Non-response Adjustment and Estimating Response Errors Using MLCA in Iranian Labor Force Survey

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Abstract

Measurement and non-response errors are among the principal non-sampling errors in surveys. Estimating these errors and devising appropriate control procedures for minimizing their effects on survey results is crucial for data quality and credibility of the resulting statistics among analysts and the public at large. In this paper, a non-response adjustment method in the ILFS (Iranian Labor Force Survey) will be proposed. Also, one type of measurement errors (classification error) using MLCA (Markov Latent Class Analysis) will be measured for economic activity status in ILFS.

Keywords: measurement errors; non-response adjustment; markov latent class analysis.

1. Introduction

Measurement error and non-response error are the most types of non-sampling errors in surveys. Despite good sampling design and interviewer best efforts to avoid non-response, it is an inevitable part of survey sampling. Since non-response error is a function of the response rate and the differences between respondents and non-respondents, it can lead to bias results if the response rate is low and/or respondents and non-respondents are dissimilar. There are different approaches to reduce or adjust this error. The most common approach to cope with this error is non-response adjustment. Alavi and Beaumont (2003) proposed a non-response adjustment strategy using logistic regression modeling in the Canadian Labour Force Survey. Another issue is measurement error which occurs when the answer to a question is inaccurate and departing from the true value. For many surveys, measurement error can also be the most damaging source of error. It includes errors arising from respondents, interviewers and survey questions which provide incorrect information. In some situations, when the data to be analyzed are categorical (either nominal or ordinal categories), the measurement errors in the observations are referred to classification errors or simply misclassification. Despite non-response error, the methods of estimating measurement errors are not simple. Different methods such as re-interview can be used as a true value to estimate the classification error (Sinclair and Gastwirth, 1998; Biemer and Forsman, 1992). Many researchers (Fuller and Chua, 1985; Sinclair and Gastwirth, 1998) used latent class (LC) modeling approach for evaluation and estimation of classification error. Also, MLC analysis offers a method to estimate the classification error in panel survey data. Wiggins (1973) first proposed MLC models, Poulsen (1982) refined the method and Biemer (2011), estimates the error in labor force data using MLCA. MLC analysis exploits the repeating nature of panel surveys to extract information on classification error from the interview data. It uses a combination of a latent Markov chain model representing the transitions among the true labor force classifications and a classification error model representing the deviations between the true and observed labor classifications.

In this paper, a non-response adjustment strategy based on the 2014 to 2016 data of the ILFS is proposed and a simulation study to compare the estimates of the relative bias (RB) for both current and proposed methods is performed. This paper also reports the findings regarding the validity of the MLC modeling approach for estimating labor force classification error for economic activity status in the ILFS. The ℓEM software (Vermunt, 1997) has been used to estimate this error.

The organization of this paper is as follows. A real data set of ILFS is explained in Section 2. In Section 3, a non-response adjustment strategy in the ILFS is presented. Section 4 describes the MLC model in the context of the ILFS and estimates the classification error. Finally, Section 5, summarizes the findings and recommends appropriate uses of the MLC method for evaluating labor force classification error. In Section 6, some conclusions are given.

2. Description of the ILFS

The Iranian Labour Force Survey (ILFS) which has been designed based on the International Labour Organization (ILO)'s recommendations [ILO; 2000] is a seasonal survey. It is a survey that interviews approximately 60,000 households each season based on a stratified multi-stage sampling plan. This survey was developed and conducted first in 2005 to obtain accurate statistics on the labor force at the level of country. The target population of ILFS is composed of all private settled households in the urban and rural areas of Iran. In order to estimate changes between periods, without losing efficiency of current level estimation, rotation sampling (according to the rotation pattern 2-2-2) is used. Weighting is carried out in three stages: (i) application of the base weight, (ii) adjustment of the weight for the unit non-response and (iii) adjustment of the weight based on population projections. This study covered the data collected on the spring 2014 up to fall 2016.

