COMPOSITE ESTIMATION FOR THE CANADIAN LABOUR FORCE SURVEY

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1. INTRODUCTION

The Canadian Labour Force Survey (LFS) is a monthly survey that follows a rotating panel design with six panels. In any two consecutive months, five sixth of the households form an overlapping sample. For the currently used generalized regression (GR) estimator, it has been observed that estimates of month to month change can be quite volatile. To alleviate this problem it seems natural to use correlated past data to improve the efficiency of the GR-estimator. The AK-composite estimator of Gurney and Daly (1965) uses past data in the form of macro-level estimates for full and overlapping samples. Consideration was given to using this estimator for the LFS, but the idea was dropped for several reasons. The optimal choice of the coefficients (A,K) is not the same for level and change estimates. Consistency with demographic counts is not ensured making it necessary to obtain some estimates sub-optimally as residuals. Similarly, to ensure that component estimates add up to the aggregate composite estimate, the estimate for one component is obtained as a (sub-optimal) residual. (This assumes optimal coefficients are used for all but one component estimates and would not be necessary if common AK values are used.) Moreover, AK estimates are not readily available for unplanned study variables. There is no such problem if one can produce a set of final weights to be used for expansion estimates of all variables. Based on Fuller (1990), the AK-weights can be computed via an additional regression calibration step in which AK estimates are used as controls along with the usual GR-controls. Finally, even with optimal AK, the gains in efficiency for some variables may be marginal; Kumar and Lee (1983).

As an alternative to GR, we examine the recently developed method of Modified Regression (MR) by Singh (1994,1996). MR is similar to GR because past month's unit (i.e. micro) level information on key study variables for the common sample is augmented to the current month data. Previous month's full sample estimates serve as regression controls after adjustment for changes in the demographic population totals. There is no problem with internal consistency with MR-composite estimates, because for all key variables, estimates are obtained simultaneously using all the control totals. A set of final weights is obtained so that estimates for other study variables can be easily obtained as expansion estimates.

In terms of efficiency gains, results of the numerical study using the LFS data, suggest that they can be substantial for change estimates and reasonably high for level estimates, for the controlled variables. However, for the non-controlled variables there may be no or marginal gains in efficiency.

In the paper, another version termed AK* is examined which was motivated by the favourable performance of micro-level use of past information. It was found from the numerical study that the efficiency of AK can be considerably improved by using AK*. However, the other limitations of AK carry over to AK*.

The organization of this paper is as follows. Section 2 provides a review of GR and AK. Section 3 describes AK* and MR. Section 4 outlines the method of variance estimation. Evaluation results for various methods are given in Section 5. Behaviour of estimates over time is discussed in Section 6. The empirical results are based on Ontario LFS data for the period 1996. The period 1988 to 1996 is used for time series analysis. Finally, Section 7 contains concluding remarks.

2. GR AND AK: REVIEW

Consider the GR estimator:

$$F_{GR} = \hat{T}_y + \hat{\beta}_{GR}^T(T_x - \hat{T}_x)$$

where T_x is a p-vector of population totals, and $\hat{T}_x$ is the corresponding vector of Horvitz-Thompson estimates,

$$\hat{T}_{x_j} = \Sigma_{k\in s}\, x_{jk} d_k$$

where d_k is the inverse inclusion probability and j refers to the j^{th} element of the p-vector and

$$\hat{\beta}_{GR}^T = y^T DX(X^T DX)^{-1}, \qquad D = \mathrm{diag}(d_k).$$

Here, y is the n-vector of y-observations, and X is the n x p matrix of x-observations. The letter F in F_{GR} signifies that the estimator is based on the full sample. F_{GR} can be expressed as an expansion estimator with GR-weights w_k^{GR}, i.e:

$$F_{GR} = \Sigma_{k\in s}\, y_k w_k^{GR}$$

where $w = d + DX(X^T DX)^{-1}(T_x - \hat{T}_x)$. The sample at each month t consists of six panels. Let i denote the tenure in sample for the i^{th} panel, i = 1, ..., 6. Let s_i denote the sample for the i^{th} panel. The full sample GR-estimator can be written in terms of part sample GR-estimates based on panels as:

$$F_{GR} = (P_1 + \ldots + P_6)/6 \ , \quad P_i = 6\Sigma_{k\epsilon s_i} y_k w_k^{GR},$$

