Current Population Survey State Variances and Design Effects November 2018

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Abstract

The Current Population Survey CPS), conducted by the Census Bureau for the Bureau of Labor Statistics (BLS), provides official labor force estimates for the United States. In the two-stage design, Primary Sampling Units (PSUs) are selected and housing units are selected within those PSUs. A variance is logically the sum of a between-PSU component and a within-PSU component. For national variances, there are enough PSUs to allow estimating total variances using a successive difference replication method. However, for a state, it is necessary to separately estimate the two components. This paper concentrates on within-PSU variance estimation for states that starts with within-PSU replicates. The calculated estimates of within-PSU replicate variances are inherently "noisy", so generalized variance functions (GVFs) are modeled over time for employment and unemployment in each state. Innovative changes in methodology and functional form allow many more years of data to be used in developing stable GVFs. Selected GVFs are graphically compared to the underlying within-PSU replicate estimates. The work allowed an interesting assessment of state within-PSU design effects.

Key Words: Successive Difference Replication, Generalized Variance Functions, Design Effects, Current Population Survey

1. Introduction

The Current Population Survey is a nationwide household survey conducted by the Bureau of the Census for the Bureau of Labor Statistics. Using a multistage stratified sample of about 72,000 households, the CPS provides official labor force estimates for the civilian non-institutional population 16 years of age and older (CNP16+). Variance estimates for the labor force estimators are based on a successive difference replication method. While this method can be used directly to produce reasonable variance estimates of national labor force estimates, it can't be used directly to estimate state variances. This paper focuses on estimating state variances. Section 2 provides a summary of the CPS sample design; Section 3 presents CPS weighting; Section 4 summarizes replication methodology for estimating state variances; Section 5 focuses on generalized variance functions (GVFs) that model state within-PSU variances; Section 6 examines state within-PSU design effects; and Section 7 provides conclusions and suggestions for further research.

2. CPS Sample Design

The CPS sample is a two-stage stratified sample designed to measure demographic and labor force characteristics of the CNP16+. The sample consists of independent samples in each state and the District of Columbia. California and New York State are divided into two areas that also have independent designs: Los Angeles County and the balance of California; New York City (the five boroughs or counties) and the balance of New York State.

The first stage of sampling involves dividing each state into Primary Sampling units consisting of either a single county or of a group of contiguous counties. Self-representing (SR) PSUs are the largest PSUs in state population and each is sampled with certainty. Smaller non-self-representing (NSR) PSUs are stratified and a single NSR PSU is sampled to represent each stratum. In the second stage of sampling, a systematic sample of clusters of about 4 housing units (called ultimate sampling units, or USUs) is selected within each SR PSU and each sampled NSR PSU.

The sample in any given month is divided into eight panels and a rotation scheme is used to rotate panels in-and-out of the CPS. A given panel is in sample 4 months, is rotated out for 8 months, then is rotated back in for another 4 months. For a given panel the eight "months in sample" can be referred to in shorthand as MIS1, MIS2, MIS3, MIS4, MIS5, MIS6, MIS7, and MIS8. The sample in any given month has one panel in each of those months in sample. For the samples in two consecutive months, six panels are in common.

3. CPS Estimation

In order to produce national and state estimates from survey data, a statistical weight for each person in the sample is developed through the following steps:

- Base weights derived from first-stage and second-stage selection probabilities
- Special weight adjustments
- Nonresponse adjustment
- First-stage adjustment for NSR PSUs
- National and state coverage adjustments to independent population controls
- Second-stage weighting adjustment to independent population controls
- Composite estimation and weighting

Basic Weights and Special Weight Adjustments

Base weights and special weight adjustments are derived from inverses of sampling probabilities. Base weights use first-stage and second-stage sampling probabilities. For a given panel, all sampled households (and persons) in a state usually have the same base weight. An ultimate sampling unit occasionally is found to have more housing units than expected, subsampling may be needed, and a special weight adjustment accounts for the subsampling.

Nonresponse Adjustment

An interview may not be obtained from an eligible household (due to weather emergencies, absence, refusal to participate, etc.). Weighting cells are defined in each state, and in each cell the weights of responding households are increased to account for the nonresponding eligible households. Note that not all sampled housing units are "eligible" to be interviewed due to vacancy, demolition, and other reasons. Through nonresponse adjustment all persons in a responding household have the same weight, but in the later weighting steps person weights in a household are allowed to be different.

First Stage Adjustment for NSR PSUs

At the time of sampling, the race distribution (Black alone versus non-Black alone) of sampled NSR PSUs in a state will differ somewhat from the race distribution of all NSR PSUs. The one-time first-stage ratio adjustment factors serve to bring the sampled NSR PSUs of a state into better alignment with all NSR PSUs (based on information at the time of sampling). The adjustments reduce the between-PSU contribution to variance that comes from sampling NSR PSUs. While the between-PSU variance is generally quite small compared to total variance at the national level, it is relatively large for some states.

Monthly Ratio Adjustments to Independent Population Controls
Demographic distributions derived from the CPS monthly sample (weighted through the first stage) will be different from the true distributions. Since age, race, sex and Hispanic population characteristics are highly correlated with labor force status and other characteristics estimated from the sample, the variance of sample estimates based on these characteristics can be reduced using appropriate weighting adjustments. The CPS estimation procedure uses ratio adjustments to force the CPS sample population distribution to equal the distribution of a set of independent population controls.

The independent population controls are produced by the Census Bureau. Starting with detailed civilian noninstitutional populations from the most recent Census, births/deaths and other information is used to update demographic CNP figures to the current month. Those CNP figures are generally recognized to be more accurate than the estimates of CNP from the CPS (weighted through the first stage).

Second-stage weighting has three steps – state, ethnicity, and race. It is preceded by a national coverage adjustment and a state coverage adjustment. Composite estimation also uses population controls and that is discussed separately.

National and State Coverage Adjustments
The national coverage adjustment corrects for interactions between race and ethnicity that cannot be addressed in second-stage weighting. Research has shown that the undercoverage of certain combinations (e.g., non-Black Hispanic) cannot be corrected with the second-stage adjustment alone. The national coverage adjustment also helps to speed the convergence of the second-stage weighting process (Robison, Duff, Schneider, and Shoemaker, 2002).

