EFFECT OF COMPOSITE WEIGHTS ON SOME ESTIMATES FROM THE CURRENT POPULATION SURVEY

Janice Lent, Stephen M. Miller, Bureau of Labor Statistics; Patrick J. Cantwell, Bureau of the Census*
Patrick J. Cantwell, Bureau of the Census, Washington, DC 20233 pcantwell@ccmail.census.gov

Key words: Raking ratio estimation, *AK* estimator, labor force estimates.

1. Introduction

National unemployment numbers are among the most closely watched economic indicators produced by the federal statistical system. Census Bureau interviewers collect data used to compute the estimated numbers, as well as a wealth of other labor force estimates, through the Current Population Survey (CPS), a monthly survey sponsored by the Bureau of Labor Statistics (BLS).

The target population of the CPS is the civilian noninstitutional population of the U.S. Although a two-stage cluster sample of *housing units* is selected, a separate weight for each *person* in the sample is computed for estimation purposes. The base weight for a CPS sample person--the inverse of the probability of selection--is adjusted through a sequence of weighting steps to account for sample households not interviewed and for undercoverage relative to independently derived population estimates for specific demographic groups. After the ratio adjustments are applied to CPS person weights, the sum of the weights of those in one of these demographic control groups is the same as the independent population estimate. These adjustments are followed by a composite estimation step that improves the accuracy of current estimates by incorporating information gathered in previous months. Composite estimation is performed at the "macro" level: the composite estimator is a function of aggregated weights for sample persons in current and prior months. Thus microdata users need several months of CPS data to compute composite estimates.

In a previous paper (Lent, Miller, Cantwell 1994) we discussed research on a method for incorporating the effect of composite estimation into the microdata weights. Under this procedure, the sum of the "composite weights" of all sample persons in a particular labor force category equals the composite estimate of the level for that category. Thus, to produce a composite estimate for a particular month, a data user could simply access the microdata file for that month and compute a weighted sum. Currently, one must access the data files for a number of months and develop a composite estimate iteratively over these months.

The composite weighting approach also allows us to improve the accuracy of labor force estimates by using different compositing coefficients for different labor force categories. Currently the same coefficients are used for all categories in order to ensure additivity across all estimates. The composite weighting method suggested by Fuller (1990) provides additivity while allowing some variation in compositing coefficients. Results of the 1994 research, summarized in the next section, indicate that this method is practical for use with CPS data.

The CPS has undergone important changes during the past three years. A new questionnaire, administered entirely by computer-assisted interviewing, was introduced in January 1994. In January 1996, due to federal budget cuts, the CPS sample was reduced by some 7,000 housing units to its current size of about 59,000 households. (About 9,000 of these households, when visited, are found to be out of scope of the CPS, i.e., vacant, demolished, or converted to nonresidential use.) Each of these changes has coincided with adjustments to the sample design and estimates published.

The recent changes in the CPS have necessitated some modifications to the composite weighting technique previously researched. In particular, the 1994 redesign may have affected the optimal values to be used for the parameters in the composite estimator. In this paper we discuss the impact of changes in the CPS on the composite weighting method desirable for the survey and examine the effect of composite weighting on the reliability of a wide range of estimates computed from CPS data.

The next section contains an overview of previous research on CPS composite weights and motivation for additional research. In Sections 3 and 4 we discuss composite estimation as currently implemented in the CPS, and how we develop composite weights to reproduce the composite estimates. In Section 5, we examine the impact of the CPS month-in-sample bias on the "optimal" coefficients to be used in the composite estimator. Section 6 provides further details of our method. Finally, in Section 7 we analyze the effects of composite weighting and the different K and A parameters on some CPS estimates.

2. Research on Composite Weighting

Our goal is to create a set of person weights for a given data month from which users will generate all the composite estimates--without going back to data from prior months. That is, when we add over the set of persons in a given labor force category with specified demographic characteristics, the sum should closely approximate the corresponding "direct" composite estimate (to be defined in Section 3).

Prior results. In our 1994 paper, we discuss research on two methods of computing composite weights for the

CPS: (1) adjusting microdata weights to composite estimates of the three major labor force categories at the national level (i.e., computing "national" composite weights); and (2) adjusting microdata weights to the same composite estimates, but at the level of the states and demographic groups ("marginal" composite weights), as will be discussed in Section 4. Our research showed that the use of national composite weights significantly increased the variance of labor force estimates for some states and demographic groups relative to the direct composite estimates. The marginal composite weighting approach--although more complicated to implement--did not increase the variances of labor force estimates and produced weights that summed to the optimal composite labor force estimates for states and important demographic groups.

Computation of the composite weights was complicated by low sample counts for the unemployed category in some of the age/sex/ethnicity and age/sex/race cells used in the CPS raking ratio adjustment. (The age/sex/ethnicity classification assigns persons to Hispanic or non-Hispanic groups according to their age and sex. Similarly, the age/sex/race grouping places persons in one of three race categories: white, black, or other.) Composite estimates of labor force levels, when based on very small sample sizes, can sometimes fall below zero. Since negative estimates would not be suitable for use in computing composite weights, some aggregation of cells for the unemployed category seemed imperative. We were concerned, however, that too much aggregation could compromise the accuracy of the estimates computed from the composite weights, in light of the results mentioned above based on national composite weights.