Also, the GR estimate based on the common sample can be expressed as

$$P_{-1} = (6/5)\Sigma_{k\notin s_1} y_k w_k^{GR} = (P_2 + \ldots + P_6)/5$$

Let $t' < t$ denote two consecutive months, and P_i' be the i^{th} panel GR-estimate for the variable y' at t'. The common sample for months t' and t consists of panels $\{1,2, \ldots, 5\}$ at time t' and $\{2, \ldots, 6\}$ at time t. The GR-estimate of y' based on the part sample common with month t is :

$$P'_{-6} = (6/5)\Sigma_{k\notin s_6} y_k' w_k'^{GR} = (P'_1 + \ldots + P'_5)/5$$

Let F' denote the full sample estimate for y' at t'. It is GR at time $t'=1$ and a composite estimator at time $t'>1$. Treating F' like the population total T_x in the usual GR, we can define two extra predictors using the past auxiliary information about y':

$$F' - P'_{-6} \ , \qquad (F' - F) - (P'_{-6} - P_{-1})$$

The first predictor will be termed as level-driven as it is a difference between two level estimates. The second predictor is termed as change-driven as it is a difference between two change estimates. It can also be interpreted as a difference between two level estimates F' and $F + (P'_{-6} - P_{-1})$ where the second estimate is the current month's estimate adjusted for change based on the common sample. For y at time t , the AK composite estimate, F_{AK} , is defined as:

$$F_{GR} + \beta_{AK1}(F' - P'_{-6}) + \beta_{AK2}(F' - (F + P'_{-6} - P_{-1}))$$

where the coefficients are chosen to minimize the variance. If only one of the predictors is used, the terms AK_1- and AK_2-composite estimates will be used. In the literature AK_2 is also known as the K-composite estimator of Hansen, Hurwitz and Madow (1953). Note that the estimator F_{AK} uses past information in the univariate sense in that for the study variable y, past information about only y' is used. If extra predictors based on several variables such as y', z', ... from the past are also used for the study variable y, then the approach will be termed multivariate. In this case, the optimal choice of the AK coefficients can be quite cumbersome. With AK estimates of a set of key variables, final weights $\{w_k^{AK}\}$ can be constructed via a regression calibration step as mentioned earlier.

3. AK* AND MR: NEW METHODS.

We define the modified predictors as given in Singh (1996) as

$$F^{*\prime} - P^{*\prime}_{-6} \ , \qquad F^{*\prime} - (F + P^{*\prime}_{-6} - P_{-1})$$

where

$$P^{*\prime}_{-6} = (6/5)\Sigma_{k\notin s_1} y'_k w_k^{GR} \ (\neq P'_{-6} = (6/5)\Sigma_{k\notin s_6} y'_k w'^{GR}_k).$$

It is assumed here that y_k' is available for all current month's respondents in the common sample. The full sample estimate F' is also transformed to $F^{*\prime}$ to reflect possible changes in demographic controls from t' to t, because $P_{-6}^{*\prime}$ now estimates current population totals for the previous months characteristic y'. If F' is expressed as an expansion estimator with composite weights $\{c_k'\}$, then one can preform regression-calibration on $\{c_k'\}$ to obtain $\{c_k^{*\prime}\}$ to satisfy current months demographic controls. The AK*-composite estimator, F_{AK^*}, is defined as

$$F_{GR} + \beta_{AK^*1}(F^{*\prime} - P^{*\prime}_{-6}) + \beta_{AK^*2}(F^{*\prime} - (F + P^{*\prime}_{-6} - P_{-1}))$$

where the AK* coefficients are chosen to minimize the variance. Analogous to AK, we can have three versions: AK^*_1, AK^*_2 and AK^*.

Instead of finding optimal coefficients in AK*, which is complicated by the fact it depends on whether the study variable is level or change, a compromise would be to use sub-optimal coefficients as is the case with GR. This is possible with the new predictors because $F^{*\prime}$ can be treated as a new GR-control and the other term in the predictor can be expressed as an expansion estimator with the current GR-weights. This defines the Modified Regression Composite Estimator, F_{MR} , as

$$F_{GR} + \beta_{MR1}(F^{*\prime} - P^{*\prime}_{-6}) + \beta_{MR2}(F^{*\prime} - (F + P^{*\prime}_{-6} - P_{-1}))$$

In the MR-formulation, the coefficients are obtained in a manner similar to GR and do not change when estimating level or change. As with AK, we can have three versions, MR_1, MR_2 and MR. MR_1 is the estimator considered by Singh and Merkouris (1995).