3. A Non-response Adjustment Strategy in the ILFS

The main approach to cope with non-response is adjusting non-response. The focus of this section is on adjusting non-response in ILFS. To achieve a successful non-response weighting, the non-response adjustment classes should be chosen appropriately. These classes should meet four criteria (International Handbook of Survey Methodology, 2008, chapter 3):

(a) response rates should vary over the classes;

(b) values of target variables should vary over the classes;

(c) respondents and non-respondents should be similar to one another within each class;

(d) class sample sizes should not be too small.

In most of the case, responding households are reweighted to compensate for the non-responding households. This reweighting is based on the assumption that the responding and non-responding households have the same characteristics within non-response adjustment classes. The weighting class adjustment (WCA) is the simplest approach which divides the sample into groups based upon variables that are known for both respondents and non-respondents and response rates often vary by these variables.

In ILFS, in the current strategy, weight of non-respondent household is adjusted within the sampled PSU and in rare cases that the whole 12 households within the sampled PSU are non-respondent, the weight of the non-respondent PSU is adjusted within the stratum that the PSU belongs to. In this paper, the proposed non-response weighting procedure includes partitioning the data into a number of non-response homogenous classes by geographical variables (such as provinces) and thematic variables (such as households size), and then reweighting based on the new class.

In order to compare the effect of reweighting for non-response adjustment on the non-response relative bias based on the current and proposed methods, a simulation study based on the following steps using data from respondent households in each quarter of ILFS from 2014 to 2016 was conducted:

1. In each quarterly ILFS data, based on the non-response rates for eligible units in each class (province, rotation group, region), the same non-response rates in respondent units for the same class, has been created. These non-response rates are created 2000 times to get 2000 pseudo samples. The number of categories in each class are: province (inc. 31 categories); rotation group (inc. 4 categories); region (inc. 41 categories: urban, rural, few capital cities);

2. Non-response adjustment classes based on current and proposed non-response (geographical and thematic variables include province, rotation group, region and household size (inc. 3 categories)) have been made.

3. Reweighting based on the current and proposed non-response adjustment classes have been applied separately on each pseudo sample.

4. Unemployment and economic participation rates have been estimated based on the current and non-

response adjusted weights, separately.
5. The estimates of the Relative Bias (RB) for both methods have been calculated using:

$$RB = [\frac{1}{2000}\sum_{i=1}^{2000}(\hat{\theta}_i - \theta)] \times \frac{1}{\theta} \times 100 \quad (1)$$

where $\hat{\theta}_i$ is the estimate of unemployment or economic participation rate for a given quarter after the reweighting on ith pseudo sample and θ is the unemployment or participation rate based on respondents answers before creating non-response for simulation from the ILFS sample. This simulation is performed for each quarter of 2014 to 2016 data of ILFS. Figure 1 presents the comparisons for each quarter of 2014 to 2016. It is clear that for most of the quarters, the proposed method reduces the non-response bias.

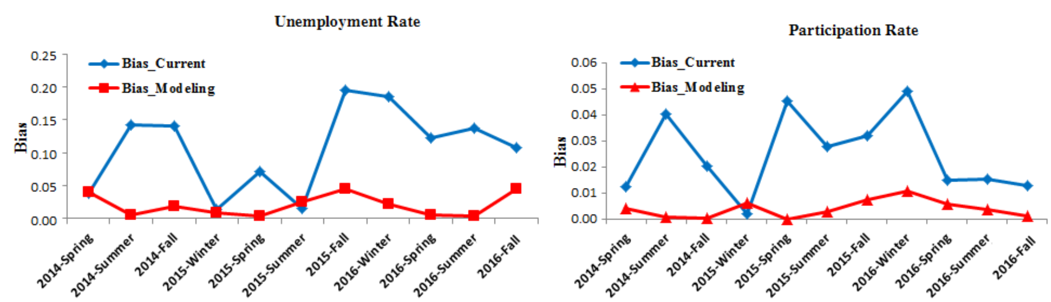

Figure 1: Comparison of relative bias of unemployment and participation rates for current and proposed methods, 2014-2016.

