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Effects of Composite Weights on Some Estimates from the Current Population Survey

Janice Lent[1], *Stephen M. Miller*[1], *Patrick J. Cantwell*[2], *and Martha Duff*[1]

We examine the effect of a new composite estimation method on estimates from the Current Population Survey, the U.S. labor force survey. Currently, the *AK* composite estimator is applied directly for each characteristic of interest. To ensure consistency, the same coefficients are used for all estimates, though they are optimal only for unemployment totals. The new method involves two steps: (1) compute composite estimates for the main labor force categories, classified by important demographic characteristics; (2) through a series of ratio adjustments, adjust the micro-data weights to agree with these composite estimates. The new technique provides increased operational simplicity for micro-data users and allows optimization of compositing coefficients for different labor force categories. We discuss the effect of the procedure on a large number of estimates produced from the survey.

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

1. Introduction

National unemployment rates are among the most closely watched economic indicators produced by the federal statistical system. U.S. Census Bureau interviewers collect data used to estimate the rates, as well as a wealth of other labor force statistics, through the Current Population Survey (CPS), a monthly survey sponsored by the U.S. Bureau of Labor Statistics (BLS). Important CPS estimates include estimates of the numbers of persons in three major labor force categories: employed, unemployed, and ''not in the labor force'' (i.e., not employed or seeking work). 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 coverage error relative to independently derived population estimates for specific demographic groups. These ratio adjustments are followed by a

[1] U.S. Bureau of Labor Statistics, Office of Survey Methods Research, 2 Massachusetts Ave. NE, Washington DC 20212, U.S.A. E-mail: lent_j@bls.gov.
[2] U.S. Bureau of the Census, Decennial Statistical Studies Division, STOP 7600, Washington, DC 20233-7600, U.S.A.
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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 micro-data users need several months of CPS data to compute composite estimates.

In a previous article (Lent, Miller, Cantwell 1994) we discussed research on a composite estimation approach, suggested by Fuller (1990), which incorporates the effect of composite estimation into the micro-data weights. The goal of this method is to create a set of person weights for a given data month from which users will be able to generate all the composite estimates without data from prior months. That is, when we add the composite weights for sample persons in a given labor force category with specified demographic characteristics (e.g., employed Hispanic males aged 16 to 19), the sum should closely approximate the corresponding ''direct'' composite estimate (to be defined in Section 2). Since 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, a data user wishing to compute a composite estimate for a given month need only access the micro-data file for that month and compute a weighted sum. 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[3]. Composite weights provide additivity while allowing some variation in compositing coefficients.

Recent changes in the CPS have necessitated some modifications to the composite weighting technique described in Lent et al. (1994). In particular, the 1994 questionnaire redesign may have affected the optimal values to be used for the parameters in the composite estimator. In this article we discuss the choice of optimal parameters and examine the effect of composite weighting on the reliability of a wide range of estimates computed from CPS data. Our results indicate that the new method is practical for use with CPS data. In the next two sections, we discuss composite estimation as currently implemented in the CPS and how we develop composite weights to reproduce the composite estimates. In Section 4, we describe the selection of coefficients for the composite estimator. Section 5 provides further details of our method. Finally, in Section 6 we analyze the effects of composite weighting on some CPS estimates and identify topics for future research.

2. 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

[3] Throughout this article, the ''current method'' of composite estimation refers to the method used in the CPS before January 1998. The ''new method'' refers to the method used for data from January 1998 and subsequent months.

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 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 (direct) CPS ''*AK*'' composite estimator 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 estimator for month h, based on a sum of weights (adjusted to agree with population estimates) for sample 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 A and K are close to optimal – with respect to variance – 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 data from sample households 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 used to produce CPS estimates for all labor force categories. 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 positively 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.

