Changes in Panel Bias in the U.S. Current Population Survey and its Effects on Labor Force Estimates October 2012

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Abstract
The U.S. Current Population Survey (CPS) is a rotating panel survey of U.S. households that measures the labor force statuses of the non-institutional civilian population. Each panel is a random sample of households that rotates into the survey for 4 consecutive months, rotates out of the sample for the next 8 months, and then rotates back into the survey for a final 4 months. CPS microdata undergo several weight adjustments so that estimated totals for various demographic characteristics match projected population totals. The final adjustment for demographic information is called the Second Stage adjustment, and it adjusts for age, race, gender, and ethnicity. The final stage of weighting--Composite estimation--employs the correlation in overlapping panels between adjacent months to reduce the variation of key labor force estimates. In the Second Stage adjustment each panel can produce an estimate of employment and unemployment, and each panel exhibits certain tendencies. This paper looks at how those tendencies have changed over time, their effects on Composite estimation, and a possible method to adjust for those effects.

Keywords: Panel Survey, Panel Bias, Composite Estimation

1. Introduction

The Current Population Survey (CPS) is a primary coincident economic indicator of the United States that measures the labor force status of US households each month. The CPS uses a rotating panel survey of US households, and one of the survey's primary data products is the unemployment rate. Panels consist of a random sample of households, and consecutive months have a large overlap in sampled households.

To produce labor force estimates the CPS uses several benchmarking steps, and the final estimation step uses a Composite estimator. The Composite estimator used by the CPS is a linear estimator that combines a post-stratified estimate with a level estimate of the over-the-month-change. The estimate of change makes use of households that are in the sample in adjacent months. The Composite estimator possesses a lower variance than either of its components, and it is unbiased provided that each panels' labor force estimates are unbiased. When those estimates are biased, then the Composite estimate is also biased.

Panel bias and its effects were discussed by Bailar (1975) and then later by Solon (1986), and multiple authors documented the effect of this bias in the intervening years. While the bias of CPS Composite estimates was mentioned in additional papers in the 1990s, there has been little research in the last decade on that bias. This paper attempts to partially fill that gap by looking at the bias in National Unemployment estimates during the past 37 years—from 1976 through 2011. This paper contains 7 parts including the introduction. Part 2 provides a quick overview of the CPS survey and estimation. Part 3 gives an overview of the biases in CPS estimates and how they have changed. Part 4 presents a discussion of how panel bias affects the CPS composite estimator. Part 5 presents an estimate of the CPS Composite estimator's mean square error and a method to minimize it. Part 6 shows the results of implementing the results from part 5. Part 7 is a discussion of the results, comparisons with previous research, and possible directions for future research.

2. CPS Survey and Estimation

2.1 CPS Sample Design

The CPS survey uses a stratified, multistage sample of US households to collect information on labor force status, demographics, income, education, and many other variables. Counties within each State are grouped together based on demographic information related to labor force and cost considerations. Cost considerations could include the distances that an interviewer must travel to conduct an in-person interview—performed the first and fifth months that a household is in the sample. More details are provided in the official documentation of CPS methodology—Tech Paper 66 (US Census Bureau, 2006).

Households are assigned to panels to guarantee a representative national sample of US households within each panel, and panels are rotated using a 4-8-4 rotation scheme. This rotation scheme uses a panel of households for 4 consecutive months. The panel then falls out of the survey for 8 consecutive months, and then it re-enters the survey for a final 4 consecutive months. Each month a panel is in the sample is referred to by a particular month-in-sample (MIS) designation. The first 4 months are referred to as MIS 1- 4. The final four months are referred to as MIS 5-8.