Another advantage with MR is that it is fairly easy to introduce more predictors. This will yield the multivariate version of MR. The regression weight- calibration can be adapted to get a single set of MR-weights, $\{w_k^{MR}\}$ which satisfy all the new controls $F^{*\prime}$ for a set of key variables, as well as the usual GR-controls. The multivariate MR-composite estimator (for the variable y belonging to the set of key variables used as controls) is given by

$$F_{MR} = \Sigma_{k\epsilon s}\, y_k w_k^{MR}$$

For any variable not included in the set of key variables, the expansion estimator with the MR weights can still be used. Although MR uses sub-optimal regression, it preforms quite well in terms of efficiencies of level and change estimates (see Section 5).

4. VARIANCE ESTIMATION

The LFS currently uses delete-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 current time. In the rotating panel design of the LFS, 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 LFS 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 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 1/6 and non-birth with probability 5/6. The resulting unconditional variance estimate would be, in general, larger than the one obtained conditionally on the panel assignment.

5. EVALUATION RESULTS

The numerical results are based on 1996 Ontario LFS data. 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 extra controls for MR are: employed, unemployed and not in the labour force by age by sex groups for a total of 12, 9 employment by industry categories, and 2 employment by full/part time categories. 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_{GR}) and the predictor (e.g., the level-driven $F'_{comp} - P'_{-6}$ at the macro-level), whereas for the change estimate, it is computed between $F_{GR} - F_{comp}$ and the predictors. The correlation is negative as expected because the estimate involving common panels is positively correlated with F_{GR} but expressed with a negative sign in the predictor. Recall that the composite estimator is used in 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 MR_2 versions of composite estimates.

5.2 AK vs. AK* vs. MR(Efficiencies Relative to GR)

Table 2 shows the optimal coefficients (e.g., β_{AK2} 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 3 compares MR (univariate and multivariate) with AK*. The possible values of β_{MR2} coefficients over the 12 month-period for the univariate MR_2 are summarized via mean, minimum and maximum. They can be compared with the corresponding optimal coefficients for AK*. MR-coefficients seem to provide a compromise and lie somewhere between level-optimal and change-optimal coefficient values. The MR-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 MR over GR

To help understand the higher efficiency gains obtained for estimates of change, consider a simple identity: $V(F-F')=V(F)+V(F')-2\mathrm{Cov}(F,F')$. If we make the approximation $V(F)=V(F')$, then the above can be reduced to $V(F-F')\approx 2V(F)(1-\rho_{FF'})$. It follows that if the extra predictors for composite estimation increase the (positive) correlation between F and F′, then the change efficiency will dominate the level efficiency.

Table 5 shows that the approximate relation between change and level efficiencies holds fairly well. It is seen that month-to-month correlation for MR 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 Other Evaluations

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

6. 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 MR without and with seasonal adjustment(SA). (The X11-ARIMA method was used.) Figure 2(a) and (b), show employment for the industry group "TRADE". At the provincial level, there is similarity between GR and MR (SA or not) series because the GR estimates have high precision to begin with. For TRADE the series are quite different. Here the GR series are highly variable so there is room for improvement by MR. Also note that because of expected high signal-to-noise ratio, seasonally adjusted MR series at the domain level looks considerably smoother than GR; in fact there is very little difference between with and without SA of GR series. It is also observed that there tends to be runs of consecutive periods where MR is either larger or smaller than GR. This is expected because of serial correlation in both series. Finally turning points in the GR and MR series tend to occur at same time points though they appear somewhat dampened with MR due to high serial correlation in MR series.

7. CONCLUDING REMARKS

The currently used GR-estimator shows instability in change estimates and various domain level estimates. The MR-composite estimator provides smoother estimate series (which, in turn, renders change estimates more stable). The MR-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 MR can be used. Although this paper was mainly concerned with MR_2 ,i.e.,with change-driven predictors (because of the 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 MR_2) 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 study of Lent, Miller and Cantwell (1994, 1996) considers the AK-calibration 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 AK*-calibration might be a better alternative in the interest of efficiency gains.