3. Computing Composite Weights

In the current CPS estimation process, the base weight for each sample person (the inverse of the person's probability of selection) is adjusted for nonresponse, and two successive stages of ratio adjustments to population controls are applied. The final adjustment procedure – a raking procedure performed independently for each of the eight sample rotation groups – ensures that sample weights sum to independent controls for states (51 totals, including the District of Columbia) as well as for 9 age/sex/ethnicity groups and 66 age/sex/race groups, specified at the national level. (For information on CPS ratio adjustments, see the *BLS Handbook of Methods*, U.S. Department of Labor 1997.) Our method of computing composite weights for the CPS imitates the raking ratio 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.

3.1. Prior results

In our 1994 article, we discuss research on two methods of computing composite weights for the CPS: (1) adjusting micro-data weights to composite estimates of the three major labor force categories at the national level (i.e., computing ''national'' composite weights); and (2) adjusting micro-data weights to the same composite estimates, but at the level of the states and demographic groups (''marginal'' composite weights), as will be discussed below. 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. Though CPS weights for sample persons are always positive, composite estimates of labor force levels based on very small samples can sometimes fall below zero due to the nature of the composite estimation formula. (See Section 2.) 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 – in light of the results mentioned above based on national composite weights – that too much aggregation could compromise the accuracy of the estimates computed from the 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 view of the possibility of changes in the CPS sample size, we decided to research a method of computing composite weights using a flexible cell-collapsing scheme.

3.2. The method

Composite weights are produced only for sample persons aged 16 or older. Adjustment of micro-data weights to the composite estimates for each labor force category proceeds as follows. For simplicity, we describe the method for estimating the number of people unemployed (**UE**); analogous procedures are used to estimate the number of people employed and the number not in the labor force. Data from all eight rotation groups are combined for the purpose of computing composite weights.

1. For each state j, the direct (optimal) composite estimate of **UE**, comp($\mathbf{UE}_j$), is computed. Similarly, direct composite estimates of **UE** are computed for each age/sex/ethnicity group and each age/sex/race group.
2. Sample records are classified by state. Within each state j, a simple estimate of **UE**, simp($\mathbf{UE}_j$), 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($\mathbf{UE}_j$)/simp($\mathbf{UE}_j$).
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, for a given state, the ‘‘composite weight estimate’’ of the number of people not in the labor force is defined as the residual from the state control total. The demographic group cells are treated similarly.

3.3. Collapsing cells

In our earlier 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, by which person weights are controlled to population estimates, age/sex/ethnicity and age/sex/race cells are collapsed when their adjustment factors – defined as independent population estimates divided by weighted cell totals – fall below 0.6 or above 2.0. During computation of composite weights for persons who are unemployed, some further collapsing of cells is needed to control the effect of composite estimation and prevent undesirable results, e.g., negative estimates of unemployment totals. Since most CPS sample persons are employed, no cell collapsing is needed for estimating employed, i.e., all cells contain sufficient sample[4]. For unemployed, a cell is collapsed with an adjacent age cell (in the same sex/ethnicity or sex/race group) if it

a) contains fewer than 10 sample person records; *or*
b) results in a ratio of comp($\mathbf{UE}_i$) to simp($\mathbf{UE}_i$) that is less than 0.7 or larger than 1.3.

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 weight estimate for the latter characteristic is determined by subtracting the estimated number of people who are employed or unemployed for the cell from the population control for the cell.

4. Optimal Compositing Parameters

Our method of computing composite weights 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 for month-to-month change or annual average (defined here as an average over any twelve consecutive months).

4.1 Criteria for selecting new K and A parameters

To determine appropriate values of K and A, we attempted to minimize the mean squared error of the resulting AK composite estimators. To compute the variances, we had 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 Section 2, 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 for unemployed (UE) and for employed (EMP) and civilian labor force (CLF) are displayed in Table 1. They are slightly smoothed from the results given in Breau and Ernst (1983) and Adam and Fuller (1992).