2.2 CPS Estimation

The CPS uses several stages of estimation. These steps are discussed in greater detail in Tech Paper 66 (10-1), and this paper provides only the formula for the Composite estimation. After nonresponse adjustments, the CPS uses several post-stratification estimation steps. Adjustment cells are formed, and sampling weights are adjusted so that weighted sums of respondents match projected population totals for each cell. Post-stratification occurs for three main estimation steps:

1. Coverage adjustment: The coverage estimation step attempts to correct for differences between the projected and sample-based estimates of populations for race and ethnicity combinations (Robison and Duff 2003). This step prepares the sample for the next estimation stage—speeding convergence in that stage. It also provides some control for the Asian population. Since race and ethnicity combinations are sparse, it was necessary to combine panels to guarantee a suitable number of respondents for each weighting cell. Panels i and $i+4$ were combined (for $i = 1, 2, 3, 4$).

2. Second Stage estimation: The Second Stage (SS) estimation step is more commonly referred to as a ratio-raking adjustment (US Census Bureau, p. 10-10), and it is a form of calibration (Deville and Sarndal 1992). SS estimation consists of three main steps, and it adjusts for race, sex, age, and ethnicity for national and statewide populations.

3. Composite estimation: Composite estimation in the CPS combines two estimates to improve the variance of level estimates and estimates of over-the-month change.

The Composite estimator used by the CPS is called the AK Composite estimator, and it takes the following form:

$$Y_t^{'} = (1-K)\hat{Y}_t + K\left(Y_{t-1}^{'} + \frac{4}{3}\Delta_{t-1,t}\right) + A\beta_t$$

$$\hat{Y}_t = \sum_{i=1}^{8} x_{i,t} \;\; ; \;\; Y_0^{/} = \hat{Y}_0$$

$$\Delta_{t-1,t} = \sum_{\substack{i=2,3,4,\\6,7,8}} x_{i,t} - \sum_{\substack{i=1,2,3,\\5,6,7}} x_{i,t-1} \;;\; \beta_t = \sum_{i=1,5} x_{i,t} - \frac{1}{3}\sum_{\substack{i=2,3,4,\\6,7,8}} x_{i,t}$$

The first two summands of this estimator consist of a weighted average between the SS estimate and a difference estimator involving the previous months AK Composite estimate. The difference estimator (4/3 $\Delta_{t-1,t}$) uses households common to both the current and previous months. The final term ($A\beta_t$) reduces the variance and helps to counteract the effect of CPS' panel bias (Huang and Ernst 1981).

Breau and Ernst considered a Generalized Composite Estimator (1983), hereafter referred to as the GCE. The GCE has the following form:

$$\begin{aligned} Y_t^{'} &= \sum_{i=1}^{8} a_i x_{i,t} - K\sum_{i=1}^{8} b_i x_{i,t-1} + KY_{t-1}^{'} \\ \sum_{i=1}^{8} a_i &= \sum_{i=1}^{8} b_i = 8 \end{aligned} \tag{1}$$

As the name indicates, the AK estimator is a specific form of the GCE. Table 1 shows the *a* and *b* parameter values of the GCE for the AK estimator.

Table 1: *a* and *b* parameter values for the AK Composite estimator using the GCE.

MIS	***a***	***b***	***MIS***	***a***	***B***
1	1 – K + A	4/3	5	1 – K + A	4/3
2	1 + (K – A)/3	4/3	6	1 + (K – A)/3	4/3
3	1 + (K – A)/3	4/3	7	1 + (K – A)/3	4/3
4	1 + (K – A)/3	0	8	1 + (K – A)/3	0

Breau and Ernst also discuss minimizing the variance of the GCE for multiple labor force estimates and the resulting effects on the bias. Those results are discussed in section 7.

