the estimating model then becomes:

$$[5] \quad P(t) = aA + bAB + cAD + u$$

Variable D measures the within county changes in the population to symptom relationship. Inclusion of D, though, results in an identification problem as its form includes the dependent variable (P(t)). After exploring several alternatives, we chose to preserve the form of D, but make it a constant for estimates during the decade. By holding D constant at its 1980 level, we expect the estimates to worsen as the decade progresses, but this will be true of <u>any</u> estimate formulation.

Final Model Specification

Analysis of the linear least squares model showed a tendency towards unstable variance of the error term. In an attempt to stabilize the variance of the error term, two transformations of the dependent variable were tried: a power and a log transformation. The power transformation resulted in a model similar to the linear form. The log transformation not only removed the proportional variance of the error term and solved this instability problem but also resulted in a more convenient form. The model becomes:

[6] $\log P - \log A = a + bB + cD + e.$

Therefore, in order to solve for P, we add log A to both sides of the equation rather than multiply; there is no proportional error problem. In addition, there is no reason to move log A to the right side of the equation in order to estimate regression coefficients.

After exploring the population-symptom ratio for county and city groupings, we developed six additional variables to account for specialized variability. These variables are:

1. Population Change (PG). We considered two forms of incorporating population growth into the models. The first was to use the population change from 1970 to 1980 as a variable, defined as POP80/POP70. (This term would not be revised in future years.) The second was to use two dummy variables, the first to denote rapidly growing places (greater than 25% between 1970 and 1980) and the second to denote declining places.

   After trying both forms, it became clear that for most groups the model using the actual population change was more accurate in estimating 1980 population while the model with dummy variables was slightly more sensitive to changes in the symptom data and was slightly better at picking up a turnaround in a place's growth pattern. However, these advantages were not enough to compensate for the overall loss of accuracy experienced with the dummy variables, so the actual population change was used.

2. County Population (CP). The 1980 county population was introduced as a separate variable. This will be updated every year with the new county population estimate.

3. County Type. Two dummy variables were used to divide the 87 counties in the state into three sections. The first, METRO, was used to denote 11 counties in the Twin Cities Metropolitan Area. The second, FARM, denotes agricultural counties, defined as counties with a greater percentage of agricultural land than the state as a whole. Four counties are classified as both METRO and FARM.

4. City/Township (CT). As analysis of symptom data showed that townships had a systematically lower TN to population ratio than did cities, a problem obviously caused by township residents listing city addresses. To compensate for this, a dummy variable distinguishing cities from townships was added.

5. Cities and Townships With Same Name (SN). The city/township confusion seems particularly acute when a city and township share the same name. In these cases a dummy variable was added with a value of one for townships having the same name as a city in the same county.

6. <u>Township Bordering on Large City</u> (BORD). The symptom-to-population ratio was also severely skewed in townships that border on large cities. While the addition of township tax returns is not enough to seriously affect a large city, the resulting deficit can have an effect on a much smaller township. Therefore, a dummy variable with a value of one for townships bordering on cities with 10,000 people or more.

We can also, of course, transform variables on the right side of the equation. If we transform P, we should therefore apply the same transformation to B, which includes TN. Similarly the relationship between population and population change (PG) should also be linear, and therefore PG should also be transformed. The final model form, then, is

[7] $\text{Log } P - \text{Log } A = a + b \text{ Log } B + cD + d \text{ Log } PG + v(i)\ V(i) + e$, where $V(i)$ = dummy variables described above.

Stratification of Places

Following earlier recommendations to improve estimate accuracy by stratification (Rosenberg, 1968) and use of different equations for different categories of places (Martin and Spar, 1981), we decided to jointly stratify by place population and relative place to county population. Group specifications are listed on Table 2. Note that it is possible for a MCD to belong to more than one group. In general, regression estimates tend to be more accurate near the middle of the range of estimates they produce and less accurate at the extremes. By overlapping the group boundaries we in effect cut out the extremes, as well as eliminate some of the arbitrariness of the group boundaries. This does, however, mean that we must make some subjective decisions regarding which estimate to use, or whether to average, thereby subjecting the estimates to greater scrutiny. In practice slightly more than half of the state's MCDs are in more than one group, about ten percent in three groups, and a few in four.

