Estimation of the Change in Total Employment Using the U.S. Current Employment Statistics Survey

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ABSTRACT[1]

In every month on the first working Friday, the U.S. Bureau of Labor Statistics (BLS) releases its preliminary estimates of the total non-farm business payroll employment and the change in total employment from the prior month. These estimates are produced using the Current Employment Statistics (CES) survey which is an on-going national probability sample survey of all non-farm establishments in the United States. The preliminary estimates are revised a number of times to incorporate late reporting in the CES sample and the most recent benchmark population information. In this paper, we develop a statistical method which has the potential to minimize the amount of revision between the preliminary estimates and the second revision of the estimates. Based on the historical data, we first build an appropriate model which links these two estimates and then use this relationship to predict the second revision from the knowledge of the preliminary estimates for the current month. The preliminary results obtained from our study are encouraging.

Keywords: CES, Bayesian Hierarchical Model, Weighted link relative estimator, Composite estimator.

Introduction

Current Employment Statistics (CES) is an important monthly survey conducted by the U.S. Bureau of Labor Statistics (BLS). The survey provides monthly data on employment, earnings and hours of nonagricultural establishment in the U.S. The monthly data refer to the pay period that includes the 12th of the month, a period that is standard for all Federal agencies collecting employment data from business establishments. Employment covers all employees and subcategories of workers for certain industries, e.g. production workers in manufacturing and mining industries, construction workers in construction industry, and nonsupervisory workers for the remaining private sector industries. Aggregate payroll, that is the income sum from work before tax and other deductions, are used to estimate total earnings by U.S. workers reported on establishment payroll. The survey also contains estimates for total hours worked and paid overtime hours. In addition, some other derived series such as average hourly earnings, real earnings and straight-time average hourly earnings are also provided.

CES provides above statistics at considerable geographic and industrial details. At the national level, estimates of employment, earnings and hours are provided for 5200 NAICS industries, representing 92% of four-digit, 86% of five-digit and 44% of six-digit NAICS industries. For the fifty States, District of Columbia, Puerto Rico, the Virgin Islands, and 288 metropolitan areas, detailed NAICS industry series are published both by BLS and State Employment Security Agencies (ESA) that cooperate with BLS in collecting the State and area information.

The sample design of CES is a stratified, simple random sample of establishments, clustered by UI accounts. Strata are defined by state, NAICS industry, and employment size. Sampling rates for the strata are determined through an optimum allocation formula. In 2003, the CES sample included about 160,000 businesses and government agencies representing approximately 400,000 individual worksites. This is a sample from 8 million non-farm business establishments (defined as an economic unit that produces goods

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[1] Any opinions expressed in this paper are those of the authors and do not necessarily reflect the official policy or position of the U.S. Bureau of Labor Statistics

or services) in the United States. The active CES sample covers approximately one-third of all non-farm payroll workers. CES uses a weighted link-relative estimator to estimate the total employment, earning and hours. Weighted link-relative estimator uses a weighted sample trend within an estimation cell to move forward the prior month's estimate for that cell.

The CES is the first major economic indicators released each month along with the Current Population Survey. Uses of the survey are significant both in terms of their impact on the national economic policy and private business decisions. It supplies a significant component in the Index of Coincident Economic Indicators that measures current economic activity, and leading economic indicators forecasting changes in the business cycle. The CES earnings component is used to estimate preliminary personal income of the National Income and Product Accounts. U.S. productivity measures are based on the CES aggregate hours data. The BLS and state ESAs conduct employment projections based on the CES data. Business firms, labor unions, universities, trade associations, and private research organizations use the CES data to study economic conditions and to develop plans for the future.

Preliminary CES estimates are generated three to four weeks after the survey reference period, a pay period containing the 12th of the month, or 5 business days after the deadline to hand in the requested information. The speed of delivery can increase late response and nonresponse resulting in large revisions of preliminary estimates in the subsequent months. Currently preliminary estimates are based on only about 74% of the total CES sample. Two subsequent revisions in the next two months, however, incorporate the late reporters. Though the final revisions, also called the third closing estimates, are released two months later, the preliminary estimates are the most critical in terms of different uses and tend to receive the highest visibility. Many short term financial decisions are made based on preliminary estimates. Current economic conditions are assessed based on these immediately available data. Large revisions in the subsequent months help obtaining the most accurate statistics, though some damage may have already been made by relatively inaccurate preliminary estimates. Revisions also cause confusions among users who may regard the difference as sampling errors. Some users on the other hand perceive the survey performance based on the magnitude of the revisions.