Kumar and Lee (1983) and others have shown that estimates from a new rotation group

Table 1. Correlations for a specific rotation group r months apart

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

[4] A collapsing procedure for employment cells – similar to that used for unemployment – is included in the algorithm used for production purposes, though research showed actual collapsing to be very unlikely for the employed category.

and the retiring group it replaces are generally correlated, although the correlations are much smaller than the corresponding ones for the same group. Here, we assume that estimators $x_{h,i}$ and $x_{h-r,j}$ from different rotation groups are uncorrelated.

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 values 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

$$E(x_{h,i})/E\left(\sum_j x_{h,j}/8\right)$$

so that an index larger than 1 implies an overestimate in that month relative to the average over the 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. We define the month-in-sample bias of a composite estimator as its bias relative to Y_h – obviously an arbitrary definition of bias.

For each labor force characteristic (employment and unemployment), we considered three measurements when choosing the parameters K and A: monthly level, month-to-month change, and annual average. It is easy to see from the definition of the composite estimator that changing the K parameter has different effects on the three 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 K, A pair – 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 employment and unemployment – that gave good results overall.

4.2. *Effects of changes in the CPS*

Recent changes in the CPS affect the choice of values for the K and A parameters. A new computer assisted personal interviewing (CAPI) instrument replaced the paper-and-pencil questionnaire in January 1994. New geographic areas were gradually phased into the sample between April 1994 and June 1995. Since the correlation structure of CPS estimates depends primarily on the sample rotation scheme, we did not expect it to be significantly affected by the implementation of the new questionnaire or the phase-in of new sample areas[5]. We expected, however, that the changes in the questionnaire might have affected the month-in-sample bias factors. To complicate the situation, in early 1994 there was actually a mixed mode effect: The new instrument was introduced in January, which meant that in March, for example, a household may have been interviewed for the seventh time, but only the third time under the CAPI format. To compute the new bias factors, we wanted

[5] Several months after our research was completed, new correlation estimates were computed using more recent CPS data. As expected, they differed little from the smoothed values shown here.

Table 2. Bias indices used in study of competing estimators

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

[a]Set 1 covers 9/95 to 12/95; Set 2 covers 1/95 to 10/95.

data free of transition effects from the sample design and questionnaire changes. We decided to use data from September through December 1995 to estimate a set of month-in-sample bias factors. (See Mansur 1996.) The factors are given in Table 2 and labeled Set 1.

4.3 Comparing Mean Squared Errors (MSEs) among K,A pairs

In our previous research (Lent et al. 1994), we could not anticipate how the bias factors might change after 1994 with the implementation of the new questionnaire and the phase-in of new sample units. We therefore selected optimal K, A parameters based only on the variances of the competing estimators. 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, $K = .4$, $A = .3$; for measuring the number employed, $K = .7$, $A = .4$.

We continued our search for the optimal K, A parameters by adding to the variances (as computed in Cantwell, 1990) an estimated squared bias term. Since we assume that the bias is additive and constant across months, the bias term is 0 for estimates of month-to-month change. For measuring unemployed, our preliminary choice – considering monthly level, month-to-month change, and annual average simultaneously – was the K, A pair (.2, .2). Strong competitors – weighting the three mean squared errors – were (.2, .3), (.3, .4), and (.1, .1). For employed, our preliminary choice was (.5, .5), with each of (.5, .6), (.4, .4), and (.6, .7) doing almost as well.

Before making a choice, however, 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 would perform if the true bias factors differed 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 K, A, pair and comparing among pairs, we selected our ‘‘optimal MSE’’ (or ‘‘OPTMSE’’) coefficients: (.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. 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). When considering the OPTMSE parameters, however, we must keep in mind our unverified assumption of unbiasedness for the ratio estimator Y_h.

5. Composite Weighting Research

We examined a wide variety of estimates to determine what effect the composite weighting procedure had on those variables that were no longer being directly composited. Using data from several months, we estimated summary statistics and their variances.