The state coverage adjustment step compensates for state-level differences in sex, age, and race coverage. Research has shown that estimates of characteristics of certain racial groups (e.g., Blacks) can be far from the population controls if a state coverage step is not used.

Second-Stage Weighting
The second-stage weighting ratio adjustments decrease variance in the great majority of sample estimates. The procedure is also reduces the bias due to coverage errors. The benchmark procedure adjusts the weights for persons so that they add to three sets of population controls:

- State Step -- CNPs by sex and age (0−15, 16−44, 45 and older) for Los Angeles County, balance of California, New York City, balance of New York, each of the other 48 states, and the District of Columbia
- Ethnicity Step -- National CNPs for 26 Hispanic and 26 non-Hispanic age-sex categories
- Race Step -- National CNPs for 56 White, 36 Black, and 34 residual race age-sex categories

Note that the adjustment is done separately for each of four month-in-sample pairs (MIS1 and MIS5; MIS2 and MIS6; MIS3 and MIS7; MIS4 and MIS8). The weights for a demographic group in a pair are adjusted to sum to one-fourth of the corresponding control total.

After any given step, the weights that "match" the controls for that step will no longer exactly match the controls for a prior step. A raking process (also known as iterative proportional fitting) with ten iterations is used to simultaneously nearly match all population controls.

Composite Estimation and Weighting

Most official CPS labor force estimates are derived using composite weights. (The most important estimates are seasonally adjusted.) Originally the CPS composite estimator equally weighted 1) a current month second-stage estimate and 2) a composite estimate from the preceding month updated to the current month with an estimate of month-to-month change. Over time, the CPS refined the composite, updating the weights used in the weighted average as well as adding a component that captures the net difference between the incoming and continuing parts of the current month's sample. In 1998, BLS introduced a composite weighting method that allows more operational simplicity for microdata users as well as determining better compositing coefficients for different labor force categories.

For a core set of adult (16+) CNPs from each second-stage step, composite estimates of employment and unemployment are computed each month (not-in-labor-force is derived by subtracting employment and unemployment from the corresponding CNP). A raking procedure with 10 iterations is used that is similar to second stage weighting. But in composite weighting the sets of composite estimators are used as the controls.

4. Using Replication to Estimate Variances

Replicate variance methods appropriate for complex surveys tend to yield "noisy" estimates of variance. For both national and state variances, generalized variance functions are used to deal with that noisiness. Other sections of this paper focus on modeling for state GVFs and the associated design effects.

A successive difference replication method with 160 replicates is used for estimating CPS variances. In general:

- In self-representing Primary Sampling Units, replicate assignments are made using ultimate sampling units. For a given replicate, each USU is assigned a multiplicative weighting factor of 1.7, 1.0, or 0.3 that is applied to the weights of all persons in the USU.
- For non-self-representing PSUs, replicate assignments are made using entire PSUs. For a given replicate, each USU is assigned a multiplicative weighting factor of 1.7, 1.0, or 0.3 that is applied to the weights of all persons in the NSR PSU.

The replicate variance estimator for the characteristic of interest, Y, is a sum of squared differences between estimates for each replicate r and the full sample estimate 0.

$$\hat{Var}\left(\hat{Y}_0\right) = \frac{4}{160}\sum_{r}^{160}\left(\hat{Y}_r - \hat{Y}_0\right)^2 .$$

The general formula can be applied using weights from any stage of estimation. Using composite weights (the final CPS weights), the replication method describes is suitable for obtaining total variance estimates for the nation. "Total" is used in the sense that for the nation it is unnecessary to decompose the variance estimate to a sum of within-PSU and between-PSU components. Such a decomposition is also unnecessary for states where all PSUs are SR PSUs – that is, states where there is no between-PSU variance.

State Within-PSU Replicates

Most states contain a small number of NSR sample PSUs, too few to support assignments to 160 replicates. For those states, a decomposition of variance to within-PSU and between-PSU components is necessary.

$$Var\left(\hat{X}\right) = Var_W\left(\hat{X}\right) + Var_B\left(\hat{X}\right)$$

The within-PSU portion of the variance is estimated using within-PSU replicates and weighting factors. To form within-PSU replicates, the first stage of sampling NSR PSUs is ignored. Even in NSR PSUs the replicate assignments are made using ultimate sampling units.

Estimating State Between-PSU Variances

Although not the principal subject of this paper, the between-PSU contributions to variance are incorporated into state generalized variance functions. American Community Survey 5-year data on employment and unemployment is available for all counties, and therefore for all NSR PSUs. That data can be used to approximate the between-PSU variances for a stratum with N_h NSR PSUs, and for H strata those sum to the state between-PSU variance. In the following formula, p_{hi} is the probability of selecting a PSU.

$$\hat{V}_b\left(\hat{Y}\right) = \sum_{h=1}^{H} \sum_{i=1}^{N_h} p_{hi} \left(\frac{\hat{Y}_{hi}}{p_{hi}} - \hat{Y}_h\right)^2$$

5. Modeling State Within-PSU Variances with GVFs

In one sense state replicate estimates of within-PSU variance are the standard. The monthly replicate within-PSU standard errors of Alaska's employment are plotted in Figure 1 for over a decade. (All figures are at the end of this article.) The replicate standard errors are quite noisy; this project developed a GVF model that is much more stable. Certainly the GVF should pass through the replicate standard errors and Figure 5 emphatically shows why this project was started. Estimates from the old GVF in green do not pass through the replicate standard errors whereas estimates from the new GVF in red do pass through them.