The amount of revisions varies across geography and depends on the industry, time of a year, location and other factors. The percent revisions at the state and local levels are generally higher than those at the national level. However, even a very tiny percentage revision at the national level could change the employment situation dramatically. The current total U.S. non-farm employment stands at about 130 million and the average monthly change in employment (mostly increase) since 1995 is about 131,000. Therefore roughly a 0.1% revision can turn a job increase to a decrease situation. At the state and area level, the average revision is about 1%, a more significant level of revision is expected. (Since at state level revision could be positive or negative, at national level the gross revision should be lower. Compared to the national level, state level estimates generally have proportionally higher sampling errors.

The CES program has made efforts to make the preliminary estimates as accurate as possible in order to avoid large subsequent revisions. For example, since the amount of revisions is associated with late reporting and nonresponse, program office has taken steps to improve on response rates through updating and completing current establishment address information, sending advanced notice, providing nonresponse prompts, improving marketing of the survey, expanding survey collection modes (e.g. internet) etc. Efforts have been also made in estimation through seasonal adjustments and business birth/death imputations.

In this paper, we propose a statistical procedure that aims to reduce the gap between the primary and final estimates using historical data. To this end, in section 2 we propose a two-level model. The purpose of the first level is to link the preliminary estimate to its second revision. The second level is used to understand the effects of geographical area, industry and the month of a year on the second revisions. Using the two-level model, we develop an empirical best prediction (EBP) method to predict the second revisions for the current month using the knowledge of the preliminary estimates. Historical data are used to fit the two-level model. In section 4, we use CES data on the preliminary and second revision estimates for the period March 2003-March, 2004 to fit the two-level model. We compare the proposed EBP with the preliminary estimator in predicting the second revisions for April, 2004. Since second revisions for April, 2004, are available, such evaluation method offers a robust method.

Prediction of the Third Closing Growth Rate

Let y_{ijkt} and w_{ijk} denote the month *t* employment and the associated survey weight for establishment k belonging to industry *i* and area *j* in the CES monthly sample *s* $(i=1,\cdots,I; \quad j=1,\cdots,J_i; k=1,\cdots,K_{ij};$ $t=1,\cdots,T)$. Note that the sampling weight for a sampling unit does not change over time. Let $s_{1t} \subset s_{3t} \subset s$, where s_{1t} (s_{3t}) denote the set of sampling units that responded in month t when the first closing (third closing) estimates are produced. The design-based estimates of the employment growth rates for industry *i*, area *j*, and month *t* at the first and third closings are given by

$$R_{1ijt} = \frac{\sum_{i \in s_{1t}} w_{ijk} y_{ijkt}}{\sum_{i \in s_{1t}} w_{ijk} y_{ijkt-1}}, \; R_{3ijt} = \frac{\sum_{i \in s_{3t}} w_{ijk} y_{ijkt}}{\sum_{i \in s_{3t}} w_{ijk} y_{ijkt-1}}.$$

For the current month $t=T$, we have R_{1ijT}, but not R_{3ijT}. We are interested in an adjustment to R_{1ijT} so that the adjusted R_{1ijT}, say $\hat{R}_{3ijt}$, and R_{3ijt} are as close as possible. We propose to achieve this goal by applying a suitable two-level model. To this end, define

$z_{1ijt} = \log(R_{1ijt}),$ and $z_{3ijt} = \log(R_{3ijt}).$

Assume the following two-level model:

Model 1:

Level 1: $z_{1ijt} \mid \theta_{ijt} \underset{\sim}{ind} \; [a_{ijt} + b_{ijt} z_{3ijt}, \sigma^2_{ijt}];$

Level 2: $z_{3ijt} \underset{\sim}{ind} \; [\eta_{ijt}, \tau^2_{ijt}],$

where [*m* ,*v*] denote a probability distribution with mean *m* and variance *v*. The parameters $a_{ijt}, b_{ijt}, \sigma^2_{ijt}, \eta_{ijt}$ and τ^2_{ijt} are all assumed to be known. The mean of Level 2, i.e. η_{ijt} is assumed to be related to labor market factors such as the month of a year, industry group and geography , see Remark 2 below.