Test Results for 1980

Each of the fifteen groups was randomly divided in half. The first half was used to derive the models which were then tested on the second half. Models were estimated using ordinary least squares techniques, with no attempt made to force each variable into every model. The resulting models are shown in Table 3. As can be seen, the B and D terms are found in all models, with the population change variable found in all but one. At the other extreme, the "city/township" and "bordering on large city" dummy variables are each found in only one group. The county type dummy variables were the most important dummy variables, with ten out of the fifteen models including the "FARM" variable and seven of ten the "METRO" variable.

Results were measured in terms of percent difference between the estimate and the 1980 Census, and the distribution of these error rates within each group is shown on Table 4. It should not be surprising that the results are not the same for each group, nor that the largest percentage errors are often found in the smallest places. Yet it should be noted that with the exception of a few extreme cases, error rates are exceptionally low for subcounty estimates. Even in the group modeled most poorly (Group 4), almost 90% of the estimates were within 10% of the census. To put this in perspective, recognize that for this group a 10% error is at most 30 people.

Tables 5 and 6 summarize the results to the state level and by size of place respectively. Before county controls are applied, the overall (statewide) median absolute error is 1.6%, and even at the 90th percentile, the error is only 6%. Less than 5% of the places had errors greater than 8.7%.

The distribution of errors by size of place indicates greater errors for the smaller places. But even for places with less than 250 population, more than three-fourths are within 5% and only 5.6 are greater than 10%.

Sensitivity Analysis

While it is important to know how well the models perform under current circumstances, it is also important to know how well they perform when circumstances change. Accordingly, we conducted sensitivity analysis both by examination of partial derivatives for each of the variables in the models and by simulating symptomatic and population changes.

Derivatives

Despite the number of independent variables in the models, most are fixed for all post-censal periods. Only three measures will change from year to year: TN, CTN, and CP. If we rewrite model [7] to read:

$$P = \text{Exp}\ (\log A + a + b \log B + cD + d \log PG + fCP + vi\ Vi)$$

then

$$\frac{dP}{dTN} = (bTN^{b-1}) * B'^{b} * A * Z$$

$$\frac{dP}{dCP} = (1 + fCP) * A' * B^{b} * Z$$

$$\frac{dP}{dCTN} = (-b\ CTN^{-b-1}) * B''^{b} * A$$

where

$$B' = B/TN = (1/CTN) \ / \ (TN_{70} / CTN_{70})$$

$$B'' = B*CTN = TN/(TN_{70}/CTN_{70})$$

$$A' = A/CP = P_{70}/CP_{70}$$

$$Z = \text{Exp}\ (a + cD + d \log PC + fCP + vi\ Vi)$$

While these derivatives will differ for each place estimated, a useful summary is based upon the mean value of the derivatives within each group, as shown in Table 7. From the table, it can be seen that TN is by far the most important component of change. For 12 of the 15 groups, the mean derivative of population with respect to TN ranges between 0.8 and 1.4. For these groups, a change of one tax filer leads approximately to a change of one person. The partial effects of CP and CTN are much smaller and generally counter one another, though within some counties, where CP/CTN ratios might substantially diverge from one, the effect could be more than marginal.

Simulation of Symptomatic and Population Change

Analysis of partial derivatives yield only limited information as only one variable can change at a time. In an effort to assess the impact of a simultaneous change in all three variables, the models were run using hypothetical scenarios of symptom and population change. Each model was run on two typical places from each group. For each place selected, two scenarios were created; one assuming a continuation of recent past trends and the other assuming a reversal in trends.