3. Month-in-sample Bias

3.1 Calculating Bias

The Month-in-sample (MIS) bias is measured by comparing a labor force estimate for a single MIS to the labor force estimate using all panels. There are two types of MIS bias, additive and multiplicative. The following formulas give the general formulation for MIS bias (Solon, 1986).

$$\text{Additive MIS Bias: } E\left(x_{i,t}\right) = \frac{1}{8}Y_t + d_{i,t}$$

$$\text{Multiplicative MIS Bias: } E\left(x_{i,t}\right) = \frac{1}{8}Y_t\left(1 + m_{i,t}\right)$$

MIS bias is important to consider because the SS and Composite estimators have the same expectation provided that the MIS estimates are not biased (Rao and Graham, 1965). When bias is present, then those two estimators give different values. MIS bias in CPS was discussed initially by Bailar (1975). Her results showed the difference between the Composite and Second Stage estimates for monthly and change estimates assuming a constant additive bias. Huang and Ernst (1981), Breau and Ernst (1983), and Cantwell (1992) all give general (and sometimes empirical) estimates of the effect of MIS bias on Composite estimates. Each author considers the additive MIS bias, and all bias results—except for Bailar's—are with respect to the Second Stage estimator. For a different perspective on the type of MIS bias, consult Solon. We consider only the additive MIS bias in this paper because it is mathematically easier to work with, and we could find no evidence of multiplicative bias in recent years. For example, when the unemployment rate rose substantially during the 2008 recession the additive MIS bias tended to remain steady, while the multiplicative MIS bias changed substantially—a behavior we may expect in the presence of an additive bias. Bailar and Solon both state that estimates of change are unbiased under an additive MIS bias, yet they are biased under a multiplicative MIS bias. An analysis of change estimates shows no evidence of bias, while level estimates do.

3.2 Changes in MIS Bias

Chart 1 shows the average, additive MIS bias for each year from 1976 through 2010. The y-axis shows the additive MIS bias, and the x-axis denotes the MIS. The MIS are labeled in each graph. Note the general shape of the bias has an elevated level for MIS 4 and 8 from 1976 through 1990. After 1990 that pattern begins to change. By 2010 the MIS bias shows a downward slope from MIS 1 through MIS 8.

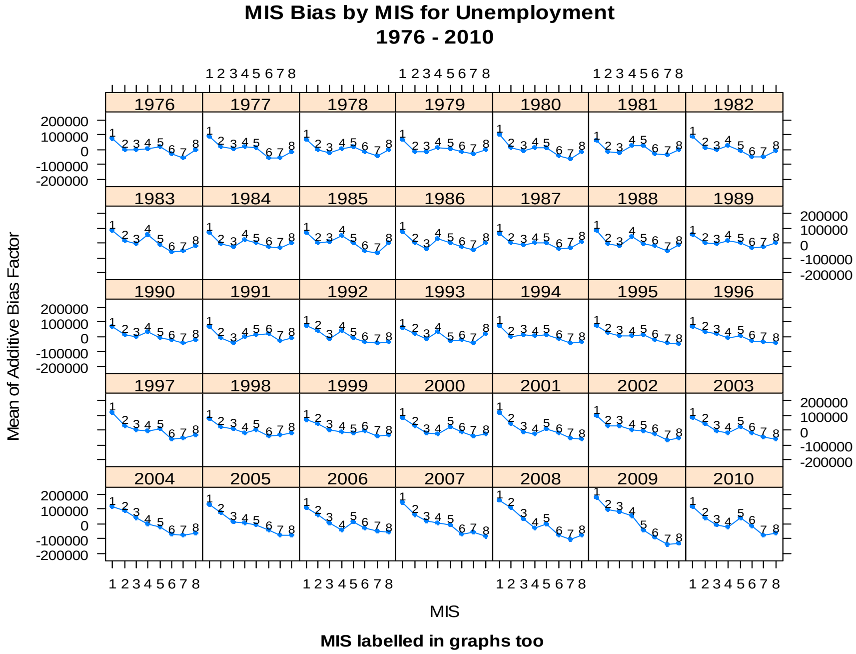

Chart 1: Plot of yearly average of MIS bias (y-axis) for each MIS (x-axis). A different plot is shown for each year.