We found that collapsing cells whose sample counts were expected to be less than twelve did not significantly increase the variance of the resulting estimates. In the case of one age/sex/ethnicity group, collapsing cells actually appeared to *decrease* the variance of estimates computed from the composite weights. However, collapsing in this way may have an adverse effect on the bias of the procedure.

Need for new research. In the course of our 1994 research, we developed a set of age/sex/ethnicity and age/sex/race cell definitions suitable for use in computing composite weights, given the CPS sample size as of 1994. Due to a BLS cost cutting effort, however, the CPS sample size was reduced by about 7,000 households (roughly 11,000 adult interviews) in January 1996, so we wanted to revisit the previous demographic cell definitions. In view of the possible future changes in the CPS sample size, we also investigate a flexible cell-collapsing scheme.

A second motivation for further research on composite weights lies in the problem of estimating optimal compositing coefficients for labor force categories. In our previous research, we selected coefficients that minimized the variances of the resulting estimates. But CPS estimates are also subject to month-in-sample bias. (This type of bias and its effect are discussed in Section 5.) The CPS underwent a major redesign in January 1994, and the new data collection procedures may have affected the month-in-sample bias pattern of CPS estimates. In 1994, we focused exclusively on the variance of the estimates because we did not have sufficient post-redesign CPS data to estimate the new month-in-sample bias pattern. It is now possible to choose compositing coefficients to minimize the estimated mean squared error--defined here as the variance plus the square of the month-in-sample bias--of labor force estimates.

Just as important, additional research is also needed to determine the effect of composite weighting on CPS estimates other than major labor force estimates for states and demographic groups. Currently, estimates of the numbers of persons employed full and part time, for example, are composited individually; computing these estimates as sums of composite weights may yield different results. In this paper, we examine the accuracy of composite weight estimates of employment by full and part time and by industry and occupation, as well as unemployment estimates by reason for and duration of unemployment.

3. Composite Estimation in the CPS

In order to balance reliability requirements for estimates of monthly level and month-to-month change, the CPS employs a "four-eight-four" sample rotation scheme: each sample household entering the CPS remains in sample for four months, leaves the sample for eight months, and then re-enters for an additional four months--the same four calendar months it spent in the sample after its initial entry. Eight panels or "rotation groups," approximately equal in size, make up each monthly CPS sample. The eight rotation groups in sample for a given month can also be considered "month-in-sample" groups: one group is in sample for the first time, another for the second time, etc. Six of these groups--three quarters of the sample--continue in sample the following month, and due to the four-eight-four rotation pattern, half of the households in a given month's sample are back in the sample for the same calendar month one year later. The sample overlap improves estimates of change over time. Through composite estimation, the positive correlation among CPS estimators for different months is increased and used to improve the accuracy of monthly labor force estimates.

Let $S = \{2,3,4,6,7,8\}$, the set of indicators of the month-in-sample groups in the CPS sample for a given month h that were also in sample in month h-1. The current CPS "*AK*" composite estimator (also called the "direct" estimator in this paper) for a labor force total (e.g., the number of persons unemployed) in month h is given by

$$Y_h'' = (1-K)\,Y_h + K(Y_{h-1}'' + \Delta_h) + A\,\beta_h \,,$$

where

$x_{h,i}$ is the ratio estimate for month h, based on data from persons completing their ith monthly interview in month h;

$$Y_h = \frac{1}{8}\sum_{i=1}^{8} x_{h,i} \;;$$

$$\Delta_h = \frac{1}{6}\sum_{i\in S}(x_{h,i} - x_{h-1,i-1}) \;;$$

$$\beta_h = \frac{1}{8}\left\{\sum_{i\notin S} x_{h,i} - \frac{1}{3}\sum_{i\in S} x_{h,i}\right\};$$

$K = 0.4$, and $A = 0.2$.

The values given above for the constant coefficients K and A are close to optimal for monthly estimates of unemployment level. The coefficient K determines the weight, in the weighted average, of each of two estimators for the current month: (1) the current month's ratio estimator Y_h (given a weight of $1-K$) and (2) the sum of the previous month's composite estimator Y_{h-1}'' and an estimator Δ_h of the change since the previous month. The estimate of change is based on sample data common to months h and h-1. The coefficient A determines the weight of β_h, an adjustment term that reduces both the variance of the composite estimator and the bias associated with time in sample. (See Breau and Ernst 1983, Bailar 1975.)

The composite estimator, with its current values of K and A, is applied to all CPS estimates. Optimal values of the coefficients, however, depend on the correlation structure of the characteristic to be estimated. Research has shown, for example, that higher values of K and A result in more reliable estimates for employment levels, because the ratio estimators for employment are more strongly correlated across time than those for unemployment. But the same coefficients are used for all characteristics in order to ensure additivity of estimates and maintain consistency with independently derived population estimates. The composite weighting approach allows variation in compositing coefficients, thus improving the accuracy of labor force estimates, while ensuring--by means of a "raking" ratio adjustment process--the additivity of estimates.