Form of the Model or GVF

Explicit modeling was considered, but instead a simple form of generalized variance function was used. It was an adaptation of the GVF already in use for estimating state within-PSU variances. Sometimes we say a GVF of this form smooths out the replicate variances, but it is not a statistical smoother. The following formula is for an estimate of a monthly total of a binomial count variable. (Example: total unemployed where the variable is 1 for an unemployed person and 0 otherwise.) An alternate form with a and b parameters is also given.

$$\hat{V}ar_{GVF,Wm}\left(\hat{X}\right) = \hat{d}eff_W \hat{V}ar_{SRS,Wm}\left(\hat{X}_m\right) = \hat{d}eff_W [N_m^2 p_m (1-p_m)/n_m]$$

$$\hat{d}eff_W = \text{ averaged estimate of the monthly within-PSU design effect}$$

$$\hat{V}ar_{SRS,Wm}\left(\hat{X}\right) = \text{simple random sample estimate of the within-PSU variance of}$$

$$\text{total } \hat{X}_m = N_m p_m \text{ (finite population correction factor omitted)}$$

$$\hat{V}ar_{GVF,Wm}\left(\hat{X}\right) = \hat{d}eff_W [a_m \hat{X}_m^2 + b_m \hat{X}_m] \quad \text{for total } \hat{X}_m = N_m p_m$$

$$b_m = N_m / n_m \text{ sampling interval} \qquad a_m = -b_m / N_m$$

A design effect is commonly defined as the ratio of an actual variance to a simple random sample variance. Within-PSU replication includes all of the complexity of the CPS sample design and weighting. The monthly within-PSU design effect has this form. The numerator can be estimated using replication and the denominator can be approximated by a suitable simple random sampling formula.

$$deff_{Wm} = \frac{Var_{Wm}\left(\hat{X}_m\right)}{Var_{SRS,Wm}\left(\hat{X}_m\right)} \qquad \hat{d}eff_{Wm} = \frac{\hat{V}ar_{rep,Wm}\left(\hat{X}_m\right)}{\hat{V}ar_{SRS,Wm}\left(\hat{X}_m\right)}$$

The previous formulas omit the subscript m from the design effect. Monthly replicate variances are volatile, so the monthly design effects are also volatile, and some averaging over time is required. Other quantities include a monthly subscript m since for those it makes sense to use the most current information (if possible).

Sampling Intervals of the Form *N/n* or *N/r* (the b parameter)

The simplicity of the simple random sampling formula is somewhat deceptive. Estimates of employment and unemployment are person estimates, but the states samples are two-stage samples of ultimate sampling units of households. There is no sample of n_m persons from a monthly frame of N_m persons, although the number of person responses r_m can be observed.

Reasonable proxies of the sampling interval (the b parameter) are needed for the within-PSU GVF formulas to be useful. The old GVFs used sampling intervals for ultimate sampling unit selection in a state. With few exceptions that sampling interval was equal to the base weight for all USUs, households, and persons in a panel. Refer to the bottom green line for Alaska base weights for over a decade. In the flat periods all eight panels in the CPS had the same base weight. In the transitions from one flat period to another different panels have different sampling intervals and base weights – so some averaging of the base weights is needed in those months to derive a usable proxy sampling interval. The plot shows simple averages of the base weights of respondents.

Using simple averages of weights, a proxy sampling interval can be derived for any stage of estimation. Other averages and alternatives for numerators and denominators were examined, but none proved more useful than simple averages. This project concentrated on base weights, nonresponse adjusted weights, and composite weights.

- After base weighting, the special weight adjustment step has little effect.

- Nonresponse adjustment weights jump up. Alaska's blue line in figure 2 for average nonresponse adjusted weights is above the green line for base weights. The next weighting step, first stage adjustment, does not change average weights very much.
- Benchmarking or controlling to population controls causes another upward jump in weights (the top red line in figure 2). The jump is due to relative undercoverage of the CPS (through first-stage weighting) compared to the controls. Note that state averages of second-stage weights and composite weights are essentially the same.

Different SRS Interpretations of the Three Proxy Sampling intervals

Interpreting the three proxy sampling intervals is easier to give by example than by formula. Data for January 2016 in Alaska for r=1,199 CNP16+ responses is used. The sum of nonresponse adjusted weights for respondents is 485,386. It is a reasonable estimate of the size of frame of CNP16+ persons that could be constructed, but not a perfect frame. A frame that 1) starts with the CPS housing unit frame for Alaska, 2) applies CPS eligibility rules to every housing unit on the frame, and 3) identifies CNP16+ persons with the CPS procedures for creating household rosters.

- Nonresponse adjusted weight proxy sampling intervals of the form N/r
  $405 = SI_{NR} = N_{NR}/r = 485{,}336/1{,}199$
  485.336 is the sum of the person nonresponse adjusted weights
  In the GVF, N_{NR} is treated as a known frame N; response r is used
- Base weight proxy sampling intervals of the form N/n (100% response)
  $351 = SI_{BW} = N_{BW}/r = 420{,}619/1{,}199 = 485{,}336/1{,}383 = N_{NR}/n$
  420.619 is the sum of the person base weights (difficult to interpret)
  But apply nonresponse adjustment to numerator and denominator!
  In the GVF, N_{NR} is treated as a known frame N and n=1,383
  (Whereas r is observed, n is an estimate that is treated as known)
- Composite weight proxy sampling intervals of the form N'/n
  $453 = SI_{Comp} = N_{Comp}/r = CNP16+/r = 542{,}648/1{,}199$
  542,648 is the sum of the person nonresponse adjusted weights
  In the GVF, N_{NR} is treated as a known frame N; response r is used
  But the ratio CNP16+/N_{NR} = is applied to all estimates
  A ratio estimator, not the basic SRS estimator

To summarize, the three different sampling interval proxies allow for three different interpretations of the simple random sample part of the GVF formula.

- Avg. base weight: SRS assuming 100% response n
- Avg. nonresponse adjusted w eight: SRS but using response r
- Avg. composite weight: SRS with r, ratio estimate to CNP16+

The three different proxies are associated with very different design effects, as discussed in the next section.

Use of Average Composite Weights as a Proxy for the Sampling Interval

Very reasonable stable GVFs were created using all three proxies. For the final state within-PSU GVFs that were adopted, proxy sampling intervals based on average composite weights were used. Composite weighting reacts to monthly changes in population controls, monthly changes in employment and unemployment, and to monthly fluctuations in response rates – the same changes/fluctuations that affect estimated within-PSU variances from replication. This helps stabilize design effects (covered in the next section) and gives the GVFs using the composite weight proxies an edge over the two other proxies.