Chart 2 provides another view of the MIS bias changes. Chart 2 plots time on the x-axis and the additive MIS bias on the y-axis. All 8 MIS are plotted together, and the legend indicates the color for each MIS. A LOWESS regression fit (*f* parameter set to .35) is plotted instead of the actual time series to aid interpretation. The vertical reference lines indicate the 1994 and 2003 CPS redesigns. Charts 1 and 2 provide similar information and demonstrate the changing patterns. Prior to 1990, the MIS biases were somewhat stable. After 1990, the bias patterns change considerably. The next section demonstrates the effect of these changes on the AK Composite estimator.

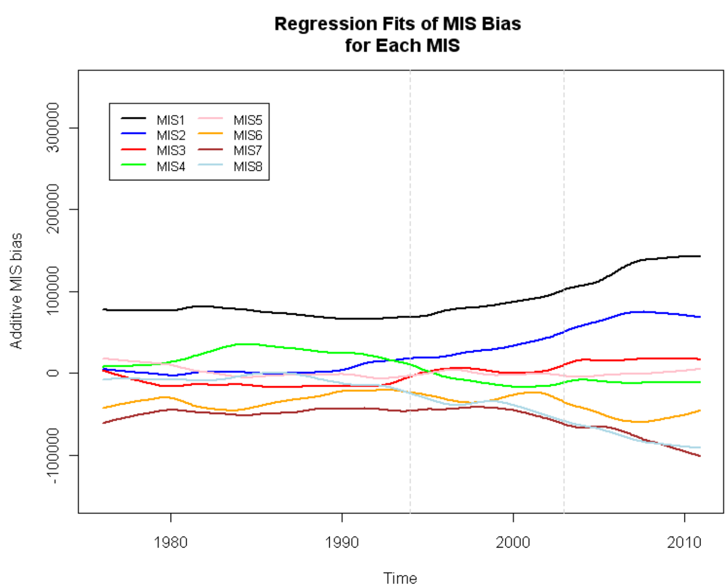

Chart 2: Time series plot of MIS biases. Actual values smoothed with LOWESS.

3.3 Effects of Bias

We begin by rewriting the AK Composite estimator with respect to the MIS differences.

$$Y_t^{'} = \hat{Y}_t - K\hat{Y}_{t-1} + \frac{4}{3}K\sum_{i=4,8}\hat{d}_{i-1,t-1} - \frac{4}{3}(K-A)\sum_{i=1,5}\hat{d}_{i,t} + KY_{t-1}^{'}$$

$$\hat{d}_{i,t} = x_{i,t} - \frac{\hat{Y}_t}{8} \quad ; \quad \sum_{i=1}^{8}\hat{d}_{i,t} = 0$$

We also make the following assumptions about the Second Stage estimate and each MIS estimate.

$$E\left(\hat{Y}_t\right) = Y_t \quad ; \quad E\left(x_{i,t}\right) = \frac{Y_{i,t}}{8} \quad ; \quad \mathrm{E}\left(\hat{d}_{i,t}\right) = \frac{Y_{i,t} - Y_t}{8}$$

$Y_{i,t}$ are panel i's estimate of the population value Y_t. The $\hat{d}_{i,t}$ are monthly estimates of the MIS bias for each panel. The important assumption for the remaining sections is that the Second Stage estimate is unbiased, and that assumption is discussed in section 4. Carrying out the recursion we have the following result for the AK Composite estimator.

$$Y_t^{'} = \hat{Y}_t + \frac{4}{3}K\left(\sum_{i=4,8}\sum_{j=0}^{t-1}\hat{d}_{i,j}K^{t-1-j}\right) - \frac{4}{3}(K-A)\left(\sum_{i=1,5}\sum_{j=1}^{t}\hat{d}_{i,j}K^{t-j}\right)$$

The Composite estimator is therefore just the sum of the SS estimator and the products of coefficients and the MIS biases. If the expected value of the Bias for each MIS is the same each month, then we have the following result for the Bias for large values of t:

$$E\left(Y_t^{'} - Y_t\right) \approx \left(\frac{4}{3}K\left(\sum_{i=4,8}d_i\right) - \frac{4}{3}(K-A)\left(\sum_{i=1,5}d_i\right)\right)\frac{1}{1-K} \qquad (2)$$