5.1. Date

The composite estimates used to compare four competing procedures (as defined in the next section) were computed for the months January through December 1996. *For each procedure*, we composited data from February 1996 with the January 1996 composite estimates, then March 1996 with February 1996, and so on. We used composite estimates from May through December 1996 for our comparisons.

5.2. Characteristics analyzed

In addition to labor force status (employed, unemployed, not in the labor force) by state, age, sex, race, and ethnicity, we 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 2,489 characteristics that BLS and Census Bureau data users had identified as being of interest. These characteristics ranged from basic ones, like the number of people unemployed, to very specific ones, like the number of white males 20 years old or older working multiple jobs, full-time on one job and part-time on others. Some of these estimates – especially those for the more detailed characteristics – were based on very small samples.

5.3. Analysis and summary statistics

We computed an estimate of the coefficient of variation (CV) and the relative root MSE – defined here as the squared root of the estimated MSE divided by the estimated level – for each variable of interest and each data month, under the current procedure (a version of direct compositing) and under the composite weighting method (with three sets of K, A parameters). The variance estimates used to construct the CVs were obtained by the method of generalized replication described by Fay and Train (1995), with 160 replicates. As an estimator of the squared bias of the composite estimators, we used

$$\hat{B}^2(Y''_h) = (Y''_h - Y_h)^2 - \hat{V}(Y''_h - Y_h)$$

where, as in Section 3, Y''_h is a composite estimator (with the specified coefficients) for month h and Y_h the ratio estimator. The estimator $\hat{B}^2$ is easily shown to be unbiased provided that the variance estimator $\hat{V}$ is unbiased. For our application, we used variance estimates computed by replication as described above. These variance estimates are known to be quite variable and to have a slight upward bias. For the purpose of comparing MSEs of composite estimates produced by different procedures, we averaged the root MSE estimates over several months to improve stability. To evaluate differences between the composite estimates themselves, we computed the differences for each of the 160 replicates, and used the replicate estimates of the differences to calculate a standard error for each difference. We then computed approximate *t*-statistics by simply dividing the estimated differences by their standard errors.

6. Analysis and Observations

For each of the 2,489 characteristics studied, we first computed estimates and coefficients of variation (CVs) for the four estimation procedures:

(A) the direct (current) production estimator, which determines the composite estimate separately for each characteristic with coefficients $(K, A) = (.4, .2)$;
(B) the composite weighting estimator (the new method – computing estimates as sums of composite weights) with the current coefficients $(K, A) = (.4, .2)$;
(C) the composite weighting estimator with the *optimal MSE* (OPTMSE) coefficients $(K, A) = (.2, .3)$ for unemployed and (.5, .6) for employed; and
(D) the composite weighting estimator with the *optimal variance* (OPTVAR) coefficients $(K, A) = (.4, .3)$ for unemployed and (.7, .4) 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 among the latter three indicate how well different pairs of coefficients perform when used in the composite weighting procedure.

6.1. *Coefficients of variation*

For the new method with OPTMSE coefficients, the average CV for estimates of monthly level (over all characteristics and all months) was slightly higher (12.492%) than that for the current production estimator (11.714%). 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 and current coefficients produced an average CV of 12.497%.

Because we were reluctant to merely average the CVs over the 2,489 characteristics in the study, however, we computed two additional averages. First, we deleted certain characteristics (254 out of 2,489) that could throw off the analysis: all those for which either the production estimates were negative or CVs exceeded 50% for one or more methods tested. Estimates of these characteristics were typically based on data for very few sample cases. 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 for the composite weighting method are higher (8.478% to 8.260%) than those for the current method. But there is little 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, which are perhaps the most important CPS estimates, as well as on those

Table 3. Coefficients of variation for monthly estimates under the four methods, based on data for May–December, 1996