4. Measurement Errors and Markov Latent Class Models for Panel Data

Measurement errors can arise from interviewers, respondents, interview and setting and questionnaire. A type of measurement errors is classification error which occurs when the data to be analyzed are categorical. In this section, the method of estimating classification errors using MLCA (Biemer, 2011) which are appropriate for evaluating the measurement error in panel survey data without the need for special re-interview or response replication studies, will be illustrated.

4.1. Markov Latent Class Models for Panel Data

MLC analysis exploits the repeating nature of panel surveys to extract information on classification error from the interview data. Markov latent class models were first proposed by Wiggins (1973) and refined by Poulsen (1982). MLC analysis may be the only way to evaluate measurement error in panel surveys where a re-interview program is not possible. MLC analysis also allows bias estimation, while traditional re-interviews do not (Biemer and Bushery, 2001; Biemer, 2011).
Let A_t be the observed data at wave t and X_t denote the observable true value of A_t at wave t. Also, the cross-classification of the variable A at three waves is denoted by $A_1A_2A_3$. The MLC model contains two components: (1) the structural component ($\pi^{X_1X_2...X_T}_{x_1x_2...x_T}$) that describes the interdependencies between the X_t, $t = 1, ..., T$ and the model covariates (grouping variables) which represent the time-to-time transitions among the true classifications and (2) the error component ($\pi^{A_1A_2...A_T|X_1X_2...X_T}_{a_1a_2...a_T|x_1x_2...x_3}$) describing the interactions between A_t at each wave $t = 1, ..., T$ and X_t and other model covariates which represent the deviations between the true and observed classifications.
In MLC model, in order to have reduction in the number of parameters, the transition probabilities can be assumed to be stationary or time- homogeneous in which the transition probabilities are the same for any two consecutive (stationary transition probabilities).
Let $A_1A_2A_3$ denote the $K \times K \times K$ cross - classification table for the observations for n persons interviewed at waves 1, 2, and 3. Applying the Markov property on the structural component of the model ($\pi^{X_1X_2X_3}_{x_1x_2x_3}$), applying the Independent Classification Error (ICE) and homogeneous error probability assumptions on the measurement component ($\pi^{A_1A_2A_3|X_1X_2X_3}_{a_1a_2a_3|x_1x_2x_3}$) and under assumption of time - homogeneous classification error,

Table 1: Data from ILFS, cross - classification of three consecutive seasons (Fall 2013, Winter 2014 and Fall 2014).

		Fall 2014								
		EMP			UNE			INA		
	Winter 2014	EMP	UNE	INA	EMP	UNE	INA	EMP	UNE	INA
Fall 2013	EMP	6401	193	507	208	56	36	589	50	536
	UNE	179	111	60	35	157	76	32	65	130
	INA	366	55	762	29	50	263	387	129	14518

the joint probability that an individual is classified in cell (a_1, a_2, a_3) in the table is

$$\pi^{A_1A_2A_3}_{a_1a_2a_3} = \sum_{x_1}\sum_{x_2}\sum_{x_3} \pi^{X_1}_{x_1}\pi^{X_2|X_1}_{x_2|x_1}\pi^{X_3|X_2}_{x_3|x_2} \times \pi^{A|X}_{a_1|x_1}\pi^{A|X}_{a_2|x_2}\pi^{A|X}_{a_3|x_3}.$$

where x_1, x_2, x_3, a_1, a_2 and a_3 assume the values 1,2,...,K.
MLC models can be used by one or more grouping variables which are denoted by G with L levels. Grouping variable is used to identify an individuals membership in L population subgroups which lead to nonhomogeneous transition probabilities. Let π^g_G denote the proportion of the population belonging to group g, for $g = 1, ..., L$ and $GA_1A_2A_3$ denotes the LK^3 cross-classification table for the n sample members classified by G as well as their observed states for three panel waves. Then, in its most general form, the first - order MLC model specification of joint probability for cell (g, a_1, a_2, a_3), which is assumed that an individuals classification by G does not change over the waves and time homogeneous error probability assumption was hold ($\pi^{A|GX}_{a_1|gx_1} = \pi^{A|GX}_{a_2|gx_2} = \pi^{A|GX}_{a_3|gx_3}$), is

