Evaluation of the Practical Utility of Small Domain Estimators for the U.S. Current Employment Statistics Program

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1. Introduction

Small area estimation, also known as small domain estimation, is a topic that has received a considerable amount of attention in the Federal statistical system over the past three decades. The central small domain issue arises from a confluence of three phenomena. First, over the past several decades, government statistical agencies have tended produce estimates using "direct estimation" methods, in which one uses data primarily from the domain of interest. For large-scale aggregates (e.g., estimation of employment totals, unemployment rates or disease prevalence rates in the full population or large subpopulations), this approach tends to produce estimators with satisfactory statistical properties, given a sufficient data collection budget. Second, over the past three decades, many stakeholders have expressed strong interest in obtaining estimates for much smaller subpopulations. Due to the resulting dilution of effective sample sizes, direct estimation methods would provide satisfactory estimators for these smaller domains only if sample sizes were increased to a point at which data collection budgets would be prohibitively large. Third, in response to this problem, the statistical community has developed a set of general methods, sometimes known as "indirect estimation methods" or "small domain estimation methods," which "borrow information" through the use of auxiliary data and modeling constraints. From a management point of view, the use of small domain estimation methods in place of traditional direct estimation methods constitutes an attempt to substitute a given amount of mathematical statistics and computational labor for a much larger amount of data collection labor. As a price associated with this substitution effort, an agency incurs additional components of statistical uncertainty (or risk) arising from possible model equation errors and model misspecification.

Due to the abovementioned factors, small domain estimation involves a very rich set of technical, management and policy issues. For some general background, see, e.g., Fay and Herriot (1979), Platek et al. (1987), Ghosh and Rao (1994), Schaible (1996), Shen and Louis (1998), Singh et al. (1998), Schirm et al. (1999), National Research Council (2000 a, b) and references cited therein.

For many end users of small domain information, the perceived practical utility of this information depends primarily on the extent to which the information contributes to formal or informal inferences regarding the underlying domain estimands and relationships among those estimands. For example, one generally prefers to use point estimators and measures of uncertainty that permit construction of sufficiently narrow confidence intervals, or construction of associated hypothesis tests with sufficiently low rates of Type I and Type II errors. Application of this general idea to specific cases can lead to consideration of several distinct inferential goals, including the following.

(1) Inference for a single prespecified mean or total of a given domain.

(2) Inference for each mean or total in a large class of domain means or totals.

(3) Simultaneous inference for several functions of a vector of domain means or totals.

(4) Inference for a subset of means or totals, conditional on indications that these quantities deviate from a simple prespecified set of conditions.

Each of goals (1)-(4) has important potential implications for small domain work for the development and evaluation of small domain estimators for the Current Employment Statistics program. Technical features and detailed solutions require extensive development which will be provided elsewhere. In the interest of space, the cuirrent paper provides some general background relevant to goals (1)-(4), and on small domain estimation for the Current Employment Statistics program. Section 2 reviews some salient features of the Current Employment Statistics program, with principal emphasis on issues related to small domain estimation and likely users of small domain estimates. Section 3 notes some contrasts between the user needs described in Section 2 and traditional statistical approaches to sample surveys. Section 4 briefly provides additional discussion of goals (1)-(4).

2. Small Domain Estimation in the Current Employment Statistics Program

The Current Employment Statistics program is closely related to another Bureau of Labor Statistics program known as the Covered Employment and Wages (or ES-202) program. The ES-202 program constitutes a nominal census obtained from state unemployment insurance tax files, obtained at the establishment level on a monthly basis. Due to lags in payment and processing of unemployment insurance taxes, the ES-202 data become available several months after a reference period. For example, ES-202 data for the January, February and March of a given year generally become available in August of the same year. Because economic policymakers need more timely estimates of aggregate employment totals, the BLS developed a federal-state cooperative program known as the Current Employment Statistics (CES) program. The previous CES sample design used a quota sampling plan in which states had a substantial degree of discretion regarding the specific sample units to be selected. In many cases, the states used this discretion to allocate sample units to specific industries and metropolitan areas in which they had special interest, and then used the resulting data to produce estimates for these industries at the metropolitan area level.