In all cases, it was necessary for simplicity to assume that symptoms change in the same proportion as population, although this is probably unrealistic. Results are presented in Table 8.

The mean absolute error of the scenarios is 3.07%; slightly elevated from the 1980 test error of 2.18% for the same places. This result strengthens our confidence in the models, but cautious optimism is still required because these error percentages are sensitive to the selection of places.

In most cases, the models performed quite well in picking up both the continuation of present trends and their reversal. The exception is Group 4, characterized by very small places representing very small proportions of the county. Here, the models picked up a continuation of trends with reasonable accuracy, but did not perform well when confronted with a reversal. Analysis of derivatives indicated that model 4 is relatively insensitive to a change in total individuals (TN), and this analysis confirms the problem, particularly when local tax filers and the other symptoms change in the opposite directions. The problem in model 4, and to a lesser extent in models 14 and 15, is clearly one of an insufficient reaction to change rather than one of too much sensitivity.

Conclusions

The Minnesota State Demography Unit is faced with the challenge of preparing annual population estimates of all cities and townships in the state. To meet this challenge, an estimation method has been developed with the following steps:

1. Analysis of available data indicated that the number of state income tax filers plus the number of joint married returns and dependents, coded by place of residence in tax year, would be the only regular and reliable source of symptom information.

2. The ratio-correlation method was revised to deal with known biases and error rate inflations. Dummy variables were considered to account for some known Minnesota-specific effects. The basic model was transformed to a log specification.

3. Places to be estimated were divided into 15 overlapping groups according to their absolute size and relative size within the county. Each group was divided into a test group and a treatment group by random selection.

4. A model was estimated for each treatment group and results tested against each test group.

The results exceeded our expectations. The overall median absolute error is low, only a few outliers were identified in treatment or test groups, and the model seems to work well even for places less han 500 population. Sensitivity analysis leads us to believe that the integrity of the method will be maintained in subsequent years.

The portability of the method to other states remains to be tested. However, states with an existing income tax might consider this as a candidate due to its relatively low cost and evident accuracy.

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Table 1: Distribution of MCD's in Minnesota According to 1980 Census Population

Size of Place	Percent of All Places	Cumulative Total
0 - 249	29.0	29.0
250 - 499	32.1	61.1
500 - 999	20.1	81.2
1,000 - 2,499	11.2	92.4
2,500 - 4,999	3.6	96.0
5,000 - 9,999	1.7	97.7
10,000 +	2.3	100.0

Table 2: Place Stratification

Group	1980 Population	1970 Ratio of Population to County Population
1	2,500 and over	Less than 3%
2	7,000 and over	Greater than 2%
3	2,500 - 9,999	Greater than 2.5%
4	0 - 299	Less than 1%
5	0 - 999	Greater than 3%
6	150 - 499	Less than 1.5%
7	750 - 2,499	Greater than 3%
8	1,000 - 3,999	Less than 1.5%
9	500 - 1,499	Less than 20%
10	1,000 - 3,999	1.5% - 5%
11	0 - 499	2.5% - 5%
12	500 - 999	1.5% - 5%
13	300 - 499	1.0% - 2.5%
14	0 - 299	1.5% - 3.0%
15	0 - 499	1.0% - 2.0%

Table 3: Model Coefficients

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Intercept	-0.941	-1.052	-0.908	-0.306	-0.732	-0.737	-0.846	-0.542	-0.783	-0.912	-0.704	-0.885	-0.739	-0.494	-0.639
Log B	1.0	1.010	0.926	0.166	0.627	0.648	0.839	0.547	0.663	0.830	0.624	0.775	0.665	0.389	0.525
D	0.928	1.050	0.891	0.139	0.705	0.682	0.799	0.499	0.721	0.882	0.677	0.857	0.708	0.461	0.586
Log PG		-0.019	0.041	0.796	0.307	0.309	0.117	0.433	0.297	0.151	0.294	0.169	0.245	0.508	0.409
CP				5.25×10^{-7}	-3.08×10^{-6}			1.28×10^{-7}	9.14×10^{-8}		-2.6×10^{-6}		-1.31×10^{-6}	-3.68×10^{-6}	-1.55×10^{-6}
METRO			-0.024	-0.262			-0.043	-0.079	-0.099	-0.041		-0.078			
FARM			0.010	0.109	0.041		0.017	-0.031	0.024		0.040		0.031	0.068	0.054
CT							0.019								
SN							-0.013		-0.008					0.015	
BORD									0.018						

