Improving CES Preliminary Employment Estimate through Statistical Model

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Bogong T. Li, and Partha. Lahiri
OSMR, Bureau of Labor Statistics and
JPSM, University of Maryland

Abstract[1]

The U.S. Bureau of Labor Statistics (BLS) releases estimates of total non-farm business payroll employment changes every month. These estimates have significant impact on US economic policy and financial market decision makers. However these estimates are produced based only on "preliminary" Current Employment Statistics (CES) survey results, final estimates are release two months later. In this paper, we develop a statistical model based on historical CES data with the following goals in mind: (1) validate factors that affect monthly employment changes, (2) measure the magnitude of these effects on monthly employment movement, (3) prove in part some underlying economic factors affecting national and regional employment changes. We then use prediction results from the model to produce improved preliminary estimates that is more accurate than the current preliminary estimates.

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

1. Introduction

People interested in financial news may have noticed during the first Friday on every month, a widely watched monthly U.S. payroll employment figure is released to the public. A long waited number accompanying speculations from Wall Street analysts to academic economists finally settles. The flurry and judgements about Fed decision on interests begin, as demonstrated by this CNN-Money news reports shown in figure 1. The quoted payroll employment, or number of positions offered by U.S. non farm employers is the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) statistics' estimate of total employment.

Figure 1: News media reports U.S. job growth based on statistics produced by the Bureau of Labor Statistics

CES is one of many important monthly surveys conducted by BLS. The survey provides monthly data on employment, earnings and hours of nonagricultural establishment in the U.S. It 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.

CES Employment estimates cover all employees and subcategories of workers for certain 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

[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

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 or services) in the United States. The active CES sample covers approximately one-third of all non-farm payroll workers.

2. Discrepancies between First and Third Closings

What the employment estimate shown in figure 1 is the preliminary CES estimates. Preliminary 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. Considerable amount of establishments have difficulties to respond in time. Currently preliminary estimates are based on only about 74% of the total CES sample. Two subsequent revisions in the next two months incorporate the late reporters. 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.

Source of the discrepancy varies, though major contribution is the large amount of late reporter. However as illustrated in Figure 2, other common factors that affect survey accuracy applies here as well. These factors, despite CES program efforts to reduce late reporting, will not be affected by. Other measures may be necessary, such as modeling the survey data, may be considered to improve survey data based on historical data and estimation of error.

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.

3. CES Estimator for Total Employment and Change

Current CES program uses weighted link-relative estimator to estimate the current month employment level, i.e. using a weighted sample trend within an estimation cell to move forward the prior month's estimate for that cell, e.g. for the all employee estimate, as the next formula shows

$$\hat{Y}_t^{(k)} = \sum_{c=1}^{C} \left[\frac{\sum_{i \in s_{t,(t-1)k}} w_{ci} y_{tci}}{\sum_{i \in s_{t,(t-1)k}} w_{ci} y_{(t-1)ci}} \hat{Y}_{(t-1)c}^{(k+1)} \right]$$

$$= \sum_{c=1}^{C} \left[LR_{t,(t-1)c}^{(k)} \hat{Y}_{(t-1)c}^{(k+1)} \right]$$

Where $\hat{Y}_t^{(k)}$ is the aggregated employment estimate of month *t* at closing *k*, y_{ijkt} and w_{ijk} denote the month *t* employment and the associated survey weight for establishment *i* within estimation cell *c*, where

$$\frac{\sum_{i \in s_{t,(t-1)k}} w_{ci} y_{tci}}{\sum_{i \in s_{t,(t-1)k}} w_{ci} y_{(t-1)ci}} = LR_{t,(t-1)c}^{(k)}$$, is the link relative.

4. Proposed Improvement Based on Predictive Model

In order to make notation consistent to our later analysis, we need to reorganize the notation as follows. 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*. 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

$$R_{ijt}^{(1)} = \frac{\sum_{i\in s_{1t}} w_{ijk} y_{ijkt}}{\sum_{i\in s_{1t}} w_{ijk} y_{ijkt-1}},$$

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

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

Model:

Level One: $z_{ijt}^{(1)} \mid z_{ijt}^{(3)} \overset{\text{iid.}}{\sim} N(a_{ijt} + b_{ijt} z_{ijt}^{(3)},\ \sigma_{ijt}^2);$

Level Two: $z_{ijt}^{(3)} \overset{\text{iid.}}{\sim} N(\eta_{ijt},\ \tau_{ijt}^2),$

The parameters $a_{ijt}, b_{ijt}, \sigma_{ijt}^2, \eta_{ijt}$ and τ_{ijt}^2 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. Under the above model and squared error loss, the best predictor (BP) of $z_{ijT}^{(3)}$ is given by

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

where

$$w_{ijT} = \frac{b_{ijT}^2 \tau_{ijT}^2}{b_{ijT}^2 \tau_{ijT}^2 + \sigma_{ijT}^2},\ z_{ijT}^{(1)*} = \frac{z_{ijT}^{(1)} - a_{ijT}}{b_{ijT}}.$$

and

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

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.

The parameters $\mu,\ \alpha_i,\ \beta_j$ 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) $\hat{z}_{ijT}^{(3)EBP}$ of $z_{ijT}^{(3)}$. Then we take the reverse transformation to predict $R_{ijT}^{(3)}$, i.e., $\hat{R}_{ijT}^{(3)} = \exp(\hat{z}_{ijT}^{(3)EBP}).$ Figure 3 illustrates relationship between various parameters in the model.

