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Regression Composite Estimation for the Canadian Labour Force Survey with a Rotating Panel Design

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Abstract

We consider the regression composite estimation introduced by Singh (1994, 1996; termed earlier as "modified regression composite" estimation), a version of which (suggested by Fuller 1999) has been implemented for the Canadian Labour Force Survey (CLFS) beginning in January 2000. The regression composite (rc) estimator enhances the generalized regression (gr) estimator used earlier for the CLFS and the well known Gurney-Daly *ak*-composite estimator in several ways. The main features of the rc-estimator are: (a) it considerably improves the efficiency of level and change estimates for key study variables resulting into less volatile estimate series; (b) it is calculated like the gr-estimator as a calibration estimator such that all the usual poststratification controls used in gr as well as the new controls corresponding to correlated variables from the previous time point are met; and (c) it respects the internal consistency of estimators without having to calculate part estimates differently as residuals. The main innovations used in rc-class of estimators entail: (a) using the idea of working covariance matrix in estimating functions as an alternative to superpopulation modeling for defining regression coefficients for the predictors in the gr-estimator, (b) treating random controls (the ones based on the key correlated variables from past) as fixed, while computing the regression coefficients, similar to two-phase estimation, and motivated from the working covariance idea, and (c) that of the use of micro-matching to obtain previous time point's micro-level auxiliary information for realizing higher correlation with the present time point's study variables. As a by product, a new version of the *ak*-estimator which uses the micro-matching based predictors from past rather than the traditional macro-level is recommended in the interest of higher efficiency gains. The paper also presents an interesting heuristic justification of the smoothness feature of composite estimates using the amortization idea. Empirical results based on the Ontario 1996 CLFS data are presented for comparison of various estimators.

Key Words: Generalized regression; Modified regression; Estimating functions; Regression calibration.

1. Introduction

In the case of repeated surveys with partially overlapping samples, it is well known (see, *e.g*., Cochran 1977, Chapter 12) that estimates of level at a point in time and change between two time points can be improved by regressing the usual cross-sectional estimator (typically regression or simply Horvitz-Thompson) on the new predictors provided by the correlated observations on the overlapping subsample from the previous time point. Such methods of estimation belong to the class of composite estimation, and a simple version of which known as the *k*-composite estimator was proposed some time ago by Hansen, Hurwitz and Madow (1953), and examined further by Rao and Graham (1964), Binder and Hidiroglou (1988) provide an excellent review of the literature on estimation with repeated surveys. Note that there is an associated loss of efficiency in estimates aggregated over several time points due to increased positive correlation between composite estimates of successive time points. This is, however, probably a small price to pay because it is not the aggregate, but the level and change estimates that need more precision. The *ak*-composite estimator of Gurney and Daly (1965) provides an improved version of the *k*-composite estimator by reducing the variance further, an alternative simpler justification of which was provided by Wolter (1979).

The composite estimator considered in this paper was developed in the context of the Canadian Labour Force Survey (CLFS). The CLFS is a monthly survey that follows a rotating panel design with six panels. In any two consecutive months, five sixth of the households form the overlapping sample. It was in January 2000 that the CLFS started using a version (suggested by Fuller 1999) of the composite estimators introduced by Singh (1994, 1996) termed originally as "modified regression composite" estimators, which will be referred to in this paper as simply "regression composite" or rc-estimators. Before January 2000, CLFS used the generalized regression (gr) estimators of Cassel, Särndal, and Wretman (1976) and Särndal (1980) which were based on only cross-sectional (*i.e*., present month's) data. It has long been felt that the estimator for CLFS could be improved using the composite estimation idea in the sense that estimates of level and change would be more efficient, and hence the resulting series would be more stable, *i.e*., less volatile. There are four goals that the rc-estimator attempts to meet in modifying the gr-estimator:

(i) It should considerably increase the efficiency of level and change estimates so that the estimate series becomes smoother or less volatile.
(ii) It can be computed as a calibration estimator like the gr-estimator so that the existing estimation software system can be used with little modification,

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(iii) The final calibrated weights should continue to satisfy the usual demographic and geographic controls used in the gr-estimator in addition to some new controls based on past month's variables, and

(iv) The estimator should have the internal consistency property in that the part composite estimators add up to the whole, *e.g*., estimates for Employed (E), Unemployed (U), and Not in the Labour Force (N) should add up to the total eligible population in the domain of interest.

The *ak*-estimator was studied by Kumar and Lee (1983) in the context of CLFS, and it was found that it didn't give substantial gains in efficiency as required by goal (i). The goal (iv) was, of course, known to be not satisfied by the *ak*-estimator because the (optimal) coefficients a and k used for combining several present month's estimators (in fact three of them, one is the usual estimator based on the present month, and the other two are built on predictors from the past month) turn out to be specific to the characteristic such as E. A solution (although rather undesirable) is to designate one of the components as least important (say, N) and then obtain its estimate as a residual. The goals (ii) and (iii) can, however, be met by the *ak*-composite weighting suggested by Fuller (1990), and studied for the US Current Population Survey context by Lent, Miller, and Cantwell (1994, 1996). The goal (ii) is important especially for unplanned study variables for which the coefficients (a, k) are not known in advance. The rc-estimator meets all the four goals, in particular the goals (i) and (iv), by making use of the following three innovations:

(i) The design-based estimation in the presence of correlated predictors can be cast in an estimating functions framework as defined by Godambe and Thompson (1989), and then use the idea of working covariance matrix as in Liang and Zeger (1986) to obtain an alternative to the superpopulation modelling to compute regression coefficients. The resulting regression estimates, like gr, are only suboptimal under the design randomization.

(ii) The previous month's full sample composite estimates used as regression controls for present month's estimation can be treated as fixed using the working covariance idea for computational simplicity without violating the design consistency property. For variance estimation, the extra variation due to random controls should, of course, be accounted for.

(iii) Using micro-matching of the present month's overlapping subsample with the previous month, information about key study variables from the previous month is augmented to the present month's data. These now serve as additional covariates deemed to be highly correlated with the present month's study variable.

These innovations allow for computation of all estimates using the gr-system, thus avoiding the need of having to compute parts of estimates as residuals in the interest of internal consistency. The feature of micro-matching gives rise to desired gains in efficiency. In practice, it would often be the case that some of the present month's respondents in the overlapping sample were nonrespondents in the previous month, and so imputation might be necessary. In the case of CLFS, this is a small fraction, and the Hot Deck method with donor classes defined by demographic, geographic (sub-provincial economic regions), type of area (rural/urban), present month's employment status, and industry group is used to fill in the missing values. It may be noted that sometimes imputation may be necessary not due to non-response at the previous time point, but due to the household's move. Assuming that on the average, households that move in the dwellings sampled at the present time t are similar to the households that move out at t, then even though movers may have different employment characteristics than nonmovers, the imputation for movers is not expected to introduce any new bias as current month's employment status among other covariates is taken into account.