Method, parameter values		Average percent coefficients of variation (CVs) and average percent relative mean squared errors (RMSEs)					
		Over all 2,489 cases		Dropping ''small sample''[a] cases		Weighted analysis[b]	
		%CV	%RMSE	%CV	%RMSE	%CV	%RMSE
(A)	Current method Current K, A	11.714	11.397	8.260	8.370	4.669	4.808
(B)	Comp. wgt. method Current K, A	12.497	12.612	8.478	8.501	4.776	4.824
(C)	Comp. wgt. method OPTMSE K, A	12.492	12.587	8.472	8.470	4.781	4.778
(D)	Comp. wgt. method OPTVAR K, A	12.490	12.628	8.470	8.509	4.730	4.791

[a]Cases where the current estimate was negative in one or more months, or the CV for one or more methods was larger than 50%.
[b]The small sample characteristics were also dropped in the weighted analysis.

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
- all other estimates received a weight of 0.25/CV

In both cases CV represents the *percent* CV 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, except that the reduction in CV resulting from use of the OPTVAR parameters rather than the OPTMSE parameters was slightly more pronounced.

Using the estimates of variance and squared bias for the set of characteristics, we repeated the analysis using the estimates of relative mean squared error (RMSE) in place of the CV. (The weights used in the weighted analysis, however, were still based on CV, as an estimator's CV is a better indicator of its relative sample size.) As the data in Table 3 indicate, the weighted analysis showed little difference between RMSEs for the four methods tested. The composite weighting method, when implemented with the OPTMSE or OPTVAR parameters, performs very slightly better on average than the current method implemented with the current parameters. Moreover, the OPTVAR parameters gave an average weighted RMSE value of 4.791%, close to the 4.778% obtained from the OPTMSE parameters.

For estimates of month-to-month change, we compared the standard errors of composite

Table 4. Standard errors, relative to current standard errors, for estimates of month-to-month change, based on data for May–December, 1996

Method, parameter values	Average relative standard errors		
	Over all 2,489 cases	Dropping "small sample"[a] cases	Weighted analysis[b]
(B) Comp. wgt. method Current K, A	1.077	1.085	1.051
(C) Comp. wgt. method OPTMSE K, A	1.091	1.101	1.081
(D) Comp. wgt. method OPTVAR K, A	1.074	1.080	1.044

[a]Cases where the current estimate was negative in one or more months, or the CV was larger than 50% for one or more methods.
[b]The small sample characteristics were also dropped in the weighted analysis.

weight estimates (with the three pairs of parameter values tested) against the corresponding standard errors resulting from the current compositing technique. The figures in Table 4 are average ratios of composite weight standard errors to current method standard errors. Since direct compositing increases month-to-month correlations more than composite weighting – for estimates other than those used as controls – it is reasonable that all the numbers in Table 4 exceed 1. Though the differences between ratios for the various pairs of parameters are fairly close, all three columns of the table show the lowest ratios for the OPTVAR parameters.

For the following reasons, we decided to recommend use of the parameter values of Method D – that is, (.4, .3) for unemployed and (.7, .4) for employed.

1. Optimality with respect to variance does not depend on the – as yet unverified – assumption that the ratio estimator Y_h contains no month-in-sample bias.
2. Variance rather than MSE is the estimated measure of error published by the BLS and used in economic analysis of CPS data.
3. With respect to relative MSE, the OPTVAR parameter values performed almost as well as the OPTMSE values. Given the "noise" in our estimates of bias, we cannot firmly establish a difference between the two sets of values in this regard.
4. For unemployment, the OPTVAR parameter values are nearly identical to the current parameter values; their introduction would not create a discernible break in the most important CPS series.