Table 4: Absolute Error Rates of Individual Models

Group	Median Error	75th Percentile	90th Percentile	95th Percentile	Maximum Error
1	1.2%	1.5%	1.7%	7.5%	7.7%
2	0.4%	0.5%	0.9%	1.6%	3.1%
3	1.0%	1.7%	2.4%	2.9%	3.7%
4	3.9%	7.4%	10.6%	12.0%	38.2%
5	2.5%	3.9%	7.0%	10.0%	54.5%
6	3.1%	5.3%	8.8%	12.6%	69.5%
7	1.4%	2.3%	3.3%	7.5%	13.4%
8	1.7%	2.7%	3.9%	8.7%	10.0%
9	1.9%	3.5%	5.4%	7.0%	31.5%
10	1.2%	2.1%	3.2%	4.5%	16.9%
11	2.0%	3.5%	5.3%	16.3%	49.4%
12	1.6%	2.9%	4.5%	6.3%	18.3%
13	2.3%	3.4%	5.0%	7.9%	24.4%
14	2.9%	4.3%	5.9%	7.9%	20.6%
15	2.8%	4.7%	6.6%	10.5%	68.1%

Table 5: Statewide Absolute Error Rates

	Before County Controls	After County Controls
Median Error	1.6%	1.4%
75th Percentile	3.3%	2.9%
90th Percentile	6.0%	5.5%
95th Percentile	8.7%	8.1%
Maximum Error	68.2%	67.1%

Table 6: Distribution of Absolute Errors by Size of Place

		Error Percentage	
MCD Size	Less than 5%	5% to 10%	Greater than 10%
0 - 249	77.8%	16.6%	5.6%
250 - 499	90.4%	6.4%	3.2%
500 - 999	92.0%	6.1%	1.9%
1,000 - 2,499	96.7%	3.0%	0.3%
2,500 - 4,999	98.0%	0	2.0%
5,000 - 9,999	100.0%	0	0
10,000 +	100.0%	0	0

Table 7: Mean Derivatives by Group

Group	$\frac{dPOP}{dTN}$	$\frac{dPOP}{dCPOP}$	$\frac{dPOP}{dCTN}$
1	1.36	.020	-.020
2	.99	.222	-.228
3	1.06	.167	-.164
4	.23	.006	-.001
5	.77	.041	-.028
6	.83	.009	-.006
7	1.02	.076	-.069
8	.76	.012	-.006
9	.81	.032	-.022
10	1.06	.038	-.032
11	.78	.031	-.021
12	.92	.029	-.023
13	.78	.018	-.012
14	.44	.021	-.008
15	.62	.016	-.009