In the concluding section 6, a method is suggested to diagnose the impact of this imputation. This impact may be serious for surveys with high fraction of previous month's missing values for the present month's respondents in the overlapping subsample. A possibly simple way out would be to redesign the questionnaire so that the interviewer is prompted by the instrument CATI software (computer assisted telephone interviewing commonly used now-a-days) while administering the interview in second or later months, whether the respondent was nonrespondent at the previous month. If so, then the interviewer administers a rather short supplementary questionnaire in order to elicit the respondent's employment status for the previous month. This idea is similar to the method suggested by Hansen-Hurwitz-Madow for completely nonoverlapping repeated surveys, but each respondent is asked questions for the present as well as the previous time point, see Cochran (1977, page 355).

The organization of this paper is as follows. Section 2 presents a heuristic motivation using the amortization idea of why composite estimation, in general, is expected to provide desired smoothing of the estimate series. Section 3 defines various estimators, and discusses their computation via the gr-system. A new version of the *ak*-estimator, denoted by ak^*, is also proposed. The estimator uses predictors from previous month based on micro-matching, and is expected to give high gains in efficiency. Section 4 considers variance estimation by the currently used method of jackknife. An empirical comparison of the estimators is presented in section 5 using the Ontario 1996 CLFS data. Finally section 6 contains concluding remarks.

2. Series Smoothing by Composite Estimation: Heuristics

In this section, we present an interesting heuristic justification (based on the amortization idea rather than the shrinkage) of why smoothing of the estimate series is expected by composite estimation. (Using only the shrinkage idea, the series can be smoothed but it may not cross the original series often enough. With amortization, however, the left-over part after shrinkage is accounted for gradually over time, thus allowing for the smoothed series to cross the original one more often.) Consider the panel rotation scheme similar to that of the CLFS and let γ denote the fraction of the panels rotated out; in the case of CLFS, γ is 1/6. Denote the cross-sectional estimator (typically gr) at time t based on all panels, *i.e.*, the full sample, by F_t, the estimator based on only the birth (*i.e.*, rotate-in) panel by B_t, and the one based on nonbirth panels (*i.e.*, the subsample at t overlapping with the past sample at $t-1$) be $\bar{B}_t$. Similarly, denote the estimator based only on the death (*i.e.*, rotate-out) panel by D_t, and the one based on nondeath panels (*i.e.*, the subsample at $t-1$ overlapping with the present sample at t) be $\bar{D}_t$. We have

$$F_t = \gamma\, B_t + (1-\gamma)\,\bar{B}_t \tag{2.1a}$$

$$F_{t-1} = \gamma\, D_{t-1} + (1-\gamma)\,\bar{D}_{t-1}. \tag{2.1b}$$

Suppose, the series $\{F_t\}$ is too volatile, and we wish to smooth it. In the following it is assumed that there is no rotation group bias (Bailar 1975), *i.e.*, different rotation groups have the same expected value. Thus F_t is unbiased but may be unstable. This set-up is the traditional one for composite estimation in which different unbiased estimates are combined optimally to get a more efficient estimate. However, see the discussion at the end of this section for an alternative perspective on composite estimation in the presence of rotation group bias. Now denote the smoothed series by $\{C_t\}$, and consider the identity:

$$F_t = C_{t-1} + (F_t - F_{t-1}) + (F_{t-1} - C_{t-1}). \tag{2.2}$$

The above relation can be interpreted as follows. The estimate C_{t-1} at $t-1$ is adjusted by the fluctuation $(F_t - F_{t-1})$ at the next time point t in the F-series, and the existing gap $(F_{t-1} - C_{t-1})$ at the time point $t-1$. If we define C_t after full adjustments for these two differences, then C_t would be the same as F_t and there would be no smoothing of the F-series. This suggests that the adjustments for the differences $(F_t - F_{t-1})$ and $(F_{t-1} - C_{t-1})$ should be accounted for only partially as C-series moves from C_{t-1} to C_t. The remaining portions of the differences should be amortized gradually over future time points. All these adjustments should be done without affecting unbiasedness of the estimator C_t. The difference $(F_{t-1} - C_{t-1})$ is zero in expectation assuming unbiasedness of C_{t-1} and F_{t-1} (which is so under the assumption of no rotation group bias) and therefore amortizing parts of it would not affect unbiasedness of future estimates C_t. However, the difference $F_t - F_{t-1}$ is not zero in expectation, and care should be exercised in amortizing part of this difference. Observe that

$$F_t - F_{t-1} = (\bar{B}_t - \bar{D}_{t-1}) + \gamma(B_t - \bar{B}_t) + \gamma(\bar{D}_{t-1} - D_{t-1}). \tag{2.3}$$

The first term on the RHS is the change estimate based on common panels, while the second and third terms represent birth and death effects at t and $t-1$ respectively. The last two terms are zero functions (*i.e.*, are zero in expectation) but the first one is not. (Fortunately, the first term is expected to be stable as it is a difference of two highly correlated estimates.) Therefore, it is the second and third terms that should be amortized. Now, write (2.2) as

$$\begin{aligned} F_t &= C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + \gamma(B_t - \bar{B}_t) \\ &\quad + [\gamma(\bar{D}_{t-1} - D_{t-1}) + (F_{t-1} - C_{t-1})] \\ &= C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + \gamma(B_t - \bar{B}_t) \\ &\quad + [(\bar{D}_{t-1} - F_{t-1}) + (F_{t-1} - C_{t-1})] \\ &= C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + \gamma(B_t - \bar{B}_t) + (\bar{D}_{t-1} - C_{t-1}) \end{aligned} \tag{2.4}$$

and define two amortization factors δ_{1t}, δ_{2t} between 0 and 1, and then define the smoothed series $\{C_t\}$ as

$$C_t = C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + \delta_{1t}\gamma(B_t - \bar{B}_t) + \delta_{2t}(\bar{D}_{t-1} - C_{t-1}). \tag{2.5}$$

The term with δ_{1t} in (2.5) represents shrinkage of the birth effect at t which C_t tries to account for, while the term with δ_{2t} refers approximately to shrinkage of the death effect at the past time $(t-1)$ which C_t tries to make up for the present time t. Also, it would be desirable to set $\delta_{2t} < \delta_{1t}$ in order for the series $\{C_t\}$ to track $\{F_t\}$ better so that they have similar trend over time, *i.e.*, give more importance to the current birth effect than the past death effect. (In fact, a rigorous justification under fairly general conditions of why one should set $\delta_{2t} < \delta_{1t}$ comes from optimality considerations in which variance of C_t is minimized to obtain the best linear combination of three unbiased estimators, $F_t, C_{t-1} + \bar{B}_t - \bar{D}_{t-1}$, and $F_t + C_{t-1} - \bar{D}_{t-1}$ of the present month's population total; see (2.8) at the end of this section for the actual expression). Now, to see the connection with the well known composite estimates defined in the next section, define $0 < a_t, b_t < 1$, so that $\delta_{1t} = 1 - b_t, \delta_{2t} = 1 - b_t - a_t$. We have

$$C_t = C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + (1-b_t)\gamma(B_t - \bar{B}_t) + (1 - b_t - a_t)(\bar{D}_{t-1} - C_{t-1}). \tag{2.6}$$