Figure 4 is plot of Alaska's employment within-PSU standard errors based on 1) replicate composite weights in black 2) a simple random sample with ratio adjustment approximation that uses composite weight proxy sampling intervals (blue), and 3) the final modeled within-PSU GVF standard errors that include a design effect (red). Even without a design effect the SRS approximation of the blue line already passes through the replicate weights reasonably well. Depending on the state, a design effect reasonably close to 1.0 serves to pull the SRS approximation up or down to be a better fit to the SRS approximation.

Note that for the two other proxies, the SRS approximations of within-PSU variance are quite a bit lower than the estimated replicate within-PSU variances. In both cases, the associated design effects compensate for this, but in general those design effects are not "reasonably close to 1.0".

Along with the state monthly employment and unemployment estimates themselves, the estimated variances from the new GVFs are principal inputs to Local Area Unemployment Statistics time series models. All monthly variables are derived from CPS microdata, and the computations are fully incorporated in monthly computer processing. (Previously the LAUS processing required annual intervention for updating GVFs.) The design effects are based on long-term averages and are monitored for possible shifts.

6. State Within-PSU Design Effects

The rest of this paper focuses on the new state within-PSU design effects. A comparison is made to comparable national design effects and to old design effects. The general formula for a monthly design effect is repeated here. The numerator can be estimated using replication. The denominator can be approximated by a suitable simple random sampling formula, and three options were presented in the previous section.

$$deff_{Wm} = \frac{Var_{Wm}\left(\hat{X}_m\right)}{Var_{SRS,Wm}\left(\hat{X}_m\right)} \qquad \hat{d}eff_{Wm} = \frac{\hat{V}ar_{rep,Wm}\left(\hat{X}_m\right)}{\hat{V}ar_{SRS,Wm}\left(\hat{X}_m\right)}$$

Old State Within-PSU Design Effects

Sets of total replicate weights were created for February through December 1987. (Note that creation of total and within-PSU replicate weights is now part of regular monthly production.) State total variances were computed using the total replicate weights. State within-PSU variance was obtained by subtracting out between-PSU variance. The within-PSU design effects where obtained by dividing the resulting within-PSU variance by an estimate of the variance computed assuming a simple random sample using base weights as a proxy tor the sampling intervals (b parameters).

Scanning any "old" column in table 1, the state design effects are more variable than the ones in the "new" column. While using total replicates to estimate state total variances is problematic in states with few NSR PSUs, a problem affecting all states was the restriction to 11 months of replicates. Sensitivity analysis for this project showed that several years of monthly data was needed; average state design effects in the "new" columns are less variable mainly because over a decade of data was used. Note that design effects in the "new" columns are lower than those in the old columns. That is due to the proxy sampling interval shift from base weights to composite weights.

In figure 5, estimated standard errors from the old GVF for Alaska employment (green) are quite a bit above the estimated standard errors from replication. The estimated standard errors for the new GVF (red) pass through the estimated standard errors for replication. Similar observations can be made about employment and unemployment plots for most of the states, and with no exceptions the problem was with the old design effects.

New State Within-PSU Design Effects

Estimated monthly state within-PSU design effects for employment and estimated monthly state within-PSU design effects were computed using all three proxy sampling intervals in SRS-type denominators.

- Avg. base weight: SRS assuming 100% response n
- Avg. nonresponse adjusted w eight: SRS but using response r
- Avg. composite weight: SRS with r, ratio estimate to CNP16+

Monthly numerators used within-PSU replicates. That is better that using total replicates and backing out the between-PSU portion of variance.

Data for over a decade was used. The time period spanned the post-2008 recession when unemployment doubled. The CNP16+ increased over the time period, and the national response rate decreased from 93% to 87%. The monthly estimated design effects were carefully examined for slope or other changes over time. Although only detectable by combining states, estimated design effects using base weights did have a slight slope. Otherwise, estimated monthly state design effects were volatile (requiring averaging over time), but generally showed no systematic change over the decade.

The three sampling interval proxies differ in how much "work" the design effects must do.

- Composite weight proxies yield estimated within-PSU design effects reasonably close to 1.0. The replicate numerator and SRS denominator are harmonized in that both incorporate monthly information on changes in the CNP16+, the changes in estimates of labor force, and changes in response rates.
- Nonresponse adjustment weight proxies yield higher estimated within-PSU design effects. That is since the effect of relative undercoverage is omitted from the SRS-type denominator, lowering the SRS-type variances (when compared to composite weights).
- Base weight proxies yield still higher estimated within-PSU design effects. That is since the effect of nonresponse is omitted from the SRS-type denominator, lowering the SRS-type variances even more (when compared to nonresponse adjusted weights).

Most analysis (comparing the within-PSU GVFs and estimated within-PSU design effects from the three sampling interval proxies) used simple averages of monthly design effects over the entire time span.

- Base weight within-PSU GVFs for states showed some mild systematic bias over time since deteriorating response over the decade was not reflected in the SRS-type formula or in the average design effects.
- Composite weight within-PSU GVFs for states were marginally preferable to nonresponse adjusted weight within-PSU GVFs for states. Averages of deviations

(estimated replicate variances versus estimated variances from GFS) were marginally smaller. Presumably that is because monthly changes in state CNP16+ that affect estimated replicate variances are also in the SRS-type portion of the GVF formula.

Magnitudes of State and National Within-PSU Design Effects
The table here is restricted to estimated design effects using average composite weights as proxies for sampling intervals. State stratification, and using sampling intervals ranging from about 300 to about 3,000, has a large impact on national CPS variances. The national within-PSU design effects shown are unaffected by state stratification, but are influenced by the complex CPS benchmarking to population controls and the variance advantages of composite weighting.