Table 8: Response to Models to Hypothetical Population Change Scenarios

Group	County	MCD	1980 Census	80 Est. Error %	Assumed Percent Change City	Assumed Percent Change County	Error Number	Error %
1	Dakota	Farmington C.	4,305	1.4	+10	+ 7	63	1.4
					+ 2	+ 7	60	1.4
1	St. Louis	Eleveth C.	5,042	0.6	+ 3	+ 1	-31	-0.6
					- 3	+ 1	-10	-0.2
2	Kandiyohi	Willmar C.	14,723	-0.3	+ 9	+ 6	-48	-0.3
					- 2	+ 2	-54	-0.4
2	Mower	Austin C.	22,342	0.8	- 5	- 2	156	0.7
					+ 3	- 2	189	0.8
3	McLeod	Glencoe C.	4,302	-0.3	+ 4	+ 2	-21	-0.5
					- 1	+ 2	-4	-0.1
3	Itasca	Harris T.	3,007	-1.6	+ 8	+ 5	-58	1.8
					+ 2	+ 5	-41	1.3
4	Pennington	Hickory T.	130	5.4	+ 8	+ 3	3	1.7
					- 2	+ 3	13	10.3
4	Crow Wing	Cuyuna C.	157	-0.6	+10	+ 6	-6	-3.5
					- 1	+ 6	9	5.8
5	Pipestone	Eden T.	361	-1.9	- 8	- 5	-7	-2.1
					- 2	+ 2	-6	-1.8
5	Chisago	Harris C.	678	8.1	+ 6	+10	68	8.8
					+ 4	+ 2	51	7.2
6	Douglas	Garfield C.	284	2.8	+12	+ 7	3	1.0
					+ 2	+ 7	12	4.4
6	Aitkin	Spalding T.	216	0.9	+ 6	+ 3	0	0.0
					- 2	+ 3	14	6.6
7	Kanabec	Arthur T.	1,435	-0.6	+10	+ 6	-54	-3.4
					- 2	+ 2	-30	-2.2
7	Jackson	Lakefield C.	1,845	-0.9	+ 2	- 2	-30	-1.7
					- 3	0	-20	-1.2
8	Olmsted	High Forest T.	1,545	-2.6	+10	+ 3	-92	-5.4
					+ 1	+ 6	-5	-0.4
8	Anoka	Lexington C.	2,150	1.2	- 1	+ 4	77	3.6
					+ 3	+ 4	39	1.8
9	Otter Tail	New York Mills C.	895	1.1	+ 8	+ 5	1	0.2
					- 2	+ 5	31	3.5

Table 8: Response to Models to Hypothetical Population Change Scenarios (Continued)

Group	County	MCD	1980 Census	80 Est. Error %	Assumed Percent Change City	Assumed Percent Change County	Error Number	Error %
9	Fillmore	Fillmore T.	561	-3.4	- 3	+ 1	-11	-1.9
					+ 2	+ 1	-21	-3.7
10	Carlton	Moose Lake C.	1,141	-0.4	- 3	+ 2	35	3.1
					+ 4	+ 2	23	2.0
10	Stearns	Le Sauk T.	2,009	1.9	+ 7	+ 5	-40	-1.9
					+ 3	+ 5	-38	-1.8
11	Lincoln	Limestone T.	233	0.4	- 5	0	6	2.5
					- 2	- 3	1	0.1
11	Lake	Beaver Bay C.	283	-4.6	- 2	0	-11	-4.0
					+ 4	- 2	-19	-6.5
12	Freeborn	Geneva T.	574	-3.7	- 3	- 2	-19	-3.3
					+ 2	- 2	-26	-4.5
12	Polk	Fertile C.	869	-2.2	- 3	+ 2	-7	-0.9
					+ 4	+ 2	-21	-2.6
13	Stevens	Donnelly C.	317	0.6	+ 6	+ 1	-4	-1.2
					- 5	+ 1	13	4.2
13	Winona	Freemont T.	375	4.8	+ 4	+ 2	15	3.8
					- 4	+ 2	22	6.0
14	Lac Qui Parle	Arena T.	208	-0.5	- 4	- 2	2	1.0
					+ 3	- 2	-7	-3.3
14	Clearwater	Shevlin C.	193	6.7	+ 5	+ 8	17	8.4
					- 1	+ 8	24	12.6
15	Meeker	Darwin C.	279	3.9	- 7	+ 8	27	10.4
					+ 4	+ 4	11	3.8
15	Marshall	Holt T.	162	-1.2	- 7	- 2	2	1.3
					+ 2	- 2	-4	-3.4