It is interesting to note that if $b_t = 0$, there would be no dampening of the birth effect, and the C-series is expected to be closer to F-series, *i.e.*, there is less smoothing and the two would cross each other more often. If $a_t = 0$, the past effect represented by $(\bar{D}_{t-1} - C_{t-1})$ is dampened less. This would imply more smoothing of the *F*-series, and the two series are expected to cross each other less frequently. Finally, if $a_t, b_t > 0,$ then the behaviour of the *C*-series relative to the *F*-series would be somewhere in the middle. Moreover, if b_t is high (close to 1), there would be quite a bit of smoothing of the *F*-series because there is high amortization of both the birth and death effects. In these situations, one would expect sustained gaps between *F* and *C* series over time before they cross each other. Notice that parts of the term $\gamma(B_t - \bar{B}_t)$ that get amortized over $t, t+1, \ldots$ decrease as t increases. They are given by $b_t \gamma(B_t - \bar{B}_t), (b_{t+1} + a_{t+1}) b_t \gamma(B_t - \bar{B}_t), \ldots$. Similarly, the amortized parts of $(\bar{D}_{t-1} - C_{t-1})$ are

$$(b_t + a_t)(\bar{D}_{t-1} - C_{t-1}),$$
$$(b_{t+1} + a_{t+1})(b_t - a_t)(\bar{D}_{t-1} - C_{t-1}), \ldots .$$

Clearly, when b_t is large, it will take several time points for completing the amortization. However, as explained earlier, this would not introduce bias because the effects being amortized are zero functions under the assumption of no rotation group bias.

The expression (2.6) can be cast into a more familiar expression of the composite estimator as follows:

$$\begin{aligned} C_t &= C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + (1-b_t)(F_t - \bar{B}_t) \\ &\quad + (1-b_t)(\bar{D}_{t-1} - C_{t-1}) + a_t(C_{t-1} - \bar{D}_{t-1}) \quad (2.7a) \\ &= C_{t-1} + (\bar{B}_t - \bar{D}_{t-1}) + (1-b_t)(F_t - \bar{B}_t + \bar{D}_{t-1} - C_{t-1}) \\ &\quad + a_t(C_{t-1} - \bar{D}_{t-1}) \quad (2.7b) \\ &= F_t + b_t[C_{t-1} - (F_t + \bar{D}_{t-1} - \bar{B}_t)] \\ &\quad + a_t(C_{t-1} - \bar{D}_{t-1}) \quad (2.7c) \\ &= F_t + (b_t + a_t)(C_{t-1} - \bar{D}_{t-1} + \bar{B}_t - F_t) \\ &\quad + a_t(F_t - \bar{B}_t). \quad (2.7d) \end{aligned}$$

The expression (2.7d) coincides with the *ak*-estimator (see next section) when $a_t = a$ and $b_t + a_t = k.$ In practice, the values of a_t and b_t can be determined optimally or suboptimally using regression (see next section). The partial regression coefficients a_t, b_t satisfy $0 < a_t < b_t < 1$ in general, because the direct estimator F_t is expected to be more positively correlated with the predictor $F_t + (\bar{D}_{t-1} - \bar{B}_t),$ *i.e*, $\bar{D}_{t-1} + \gamma(B_t - \bar{B}_t)$ than with the predictor $\bar{D}_{t-1};$ both predictors being unbiased estimates, like $C_{t-1},$ of the population total parameter at the previous time point $t-1.$ It follows from (2.7c) that the estimator C_t can be written as a linear combination of the three unbiased estimators mentioned earlier, and is given by

$$\begin{aligned} C_t = (1-b_t-a_t)F_t + b_t(C_{t-1} + \bar{B}_t - \bar{D}_{t-1}) \\ + a_t(F_t + C_{t-1} - \bar{D}_{t-1}). \quad (2.8) \end{aligned}$$

The above heuristic motivation corresponds to the variance reduction considerations under the assumption of no rotation group bias when combining three unbiased estimators of the population total at $t.$ In the presence of rotation group bias, however, all the three estimators become biased with possibly different magnitude and direction, and what composite estimation does is to adjust each one of them so that the adjusted value for each is equal to a common value given by the composite estimator. (For example, in the case of two estimators $\hat{\theta}_1$ and $\hat{\theta}_2$ of θ, the linear combination $\lambda\hat{\theta}_1 + (1-\lambda)\hat{\theta}_2$ can be written as $\hat{\theta}_2 + \lambda(\hat{\theta}_1 - \hat{\theta}_2)$ or $\hat{\theta}_1 + (1-\lambda)(\hat{\theta}_2 - \hat{\theta}_1)$ implying that the two original estimators are adjusted appropriately to converge to a common value.) The relative weight in combining the three estimators depends on the criterion of minimum variance. Ideally, it should be based on the minimum MSE criterion, but it is hard to get a handle on bias because it can't be estimated. Clearly the composite estimator is not bias free, and it can only be speculated that the overall bias of the estimator is reduced by compositing. Similarly if, instead, a suboptimal regression is used in constructing the composite estimator (as in rc-estimation, see the next section), then what composite estimation does is to adjust the sampling weights in the full sample (which are generally gr-weights) so that $F_t - (\bar{B}_t - \bar{D}_{t-1}),$ and $\bar{D}_{t-1}$ with adjusted weights become equal to $C_{t-1};$ the C_{t-1} serve as new controls in the calibration step. This is another way of adjusting the three estimators to a common value, but again bias of the resulting composite estimator remains unknown. The above discussion of two perspectives on composite estimation has some similarity with the dual property of poststratification in terms of both variance and (coverage) bias reduction, see Singh and Folsom (2000).

3. Composite Estimators: New and Old

We start with the cross-sectional estimator at time *t* of the total $\tau_y(t)$ defined as gr, which is given by

$$\hat{\tau}_{y(\text{gr})}(t) = \sum\nolimits_{k \in s(t)} y_k(t)\, w_{\text{gr}}(t,k), \quad (3.1)$$

$$\begin{aligned} &w_{\text{gr}}(t,k) \\ &= d(t,k)[1 + x_k(t)'(X(t)'\Delta(t)X(t))^{-1}(\tau_x(t) - \hat{\tau}_x(t))], \quad (3.2) \end{aligned}$$

where $d(t,k)$'s are the initial design weights adjusted for nonresponse, $x_k(t)$ is a *p*-vector of covariates used for calibration (or poststratification), $X(t)$ is the $n(t)xp$ matrix of *x*-observations, $n(t)$ is the sample size, $\Delta(t)$ is diag $(d(t,k)),$ $\tau_x(t)$ is the known *p*-vector of calibration controls, and $\hat{\tau}_x(t)$ is the corresponding vector expansion estimates based on *d*-weights. In terms of the notation, $F_t, \bar{B}_t,$ and B_t of the previous section, F_t here can be taken as the gr-estimator (3.1), and $\bar{B}_t$ is gr-estimator based on nonbirth panels given by

$$\bar{B}_t = (1-\gamma)^{-1} \sum_{k \in s(t|t-1)} y_k(t)\, w_{\text{gr}}(t, k), \qquad (3.3)$$

where $s(t\,|\,t-1)$ is the subsample at t matched with the sample at $t-1$. The estimator B_t is also a gr-estimator, and is given by

$$B_t = \gamma^{-1} \sum_{k \in s(t)-s(t|t-1)} y_k(t)\, w_{\text{gr}}(t, k), \qquad (3.4)$$

where the sum is over the subsample defined by the birth panel at t.