4. Computing Composite Weights

Our method of computing composite weights for the CPS imitates the second-stage adjustment currently performed: sample person weights are raked to force their sums to equal population totals. But composite labor force estimates are used in place of independent population estimates, and the raking process is performed separately within each of the three major labor force categories: employed, unemployed, and those not in the labor force.

Composite weights are produced only for sample persons aged 16 or older. The process begins, as it does now, by computing a CPS weight for each adult in the survey. The initial weight (the inverse of the probability of selection) is adjusted for nonresponse. First- and second-stage adjustments to population controls are applied. The latter raking procedure ensures that sample weights add to independent controls across states (51 totals, including the District of Columbia), across 9 specified age/sex/ethnicity groups, and across 64 specified age/sex/race groups.

Adjustment of microdata weights to the composite estimates for each labor force category proceeds as follows. For simplicity, we demonstrate the method here for estimating the number of people unemployed (**UE**); the procedure would be the analogous for measuring the number of people employed or those not in the labor force.

1. For each state j, the direct (optimal) composite estimate of **UE**, comp(**UE**$_j$), is computed. Similarly, direct composite estimates of **UE** are computed for each age/sex/ethnicity group and each age/sex/race group.

   [Note: Following step 1, records from all eight rotation groups for the month are combined.]

2. Sample records are classified by state. Within each state j, a simple estimate of **UE**, simp(**UE**$_j$), is computed by adding the weights of all unemployed sample persons in the state.

3. Within each state j, the weight of each unemployed sample person in the state is multiplied by the following ratio: comp(**UE**$_j$) / simp(**UE**$_j$).

4. Sample records are cross-classified by age, sex, and ethnicity. Within each cross-classification cell, a simple estimate of **UE** is computed by adding the weights of all unemployed sample persons in the cell.

5. Weights are adjusted within each age/sex/ethnicity cell in a manner analogous to step 3.

6. Steps 4 and 5 are repeated for age/sex/race cells.

7. Steps 2-6 are repeated five more times--a total of six iterations.

Note that, when applying this procedure to the number of people employed, different optimal coefficients are used in step 1 to compute the direct composite estimate. Then, in a given state, the direct composite estimate of the number not in the labor force is obtained as the residual from the state control total. The demographic group cells are treated similarly.

Collapsing cells. In our 1994 research on composite weights, we developed a fixed set of cell definitions--slightly different from those used in the adjustment to population controls--for use in composite weighting. Here we describe a flexible collapsing scheme that worked well in our current research.

In the CPS second-stage adjustment, where person weights are controlled to population estimates, age/sex/ethnicity and age/sex/race cells are collapsed when their adjustment factors fall below 0.6 or above 2.0. But when computing composite weights for persons who are unemployed, some further collapsing of cells is used to enhance the stability of the procedure. (The criteria do not affect the cell definitions for estimating employed.) In particular,

a) if a cell contains fewer than 10 sample person records, the cell is collapsed; and

b) if the ratio comp($\mathbf{UE}_i$)/simp($\mathbf{UE}_i$) is less than 0.7 or greater than 1.3, the cell is collapsed.

When two cells are collapsed to estimate **UE**, they must also be collapsed to estimate the number not in the labor force. This follows because the composite estimate for the latter characteristic is determined by subtracting the number employed and unemployed for the cell from the population control for the cell.

5. Optimal Compositing Parameters

The method of developing composite weights in this paper allows us to assign different pairs of *K,A* compositing parameters for measuring different characteristics. But the parameters we use will be a compromise selection; they must produce variances and biases that are acceptably small for several types of estimates. A *K,A* pair that works well for estimating monthly level may not perform as well when estimating month-to-month change or annual average.

Criteria for selecting new K and A parameters. To determine appropriate values of K and A for CPS, we attempted to minimize the mean squared error of the resulting AK composite estimators. To compute the variances, we need to approximate the relevant correlations between rotation group estimates. For any labor force characteristic, the estimates for different months from the same rotation group are correlated because of their common respondents. Using the notation from the previous section, let $x_{h,i}$ and $x_{h-r,j}$ be estimators from the same rotation group r months apart. The correlation between the two estimators depends on the characteristic being measured and generally decreases as r increases. Several studies provide estimated correlations between rotation groups for specific characteristics and different values of r. The numbers we used are slightly smoothed from the results given in Breau and Ernst (1983) and Adam and Fuller (1992). They are displayed in Table 1.

Table 1. Correlations for a Specific Rotation Group r Months Apart

r Months Apart	ρ_r for UE	ρ_r for EMP, CLF
1	.50	.80
2	.40	.75
3	.35	.70
4 through 8	*	*
9	.20	.57
10	.20	.56
11-15	.20	.55

* Under CPS's 4-8-4 rotation design, a specific rotation group is never in sample in month h and month $h+r$, where r is 4, 5, 6, 7, or 8.

Here, we assume that estimators $x_{h,i}$ and $x_{h-r,j}$ from different rotation groups are uncorrelated. Kumar and Lee (1983) and others have shown that estimates from a new rotation group and the retiring group it replaces are generally correlated, although the correlations are much smaller than the corresponding ones for the same group.