Under the above model and squared error loss, the best predictor (BP) of z_{3ijT} is given by

$$\hat{z}^{BP}_{3ijT} = w_{ijT} z^*_{1ijT} + (1 - w_{ijT}) \eta_{ijT},$$

where

$$w_{ijT} = \frac{b^2_{ijT} \tau^2_{ijT}}{b^2_{ijT} \tau^2_{ijT} + \sigma^2_{ijT}}, \; z^*_{1ijT} = \frac{z_{1ijT} - a_{ijT}}{b_{ijT}}.$$

Remark 1: The parameters $a_{ijT}, b_{ijT}, \sigma^2_{ijT}$ and τ^2_{ijT} of Model 1 are generally unknown and need to be estimated. Note that $a_{ijT}, b_{ijT}, \sigma^2_{ijT}$ and τ^2_{ijT} are not estimable unless we make a simplifying assumptions on them. Basically, we need to assume that these parameters do not depend on all the three factors. There are several possibilities and we need to investigate them carefully

Remark 2: In order to reduce the number of parameters of Model 1, $a_{ijt}, b_{ijt}, \eta_{ijt}$, σ^2_{ijt} and τ^2_{ijt} can be assumed to be random with or without assumptions mentioned in Remarks 1. However, we do not consider this case in this paper.

After making appropriate assumptions noted in Remarks1, we can proceed to estimate the parameters of the two-level model. To this end, we use all the available data, i.e. $\{z_{1ijt}, i=1,...,I; j=1,...,J_i, t=1,...,T\}$ and $\{z_{3ijt}, i=1,...,I; j=1,...,J_i; t=1,...,T-1\}$. PROC REG and GLM in SAS can be used for this estimation. To illustrate our method, we assume

$a_{ijt} = a_{it}, b_{ijt} = b_{it}, \sigma^2_{ijt} = \sigma^2_{it}, \tau^2_{ijt} = \tau^2_{it}$

for all i, j, t. That is, there is no geographical effect on these parameters. The parameters a_{it}, b_{it}, σ^2_{it} are estimated using the linear regression model given by Level 1 of Model 1. We need to make an appropriate assumption on the structure of η_{ijt}. A model with all possible main effects is given by:

$$\eta_{ijt} = \mu + \alpha_i + \beta_j + \gamma_t,$$

where

μ: overall effect;

α_i: fixed effect due to the ith industry;

β_j: fixed effect due to the jth state;

γ_t: fixed effect due to the tth month.

We make all the standard restrictions on the fixed effects.

The parameters μ, α_i, β_j and γ_t estimated by fitting Level 2 of Model 1. Plugging in the estimators of all the model parameters, we get the following empirical best predictor (EBP) of z_{3ijT} :

$$\hat{z}_{3ijT}^{EBP} = \hat{w}_{ijT} z_{1ijT}^{*} + (1 - \hat{w}_{ijT})\hat{\eta}_{ijT},$$

where

$$\hat{w}_{ijT} = \frac{\hat{b}_{iT}^2 \hat{\tau}_{iT}^2}{\hat{b}_{iT}^2 \hat{\tau}_{iT}^2 + \hat{\sigma}_{iT}^2},$$

$$z_{1ijT}^{*} = \frac{z_{1ijT} - \hat{\alpha}_{iT}}{\hat{b}_{iT}},$$

$$\hat{\eta}_{ijT} = \hat{\mu} + \hat{\alpha}_i + \hat{\beta}_j + \hat{\gamma}_T,$$

for all i and j.

We take the reverse transformation to predict R_{3ijT}, i.e., $\hat{R}_{3ijT} = \exp(\hat{z}_{3ijT}^{EBP})$.