The *ak*-composite estimator uses the macro-level past information for the new predictors, and can be defined as

$$\begin{aligned} C_{t(ak)} &= F_t + k(C_{t-1(ak)} - \bar{D}_{t-1} + \bar{B}_t - F_t) \\ &\quad + a(F_t - \bar{B}_t) \\ &= F_t + (k-a)(C_{t-1(ak)} - \bar{D}_{t-1} + \bar{B}_t - F_t) \\ &\quad + a(C_{t-1(ak)} - \bar{D}_{t-1}). \end{aligned} \qquad (3.5)$$

Here the coefficients a, k for level estimation are obtained by optimally regressing F_t on the two predictor zero functions, based on the past information, namely, $C_{t-1(ak)} - (F_t + \bar{D}_{t-1} - \bar{B}_t)$, and $C_{t-1(ak)} - \bar{D}_{t-1}$. Thus, a, k depend on the sample design as well as on the study variable y, in particular, they are not even the same for level and change estimates for the same y. For change estimation, $F_t - C_{t-1(ak)}$, and not F_t is regressed optimally on the above predictors. In practice, a, k are estimated by performing a grid search on the interval (0, 1) such that the variance of C_t is minimized. As mentioned earlier, typically a is smaller than k. In defining the above two new predictor zero functions based on past information, two estimators of $\tau_y(t-1)$ are first formed: one is $\bar{D}_{t-1}$ based on the nondeath panels at $t-1$ (*i.e.*, subsample at $t-1$ matched with the sample at t), and the other is $F_t + (\bar{D}_{t-1} - \bar{B}_t)$ which is the gr-estimator at time t adjusted for change from $t-1$ to t estimated from the common sample. Clearly, if there is no overlap in the panel design, then all the predictor zero functions become no longer meaningful resulting in no change in F_t by composite estimation. Similarly, if there is a complete overlap, then, $\bar{B}_t = F_t$, and again there is no effect on F_t of composite estimation. This may at first seem counter-intuitive, because the past data (y_{t-1}) is correlated with the present (y_t) due to sample overlap. However, complete overlap amounts, in principle, to collecting a single sample of multivariate data on y with elements corresponding to y at different time points. Using this analogy, there is no room for improvement (in the design-based framework) as there is no larger sample with additional information. In the case of no overlap, additional information is there but it doesn't help as it is uncorrelated. Note, however, that at the first stage, psu's (primary sampling units) in CLFS remain common over several years before they are rotated out. Therefore, efficiency gains due to partial overlap are realized mainly from the reduction of the second stage variance component.

Furthermore, note that the estimator $C_{t(ak)}$ uses past information in the univariate sense in that for the study variable y, past information about only y_{t-1} is used. If new predictors based on several variables such as $y_{t-1}, z_{t-1}, \ldots$ from the past are also used for the study variable y, then the composite estimation becomes multivariate. However, the optimal choice of the (a, k) coefficients for the multivariate case can be quite cumbersome.

The rc-class of estimators is given by

$$\begin{aligned} C_{t(\text{rc})} &= F_t + b_{t(\text{rc})}(\tilde{C}_{t-1(\text{rc})} - \bar{D}^*_{t-1} + \bar{B}_t - F_t) \\ &\quad + a_{t(\text{rc})}(\tilde{C}_{t-1(\text{rc})} - \bar{D}^*_{t-1}) \end{aligned} \qquad (3.6)$$

where $\tilde{C}_{t-1(\text{rc})}$ denotes the $t-1$ estimator for the study variable (y) after the $(t-1)$-calibration weights are further calibrated to meet the controls used for poststratification by gr at time t. Thus $\tilde{C}_{t-1(\text{rc})}$ is an estimate of the population total at t for the y-variable at $t-1$. The starred $\bar{D}^*_{t-1}$ signifies that it is based on the subsample at t matched with the sample at $t-1$, but uses the gr-weights at t as the y values from $t-1$ are augmented to the sample at t by micromatching. (Note that the estimator $\bar{D}^*_{t-1}$ involves, in general, imputed values, and may suffer from bias due to imputation. For a diagnosis and adjustment for this bias, see section 6.) The coefficients $b_{t(\text{rc})}$ and $a_{t(\text{rc})}$ are computed similar to gr of (3.1); see below for more details. These coefficients are suboptimal unlike (a, k). However, like (a, k), they are y-specific, and in the case of multivariate they depend on the key set of study variables chosen from past for new controls, but they can be computed easily as they are suboptimal in nature. Thus with rc-estimation, it is fairly easy to introduce more predictors. The predictors $(C_{t-1} - \bar{D}_{t-1})$ and $(C_{t-1} - \bar{D}_{t-1} + \bar{B}_t - F_t)$ can be termed respectively as level-driven and change-driven as in Singh, Kennedy, Wu and Brisebois (1997). The reason for this is that not only the former is a difference of two level estimates, and the latter a difference of two change estimates, $(C_{t-1} - F_t)$ and $(\bar{D}_{t-1} - \bar{B}_t)$, but that the former tends to provide high efficiency gains in level estimation over what can be obtained in the presence of the latter, and similarly, the latter provides high efficiency gains in change estimation over what can be achieved in the presence of the former.

The idea of using the micro-level past information for the new predictors in rc-estimation can be applied to the *ak*-estimator, and thus a new estimator ak^* can be proposed.

$$\begin{aligned} C_{t(ak^*)} &= F_t + (k^* - a^*)(\tilde{C}_{t-1(ak^*)} - \bar{D}^*_{t-1} + \bar{B}_t - F_t) \\ &\quad + a^*(\tilde{C}_{t-1(ak^*)} - \bar{D}^*_{t-1}). \end{aligned} \qquad (3.7)$$

The control $\tilde{C}_{t-1(ak^*)}$ denotes the $(t-1)$ calibration estimator for y after the ak^*-composite weights are further calibrated to meet the controls used for poststratification by gr at t. (Here the ak^*-composite weights are similar to the ak-composite weights of Fuller (1990) where the composite estimators for a set of key y-variables serve as additional controls in the usual gr to obtain a set of final calibration weights. This allows for the ak-composite estimator to be computed as a calibration estimator.) The main differences between the various estimators defined above lie in the definition of regression coefficients (optimal *vs.* sub-optimal), and that of the predictors (macro-level *vs.* micro-level use of past information). Special cases of the above composite estimators can be obtained as described in Singh, *et al.* (1997) by using only one of the two predictors. For $C_{t(ak)}$, if $a=0$ (*i.e.*, only change-driven predictor is used), we get the well known k-composite estimator which can be termed as the $ak2$-estimator in the present context. If $a=k$, *i.e.*, only level-driven predictor is used, we get a new composite estimator $C_{t(ak1)}$ which can be termed as the $ak1$-estimator. Similarly for $C_{t(ak^*)}$, we get two more new composite estimators ak^*1 and ak^*2. For $C_{t(\text{rc})}$, with only level-driven predictor, we get the rc1-estimator, termed earlier as MR1 in Singh and Merkouris (1995). With only change-driven predictors, we get the rc2-estimator termed earlier as MR2 in Singh, *et al.* (1997).