When estimating the number of people unemployed, the correlations are around .50 when r is 1, and decrease gradually to about .20 when r is 15. The correlations are much higher for the number of employed and for the number in the civilian labor force. For each, the correlation is around .80 for estimates one month apart, and decreases to about .55 after fifteen months.

The second component of the mean squared error of the composite estimator derives from the "month-in-sample bias." Bailar (1975) defines and discusses the concept of month-in-sample effects caused by panel conditioning in the CPS. Briefly, for any given month and characteristic to be estimated, the expected value of the eight rotation group estimates are generally not equal, but reflect the number of previous interviews or other influences. The bias *index* for the *i*th month in sample is defined as $E(x_{h,i}) / E(\sum x_{h,j} / 8)$, so that an index greater than 1 implies an overestimate in that month relative to the other seven months. Because the composite estimator assigns different coefficients to the different rotation groups, it is generally biased relative to the simple weighted ratio estimator, Y_h.

For any labor force characteristic, we considered three measurements when choosing the parameters K and A: monthly level, month-to-month change, and annual average. Although the first two of these are commonly reported and analyzed, the third has taken on added significance with the sample cut implemented earlier this year. Until recently, the sample sizes in the eleven most populated states were large enough to support releasing monthly estimates for those states. For the remaining states, because of the smaller sample sizes, BLS released only estimates of annual average. The sample cut has driven down the size of the sample in even the largest states, allowing release of only national estimates on a monthly basis. The annual average is now the chief measure of level for the state-level estimates.

It is easy to see from the definition of the composite estimator that changing the K parameter has different effects on the several measurements. While raising K typically reduces the variance of month-to-month change, it generally increases the variance of annual average. To select an optimal pair of coefficients K and A, we computed three mean squared errors for each pair K,A--one for each of monthly level, month-to-month change, and annual average--and compared the sets across all K,A pairs. Because one pair cannot minimize the three mean squared errors simultaneously, we selected a pair--separately for measuring unemployed and the number employed--that gave the best results overall.

Effects of changes to CPS. As we mentioned above, the sample cuts in CPS implemented in January 1996 force us to weigh the measurement of annual average even more highly than before. But other changes to the survey affected our choice of the K and A parameters. A new questionnaire conducted entirely by computer-assisted interviewing replaced the paper-and-pencil instrument. This may change the correlations between rotation groups several months apart with common respondents. Unfortunately, we have not yet been able to obtain reliable estimates of these correlations measured under the new survey instrument. For that reason, we used the correlations in Table 1. Because these correlations have changed so little between the late 1970's and the late 1980's (as seen by comparing the values provided in Breau and Ernst (1983) and Adam and Fuller (1992)), we anticipate little change even with the recently implemented questionnaire.

On the other hand, we expect to see changes in the estimates of month-in-sample bias with the recent survey changes. In the new instrument, certain questions are asked of discouraged workers in each month. Between 1970 and 1994, they were asked only in months in sample 4 and 8. (Before 1970, these questions were asked only in months in sample 1 and 5.) Because these questions have a tendency to raise the estimate of the number of people unemployed, asking them in every month may well change the month-in-sample bias pattern. To complicate the situation, in early 1994 there was actually a mixed mode effect. The new instrument was first used in January 1994. Yet in March, for example, a household may have been interviewed for the seventh time, but for only the third time under the computer-assisted format.

In addition, the month-in-sample bias is affected by our introduction of new sample areas. Every ten years new areas are phased into the CPS over a period of 15 months. This process began in April 1994 and continued through June 1995. During this time, a small number of units were interviewed only four times--rather than eight--to minimize field costs as we phased out some old (1980 design) areas in favor of newly selected (1990 design) areas. This disrupted the usual 4-8-4 pattern of response. For example, some households that would normally have been interviewed for the fifth time were replaced by households in a different area just entering the survey and interviewed for the first time. Thus, during this phase-in period, the month-in-sample bias was changed temporarily.

To measure the new bias factors, we wanted to wait until (1) any effects from the new survey instrument had become fairly constant, and (2) the effects of the phase-in period had passed. By July 1995, the CPS sample contained only units from the new (1990 design) sample. For the next four months, there were decreasingly fewer units whose month-in-sample pattern differed from the usual 4-8-4. We decided to include all units starting in September 1995 and compute a set of estimated month-in-sample bias factors. Currently we have data through December 1995. (See Mansur 1996.) The factors are given in Table 2 and labeled Set 1. We will continue to add data from ensuing months as they become available, and monitor the values and variability of the estimated bias factors.

Comparing MSEs among K,A pairs. In our previous research (Lent, Miller, and Cantwell 1994), we could not anticipate how the bias factors might change after 1994 with the implementation of the new survey instrument and the phase-in of new sample units. Because of this uncertainty in measuring the bias, we selected optimal K,A parameters based only on the variances of the competing estimators--leaving out the bias component that arises from the composite estimation. We argued that, when monthly level, month-to-month change, and annual average are all considered, it would be difficult to beat the following sets of parameters: for measuring the number of people unemployed, $K = .4$, $A = .3$; when measuring the number employed, $K = .7$, $A = .4$.