$$\begin{aligned}\pi^{GA_1A_2A_3}_{ga_1a_2a_3} &= \sum_{x_1}\sum_{x_2}\sum_{x_3}\pi^G_g \times \pi^{X_1X_2X_3|G}_{x_1x_2x_3|g} \times \pi^{A_1A_2A_3|GX_1X_2X_3}_{a_1a_2a_3|gx_1x_2x_3}. \\ &= \pi^G_g \sum_{x_1}\sum_{x_2}\sum_{x_3}\pi^{X_1|G}_{x_1|g}\pi^{X_2|GX_1}_{x_2|gx_1}\pi^{X_3|GX_2}_{x_3|gx_2} \times \pi^{A|GX}_{a_1|gx_1}\pi^{A|GX}_{a_2|gx_2}\pi^{A|GX}_{a_3|gx_3}.\end{aligned}$$

Instead of the probabilistic model, a loglinear model can be specified for $m_{x_1x_2x_3a_1a_2a_3}$, the expected frequency in cell $(x_1, x_2, x_3, a_1, a_2, a_3)$. The loglinear model is

$$logm_{x_1x_2x_3a_1a_2a_3} = u^{X_1}_{x_1} + u^{X_2}_{x_2} + u^{X_3}_{x_3} + u^{A_1}_{a_1} + u^{A_2}_{a_2} + u^{A_3}_{a_3} + u^{X_1X_2}_{x_1x_2} + u^{X_2X_3}_{x_2x_3} + u^{X_1A_1}_{x_1a_1} + u^{X_2A_2}_{x_2a_2} + u^{X_3A_3}_{x_3a_3}.$$

or, in shorthand notation, $\{X_1\}$ $\{X_1X_2\}$ $\{X_2X_3\}$ $\{X_1A_1\}$ $\{X_2A_2\}$ $\{X_3A_3\}$.

5. Application of the Markov Latent Class Analysis to the ILFS Data

A common application of the MLC model is to model the classification error in labor force survey panel data. Van de Pol and Langeheine (1997) applied this model to the Netherlands Labor Market Survey; Vermunt (1996) applies it to the US Survey of Income Program Participation (SIPP) labor force series and Biemer (2004) uses it to the CPS. In this section, the measurement errors will be estimated for ILFS using MLC analysis. We use three economic activity status categories (employed (EMP), unemployed (UNE), and inactive (INA)) and consider two consecutive seasons (fall 2013 and winter 2014) and fall 2014. Because of the 2-2-2 rotation pattern of ILFS, three consecutive seasons have not suitable overlap. Therefore, three consecutive seasons are not considered in this applied data set. Let X_1 denote an individual's true labor force status in fall 2013, ($X_1 = 1$ for EMP, $X_1 = 2$ for UNE, and $X_1 = 3$ for INA). We define X_2 and X_3 analogously for winter 2014 and fall 2014. Similarly, A_1, A_2 and A_3 denote the observed labor force status for fall 2013, winter and fall 2014, respectively, with the same categories as their corresponding latent counterparts. In this part, the estimated economic activity status classification probabilities are also determined by grouping variables. For grouping variables, gender, region (urban, rural) and self - proxy response are considered. The self - proxy variable is an indicator of whether a subject's economic activity status was obtained from the subject himself/herself or from another person in the household (proxy).
To illustrate the MLC model, consider the data in Table 1, which are unweighted frequencies from Fall 2013,

Table 2: Estimated labor force classification probabilities for the stationary transition probability and time - homogeneous error probability MLC model by gender, area, self - proxy groups.