Due to well-recognized statistical problems with quota sampling, the BLS began to change the CES sample design to a probability-sampling basis in the late 1990s. For some general background on the CES probability sample design, see, e.g., Butani, Harter, and Wolter (1997), Butani, Stamas and Brick (1997), West et al. (1997) and Werking (1997).

In keeping with Congressional mandates, the probability sample was designed primarily to produce satisfactory estimates at the state and national level. However, many states and other stakeholders have expressed strong interest in continuing to produce monthly estimates of employment totals for major industries within metropolitan areas. Consequently, beginning with the January, 2003 reference period, the BLS has produced approximately 1000 monthly estimates of employment totals using a relatively simple model-based method. For some general background on this method, and alternative methods, see Eltinge et al. (2001), Harter, Wolter and Macaluso (1999) and references cited therein. For the present work, five points are of special interest. First, the estimation method uses a relatively simple weighted least squares procedure to combine data from a direct estimator, a time series estimator based on historical ES-202 data and a synthetic estimator based on state-level estimates of growth rates within a specified industry. More refined methods based on, e.g., hierarchical models, are of serious interest and may be considered for future generations of the CES small domain estimation program.

Second, because the ES-202 data generally are considered to be the "true values" of employment totals, retrospective comparison of the small domain estimates with the corresponding ES-202 values allows a direct empirical comparison of the performance of the small domain estimation method. The BLS has carried out extensive empirical evaluations based on several criteria, including mean squared error, relative mean squared error, confidence interval coverage rates and widths, and the quantiles of the absolute relative errors of the small domain estimates.

Third, because the Current Employment Statistics program is a federal-state cooperative program, the BLS worked closely with representatives of several states in an advisory group known as the Current Employment Statistics Policy Council in the development and implementation of this small domain estimation program. Within this framework, the states reported requests for small domain information from state agencies and from other stakeholders in the public and private sectors.

This work led to several potentially useful observations regarding the utility functions and constraints that were of practical importance to the production program. Perhaps most prominently, we did not encounter a single dominant intended use of the small domain estimates. To some degree, this is in contrast with some small domain estimation programs (e.g., the Small Area Income and Poverty Estimates, or SAIPE, program of the U.S. Census Bureau and the U.S. Department of Education) that are focused primarily on funding allocation formulas, and for which other uses are somewhat secondary. See, e.g., National Research Council (2000 a, b; 2001) for additional background on the SAIPE program and related issues.

Instead, different states and other stakeholders reported a heterogeneous set of estimation goals and related utility functions. For example, some states were interested primarily in estimates of total employment, others were interested in one-month changes, and others were interested in change over longer periods. In addition, some states were especially concerned about estimator performance during periods of rapid economic expansion, while others focused more on estimator performance during recessions.

Also, the states and other stakeholders varied considerably in the extent to which they were sensitive to a given magnitude of estimation error, and the criteria by which they judged the magnitudes of error (e.g., perceived smoothness of the estimated series, or comparison of the CES estimates with the ES-202 true values). For example, some states appeared to be more sensitive to the sign of an error (positive, negative or approximately equal to zero) than to its magnitude. In addition, some states reported, in qualitative terms, a loss function that appears to be asymmetric in the errors, with a greater loss incurred through positive estimation error than through a negative estimation error of the same magnitude. These asymmetric perceptions of the risks associated, respectively, with positive and negative estimation errors are consistent with observations of other forms of individual and organizational responses to uncertainty, as reported in the literature on prospect theory. For some general background on prospect theory, see, e.g., Tversky and Kahneman (1981, 1992), Kahneman and Tversky (1979, 1984) and references cited therein.