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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. TRCO	-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)

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

Table 3 — Average Relative Efficiency of AK* and MR over GR (Ontario 1996)

	Level							Change						
	MR (univariate)				MR (multivariate)	AK*		MR (univariate)				MR (multivariate)	AK*	
Variable	Avg Coeff.	Min Coeff.	Max Coeff.	Eff	Eff	Opt. Coeff	Eff	Avg Coeff.	Min Coeff.	Max Coeff.	Eff	Eff	Opt. Coeff	Eff
Employed	0.88	0.81	0.90	1.05	1.05	0.72	1.25	0.88	0.81	0.90	2.39	2.46	0.95	2.43
Unemployed	0.60	0.53	0.65	1.12	1.12	0.50	1.12	0.60	0.53	0.65	1.31	1.33	0.69	1.29
Empl. Trade	0.96	0.94	0.98	1.17	1.22	0.84	1.67	0.96	0.94	0.98	4.98	5.07	0.98	4.97
Empl. TRCO	0.95	0.93	0.97	1.37	1.42	0.87	1.88	0.95	0.93	0.97	7.47	7.52	0.98	7.59

Table 4 — Average Relative Efficiency of AK* and MR over GR for Ontario 1996 (Regular vs. Residual)

		Level			Change		
Variable		AK* Coeff.	Eff (AK*)	Eff (MR)	AK* Coeff.	Eff (AK*)	Eff (MR)
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 MR over GR (Ontario '96)

Variable	Change Eff	Level Eff	Change Eff/Level Eff	$(1-\rho_{GR})/(1-\rho_{MR})$	ρ_{GR}	ρ_{MR}
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 and SE (Difference between GR and MR)
(Level and Change for Employment in Trade, Ontario 1996)

Month	Type	GREG	MR	MR-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	20.0 ± 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

Figure 1(a) Employment in Ontario, actual

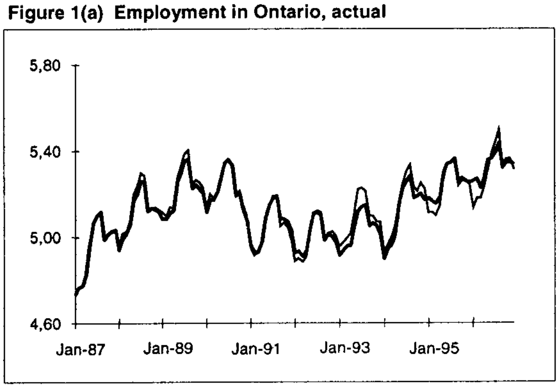

Figure 1(b) Employment, Ontario, seasonally adjusted

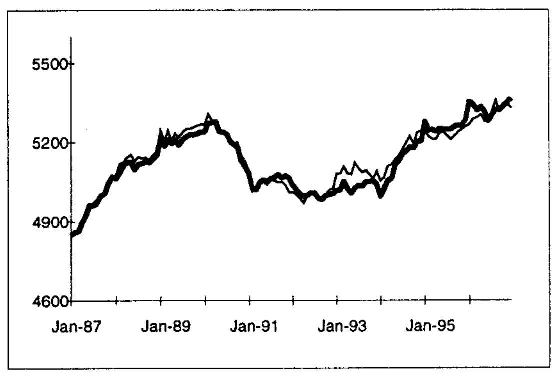

Figure 2 (a) Employment in Trade, Ontario, actual

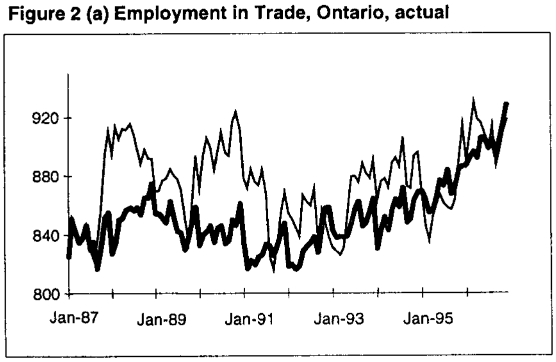

Figure 2(b) Employment in Trade, Ontario, seasonally adj.