6.2. *Differences in the estimates*

In Table 5, we compare major labor force estimates, averaged across eight months, under the new method (composite weighting with OPTVAR parameters) and the old method (direct compositing with the current K, A parameters). The third column of numbers in the table displays average monthly t-statistics for the differences in labor force totals. The t-statistics indicate that the new parameters cause slight increases in unemployment estimates; the difference for total unemployment may be considered significant. The standard errors of the unemployment estimates shown are essentially the

Table 5. Comparison of current and new composite estimates for major labor force levels

	New	New−Old	$\frac{\text{New−Old}}{\text{SE (New−Old)}}$	$\frac{\text{New}}{\text{Old}}$	$\frac{\text{SE (New)}}{\text{SE (Old)}}$	$\frac{\text{CV (New)}}{\text{CV (Old)}}$
Unemployment						
Total	7,002,440	17,695	1.9670	1.0025	1.0010	0.9984
Men 20+	2,878,176	4,948	0.8272	1.0017	0.9994	0.9977
Women 20+	2,793,006	8,267	1.3831	1.0030	0.9976	0.9946
Total 16–19	1,331,259	4,480	0.8914	1.0034	0.9987	0.9953
White	5,053,705	10,940	1.4655	1.0022	0.9992	0.9970
Black	1,610,244	6,031	1.2995	1.0038	1.0029	0.9991
Hispanic Origin	1,070,256	2,611	0.7241	1.0024	0.9946	0.9922
Employment						
Total	127,562,723	−293,226	−2.7326	0.9977	0.9411	0.9434
Men 20+	65,378,295	−98,434	−1.6910	0.9985	0.9532	0.9546
Women 20+	55,435,344	−123,506	−1.7517	0.9978	0.9399	0.9420
Total 16–19	6,749,084	−71,286	−1.9693	0.9895	1.0002	1.0107
White	108,487,464	−223,712	−2.4123	0.9979	0.9499	0.9518
Black	13,638,080	−60,419	−1.4698	0.9956	0.9700	0.9743
Hispanic Origin	11,812,965	−50,250	−1.3189	0.9958	0.9670	0.9711
Civilian Labor Force						
Total	134,565,163	−275,531	−2.5509	0.9980	0.9452	0.9471
Men 20+	68,256,471	−93,485	−1.5823	0.9986	0.9602	0.9615
Women 20+	58,228,349	−115,240	−1.6259	0.9980	0.9428	0.9447
Total 16–19	8,080,343	−66,806	−1.8054	0.9918	1.0038	1.0121
White	113,541,168	−212,771	−2.2795	0.9981	0.9494	0.9512
Black	15,248,324	−54,388	−1.3139	0.9964	0.9746	0.9781
Hispanic Origin	12,883,221	−47,639	−1.2396	0.9963	0.9639	0.9675

Notes:
All figures are averages of monthly estimates for May–December 1996.
''New'' is the composite weighting estimator with the optimal variance coefficients $(K, A) = (.4, .3)$ for unemployed and (.7, .4) for employed.
''Old'' is the direct (current) production estimator, which determines the composite estimate separately for each characteristic with coefficients$(K, A) = (.4, .2)$.

same under the current and new methods, though the new method results in slightly lower CVs. For estimates of employment and civilian labor force levels, the new parameters provide larger gains in reliability while decreasing the estimated totals. The average drop in the total estimated employment level is about 0.2% which, as the *t*-statistics indicate, is significant. Data users must therefore expect a slight break in the time series for employment and civilian labor force when the new composite estimator is implemented.

Table 6 displays estimates for some of the characteristics that appear to be most significantly affected by the composite weighting method. Most of these estimates reflect a significant method effect because, under the new method, they are no longer directly composited. The numbers in the last two columns of Table 6, however, indicate that the new method does not result in large losses in reliability. Several characteristics, in fact, show decreases in CV under composite weighting: Estimates of employed by the number of hours worked and estimates of unemployed by duration of unemployment are probably not as strongly correlated as the major labor force totals; the composite weighting method may therefore be more appropriate for these characteristics than direct compositing. For multiple-job holders, the numbers in Table 6 show little differences in the reliability of estimates computed under the current and new methods. The reliability of estimates for employment and civilian labor force by school enrollment status and educational attainment, however, appears to be adversely affected by the new method, perhaps due to strong month-to-month correlation, which the composite weighting technique fails to exploit.