As mentioned earlier, the rc-estimator is computed as a gr-estimator of (3.1), and therefore, it can be expressed as $\hat{\tau}_{y(\text{rc})}(t)=\sum_{k\in s(t)} y_k(t) w_{\text{rc}}(t,k)$. The $X(t)$-matrix is expanded to $n(t)\times(p+2q)$ matrix $X(t)^*$ where $2q$ represents the number of new predictors, the factor 2 signifying the pair of level-driven and change-driven predictors. The (random) control totals $\tilde{C}_{t-1(\text{rc})}$ corresponding to the key set of y-variables from $t-1$ selected for composite estimation are treated as fixed (during the computation of regression coefficients) like the other (nonrandom) gr-controls. Now, since the level-driven predictor can be written as

$$\begin{aligned}\bar{D}^*_{t-1} &= (1-\gamma)^{-1}\sum\nolimits_{k\in s(t|t-1)} y_k(t-1) w_{\text{gr}}(t,k)\\ &= \sum\nolimits_{k\in s(t)} (1-\gamma)^{-1} y_k(t-1) 1_{k\in s(t|t-1)} w_{\text{gr}}(t,k) \quad (3.8)\end{aligned}$$

the column of the $X(t)^*$-matrix corresponding to this predictor consists of $n(t)$-values of $(1-\gamma)^{-1} y_k(t-1) 1_{k\in s(t|t-1)}$. Similarly the change-driven predictor can be written as

$$F_t+\bar{D}^*_{t-1}-\bar{B}_t = \sum\nolimits_{k\in s(t)}\begin{pmatrix} y_k(t)+(1-\gamma)^{-1}(y_k(t-1)\\ -y_k(t)1_{k\in s(t|t-1)})\end{pmatrix} w_{\text{gr}}(t,k) \quad (3.9)$$

and the corresponding column of the $X(t)^*$ matrix consists of the $n(t)$-values of $y_k(t)+(1-\gamma)^{-1}(y_k(t-1)-y_k(t))1_{k\in s(t|t-1)}$. Once the $X(t)^*$ matrix is defined, the gr-system can be used to compute the calibration weights $w_{\text{rc}}(t,k)$ as in (3.2). Note that the calibration weights $w_{\text{rc}}(t,k)$ can be used for estimation of all study variables although they depend explicitly only on the key set of study variables chosen for the new predictors from correlated past information. Also note that although the rc-estimator of (3.6) was defined as the gr-estimator plus regression-adjustments for the new predictors, computationally it is convenient to perform a gr-calibration on the design weights when all the old and new calibration controls are considered simultaneously. This way computation for the multivariate rc-estimator is not much different from the univariate rc-estimator. Alternatively, one could compute the rc-estimator as an adjusted gr as in (3.6), but the coefficients for the new predictors would be partial regression coefficients, and therefore do not have the standard form of the gr-coefficients.

Finally we note that with composite estimation, one would expect higher efficiency gains for change estimates $(C_t - C_{t-1}\ vs.\ F_t - F_{t-1})$ than those for level estimates $(C_t\ vs.\ F_t)$. To see this, consider a simple identity: $V(F_t - F_{t-1}) = V(F_t)+V(F_{t-1}) - 2\text{Cov}(F_t, F_{t-1})$. Typically $V(F_t)\approx V(F_{t-1})=\sigma^2_{\text{gr}}$ (say), then the above can be reduced to $V(F_t - F_{t-1})\approx 2\sigma^2_{\text{gr}}(1-\rho_{\text{gr}})$. Similarly, $V(C_t - C_{t-1})\approx 2\sigma^2_{\text{rc}}(1-\rho_{\text{rc}})$. Thus the change efficiency is approximately the level efficiency times $(1-\rho_{\text{gr}})/(1-\rho_{\text{rc}})$. It follows that if the new predictors for composite estimation increase considerably the (positive) correlation between C_t and C_{t-1}, then the change efficiency will highly dominate the level efficiency.

4. Variance Estimation

The CLFS currently uses delete-one psu jackknifing to find variance of the gr-estimate. The method of jackknifing is valid (for cross-sectional surveys) if the psu-level estimates have identical mean and variance, and the psu selection can be treated as with replacement. When psu selection is without replacement the variance estimate becomes conservative if the (common) covariance between the psu-level estimates is negative. This is generally the case. For repeated surveys, a third condition that psu's are common (or connected) over time is needed. When this is the case the survey can be viewed as cross-sectional by treating the vector of observations (psu-level estimates) over time as a single observation collected at the conceptual end point in time. In the rotating panel design of the CLFS, psu's are not rotated out for a number of years, but the within psu units are rotated every six months. Each psu in the CLFS corresponds to a single panel which is either birth or non-birth. Note that to meet the conditions of jackknifing, it is not necessary that the same set of units be used to obtain psu-level estimates. The condition that psu-level estimates have common mean and variance within a stratum is reasonable on the grounds that the panel estimates have common mean and variance. For composite estimation, although birth and non-birth panels are treated differently, panel-level composite estimates should have identical mean and variance unconditionally on the panel assignment. This is so because the panels are assigned at random; a panel could have been birth with probability

$\gamma = 1/6$ and non-birth with probability $1-\gamma = 5/6$. The resulting unconditional variance estimate will not be smaller than the one obtained conditionally on the panel assignment. Thus the method of jackknifing is expected to provide a conservative variance estimate in the CLFS context. Note that the above considerations for measures of uncertainty do not involve rotation group bias that may be present.

5. Evaluation Results

The numerical results are based on 1996 Ontario CLFS data, see Singh, *et al.* (1997). The auxiliary variables for gr are population counts corresponding to 16 age-sex groups, 11 economic regions, 10 census metropolitan areas, and 6 panels. Each panel control specifies 1/6 of the 15+ population. The new controls (30 in all) for rc corresponding to only change-driven predictors are: employed, unemployed and not in the labour force by age (young and old) by sex groups for a total of 12, employment by industry categories for a total of 16, and 2 employment by full/part time categories. In fact, these 30 new controls reduce to only 28 because of linear dependence. The multivariate rc-estimator involves these 28 extra controls, while the univariate rc involves just one extra control. The average relative efficiency shown in various tables is computed as the average variance of gr over 12 months of 1996 divided by the average variance of the composite estimator over 12 months.

5.1 Macro-level *vs.* Micro-level Predictors

For level-estimates, the correlation is computed between the current month level estimate (*i.e.*, F_t) and the predictor (*e.g.*, the level-driven $C_{t-1} - \bar{D}_{t-1}$ at the macro-level), whereas for the change estimate, it is computed between $F_t - C_{t-1}$ and the predictors. The correlation is negative as expected because the estimate involving common panels is positively correlated with F_t but expressed with a negative sign in the predictor. Recall that the composite estimator used is the *ak* with macro-level and ak^* with micro-level predictors.

It is seen from Table 1 for the four key variables (employed, unemployed, employed in Trade, and employed in Transportation and Communication (TRCO)), for each of the level-driven and change-driven predictors, micro-level predictors outperform macro-level in terms of high correlation.

Between level- and change-driven predictors at the micro-level, change-driven is seen to out-perform level-driven. Similar results hold for other key variables. In view of these correlations, other evaluation results shown below pertain to only *ak*2, ak^*2, and rc2 versions of composite estimates. The rc-estimator with both level- and change-driven predictors was not included in the interest of keeping down the number of extra controls.