We have already presented the basic ingredient for adjusting the preliminary employment estimates. To illustrate this, suppose we are interested in predicting the third closing employment for industry i at current time T, say Y_{3iT}, at the time we make preliminary estimates for month T. Note that

$$Y_{iT} = \sum_{j=1}^{J_i} Y_{ijT} = \sum_{j=1}^{J_i} R_{3ijT} Y_{ijT-1}.$$

where Y_{3ijt} denote the third closing total employment for industry i, state j and time t. An estimator of Y_{iT} is thus obtained as:

$$\hat{Y}_{iT} = \sum_{j=1}^{J_i} \hat{R}_{3ijT} \hat{Y}_{ijT-1}.$$

Numerical Results

In this section, we evaluate the proposed EBP method in comparison with the preliminary estimator using a data set obtained from the BLS CES program. The data set contains 2652 pairs of first and third closing weighted LR estimates of total employment for all four 2-digit NAICS industries (Mining, Construction, Manufacturing and Wholesale Trade.) in all the fifty states and the District of Columbia during the period April 2003 -April 2004.

We first use scatter plots (given in Figure 1 and Figure 2) to understand the assumptions needed to reduce the number of parameters involved in Level 1 of the Model. We note the following:

(a) The industry type appears to have an effect on the regression parameters. For example, the Construction and Wholesale Trade industries appear to have weaker first and third closing LR correlations than the Mining and Manufacturing do.

(b) The month of the year appears to affect the regression, November and December being the two months that have the weakest correlation between first and third closing LRs.

The above two observations support our Level 1 assumptions considered in this paper, i.e., $a_{ijt} = a_{it}, b_{ijt} = b_{it}$ and $\sigma_{ijt}^2 = \sigma_{it}^2$.

Figure 1. Scatter plots of the first and third closing LR estimates by industrial classification.

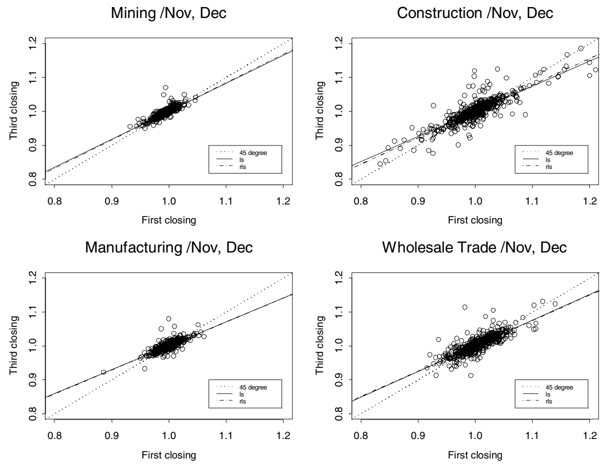
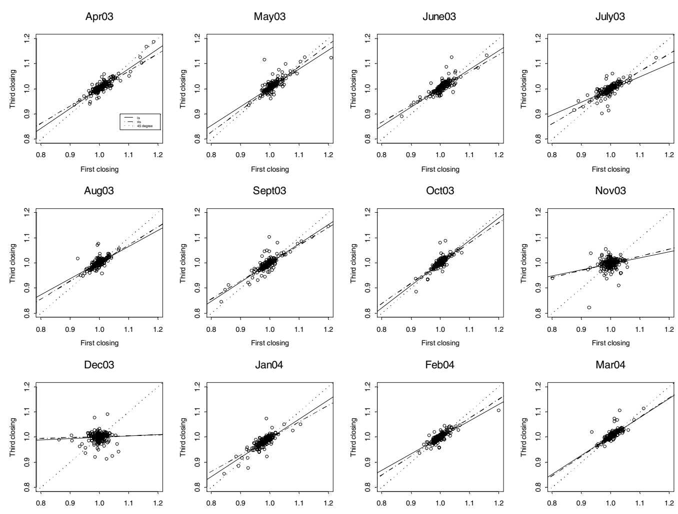


Figure 2. Scatter plots of the first and third closing LR estimates by month during March 2003 - March 2004.