Table 2. Bias Indices Used in Study of Competing Estimators

Month in Sample	Unemployed		Civilian Labor Force	
	Set 1 9/95 to 12/95	Set 2 1/95 to 10/95	Set 1 9/95 to 12/95	Set 2 1/95 to 10/95
1	1.086	1.07	1.013	1.02
2	.996	1.02	1.003	1.00
3	.983	1.01	.999	1.00
4	1.033	1.00	1.003	1.00
5	.992	1.03	.995	1.00
6	.994	.99	.995	.99
7	.987	.94	.997	.99
8	.929	.95	.995	.99

Our search for the optimal *K,A* parameters continued by adding to the variances (as computed in Cantwell, 1990) a squared bias term. For month-to-month change, this bias term is 0. The month-in-sample bias factors in Set 1 are averages based on the months September through December, 1995. For measuring unemployed, perhaps the best choice--considering monthly level, month-to-month change, and annual average simultaneously--is the *K,A* pair (.2, .2). Strong competitors--weighing the three mean squared errors--are (.2, .3), (.3, .4), and (.1, .1). For employed, our top choice was (.5, .5), with each of (.5, .6), (.4, .4), and (.6, .7) doing almost as well.

Before making our choice final, we considered the robustness of the selection, keeping in mind that the bias factors in Set 1 are estimates based on data from only four months. To see how well these *K,A* pairs perform if the true bias factors are different from those in Set 1, we computed the mean squared errors applying other sets. First, we took each factor in Set 1, subtracted 1.0, multiplied each remainder by the same constant (ranging from 0.5 up to 2.0), and added 1.0. This had the effect of drawing the factors closer to 1.0, or forcing them farther away from 1.0 We also used an estimated set of bias factors based on the months January through October, 1995. These latter factors are Set 2 in Table 2, and are documented in Mansur (1996). Although Set 2 is based on ten months of data, we are reluctant to consider these factors more reliable than Set 1 because the new instrument was still relatively fresh early in 1995 and we were in the heart of the phase-in of new sample areas.

Observing the three mean squared errors for each pair *K,A*, and comparing among pairs, we changed our optimal selections to (.2, .3) for unemployed, and (.5, .6) for employed. Although these pairs produce similar results relative to our initial selections under Set 1, they appear to work as well--sometimes much better--under alternative sets. Before making a final recommendation, we will continue to monitor the bias factors through the end of 1996.

It may be worth mentioning that we were surprised to see the "optimal" *K* values decrease so much from those we proposed in the 1994 paper (.4 for unemployed; .7 for employed). Lowering the value of *K* in the composite estimator generally places less weight on the estimator from the previous month. Yet the values of *K* and *A*--along with the month-in-sample bias factors--also determine the component of bias contributing to the mean squared errors. At the time we conducted the earlier research, we had no reliable way to predict what effects the new questionnaire and the 1990-design sample units would have on the bias factors. In the absence of good data on bias factors, we selected optimal parameters based only on variances, ignoring the potential biases.

6. Description of Composite Weighting Research

In our research we looked at a wide variety of variables to determine what effect the composite weighting procedure had on those variables that were no longer being directly composited. We did this over several months, and computed summary statistics and estimated variances of those summary statistics. Some details are given here.

Data. The composite estimates used to compare three competing procedures (as defined in the next section) were computed for the months January through June 1996. After dropping the composite estimator from January through April of 1994 (when the new CPS instrument was first in place), the Bureau of Labor Statistics started compositing again in May 1994. By December 1995, the composite estimates released by the Department of Labor had been phased in for 20 months.

We applied three procedures to the data. *For each procedure separately,* we composited January 1996 with the December 1995 composite estimates, then February 1996 with January 1996, and so on. Thus through June 1996, we obtained six months of composite estimates for comparison.

Characteristics analyzed. In addition to labor force status (employed, unemployed, not in the labor force) by state, age, sex, race, and ethnicity, we also looked at other variables including full- or part-time status, industrial classification, occupational classification, reasons for unemployment, and duration of unemployment. We obtained data and analyzed estimates for 2489 characteristics that BLS and Census Bureau data users had identified as being of interest to them. These characteristics ranged from basic ones, like the number of people unemployed, to very specific ones, like the number of white males 20 years of age or older working multiple jobs, full-time on one job and part-time on others. Some of these estimates--especially for the more specific characteristics--were based on very small samples.

Analysis and summary statistics. An estimate of the coefficient of variation (CV) was computed for each variable of interest for each month under the current procedure (direct compositing) and under the composite weighting method (with two sets of *K,A* parameters). The variance estimates used to construct the CVs were obtained by the method of generalized replication described in Fay and Train (1995). We used 160 replicates, substantially more than the 48 replicates used in our previous research using data from 1987.

When determining differences between a pair of composite estimates, we measured the statistical significance through replication. That is, we measured the difference for each of the 160 replicates, and calculated a sample standard error for these differences. The t-statistic to be evaluated then was simply the difference divided by its standard error.