New Within-PSU Design Effects						
	Employment			Unemployment		
	Minimum	Maximum	Mean	Minimum	Maximum	Mean
State	0.88	1.07*	0.96	1.06	1.27	1.15
Nation			0.75			1.16

*excluding 1.33 for South Dakota

Unemployment – The mean of the state estimated within-PSU design effects is 1.15. This is very close to the 1.16 national estimated within-PSU design effect. The range is from 1.06 (New Hampshire) to 1.27 (Alaska).

Employment – The mean of the state estimated within-PSU design effects is 0.96. The 0.75 national estimated within-PSU design effect is lower, it is assumed due to efficiencies from benchmarking and compositing. The range is from 0.88 (Utah) to 1.07 (Montana; District of Columbia), excluding the 1.33 for South Dakota as an outlier.

7. Conclusions

This paper focused on new state generalized variance functions and associated design effects for estimating within-PSU variances of monthly CPS state employment and unemployment. The estimated variances from the GVFs are important inputs to BLS Local Area Unemployment Statistics time series models of state monthly employment and unemployment.

The GVFs investigated used a design effect times an SRS-type formula. Sampling intervals for persons were needed for the SRS-type formula and three "proxies" were derived: monthly averages of base weights, nonresponse adjusted weights, and composite weights. The use of composite weights was best.

Compared to the old GVF methodology:

- Within-PSU replicate weights were used instead of total replicate weights
- Over a decade of data was used to compute very stable design effects (compared to 11 months of data and seemingly volatile design effects)
- A shift from emphasizing initial base weights to emphasizing final composite weights. SRS-type denominators of design effects incorporate monthly changes in CNP16+, labor force, and response rates. Design effects are all reasonably close to 1.0.

- All monthly parameters were seamlessly incorporated into monthly processing (as opposed to annual intervention)
- All state within-PSU GVFs were good fits to estimated variances from within-PSU replicates

Monthly estimated design effects are volatile, requiring that they be averaged to be of use in GVFs. We ended up using simple averages of monthly within-PSU design effects using over a decade of data. No systematic change over time was detected, even though the time period spanned the post-2008 recession when unemployment doubled.

There were interesting findings on within-PSU design effects, but more work can be done.

- The mean of estimated state within-PSU design effects is higher for unemployment (1.15) than for employment (0.96). Can that be quantified and attributed to factors such as benchmarking and clustering?
- For employment, the 0.75 national estimated within-PSU design effect is lower than the 0.96 state mean. How much of the difference can be attributed, to complex benchmarking to control totals, composite estimation, or other sources?
- Why is South Dakota an outlier with a 1.33 estimated within-PSU design effect for employment?
- Why do a few state plots of estimated monthly within-PSU design effects appear to have sinusoidal-like fluctuations over time?

References

Lent, Janice (1991). "Variance Estimation for Current Population Survey Small Area Labor Force Estimates"; Proceedings of the Survey Research Methods Section, American Statistical Association.

Robison, Edwin. Martha Duff, Brandon Schneider, and Harland Shoemaker (2002). "Redesign of Current Population Survey Composite Weighting"; Proceedings of the Survey Research Methods Section, American Statistical Association.

U.S. Bureau of Labor Statistics and U.S. Census Bureau (2006). Technical Paper 66: Design and Methodology, Current Population Survey.