		Model I	Model II					
			Gender		Area		Respondent	
True Classification	Observed Classification	Total	Male	Female	Urban	Rural	Self	Proxy
EMP	EMP	0.9246	0.9400	0.8082	0.9418	0.9061	0.9208	0.9269
	UNE	0.0194	0.0186	0.0085	0.0179	0.0198	0.0156	0.0210
	INA	0.0560	0.0414	0.1833	0.0403	0.0741	0.0636	0.052
UNE	EMP	0.1496	0.2016	0.0476	0.1331	0.1999	0.0991	0.1697
	UNE	0.6207	0.6049	0.5862	0.6323	0.5789	0.7166	0.6017
	INA	0.2297	0.1935	0.3662	0.2346	0.2213	0.1842	0.2286
INA	EMP	0.0289	0.0478	0.0190	0.0191	0.0434	0.0261	0.0311
	UNE	0.0078	0.0128	0.0055	0.0093	0.0053	0.0048	0.0094
	INA	0.9632	0.9393	0.9755	0.9716	0.9513	0.9692	0.9594
BIC		80003.90	45374.56	24824.16	44134.92	35667.34	27634.03	51891.52
AIC		79889.59	45270.27	24719.25	44028.46	35564.87	27532.73	51784.26

Table 3: Estimated labor force classification probabilities for the non-stationary transition probability and time - homogeneous error probability MLC model by gender, area, self - proxy groups.

		Model III	Model IV					
			Gender		Area		Respondent	
True Classification	Observed Classification	Total	Male	Female	Urban	Rural	Self	Proxy
EMP	EMP	0.9194	0.9346	0.8008	0.9354	0.9059	0.9205	0.9203
	UNE	0.0228	0.0226	0.0092	0.0194	0.0225	0.0168	0.0247
	INA	0.0578	0.0428	0.1900	0.0451	0.0715	0.0627	0.0550
UNE	EMP	0.1231	0.1660	0.0471	0.1282	0.1206	0.1028	0.1302
	UNE	0.6312	0.6207	0.6042	0.6308	0.6236	0.676	0.6209
	INA	0.2458	0.2133	0.3487	0.2410	0.2558	0.2212	0.2488
INA	EMP	0.0229	0.0365	0.0155	0.0167	0.0318	0.0219	0.0239
	UNE	0.0067	0.0102	0.0049	0.0071	0.0048	0.0039	0.0083
	INA	0.9704	0.9532	0.9795	0.9762	0.9634	0.9742	0.9679
BIC		79858.74	45302.05	24798.31	44086.97	35616.82	27622.44	51806.44
AIC		79695.44	45153.07	24648.43	43934.88	35470.43	27477.72	51653.22

winter and Fall 2014 ILFS data. Only the same persons who responded in all three waves of the ILFS are included in the table which consists of a total of 25,980 respondents. The data in Table 1 is analyzed under the assumption that X_1, X_2 and X_3 are subject to misclassification. In Tables 2 and 3, the classification error probabilities for the observations A_1, A_1 and A_3 are estimated. The EM algorithm is used to estimate parameters and the ℓEM software is used to fit the models. Four following models are fitted to the data:

Model I: Homogeneous and stationary transition probabilities and homogeneous error probabilities: $\{X_1\}$ $\{X_1X_2\}$ $\{X_2X_3\}$ $\{X_1A_1\}$ $\{X_2A_2\}$ $\{X_3A_3\}$, under constraints given by $X_1X_2 = X_2X_3$ (the transition probabilities are the same for any two consecutive waves) and $X_1A_1 = X_2A_2 = X_3A_3$

Model II: Nonhomogeneous but stationary transition probabilities and homogeneous error probabilities: $\{X_1G\}$ $\{X_1X_2\text{G}\}$ $\{X_2X_3G\}$ $\{X_1GA_1\}$ $\{X_2GA_2\}$ $\{X_3GA_3\}$, under constraints given by $X_1X_2G = X_2X_3G$ and $X_1GA_1 = X_2GA_2 = X_3GA_3$

Model III: Homogeneous and nonstationary transition probabilities and homogeneous error probabilities under constraints given by $X_1X_2 \neq X_2X_3$ and $X_1A_1 = X_2A_2 = X_3A_3$

Model IV: Nonhomogeneous but nonstationary transition probabilities and homogeneous error probabilities under constraints given by $X_1X_2G \neq X_2X_3G$ and $X_1GA_1 = X_2GA_2 = X_3GA_3$

In Tables 2 and 3, the classification error probabilities for the observations A_1, A_2 and A_3 are estimated under Model I and Model II, and then Model III and Model IV, respectively.