We continued the comparison by examining *weighted* frequencies (excluding the ''small sample'' estimates) to gauge the overall effects of the new method and new parameters on the estimates. We estimated the effect of the new method by comparing the estimates computed using the old parameters with the *old* method to those computed using the old parameters with the *new* method (A versus B). Similarly, comparing estimates produced under the new method with the old and new (OPTVAR) parameters yields an estimate of the parameter effect (B versus D). Finally, the combined effect – the difference between estimates computed under the old method and old parameters and those computed under the new method with new parameters (A versus D) – indicates the changes data users may expect when the composite weighting procedure is implemented.

The magnitudes of the combined, parameter, and method effects are illustrated in Figure 1. The first bar in each cluster 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, $m = 0, 1, \ldots, 8$. (The values of m are shown on the horizontal axis.) Similarly, the second and third bars in each cluster show the magnitudes of the parameter and method effects, respectively. As the graph illustrates, the largest group of estimates showed no significant combined, parameter, or method effect in any month. Overall, the effect of the new parameters proved larger than that of the new method.

The direction of the changes induced by the new method and parameters (not indicated by Figure 1) varies by characteristic. For employment, civilian labor force, and related characteristics, the new *parameters* tend to reduce estimates of monthly level. For characteristics related to unemployment, by contrast, the new parameters cause an overall increase in estimated monthly levels. In both cases, the effect of the new *method* on

Table 6. Item groups with significant change

	New	New–Old	New–Old / SE (New–Old)	New / Old	SE (New) / SE (Old)	CV (New) / CV (Old)
Employed, at work						
Total	121,524,111	−257,020	−2.3201	0.9979	0.9574	0.9598
40 hours	42,918,423	−820,491	−9.1143	0.9812	1.0117	1.0310
41–48 hours	14,583,711	268,737	4.9032	1.0188	1.0004	0.9822
49–59 hours	14,550,328	245,701	4.4970	1.0172	1.0059	0.9881
MEAN hours	39.6842	0.1073	5.6717	1.0027	1.0346	1.0317
MEAN hours nonagricultural	39.5829	0.1049	5.7082	1.0027	1.0313	1.0285
Employed, at multiple jobs						
Total	8,161,000	211,540	5.4068	1.0266	1.0416	1.0149
White	7,148,896	175,297	4.8943	1.0251	1.0404	1.0151
Black	743,033	28,604	2.1927	1.0400	1.0261	0.9874
Males ages 20+	4,236,574	127,193	4.5999	1.0310	1.0661	1.0342
Females ages 20+	3,547,955	82,819	3.2627	1.0239	1.0336	1.0087
Full time first job, part time second job	4,520,216	121,184	4.1447	1.0275	1.0426	1.0154
Duration of unemployment						
0–4 weeks	2,767,464	118,000	5.6388	1.0445	1.0001	0.9567
5–14 weeks	2,126,956	−54,543	−2.7175	0.9750	0.9594	0.9837
Male, 5–14 weeks	1,085,301	−18,857	−1.3573	0.9829	0.9720	0.9881
Female, 5–14 weeks	1,041,654	−35,686	−2.6200	0.9669	0.9624	0.9973
15+ weeks	2,108,021	−45,761	−2.4826	0.9788	1.0029	1.0249
MEAN (weeks)	16.2429	−0.2673	−2.1192	0.9838	1.0075	1.0241
Employed by educational attainment						
No high school diploma	16,398,059	−134,471	−2.3026	0.9919	1.0514	1.0604
High school, no college	3,548,045	−13,132	−0.4905	0.9963	1.0851	1.0889
College, no degree	26,400,506	−99,778	−1.4496	0.9962	1.0909	1.0950
B.A.	22,390,445	−24,942	−0.3905	0.9989	1.0818	1.0830