Figure 1. Alaska's Employment Replicate Within-PSU Standard Errors

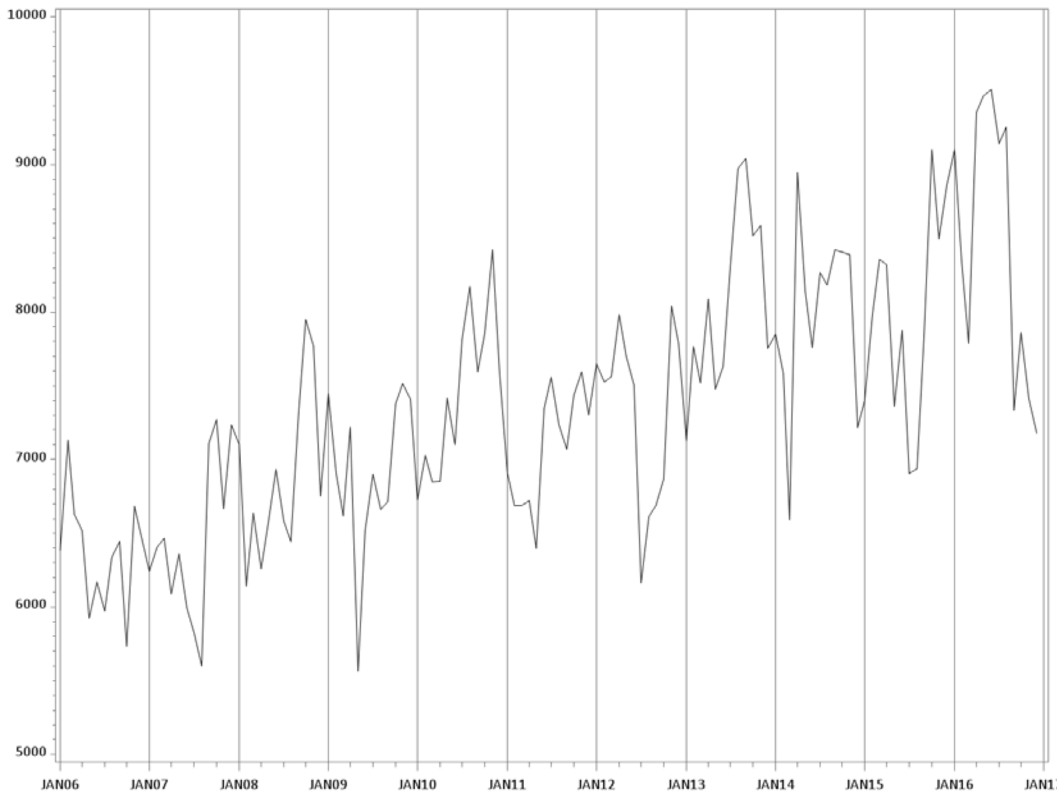

Figure 2. Alaska's Sampling Intervals

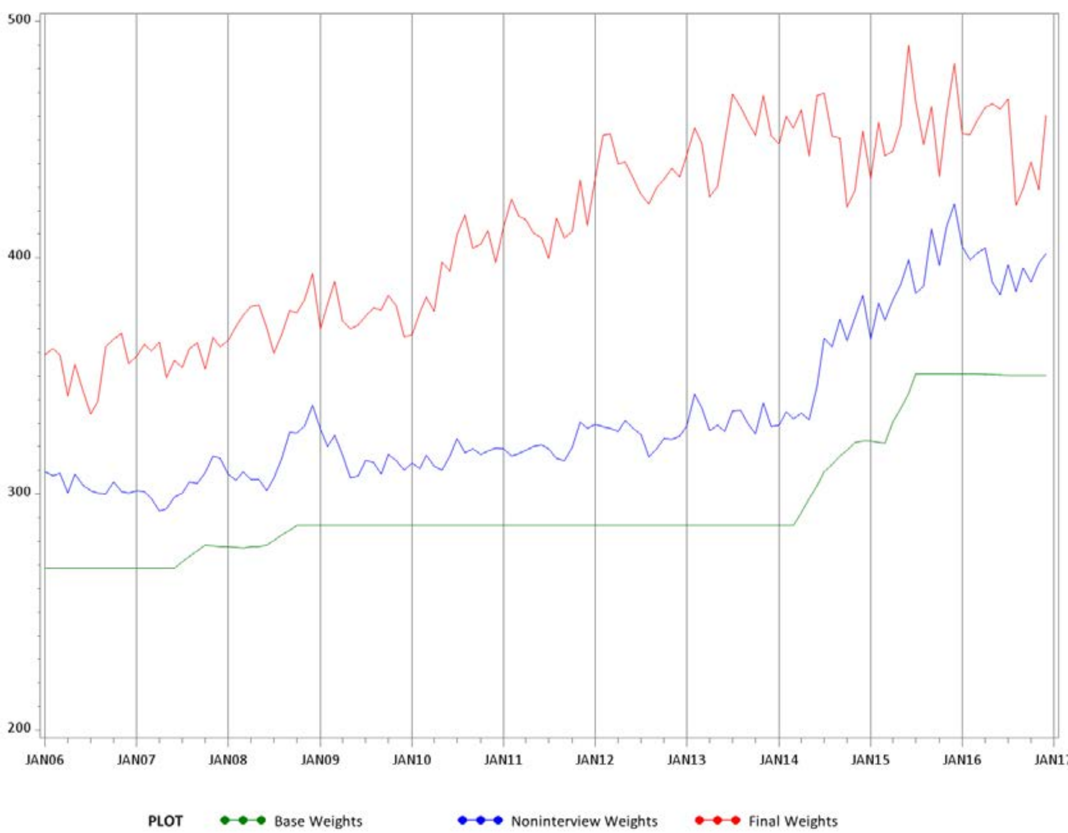

Figure 3. Alaska's Employment Within-PSU Design Effects

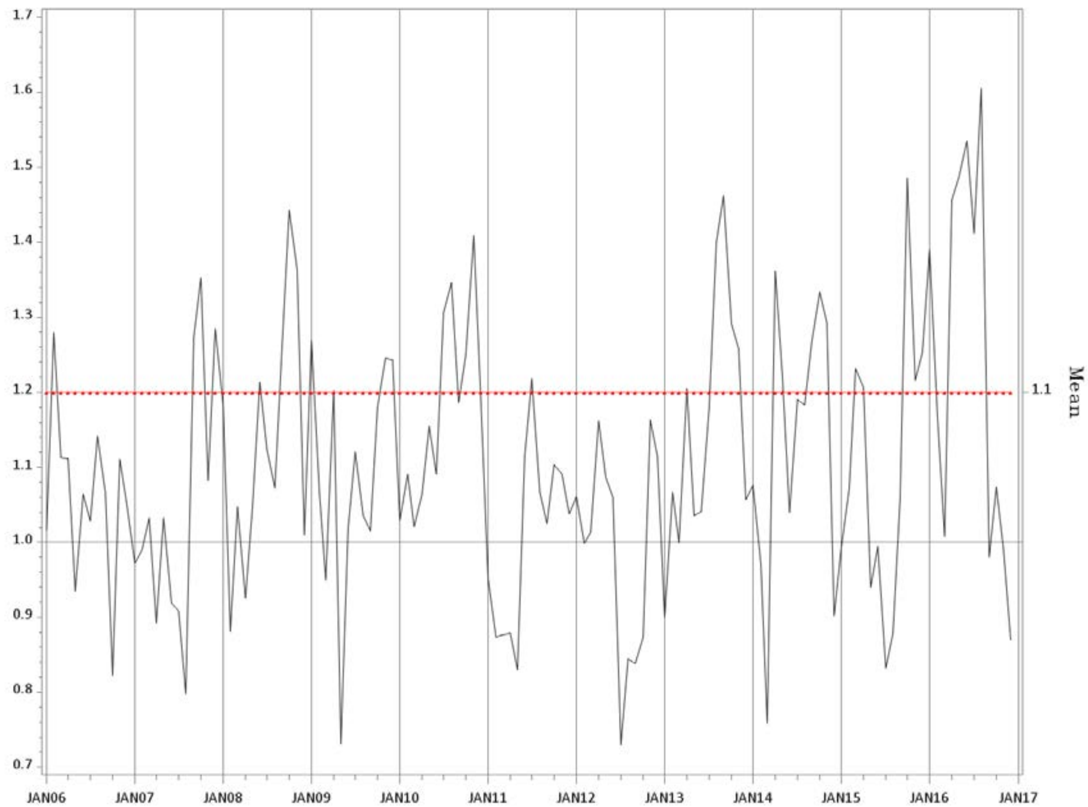

Figure 4. Alaska's Employment Standard Errors

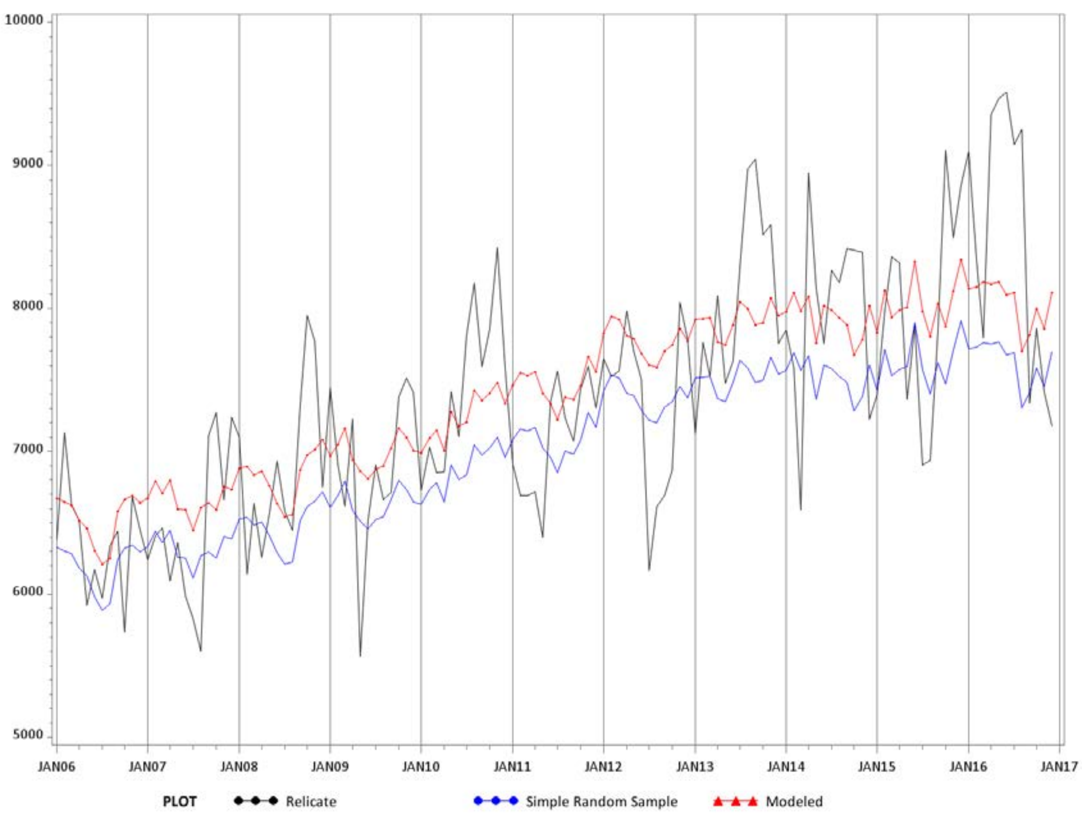

Figure 5. Alaska's Employment Standard Errors

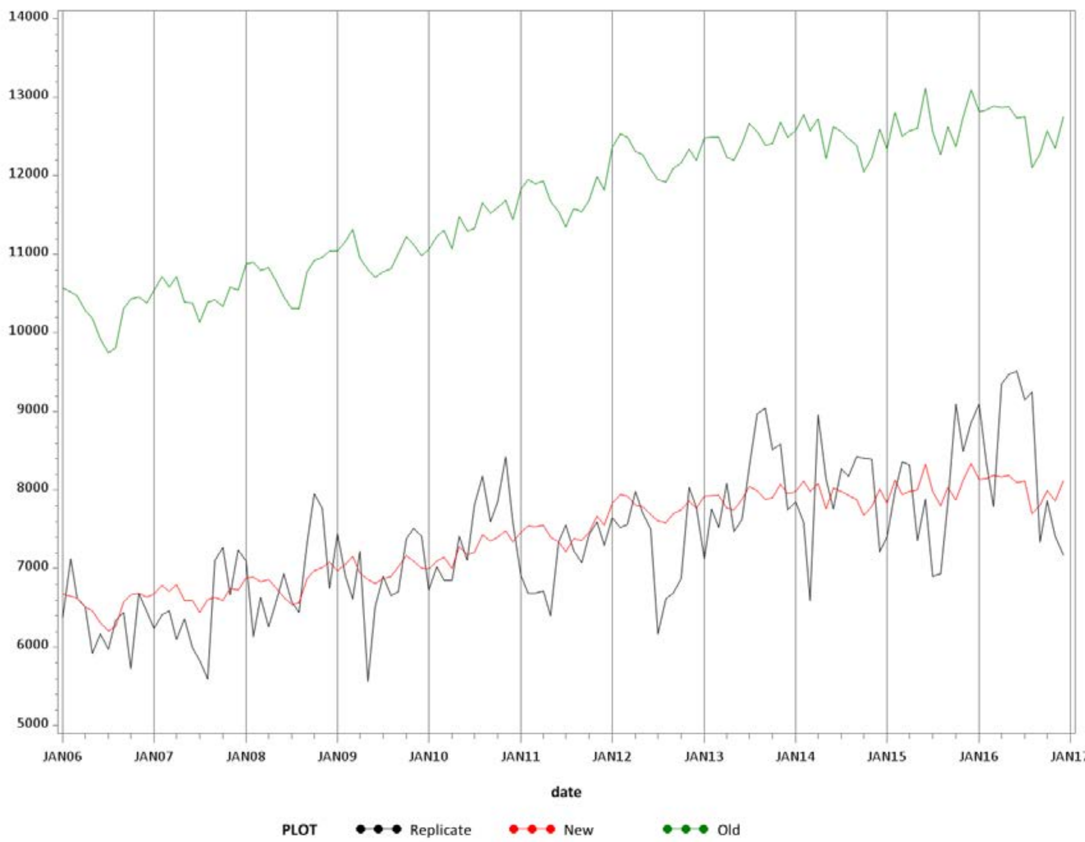

Table 1. Comparison of New to Old Within-PSU Design Effects									
	Civilian Labor Force			Employment			Unemployment		
	New	Old	Ratio	New	Old	Ratio	New	Old	Ratio
AK	1.06970	2.51926	0.42	1.10784	2.75230	0.40	1.27490	1.30270	0.98
AL	0.91456	1.40268	0.65	0.95442	1.53243	0.62	1.18677	1.27330	0.93
AR	1.02088	0.93888	1.09	1.05603	1.02573	1.03	1.14713	1.28640	0.89
AZ	0.98435	1.52095	0.65	0.98446	1.66164	0.59	1.15033	1.36010	0.85
Bal CA	0.94148	1.01995	0.92	0.95267	1.11430	0.85	1.17970	1.31470	0.90
Bal NY	0.88659	1.68321	0.53	0.88077	1.83891	0.48	1.11466	1.28750	0.87
CA	0.93834	1.01995	0.92	0.94656	1.11430	0.85	1.17647	1.33360	0.88
NY City	1.00376	1.68321	0.60	0.99412	1.83891	0.54	1.10329	1.36900	0.81
CO	0.93808	1.77257	0.53	0.93566	1.93654	0.48	1.09506	1.33560	0.82
CT	0.94503	1.77476	0.53	0.94118	1.93893	0.49	1.18619	1.28720	0.92
DC	1.07026	1.32838	0.81	1.07348	1.45125	0.74	1.20632	1.36770	0.88
DE	0.91695	1.29729	0.71	0.93350	1.41729	0.66	1.14707	1.29520	0.89