5.2 *ak vs.* ak^* *vs.* rc (Efficiencies Relative to gr)

Table 2 shows the optimal coefficients (*e.g.*, *k* for *ak*2 estimator) and the corresponding relative efficiency over gr. The optimal coefficients were found via grid-search using the same 1996 data. (In practice, this should be based on past data). It is seen that the efficiency gains can be considerable as one moves from *ak* to ak^*. The optimal coefficients vary for level and change estimates. The last two columns under each of level and change estimates show the reduction in efficiency if level-optimal coefficients are used for change estimates and vice-versa. Level-optimal coefficients seem to perform quite well for change estimates, in contrast to a drop in efficiency of level estimates when change-optimal coefficients are used.

Table 1
Average Monthly Correlation between Composite Predictor and Estimates for Level and Change (Ontario, 1996)

	Level				Change			
	Level-Driven Predictors		Change-Driven Predictors		Level-Driven Predictors		Change-Driven Predictors	
Variable	Macro	Micro	Macro	Micro	Macro	Micro	Macro	Micro
Employed	-0.27	-0.35	-0.23	-0.45	-0.35	-0.49	-0.57	-0.84
Unemployed	-0.26	-0.35	-0.24	-0.33	-0.22	-0.40	-0.39	-0.53
Empl. Trade	-0.58	-0.55	-0.58	-0.65	-0.65	-0.73	-0.91	-0.96
Empl. TRC0	-0.58	-0.55	-0.60	-0.68	-0.63	-0.70	-0.92	-0.96

Table 2
Average Relative Efficiency of *ak* and ak^* over gr (Ontario, 1996)

	Coeff				Eff (Level)		Eff (Change)		Eff (Level)	Eff (Change)
	Level Optimal		Change Optimal		Level Optimal		Change Optimal		Change Optimal	Level Optimal
Variable	*ak*	ak^*	*ak*	ak^*	*ak*	ak^*	*ak*	ak^*	ak^*	ak^*
Employed	0.42	0.72	0.48	0.95	1.05	1.25	1.28	2.43	0.72	2.21
Unemployed	0.40	0.50	0.54	0.69	1.06	1.12	1.11	1.29	1.05	1.26
Empl. Trade	0.79	0.84	0.95	0.98	1.43	1.67	2.36	4.97	0.88	4.22
Empl. TRC0	0.84	0.87	0.95	0.98	1.59	1.88	3.60	7.59	1.11	6.51

Table 3 compares rc (univariate and multivariate) with ak^*. The possible values of $b_{t(\mathrm{rc2})}$ coefficients over the 12 month-period for the univariate rc2 are summarized via mean, minimum and maximum. They can be compared with the corresponding optimal coefficients for ak^*. The rc-coefficients seem to provide a compromise and lie somewhere between level-optimal and change-optimal coefficient values. The rc-efficiencies for the change estimate are quite at par with those for ak^* but for level estimates, are somewhat lower. The efficiency gains at the aggregate level for which gr had controls are low but are high for domains without gr-controls.

Table 4 presents possible loss in efficiencies for estimates obtained as residuals in ak^*-estimation in the interest of internal consistency. It shows that caution should be exercised in practice when choosing variables for residual estimation or using compromise coefficient values in ak^*-estimation of components of an aggregate.

5.3 Change *vs.* Level Efficiencies of rc Over gr

Table 5 shows that the approximate relation (see section 3) between change and level efficiencies holds fairly well. It is seen that month-to-month correlation for rc-estimates for domains not having a corresponding population control in gr can be quite high compared to the correlation for gr. This, in turn, yields a high factor by which change efficiency exceeds level efficiency.

5.4 Point Estimate and SE of Difference Between rc and gr

Table 6 shows monthly estimates (and SE of level and change estimates) for the variable (employed in trade at the Ontario level) for gr and rc. The corresponding values for the monthly difference (rc -gr) are also shown. It is seen that the differences between rc and gr are not significant in general. Efficiencies (not shown here) of annual average and quarterly estimates of rc and gr were also computed. As expected, due to serial correlation, there may be a loss in efficiency over gr. However in terms of the coefficient of variation, this is likely to be of no practical consequence.

5.5 Time Series of Level Estimates

Figures 1(a) and (b) show level estimates of employment for Ontario for the period 88-96 for gr and rc without and with seasonal adjustment. (The X11-ARIMA method was used.) Figures 2(a) and (b), show employment for the industry group "Trade". At the provincial level, aggregated over the industry group, there is similarity between gr and rc (seasonally adjusted or not) series because the gr-estimates have high precision to begin with. At the domain

Table 3
Average Relative Efficiency of rc over gr (Ontario, 1996)

	Coeff							Eff (Change)	
	rc-univariate (level or change)			ak^*					
Variable	Avg	Min	Max	Level	Change	rc (univariate)	rc (multivariate)	rc (univariate)	rc (multivariate)
Employed	0.88	0.81	0.90	0.72	0.95	1.05	1.05	2.39	2.46
Unemployed	0.60	0.53	0.65	0.50	0.69	1.12	1.12	1.31	1.33
Empl. Trade	0.96	0.94	0.98	0.84	0.98	1.17	1.22	4.98	5.07
Empl. TRC0	0.95	0.93	0.97	0.87	0.98	1.37	1.42	7.47	7.52

Table 4
Average Relative Efficiency of ak^* and rc over gr from Ontario, 1996 (Regular *vs.* Residual)

		Level			Change		
Variable		ak^* Coeff	Eff (ak^*)	Eff (rc)	ak^* Coeff	Eff (ak^*)	Eff (rc)
Agriculture	(regular)	0.91	2.55	2.32	0.97	4.88	5.22
Agriculture	(residual)	NA	0.63	2.32	NA	3.90	5.22
NILF	(regular)	0.74	1.26	1.07	0.95	1.96	2.01
NILF	(residual)	NA	1.21	1.07	NA	1.95	2.01

Table 5
Relation Between Level and Change Efficiencies for rc (multivariate) over gr (Ontario, 1996)

Variable	Change Eff	Level Eff	Change Eff/Level Eff	$(1-\rho_{gr})$ $(1-\rho_{rc})$	ρ_{gr}	ρ_{rc}
Employed	2.46	1.05	2.34	2.65	0.77	0.91
Unemployed	1.33	1.12	1.19	1.21	0.50	0.59
Empl Trade	5.07	1.22	4.16	3.80	0.79	0.95
Empl TRCO	7.54	1.42	5.31	5.66	0.80	0.97

Table 6
Monthly Point Estimates for gr and rc and Their Differences (Ontario, 1996)
(Level and Change for Employment in Trade, Ontario, 1996)