Table 6. (Continued)

	New	New−Old	New−Old / SE (New−Old)	New / Old	SE (New) / SE (Old)	CV (New) / CV (Old)
Civilian labor force by school enrollment, ages 16–24						
Enrolled in school	6,765,246	−12,172	−0.3237	0.9982	1.0240	1.0161
Not enrolled in school	14,747,474	−92,025	−1.9351	0.9938	1.0345	1.0407

Notes:
All figures are averages of monthly estimates for May–December 1996.
''New'' is the composite weighting estimator with the optimal variance coefficients $(K, A) = (.4, .3)$ for unemployed and $(.7, .4)$ for employed.
''Old'' is the direct (current) production estimator, which determines the composite estimate separately for each characteristic with coefficients $(K, A) = (.4, .2)$.

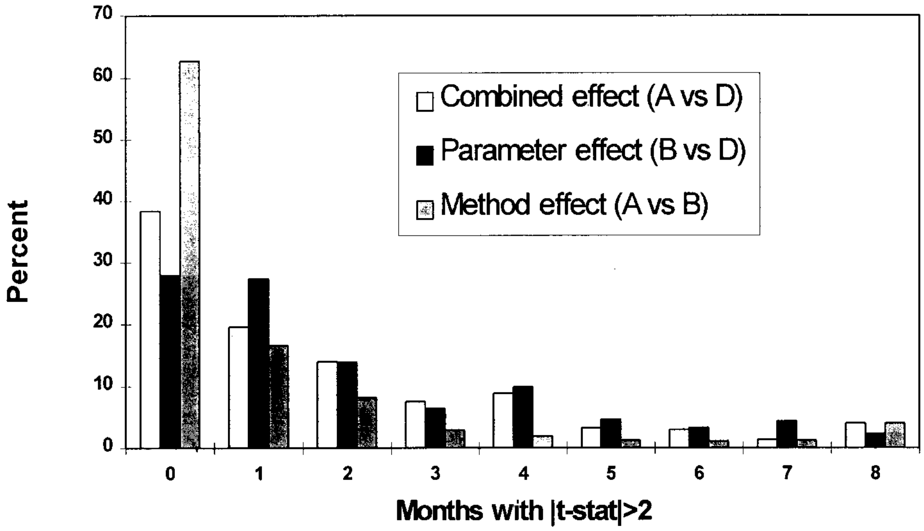

Fig. 1. Frequency of |*t-stat*| > 2
All characteristics-weighted

estimates of level is not markedly positive or negative. The combined effect therefore follows the direction of the parameter effect: it is generally negative for those characteristics relating to employment and positive for those relating to unemployment.

In summary, our research results indicate that implementation of the composite weighting approach will produce the following effects:

1. *Increased operational simplicity*. Under the current composite estimation system, micro-data users wishing to compute a composite estimate for a particular month must use micro-data for several prior months to initialize the composite estimator. The new system will enable users to compute composite estimates using only one month's composite weights.
2. *Slightly increased reliability for some major labor force estimates.* Especially for employment levels and month-to-month change in employment, the new parameter values will decrease the variances of CPS estimates.
3. *Slightly decreased reliability for some estimates no longer directly composited.* Especially for high correlation characteristics not directly related to labor force status (e.g., employed by educational attainment or school enrollment), the new method will result in more variable estimates. Further research may be directed toward modifying procedures to improve these estimates.

In March 1997, BLS management decided to implement the composite weighting procedure described here, with the OPTVAR parameters. Future research on composite weighting may include a re-examination of the geographic and demographic cell definitions used for the raking. The composite weighting technique was implemented with the same cell definitions currently used in the CPS raking ratio adjustment; we may, however, improve the reliability of some estimates by revising the cell definitions for both procedures.

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