FL	0.89226	1.54320	0.58	0.89061	1.68595	0.53	1.17079	1.31010	0.89
GA	0.91890	1.11762	0.82	0.91370	1.22100	0.75	1.12696	1.31430	0.86
HI	0.99795	1.17311	0.85	1.01571	1.28162	0.79	1.27365	1.31190	0.97
IA	0.90160	1.25851	0.72	0.92871	1.37493	0.68	1.09813	1.27880	0.86
ID	0.87076	1.31470	0.66	0.91365	1.43631	0.64	1.14494	1.26510	0.91
IL	0.91225	1.25243	0.73	0.92224	1.36828	0.67	1.12195	1.29030	0.87
IN	0.91380	1.40861	0.65	0.94635	1.53891	0.61	1.10942	1.26830	0.87
KS	0.87313	1.33347	0.65	0.88799	1.45682	0.61	1.13014	1.26480	0.89
KY	0.94231	1.66115	0.57	0.99378	1.81481	0.55	1.20389	1.28450	0.94
LA	0.93234	1.11762	0.83	0.95515	1.22100	0.78	1.17343	1.28690	0.91
Los Angeles	0.91560	1.01995	0.90	0.89961	1.11430	0.81	1.13774	1.36040	0.84
MA	1.00000	1.56030	0.64	0.99474	1.70463	0.58	1.11778	1.30010	0.86
MD	1.06971	1.27752	0.84	1.06495	1.39570	0.76	1.18374	1.31020	0.90
ME	0.98342	1.48674	0.66	0.99509	1.62427	0.61	1.10879	1.26870	0.87
MI	0.95656	1.34457	0.71	0.95314	1.46894	0.65	1.12473	1.29460	0.87
MN	1.03006	1.61762	0.64	1.01069	1.76725	0.57	1.13944	1.26570	0.90
MO	0.93071	1.55122	0.60	0.95995	1.69471	0.57	1.09142	1.28430	0.85
MS	0.91646	1.40268	0.65	0.93741	1.53243	0.61	1.16581	1.29300	0.90
MT	1.04216	1.53414	0.68	1.07292	1.67605	0.64	1.17900	1.29960	0.91
NC	0.89838	1.25075	0.72	0.90932	1.36645	0.67	1.14773	1.30680	0.88
ND	0.98611	1.73939	0.57	1.00960	1.90029	0.53	1.17956	1.28710	0.92