For eight out of the 2652 observations, the difference between the first and third closing estimates exceeds 15%. We treat these cases as possible erroneous outliers. Though in the usual production setting under the BLS CES program these discrepancies will be further investigated on a case by case basis, in this paper we treat them by the well-known "Winsorizing" procedure that weighs the outliers down according to their distances from the mean.

For our evaluation purpose, we divide the data set into two parts. The data for the period April 2003 - March 2004 are used for fitting the two-level model. We call them our training data. The data for April 2004are used to compare results with the actual third closing LRs. We call this data set evaluation data. The mean absolute relative deviation (MARD) is used to measure the overall performance of a predictor. The MARD for an arbitrary predictor is given by

$$\text{MARD} = \frac{1}{n}\sum_{i}^{n} \frac{|\,\text{predictor}_i - \text{obs. 3rd closing}_i\,|}{\text{obs. 3rd closing}_i}.$$

where n is the number of points in the evaluation data set. Obviously, the smaller the MARD the better is the predictor. To compare our EBP with the current first closing estimator, we define the percent relative improvement (PRI) as:

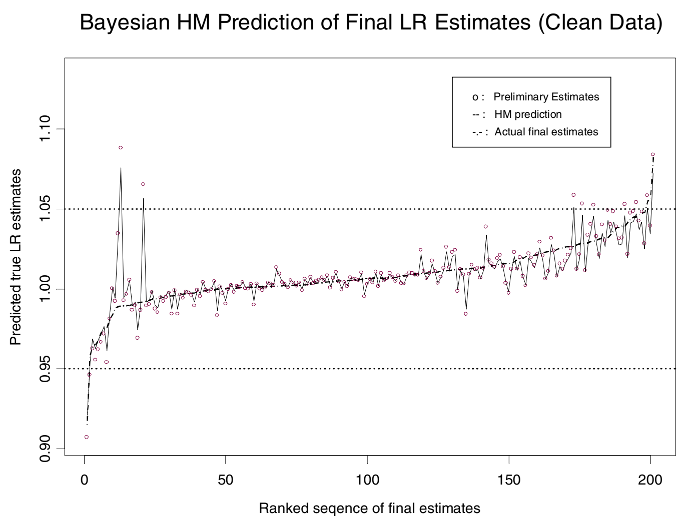
$$\mathrm{RI} = \sum_{i}^{n} \frac{|\,\mathrm{obs.1st.closing}_i - \mathrm{obs.3rd.closing}_i\,| - |\,\mathrm{predictor}_i - \mathrm{obs.3rd.closing}_i\,|}{|\,\mathrm{obs.1st.closing}_i - \mathrm{obs.3rd.closing}_i\,|}$$

The higher the PRI value the better is the case for EBP. Outliers as defined earlier are present in both training and evaluation data set. We consider four cases by excluding and including outliers in both the training and evaluation data sets. The summary results are presented in Table 1. The results show that EBP improves on the current preliminary estimators in all the four cases. Figure 3 compares the EBP and the preliminary estimates in predicting the third closing estimates.

Table 1. Percent Relative improvement (PRI) of EBP over the preliminary estimator.

		Model Training Data	
		Raw data	Outlier removed
Evaluation Data	Raw data	6.435%	6.073%
	Outlier removed	9.487%	9.131%

Figure 3. A plot of EBP, first closing and third closing estimates



Conclusion

In this paper, we attempt to exploit the relationship between the first and third closing estimates and the historical data on these two estimates to improve on the first closing estimates for the current month. In order to improve on the first closing estimates further , we need better understanding of the general two-level model proposed in this paper Both the first and third closing estimates are subject to the sampling errors which we have ignored in this paper primarily because of the unavailability of reliable sampling standard errors of these estimates. We have not discussed the problem of measuring uncertainty of our proposed empirical best predictors. The Taylor series method described in Lahiri and Wang (1991) or a resampling method (see Jiang and Lahiri 2006) could be investigated for this purpose. Although the problem is far from being solved, our paper offers a framework for making possible improvement on the preliminary estimates.

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