7. Analysis and Observations

For each of the 2489 characteristics studied, we first computed estimates and coefficients of variation (CVs) for the three estimation procedures:

(A) the direct (current) production estimator, which determines the composite estimate directly for the characteristic and uses $K = .4$ and $A = .2$;

(B) the composite weighting estimator (the new method--determining composite weights and summing them) with the current coefficients (using $(K, A) = (.4,.2)$); and

(C) the composite weighting estimator with the *new* coefficients (using $(K,A) = (.2,.3)$ for unemployed and $(.5,.6)$ for employed).

In general, comparisons between the first two should relate to the effectiveness of the new composite weighting procedure, since the *K,A* coefficients are kept the same. Comparisons between the latter two indicate how well the proposed new coefficients perform when using the composite weighting procedure.

Coefficients of variation. For the new method with new coefficients, the average CV for monthly estimates (over all characteristics and all months) was slightly higher (about 12.63%) than that for the current production estimator (11.11%). The increase in CV appears, in most cases, to be associated with the new method rather than with the change in coefficients; the new method with the current coefficients also produced an average CV of 12.63%. See Table 3.

Table 3. Coefficients of Variation Under the Three Methods

Method	Coefficients of Variation (CVs)		
	Over all 2489 cases	Dropping "small sample"[1] cases	Weighted analysis[2]
(A) Current, old *K,A*	11.11%	8.37%	4.68%
(B) Comp. Wgt., old *K,A*	12.63%	8.61%	4.75%
(C) Comp. Wgt., new *K,A*	12.63%	8.61%	4.76%

[1] Cases where the current estimate was negative in one or more months, or its CV was greater than 50%.

[2] The small sample characteristics were also dropped in the weighted analysis.

Because we were reluctant to merely average the CVs over the 2489 characteristics in the study, however, we computed two additional averages. First, we deleted certain characteristics (254 out of 2489) that could throw off the analysis: all those for which the production estimates either were negative or had CVs exceeding 50%. For these characteristics, there were typically very few sample persons. For each of the three competing methods, the average CVs with these "small sample" cases deleted are given in Table 3. Having deleted cases with high variability, we expected the average CVs--under all methods--to be lower. Again, the CVs due to the composite weighting method are higher (8.61% to 8.37%) than under the current method. But there is no difference in the average CV due to the different K,A parameters (given that composite weighting is used).

Finally, we developed a simple scheme to put greater emphasis on unemployment characteristics--among the most important CPS estimates--as well as on those characteristics that exhibit a smaller CV (generally implying a larger number of sample persons). After deleting the "small sample" cases, we used the following weighted analysis:

- each estimate relating to unemployment received a weight of 2.0/CV, and

- all other estimates received a weight of 0.25/CV,

where, in both cases, CV represents the CV *in percent* of the current production estimate.

Thus we took the inverse of the CV as an indication of an estimate's importance but corrected for the fact that unemployment estimates generally have higher CVs (fewer sample persons) than the corresponding estimates of employment and civilian labor force. Under this weighting scheme, estimates of total employment and total unemployment each bore a weight of approximately 1.0.

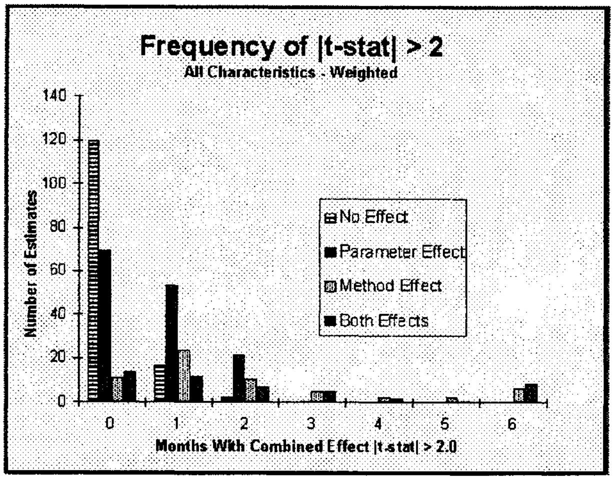
With the weighted set of characteristics, the results were similar to those obtained from the earlier analysis. It is worth noting, however, that the average CVs under the composite weighting technique are now even closer to that of the current production method.

Differences in the estimates? To consider other facets of the estimators, we examined the *raw* frequencies where the t-statistic for the difference between two methods exceeds 2.0 in absolute value. For the majority of characteristics (1659 out of 2489, 66.7%), including most major labor force characteristics and characteristics relating to industry and occupation, significant differences appear in none of the months for which we examined the data. Further, most of the significant differences between the new composite weight estimates and estimates produced under the current method appear to stem from the composite weighting method rather than from the new coefficients.

We continued by looking at the *weighted* frequencies (excluding the "small sample" estimates). The magnitudes of the parameter, method, and combined effects are illustrated by Figure 1. Each cluster of bars in Figure 1 represents the weighted number of estimates whose *t*-statistics for the combined effect exceeded 2.0 in absolute value for m of the data months, $m = 0, 1, \ldots, 6$. (The values of m are shown on the horizontal axis).