Finally, we also encountered some constraints that had serious practical effects on the specific estimators that would or would not be feasible to produce. For example, monthly production will be carried out on a relatively tight schedule, with CES data collected for the pay period including the twelfth of a given month, and with estimates to be published in the middle of the month following the reference month. One constraint that was very specific to the CES small domain program is that some metropolitan areas cover portions of more than one state, but sharing of data between states is subject to some restrictions. In addition, we encountered other constraints that are more general in nature, e.g., a programmatic preference to use estimation methods that are coherent, to the degree possible, with CES methodology implemented previously for production of state and national level estimates; and nontrivial implementation costs associated with personnel who possessed relatively rare skill sets.

3. Contrasts with Traditional Emphases in Mathematical Statistics Methods for Sample Surveys

As we consider efficient ways in which to respond to the multiple stakeholder requests and multiple constraints outlined in Section 2, it is worthwhile to consider some partial contrasts between the CES small domain issue and traditional approaches to sample survey data. With some notable exceptions, the mainstream of mathematical statistics tends to focus on questions of point estimation and inference for a well-defined quantity q (e.g., a mean, total or ratio) that is one-dimensional or is a vector with a dimension that is fairly small relative to the sample size. We then consider construction of a point estimator construct a point estimator $\hat{q}$ that will optimize a well-defined objective function. For example, we construct $\hat{q}$ to minimize sum of squares, or to maximize a likelihood or pseudolikelihood function. In this traditional framework, if we have constraints on our optimization work, they tend to be relatively mild. For example, we may constrain a variance estimate to be nonnegative, or we may seek to minimize the width $(\hat{q}_U - \hat{q}_L)$ of a confidence interval $(\hat{q}_L, \hat{q}_U)$ subject to the coverage-probability constraint

$$P[(\hat{q}_L, \hat{q}_U) \ni q_{True}] \geq 1 - a$$

Thus, in a qualitative sense, traditional mathematical statistics approaches have centered on optimization of our objective function under specific (possibly complex) stochastic structures. Examples of these structures include randomization distributions induced by complex sample designs and superpopulation distributions induced by hierarchical models.

If questioned, many applied mathematical statisticians will readily acknowledge that the abovementioned framework is imperfect, but will suggest that it captures most of the quantifiable structure that is applicable to a given estimation or inference task. Consequently, one reasons that the methods produced by this optimization approach will provide a satisfactory approximation to feasible procedures that an agency can use in practice. For related discussion, variants and partial exceptions, see, e.g., Hansen et al. (1983), Kish (1976), Harris (1972), Grzesiak and Johnson (1989) and Cochran (1977, Section 5A.3). Note that some of the features of the CES small domain program deviate substantially from this traditional framework.

4. Discussion

Historically, much of the literature on small domain estimation has tended to focus on methods related to goals (1) and (2) described in Section 1. The preceding discussion suggests that in some cases, practical work with small domain estimation and inference may lead to a deeper consideration of ideas and methods related to goals (3) (simultaneous inference) and (4) (inference conditional on indications of deviations from simple conditions). For work with simultaneous inference, it would be worthwhile to consider methods for construction of quadratic-form-based simultaneous confidence sets for linear functions of means corresponding to, e.g., one-month growth rates, multiple-month growth rates, coefficients from regression on a time index, and related contrasts. In addition, discussion of simultaneous confidence sets may lead to consideration of the relative levels of inferential power provided by, e.g., quadratic-form and Bonferroni methods, respectively. For goal (4), one may wish to consider graphical methods (e.g., quantile plots) to identify vectors of small domain estimates that are not consistent with simple null conditions, e.g., equality across metropolitan areas of underlying growth rates or equality of growth rates across several months. For cases in which these methods lead to identification of domains that deviate from the stated simple conditions, it would be important to ensure that subsequent estimation and inference steps account appropriately for potential selection effects.

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