The results of Model I and Model III in Tables 3 and 4 show that for unemployed, classification error between unemployed and inactive is bigger than the classification error between unemployed and employed. For employed, classification error between employed and inactive is larger than the classification error between employed and unemployed. For inactive, classification error between inactive and employed is larger than the classification error between inactive and unemployed. These results are similar for all MCL models with grouping variables (Model II and Model IV). Models II and IV respectively in Tables 3 and 4, show the estimated labor force classification probabilities for the stationary and non-stationary MLC model by gender, region and self - proxy groups. The results show that the classification error probabilities for men are less than women and inactive women are more likely to be correctly identified than men. Also, the probability of classification error for the rural population is more than urban population. The BIC for all stationary models (Model I and Model II) is higher than non-stationary models (Model III and Model IV). By assuming non-stationary transition probabilities, most of the time, the classification error probabilities have decreased.

6. Conclusions

In this paper, the current methodology of non-response adjustment of weights for unit non-response in the ILFS has been compared with a new methodology. It was found that the non-response adjusted weights based on the thematic and geographic variables (new classes), estimate the parameters such as unemployment and participation rates with less relative bias than the current method of reweighting which is just based on the frame and geographic variables.

Also in this paper, the MLC method was used to estimate the ILFS classification error. The estimated economic activity status classification probabilities are also determined by grouping variables. We evaluated the MLC approach for different models by BIC and AIC criteria.

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References

Alavi, A. and Beaumont, J. F. (2003). A Nonresponse Adjustment Strategy using Modeling in the Canadian Labour Force Survey. Joint Statistical Meetings - Section on Survey Research Methods.

Biemer, P. (2004). An analysis of classification error for the revised Current Population Survey employment questions , Survey Methodology , 30 (2), 127 140.

Biemer (2011). Latent Class Analysis of Survey Errors. John Wiley & Sons.

Biemer and Bushery, (2001). Estimating the Error in Labor Force Data Using Markov Latent Class Analysis.

Biemer, P. and Forsman, G. (1992). On the Quality of Reinterview Data with Applications to the Current Population Survey, Journal of the American Statistical Association, 87 (420), 915-923.

Fuller, W. and Chua, T.C. (1985). Gross Change Estimation in the Presence of Response Error, in Proceedings of the Conference on Gross Flows in Labor Force Statistics, Washington, D.C., U.S. Census Bureau and U.S. Bureau of Labor Statistics, 65-77.

De Leeuw, D., Hox, J.J. and Dillman, D.A. (2008). International Handbook of Survey Methodology. Lawrence Erlbaum Associates: New York, Taylor and Francis.

International Labour Office (ILO)(2000). Current International Recommendations on Labour Statistics, Geneva, France.

Poulsen, C.S. (1982). Latent Structure Analysis with Choice Modeling Applications, doctoral dissertation, Wharton School, University of Pennsylvania.

Sarndal C.E. and Lundstrom S. (2005). Estimation in Surveys with Nonresponse,Wiley, NewYork.

Sinclair, M. and Gastwirth, J. (1998). Estimates of the Errors in Classification in the Labour Force Survey and Their Effects on the Reported Unemployment Rate, Survey Methodology, 24 (2), 157-169.

Van de Pol , F. , and Langeheine , R. (1997), Separating change and measurement error in panel surveys with an application to labor market data, in L. L. Lyberg, P. Biemer, M. Collins, E. De Leeuw, C. Dippo, N. Schwarz, and D. Trewin, eds., Survey Measurement and Process Quality , Wiley, New York.

Vermunt, J. (1997). REM: A General Program for the Analysis of Categorical Data, Tilburg, University.

Vermunt, J. K. (1996). Log - Linear Event History Analysis: A General Approach with Missing Data, Latent Variables, and Unobserved Heterogeneity, Tilburg University Press, Tilburg, The Netherlands.

Wiggins, L.M. (1973). Panel Analysis, Latent Probability Models for Attitude and Behavior Processing, Elsevier S.P.C., Amsterdam.