Note that only two sets of MIS have an effect on the Composite estimator—MIS 1 and 5, and then MIS 4 and 8. Formula (2) shows that the difference between the Composite and SS estimators will continue to decrease (specifically, Composite – SS < 0) under the following conditions:

1. The bias for MIS 1 and 5 continues to increase.
2. The bias for MIS 4 and 8 continue to decrease.

Chart 3 is similar to chart 2, but it shows the MIS grouped together instead of showing each one separately. The bias for MIS 1 and 5 (black) has increased, while the bias for MIS 4 and 8 (red) has decreased. The blue line shows the bias for the remaining MIS. Given the black and red lines' trends we expect the estimators' differences to grow. Chart 4 plots differences in level estimates between the CPS Composite and SS estimates from February, 1998 through December, 2011. Chart 4 indicates that the difference between those two estimates grew as the MIS biases changed.

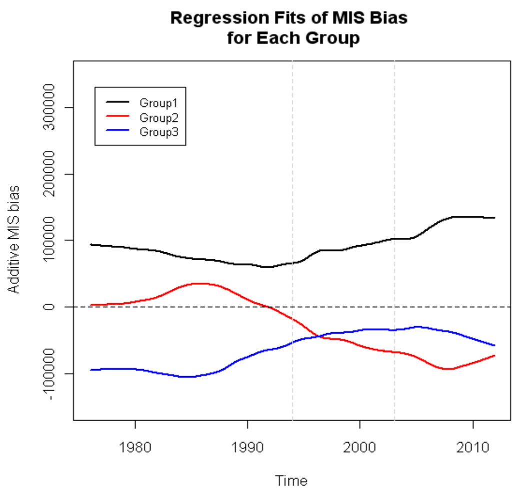

Chart 3: Time series plot of MIS Bias for select groups. Series smoothed with LOWESS.

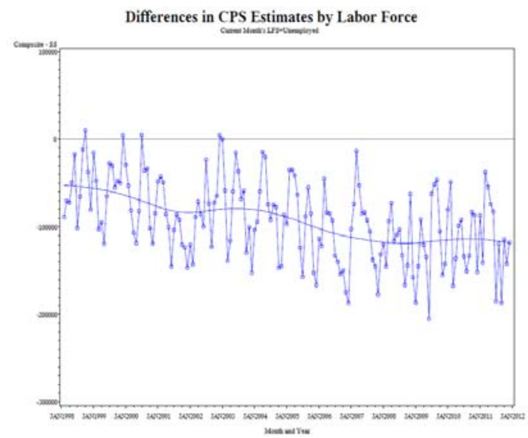

Chart 4: Time series plot of Composite Estimators bias. Bias = Composite – SS

4. Resolving Effects of MIS Bias

4.1 Reducing Bias

In attempting to resolve the effects of MIS bias we want to maintain the reduced standard errors provided by Composite estimation while reducing its bias. The AK Composite estimator allows a small tradeoff between the variance and bias for different values of *A* and *K*. One method of selecting *A* and *K* is to calculate the standard errors and bias using many different parameters, and the *A* and *K* set with the lowest MSE is chosen. This method was used by Lent et al (1998) and Huang and Ernst (1981). One alternative is to use the GCE. The additional parameters may offer some additional flexibility to better meet our goals.