NE	0.91350	0.96669	0.94	0.93815	1.05611	0.89	1.13191	1.31140	0.86
NH	0.93740	1.38958	0.67	0.93172	1.51812	0.61	1.05598	1.30860	0.81
NJ	0.96438	1.16537	0.83	0.96939	1.27317	0.76	1.15160	1.31030	0.88
NM	1.01416	1.32636	0.76	1.04312	1.44905	0.72	1.23161	1.32970	0.93
NV	0.97943	1.31470	0.74	0.95229	1.43631	0.66	1.14982	1.32250	0.87
NY	0.95050	1.68321	0.56	0.93358	1.83891	0.51	1.10642	1.32810	0.83
OH	0.86978	1.64438	0.53	0.90330	1.79648	0.50	1.12367	1.27420	0.88
OK	0.87477	1.33347	0.66	0.90640	1.45682	0.62	1.23603	1.32070	0.94
OR	0.92482	1.01130	0.91	0.92357	1.10485	0.84	1.11658	1.30190	0.86
PA	0.87702	1.04043	0.84	0.89451	1.13667	0.79	1.10696	1.28800	0.86
RI	0.98737	1.15350	0.86	0.99112	1.26020	0.79	1.07916	1.28950	0.84
SC	0.91520	1.24123	0.74	0.93435	1.35604	0.69	1.17303	1.27340	0.92
SD	1.23372	1.53414	0.80	1.33155	1.67605	0.79	1.25992	1.29010	0.98
TN	0.89816	1.38152	0.65	0.93915	1.50931	0.62	1.14276	1.29940	0.88
TX	0.89907	1.82189	0.49	0.89691	1.99042	0.45	1.13466	1.31100	0.87
UT	0.86956	1.46642	0.59	0.87839	1.60207	0.55	1.10426	1.27160	0.87
VA	0.89822	1.63424	0.55	0.89670	1.78541	0.50	1.14663	1.34230	0.85
VT	0.98778	1.38958	0.71	0.99662	1.51812	0.66	1.10461	1.29890	0.85
WA	0.92625	0.96285	0.96	0.93948	1.05191	0.89	1.12038	1.32980	0.84
WI	0.92859	1.77017	0.52	0.98108	1.93391	0.51	1.15490	1.26700	0.91
WV	0.91289	1.66115	0.55	0.95076	1.81481	0.52	1.16840	1.25940	0.93
WY	0.97504	1.53414	0.64	1.00180	1.67605	0.60	1.17964	1.29450	0.91