As the graph illustrates, the largest group of estimates showed no significant combined effect in any month. In most cases, a significant combined effect on estimates for one or two months was attributable to the new parameters. For the characteristics represented by the last cluster of bars, however, the new method caused significant changes in the estimates for all six data months.

Figure 1. Frequencies for Which the t-Statistic is Significant



Characteristics for which significant differences between the estimates from the new and current methods appear *in all six months* fall into three broad categories:

- employed by number of hours worked;

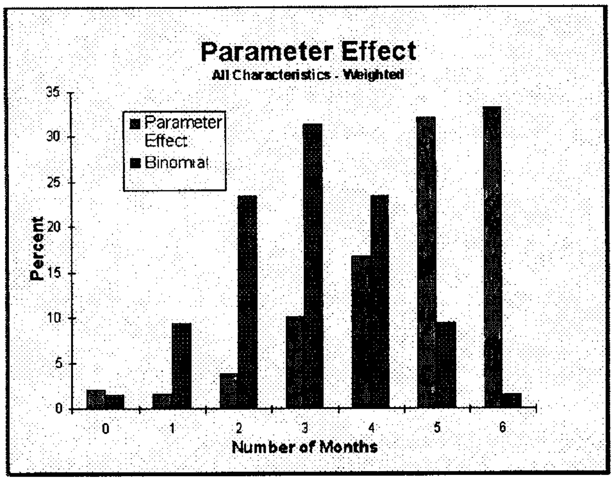
- characteristics relating to multiple job holders; and

- characteristics relating to duration of unemployment.

Most characteristics for which significant differences appear in four or five months relate to school enrollment and educational attainment. Characteristics for which significant differences appear in three months include some characteristics relating to multiple job holders, duration of unemployment, and educational attainment; they also include such key estimates as black civilian labor force (CLF) and employed by full- and part-time. In the case of black CLF, the differences are due to the change in compositing coefficients, while for employed by full- and part-time, they are due primarily to the new method.

Which estimates are larger? Figure 2 illustrates the overall effect of the new parameters *on the size of the estimates*. The first bar in each pair of bars in Figure 2 shows the percentage of estimates (again, weighted) for which the parameter effect was positive, i.e., the *new* parameters with the new method produced larger estimates than the *old* parameters with the new method, for m of the six data months, $m = 0, 1, \ldots, 6$. For comparison purposes, the binomial probabilities, expressed as percentages, are indicated by the second bar in each pair of bars. As the figure shows, the effect of the new parameters was an overall increase in the level of the estimates.

Figure 2. The Effect of the New Parameters



The effect of the new method is similarly illustrated by the bar charts in Figure 3. Again the second bar in each pair represents a binomial probability and serves only as a reference while the first set of bars describes the overall effect of the new method on the estimates examined. Comparing the first and second bars in each pair, we find that the distribution representing the method effect is much "flatter" than the binomial distribution but does not indicate an overall increase in the estimates due to the new method. The greater dispersion may be due to the strong correlation (i) between estimates from the six consecutive months for the same characteristic (induced by sample overlap), and (ii) among similar characteristics.

Figure 3. The Effect of the New Method

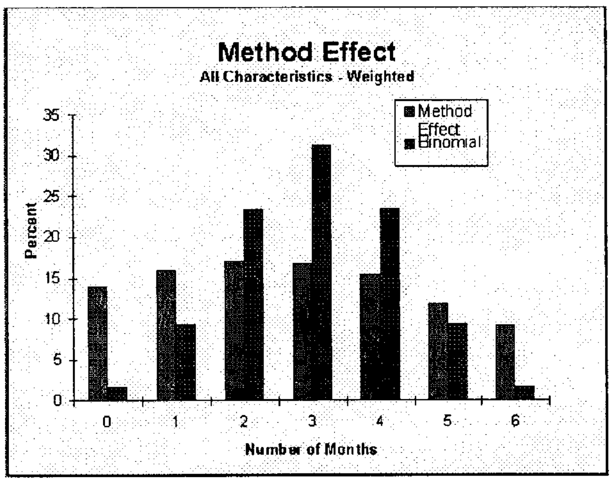
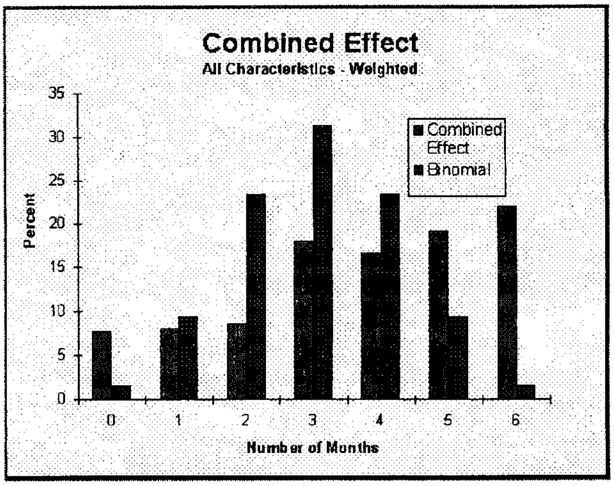


Figure 4 shows the combined effect of the new parameters and the new method on the estimates, i.e., the comparison is between estimates produced by the new method with new parameters and the corresponding estimates produced by the current method and old parameters. The combined effect is similar to the parameter effect but somewhat less pronounced.