We start be rewriting the GCE with respect to the $\hat{d}_{i,t}$ mentioned in section 3. After carrying out the recursion we have the following formula for the GCE:

$$Y_t^{'} = \hat{Y}_t + \sum_{i=1}^{8}\left(a_i \sum_{j=1}^{t} K^{t-j}\hat{d}_{i,j} - Kb_i \sum_{j=0}^{t-1} K^{t-j-1}\hat{d}_{i,j} \right)$$

Note that the sums indexed by j are inflated, integrated moving averages with an intercept. To be more specific:

$$\sum_{j=1}^{t} K^{t-j}\hat{d}_{i,j} = \left(S_{i,t} - K^t \hat{d}_{i,1}\right)\left(1-K\right)^{-1}$$

where $S_{i,t}$ is the moving average and $K^t \hat{D}_{1,i}$ is the intercept. Since $K \in [0,1)$, the $(1\text{-}K)^{-1}$ will inflate the moving average and intercept. Noting the previous equality, we can rewrite the GCE again in the following form:

$$Y_t^{'} = \hat{Y}_t + \sum_{i=1}^{8}\left(a_i\left(S_{i,t} - K^t \hat{d}_{i,1}\right) - Kb_i\left(S_{i,t-1} - K^{t-1}\hat{d}_{i,0}\right)\right)\left(1-K\right)^{-1}$$

When considering the bias and variance of this form, we decided to ignore the intercept terms for the following reasons:

1. K is fixed, so variances from the intercept terms will exponentially decay. For unemployment K = .4, so variances decay to nearly 0 after 12 to 18 months ($.4^{12}$ = 6.8 E-8, variances are about 1.0 E6).
2. We expect covariances between the intercepts, and we expect these covariances to partially cancel out the variances.
3. It is easier computationally to ignore the intercepts.

Given the first and third reasons in particular, we decided to ignore the intercept term. The Composite estimator now has the approximate value shown in equation 3:

$$Y_t^{'} \approx \hat{Y}_t + \sum_{i=1}^{8}\left(a_i S_{i,t} - Kb_i S_{i,t-1}\right)\left(1-K\right)^{-1} \qquad (3)$$

4.2 Approximate Variance and Bias of GCE

Using formula 3 we can calculate the approximate variance and bias of the GCE. Writing the variance in matrix form we have formula 4:

$$Var\left(Y_t^{/}\right) = \left[\mathbf{a}\ \mathbf{b}\right]^T VCOV\left(1-K\right)^{-2}\left[\mathbf{a}\ \mathbf{b}\right] + 2*\left[\mathbf{a}\ \mathbf{b}\right]^T COV\left(1-K\right)^{-1} + Var\left(\hat{Y}_t\right) \qquad (4)$$

Where $VCOV$ is the variance-covariance matrix of the integrated moving averages in months t and t-1, COV is the matrix of covariances between the Second Stage estimate and the integrated moving averages, and $\left[\mathbf{a}\ \mathbf{b}\right]$ is the column vector of the a and b parameters from the GCE.

Given the previous definitions the bias consists of the moving averages.

$$Bias = E\left(Y_t^{'}\right) - Y_t \approx E\left(\hat{Y}_t\right) + \left(1-K\right)^{-1}\sum_{i=1}^{8} a_i E\left(S_{i,t}\right) - Kb_i E\left(S_{i,t-1}\right) - Y_t$$

Since we defined the expected value of the Second Stage estimator $\hat{Y}_t$ to be unbiased, equation 5 shows the approximate bias of the GCE and its matrix form.

$$
\begin{aligned}
&Bias \approx \left(1-K\right)^{-1}\sum_{i=1}^{8} a_i E\left(S_{i,t}\right) - Kb_i E\left(S_{i,t-1}\right) \\
&Bias^2 \approx \left[\mathbf{a}\ \mathbf{b}\right]^T \mathbf{B}^T\mathbf{B}\left(1-K\right)^{-2}\left[\mathbf{a}\ \mathbf{b}\right]
\end{aligned}
\tag{5}
$$

B is a column vector of the MIS biases. Now that we have expressed the variance and Bias of the GCE, the approximate MSE of the Composite estimator is:

$$
MSE\left(Y_t^{/}\right) \approx \left[\mathbf{a}\ \mathbf{b}\right]^T \left(VCOV + \mathbf{B}^T\mathbf{B}\right)\left(1-K\right)^{-2}\left[\mathbf{a}\ \mathbf{b}\right] + 2*\left[\mathbf{a}\ \mathbf{b}\right]^T COV\left(1-K\right)^{-1} + Var\left(\hat{Y}_t\right) \tag{6}
$$

Before calculating parameters to minimize the MSE, we want to reiterate the assumptions that lead to this result:

1. The Second Stage estimator is unbiased.
2. The expected value of each MIS does not necessarily provide an unbiased estimate.
3. We have ignored the intercepts of the integrated moving averages.
4. The parameter *K* is held constant.