Month	Type	gr		rc		rc-gr	
January	Level	886.5	(21.0)	858.9	(17.3)	-27.6	(23.0)
	Change	-25.8	(13.2)	-21.0	(5.6)	4.8	(11.4)
February	Level	906.5	(22.9)	867.9	(17.6)	38.6	(24.6)
	Change	20	(14.2)	9.0	(4.7)	-11.0	(12.5)
March	Level	927.1	(20.8)	874.1	(18.3)	-52.9	(23.1)
	Change	20.6	(13.3)	6.2	(4.7)	-14.4	(12.5)
April	Level	914.8	(20.3)	872.5	(17.7)	-42.3	(22.4)
	Change	-12.3	(13.4)	-1.6	(5.1)	10.7	(12.5)
May	Level	912.8	(18.9)	887.6	(17.0)	-25.1	(21.8)
	Change	-2.1	(13.0)	15.1	(5.7)	17.2	(11.6)
June	Level	908.1	(17.8)	888.6	(17.2)	-19.5	(21.5)
	Change	-4.7	(12.3)	0.9	(4.9)	5.6	(11.9)
July	Level	899.9	(18.1)	881.2	(17.7)	-18.7	(23.0)
	Change	-8.2	(12.8)	-7.4	(6.7)	0.8	(10.7)
August	Level	913.9	(16.9)	888.1	(18.3)	-25.8	(22.6)
	Change	14.0	(11.5)	6.9	(5.3)	-7.1	(10.3)
September	Level	886.6	(20.4)	876.4	(19.7)	-10.2	(23.1)
	Change	-27.3	(12.6)	-11.8	(6.3)	15.6	(11.1)
October	Level	898.6	(22.9)	889.3	(19.3)	9.3	(26.1)
	Change	12.1	(13.4)	12.9	(6.6)	0.9	(11.8)
November	Level	911.2	(20.3)	902.3	(19.3)	-8.9	(25.9)
	Change	12.6	(13.9)	13.0	(7.0)	0.4	(12.6)
December	Level	917.9	(20.5)	916.3	(19.0)	-1.5	(26.0)
	Change	6.7	(12.5)	14.0	(6.1)	7.4	(10.9)

Note: SEs are shown in parentheses.

level defined by Trade, however, the series are quite different. (Note that among numerous series that were examined, this particular series was chosen here to depict the extreme scenario for gaps between gr and rc series. For almost all other series, the two series crossed each other fairly often.) Since the gr-series is highly volatile, there is room for considerable smoothing by rc. Also note that because of expected high signal-to-noise ratio, seasonally adjusted rc series at the Trade-domain level looks considerably smoother than that for the gr-series; in fact, there is very little difference between with and without seasonally adjusted gr-series. It is also observed that there tends to be runs of consecutive periods where rc is either larger or smaller than gr. This is expected because of high values of the $b_{t(\mathrm{rc})}$ coefficients (Table 3), and high serial correlation in both series (see Table 5). Interestingly, turning points in the gr and rc series tend to occur at (approximately) same time points though they appear somewhat dampened with rc due to higher serial correlation in rc-series. It may be noted that the gap between the two series would have been smaller if controls for level- driven predictors were also included.

6. Concluding Remarks

The previously used gr-estimator in CLFS showed instability in change estimates and various domain level estimates. The rc-estimator provides smoother estimate series (which, in turn, renders change estimates more stable). The rc-method departs from the traditional *ak*-composite estimation in several ways, the main points being the use of micro-matching for collection of unit-level past information for common panels, and the use of regression calibration (like gr) to produce a set of final weights for use with all study variables. Three versions of rc were examined. Although this paper was mainly concerned with rc2, *i.e.*, with change-driven predictors (because of the desired resulting smoothness in estimate series), it was found (although not reported here) that level estimates of some key variables can be further improved (in comparison to rc2) by including corresponding level-driven predictors. Thus, in practice, a good strategy might be to use a mixture of mostly change-driven and some level-driven predictors.

The version of the rc-estimator currently implemented for CLFS was suggested by Fuller (1999), and can be expressed as

Figure 1(a) Employment in Ontario, actual

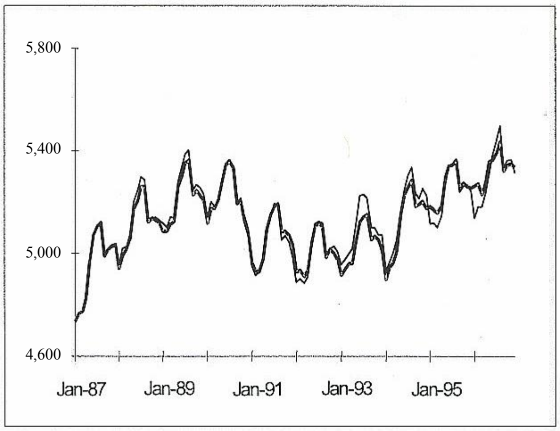


Figure 1(b) Employment, Ontario, seasonally adjusted

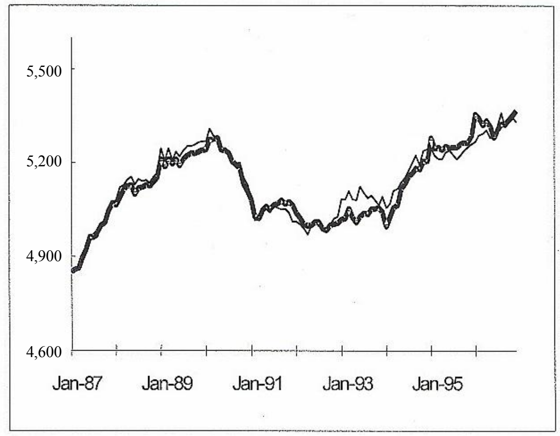


Figure 2(a) Employment in Trade, Ontario, actual

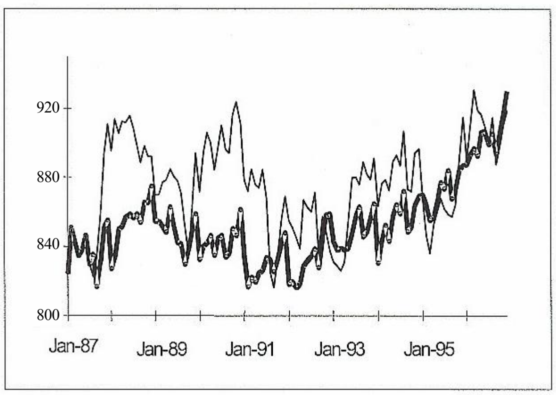
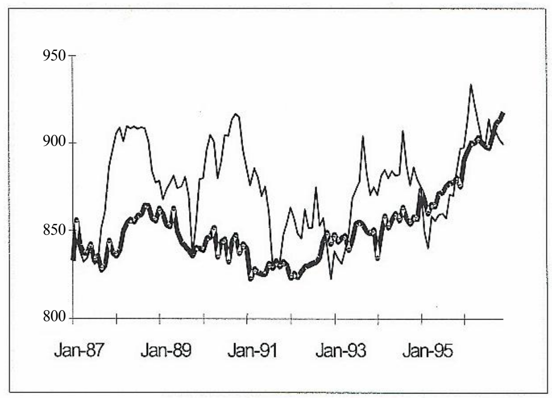
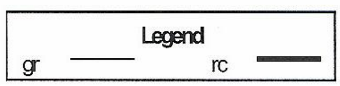


Figure 2(b) Employment in Trade, Ontario, seasonally adj.