The new compositing coefficients assign slightly more weight to data from persons being interviewed for the first or fifth time--the incoming rotation groups. Thus the slight increase in the estimates appears to be associated with the new coefficients, rather than with the new method.

Figure 4. The Effect of the New Method With the New Parameters



Other observations. We have seen that the composite weighting procedure tends to produce slightly higher CVs. Yet it controls the effect of composite estimation on the estimates. First, the new method cannot produce negative estimates of level. (For 21 of the 2489 characteristics we analyzed, the *average* estimate over the six months under the current method was less than 0.)

Secondly, by confining the ratio of the composite estimate to the second-stage estimate to the interval (0.7, 1.3) (see Section 4), the new method tends to produce a composite estimate closer to the second-stage estimate than the direct composite. In this way, the new method controls bias, under the assumption that the second-stage estimates are unbiased. Considering this result and then selecting the *K,A* compositing coefficients to reduce mean squared error, we hope that the composite weighting method will produce lower MSEs for most estimates. We plan to compare the MSEs in our next set of analyses.

8. Future Research

In the coming months, we plan to continue our investigation in several important areas. These include the following.

- For the various labor force characteristics, our current results are restricted to estimates of monthly level. We will extend the analyses to estimates of month-to-month change and, when we have enough data, annual average.

- All analyses presented in this paper were done on totals, means, or medians. We will continue by studying the effect of the new procedures on the unemployment ratio, **UE** / (**UE** + employed), and other important rates.

- Future evaluations of the composite weighting procedure and different optimal *K,A* parameter pairs will compare the relevant mean squared errors, rather than simply their variances. Using the CPS replicate weights, we plan to estimate the month-in-sample bias for each characteristic of interest and incorporate a squared bias term into the mean squared error.

- There are certain characteristics--often with very few people in the sample--where the composite weighting procedure (or the selected optimal *K,A* pair) produced significantly different estimates in two or more months. We plan to study these characteristics and try to determine underlying causes for the differences. Perhaps we can find a common link to these cases that will suggest improvements.

- Through 1996 (and beyond), we will accumulate data to develop better estimates of the month-in-sample bias factors. This will help us determine the optimal parameters *K* and *A* to use in the composite estimator.

- The month-in-sample bias factors for subgroup characteristics--such as female unemployed--differ slightly from the factors for these characteristics as a whole. How much effect this has on determining optimal *K* and *A* has not yet been studied. To keep the estimation simple, we would prefer to use the same parameters for all subgroups when estimating the same labor force characteristic. If the results imply that different *K,A* pairs (for different subgroups) would lead to significantly better estimates, we may consider other procedures that would retain additivity across the estimates.

Acknowledgments

The authors thank Bob Fay and George Train for developing the replicate weights and running variances for this research; Martha Duff for computing and graphics support; Khandaker Mansur for supplying current month-in-sample bias factors; and Nash Monsour for reviewing the paper and providing helpful comments. Special thanks go to Jon Rao for the insightful views expressed during his discussion of the papers in the session.

References

ADAM, A. and W. FULLER (1992). "Covariance of Estimators for the Current Population Survey." *Proceedings of the Section on Survey Research Methods, American Statistical Association*, pp. 586-591.

BAILAR, B. (1975). "The Effects of Rotation Group Bias on Estimates from Panel Surveys." *Journal of the American Statistical Association*, 70, 23-30.

BREAU, P. and ERNST, L. (1983). "Alternative Estimators to the Current Composite Estimator." *Proceedings of the Section on Survey Research Methods*, American Statistical Association, 397-402.

CANTWELL, P. (1990). "Variance Formulae for Composite Estimators in One- and Multi-Level Rotation Designs." *Survey Methodology*, **16**, **1**, pp. 153-163.

FAY, R. and G. TRAIN (1995). "Aspects of Survey and Model-Based Postcensal Estimation of Income and Poverty Characteristics for States and Counties." *Proceedings of the Government Statistics Section, American Statistical Association.*

FULLER, W. (1990). "Analysis of Repeated Surveys." *Survey Methodology*, **16**, **2**, pp. 167-180.

KUMAR, S. and H. LEE (1983). "Evaluation of Composite Estimation for the Canadian Labour Force Survey." *Proceedings of the Section on Survey Research Methods, American Statistical Association*, pp. 403-408.

LENT, J., S. MILLER and P. CANTWELL (1994). "Composite Weights for the Current Population Survey." *Proceedings of the Section on Survey Research Methods, American Statistical Association*, pp. 867-872.

MANSUR, K. (1996). Internal memorandum for Documentation, dated January 19, 1996, "Additional Results of the CPS Month-in-Sample Bias Research (ESTWGT90-31)," Bureau of the Census, Washington, DC.

* This paper reports the general results of research undertaken by staff of the Bureau of Labor Statistics and the Census Bureau. The views expressed are attributable to the authors and do not necessarily reflect those of these agencies.