Given that we are investigating differences between the Second Stage and Composite estimates, the first assumption is a valid one for this study, though it may not be correct (Bailar, p. 26). It was also used in previous studies to demonstrate the bias of the Composite estimator (Huang and Ernst p. 305, Breau and Ernst p. 308). The third assumption is a computational convenience. We believe that the MSE we derived in equation (6) still holds if the intercept term is not ignored, but it is simpler to ignore it. Furthermore, after a set number of months the intercepts are negligible. We believe it is important to consider the long-term behavior of the Composite estimator, and ignoring the intercepts achieves that purpose. Incorporating the intercept terms may also provide sub-optimal GCE parameters after the first year. The fixed *K* is necessary to maintain a quadratic form for the *a* and *b* parameters, and we exploit that form in the next section.

5. Minimizing the MSE of Generalized Composite Estimates

Quadratic programming is a specific version of nonlinear optimization where the objective function takes the following form:

$$
f(x) = \tfrac{1}{2}x^T Gx + x^T \mathrm{c}\ ;\ \text{subject to } \mathbf{Hx} \le \mathbf{b} \ \text{ and } \ \mathbf{x} \ge 0
$$

where *G* is a triangular-symmetric matrix, *c* is a vector, and *x* is a parameter vector subject to linear constraints. The MSE given in equation (6) has a quadratic form where $x=\left[\mathbf{a}\ \mathbf{b}\right]^T$, G=2*(***VCOV*** + $\mathbf{B}$*$\mathbf{B}^{\mathrm{T}}$), and c=2*COV, where $\mathbf{a}$ and $\mathbf{b}$ are column vectors of the parameters in equation (1). The final component of the MSE is the variance of the Second Stage estimator. Since it is constant with respect to the parameters, it does not affect the objective function's minimization. In this research the only constraints are those provided in equation (1). Breau and Ernst give no explicit constraint that the *a* and *b* parameters must be positive, but we enforce it here.

Covariances are estimated using Balanced Repeated Replication. The methodologies used in CPS are also documented in Tech Paper 66 (US Census Bureau, p. 14-1). The vector of biases (**B**) consists of the MIS biases. We calculate the additive MIS biases using the formula described in section 3.1, then calculating their integrated moving averages. A 6-year mean of these moving averages were used in **B**. The quadratic optimization was performed using PROC MINQUAD in SAS.

6. Results

To test the optimal parameters calculated in section 5 we calculate replicate standard errors for all years from 2005 – 2011 for the following 3 estimators: the current AK Composite, GCE, and Second Stage. The Composite estimates were initialized in January 2005. Table 3 shows average standard errors of level estimates for each year in our study.

Table 3: Average SE's of Monthly Estimates by Year

Year	Current AK Composite	GCE with Optimal Parameters	Second Stage
2005	150,326.66	154,307.05	152,519.36
2006	144,661.44	146,186.08	145,823.77
2007	150,545.66	152,753.23	154,062.01
2008	171,165.85	175,758.11	178,422.77
2009	208,230.01	212,182.85	216,935.82
2010	205,639.55	213,089.72	218,075.20
2011	211,467.23	217,985.27	221,384.74

Note that the average SE's during the first two years are higher for the optimal GCE than the Second Stage estimate. We attribute this increased error to the fact that we ignore the intercepts in the integrated moving averages. While the optimal parameters have a higher average error during the first two years, the error is lower than the SS estimator for all of the following years. SE's for the optimal estimator are between the Composite and Second Stage SE's after 2006.