$$C_{t(\text{rc}\alpha)} = F_t + b_{t(\text{rc}\alpha)}[(1-\alpha)(\tilde{C}_{t-1(\text{rc}\alpha)} - \bar{D}^*_{t-1} + \bar{B}_t - F_t) + \alpha(\tilde{C}_{t-1(\text{rc}\alpha)} - \bar{D}^*_{t-1})] \quad (6.1)$$

where α is prescribed (1/3, say, but in general could be y-specific), and the coefficient $b_{t(\text{rc}\alpha)}$ is computed using the gr-system as in rc-class of estimates. A simple interpretation of (6.1) can be obtained by comparing with the ak^*-estimator of (3.7). First write (3.7) as

$$C_{t(ak^*)} = F_t + k^*[(1-a^*/k^*)(\tilde{C}_{t-1(ak^*)} - \bar{D}^*_{t-1} + \bar{B}_t - F_t) + (a^*/k^*)(\tilde{C}_{t-1(ak^*)} - \bar{D}^*_{t-1})]. \quad (6.2)$$

Now, for (6.1), α can be roughly viewed as the ratio of the two optimal coefficients a^*, k^*, and the factor k^* outside the square brackets of (6.2) is replaced by the (suboptimal) regression coefficient $b_{t(\text{rc}\alpha)}$. Thus $C_{t(\text{rc}\alpha)}$ is not equivalent to the optimal ak^*-estimator, but some optimality could be preserved (if α is made y-specific) in setting the relative contribution of change and level driven predictors. Note, however, that the problem of internal inconsistency as mentioned in the introduction might arise if α is y-specific. Other attractive features of this version are that the value of α can be chosen to be well bounded away from zero (this should help to avoid sustained gaps between gr and rc series), and the number of extra controls is not doubled when both level and change driven predictors are included, thus allowing for introducing more controls as well as more degrees of freedom in variance estimation.

As a diagnostic of the impact of bias due to imputation of the previous month's employment status in view of the nonresponse of some of the present month respondents, the following simple check can be performed. The basic idea is to compute a multiplicative bias adjustment factor to the estimator $\bar{D}^{*}_{t-1}$ involving imputed values. The factor is defined as the ratio of two gr-estimators of the previous month's characteristic based on the matched subsample. The denominator is a gr-estimator for the previous month (involving imputed values) while the numerator is a gr-estimator for the previous month (not involving imputed values), both computed in a somewhat nonstandard way. For the numerator, we use the time $t-1$ respondents with their time $t-1$ responses, and after nonresponse adjustment of the design weights, construct the gr-estimator with controls for time t. For the denominator, we assume that the subsets of each of the matched subsamples at $t-1$ and t (here the matching is done with respect to each other, one forward in time and the other backward) not having the counterpart because of nonresponse, are statistically exchangeable with respect to each other. We then replace the time $t-1$ respondents who did not respond at time t by the time $t-1$ nonrespondents who responded at t, along with their imputed time $t-1$ responses as well as design weights. Now the nonresponse, and gr-poststratification (with controls for t) weight adjustments are redone for this modified full sample at $t-1$. The gr-weights so obtained are used to compute the denominator mentioned above. One can now look at the time series of this factor over several months for diagnostics on the bias due to imputation. If this is not deemed close to one, then the average of the factor over several months can be treated as a nonrandom multiplicative bias adjustment to $\bar{D}^{*}_{t-1}$. In practice, instead of adjusting $\bar{D}^{*}_{t-1}$, it would be preferable computationally to adjust the new control $\tilde{C}_{t-1(\mathrm{rc})}$ (of equation 3.6) for the corresponding characteristic by inverse of the above multiplicative factor. Alternatively, the need for imputation can be avoided altogether if the questionnaire can be modified to obtain the necessary past information as suggested in the introduction.

The study of Lent, Miller and Cantwell (1994, 1996) considers the *ak*-composite weighted estimator for the U.S. Current Population Survey as an alternative to the currently used *ak*-estimator with $a = 0.2$, $k = 0.4$. Based on our experience with ak^{*}, it may be recommended that the ak^{*}-composite weighted estimator might be a better alternative in the interest of efficiency gains.

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References

Bailar, B.A. (1975). The effect of rotation group bias on estimates from panel surveys. *Journal of the American Statistical Association*, 70, 23-29.

Binder, D.A., and Hidiroglou, M.A. (1988). Sampling in time. *Handbook of Statistics*, 6: Sampling, Elsevier Science, NY, 187-211.

Cassel, C.M., Särndal, C.-E. and Wretman, J.H. (1976). Some results on generalized difference estimation and generalized regression estimation for finite populations. *Biometrika*, 63, 615-620.

Cochran, W.G. (1977). *Sampling Techniques*. 3rd edition. John Wiley & Sons, Inc.

Fuller, W.A. (1990). Analysis of repeated surveys. *Survey Methodology*, 16, 167-180.

Fuller, W.A. (1999). The Canadian Regression Composite Estimation. Unpublished manuscript.

Godambe, V.P., and Thompson, M.E. (1989). An extension of quasi-likelihood estimation (with discussion). *Journal Statistical Planning and Inference*, 22, 137-172.

Gurney, M., and Daly, J.F. (1965). A multivariate approach to estimation in periodic sample surveys. *Proceedings of the Survey Research Methods Section*, American Statistical Association, 247-257.

Hansen, M.H., Hurwitz, W.N. and Madow, W.G. (1953). *Sample Survey Methods and Theory*, 2. New York: John Wiley & Sons, Inc.

Kumar, S., and Lee, H. (1983). Evaluation of composite estimation for the Canadian Labour Force Survey. *Survey Methodology*, 9, 178-201.

Lent, J., Miller, S. and Cantwell, P. (1994). Composite weights for the current population survey. *Proceedings of the Survey Research Methods Section*, American Statistical Assocation, 867-872.

Lent, J., Miller, S. and Cantwell, P. (1996). Effects of composite weights on some estimates from the Current Population Survey. *Proceedings of the Section Survey Research Methods*, American Statistical Association, I, 130-139.

Liang, K.-Y., and Zeger, S.L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, 73, 13-22.

Rao, J.N.K., and Graham, J.E. (1964). Rotation designs for sampling on repeated occasions. *Journal of the American Statistical Association*, 59, 492-509.

Särndal, C.-E. (1980). On π-inverse weighting versus best linear unbiased weighting in probability sampling. *Biometrika*, 67, 639-650.

Singh, A.C. (1994). Sampling-design-based estimating functions for finite population totals. Invited paper, *Abstracts of the Annual Meeting of the Statistical Society of Canada*, *Banff*, Alberta, May 8-11, p. 48.

Singh, A.C. (1996). Combining information in survey sampling by modified regression. *Proceedings of the Survey Research Methods*, American Statistical Association, 1, 120-129.

Singh, A.C., and Folsom, R.E. Jr. (2000). Bias corrected estimating functions approach for variance estimation adjusted for poststratification. *Proceedings of the Survey Research Methods*, American Statistical Association, 610-615.

Singh, A.C., Kennedy, B., Wu, S. and Brisebois, F. (1997). Composite estimation for the Canadian Labour Force Survey. *Proceedings of the Survey Research Methods Section*, American Statistical Association, 300-305.

Singh, A.C., and Merkouris, P. (1995). Composite Estimation by modified regression for repeated surveys. *Proceedings of the Survey Research Methods Section*, American Statistical Association, 420-425.

Wolter, K.M. (1979). Composite estimation in finite populations. *Journal of the American Statistical Association*, 74, 604-613.