Table 4 shows the average yearly biases for the AK Composite estimator and the optimal GCE. The optimal GCE reduces the bias substantially for all years (about -110,000 for the AK Composite and -8,000 for the optimal GCE). The optimal GCE therefore achieves our goals of reducing the bias of the Composite estimator while still decreasing the SE compared to the Second Stage estimate.

Table 4: Average Bias of Monthly Estimates by Year: Bias = Composite – Second Stage

Year	Current AK Composite	GCE with Optimal Parms
2005	-86,135	472
2006	-122,530	-36,748
2007	-103,262	-1,260
2008	-120,145	-7,161
2009	-125,360	-7924
2010	-114,735	-723
2011	-112,777	-7,730

7. Summary

The Second Stage and Composite estimators have the same expected value provided that there is no MIS bias. When that bias exists, then these two estimators will diverge from each other. If we write the Composite estimator in terms of the additive MIS biases, then we have can derive a closed form solution for the Composite estimator's bias relative to the Second Stage estimate. That bias is a function of particular groupings of the MIS bias. Between 1976 and 1990 the MIS biases where fairly stable, and the Composite estimator possessed little bias given the AK Composite estimator used in CPS. After 1990 the MIS bias began to change, and it changed in a way that increased the bias of the Composite estimator.

One way to reduce the bias is to use the Generalized Composite Estimator. Writing the GCE with respect to the MIS biases allows us to express the Composite estimator of the MSE in a quadratic form. That expression allows us treat the MSE as an objective function to minimize in a Quadratic programming problem. Breau and Ernst noticed that GCE parameters optimized for the variance sometimes had a drastic impact on the bias—sometimes overwhelming the reduced variance (p. 407). This paper's method considers the variance and bias at the same time.

Solving via quadratic minimization differs substantially from previous attempts to find parameters for the Composite estimator. Huang and Ernst, and Lent et al both create a series of estimates for K and A and then choose the parameter set that minimizes the estimated MSE. Breau and Ernst do not describe how they calculated their optimal GCE parameters. Quadratic minimization allows us to find an optimal A for a given K (provided the proper constraints) or weighted combinations of each MIS.

While the constraints allow the parameters to be free, there are alternate versions that allow us to formulate different versions of the Composite estimator. For example, if we set constraints that force certain sets of a and b parameters to be identical, then we may create a form that mimics the a and b parameters for the AK Composite estimator shown in Table 1, and derive an *A* parameter from the results. Putting the problem in the context of nonlinear optimization allows the flexibility to construct a Composite estimator that is highly restricted (AK Composite), very general (GCE), and different choices in between those two extremes.

Another possible advantage of Quadratic minimization is the use of multiple objective functions. The objective function described in section 5 involved an approximation of the MSE for a level estimate of National unemployment. We can also use the same objective function for estimates of change or demographic estimates. Since the objective function doesn't require us to use the variance and bias for the same estimate, we could use variances for monthly change estimates and the bias for monthly estimates; allowing us to focus on the variance and bias that may matter most to the CPS. Variances for demographic estimates could also be combined with the variance for a National estimate and considered at the same time. This formulation would allow us to find the "best" parameters for a wide range of estimates, though in each scenario we would lose the minimization of a particular estimate's MSE. One drawback that the current method shares with previous research is the choice of *K*. To keep the Quadratic form of the variance and bias we need to use a constant *K*, though it may be possible to construct another optimization that incorporates *K* into the minimization.

We plan to continue this paper's research by applying its methodology to different estimates (for example, change estimates and annual averages) as well as different demographic estimates. It is not plausible to apply parameters for National estimates without first understanding the effects on estimates for demographic groups. It is also important to see how the parameters change as the MIS biases change, and the how those parameter changes affect the variances.

Disclaimer

Any opinions expressed in this paper do not reflect official policy at the Bureau of Labor Statistics.

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