5. An Application

To test its ability to improve the preliminary release, we apply it to a data set 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. Our goal is to perfect the two-level model using data from April 2003 to March 2004, then produce an improved preliminary release of April 2004. Compare the improved release to the known third release of April 2004 which will differentiate the quality between the original preliminary release and the improved primary release.

Figure 4 and similar graphs for other month illustrates the strong linear correlation between the first and third closings at the Month/Industry level. A detailed model selection resulted in the specified model specified previously. State/Industry/Month LR estimates are obtained for April 2003 primary release and hence compare to that of the actual primary release. A result of such comparison is listed in table 1. Figure 5 provides a graphic comparison between the improved and original primary releases against the first closing LR.

The data fitting using our training data suggests all present model parameters are statistically significant. The third and fourth model achieved higher adjusted R-squares, RI values and lower value MAR. This suggests the slope b associates with the month t as well as the industry i. In particular, model four has lower BIC value compared to model three. Base on these observations we inclined to select model four to implement our final comparison using the evaluation data.

The improvements are at basic estimation cell level measured by percent of reduction in revision at final closing. The summary is grouped by industry and state. The average values at each level indicate the basic cell improvement is approximately between 10% and 40% in revision error reduction. The overall average in revision reduction is 29% (28.976%). Some states or two-digit industry showed large improvements, for example, the state of Alaska by 37.7% and Construction by 42.2%.

Figure 5 illustrates the difference between current preliminary estimate $R_{ijT}^{(P)}$ (perforated line) and EBP estimate $\hat{R}_{ijT}^{(F)}$ (solid line). The solid pink bars are actual growth rate at respective basic estimation cell level, situated in the order of magnitude along x-axis. Overall, the EBP $\hat{R}_{ijT}^{(F)}$ is closer in distance to the actual growth than current preliminary estimate, though there are a few exceptions. The direction of revision (growth rate increase vs. decrease) largely agrees between the two methods of prediction.

6. Conclusion

In this paper, we attempt to exploit the relationship between the preliminary and final 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. As a result of fitting the general mean structures using a training data set, we are able to select from many and produce final employment growth estimates that require in average 30% less in third closing revision, compared with current preliminary estimates. All parameters associated with the model are statistically significant, given fitting through the data available.

Both the preliminary and final 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 promising framework for making possible improvement on the preliminary estimates.

Attachments

Figure 3: A two-level hierarchical model for monthly employment link relatives

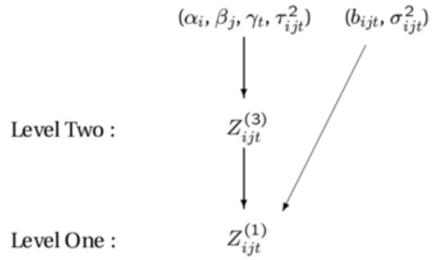

Figure 4: Scatter plot of the third closing LRs vs. the first closing LRs for the month of September 2003 at four 2-digit NAICS industries.

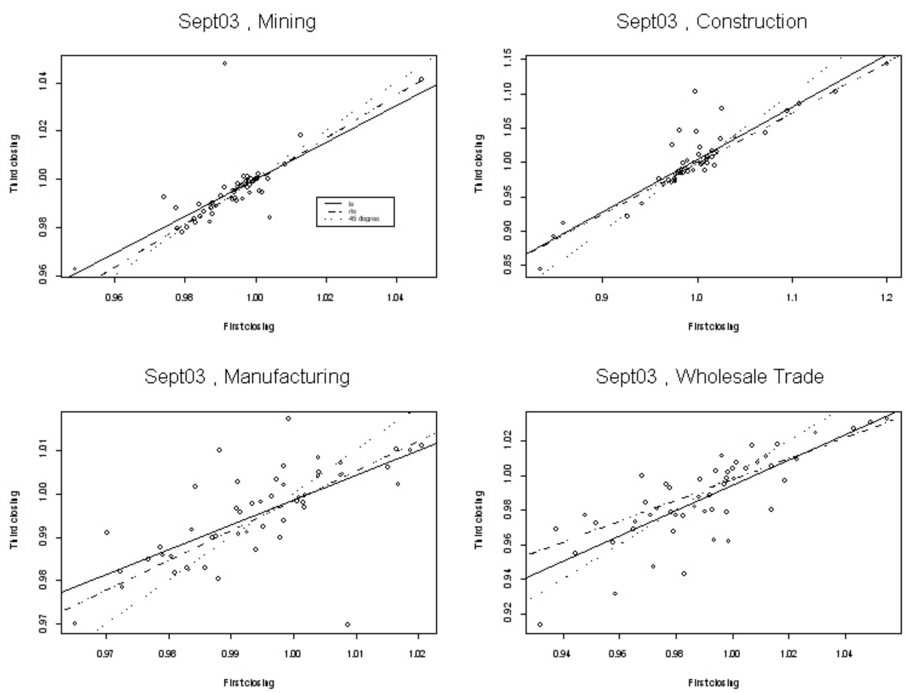

Figure 5: Model improvement to CES monthly preliminary employment change estimates

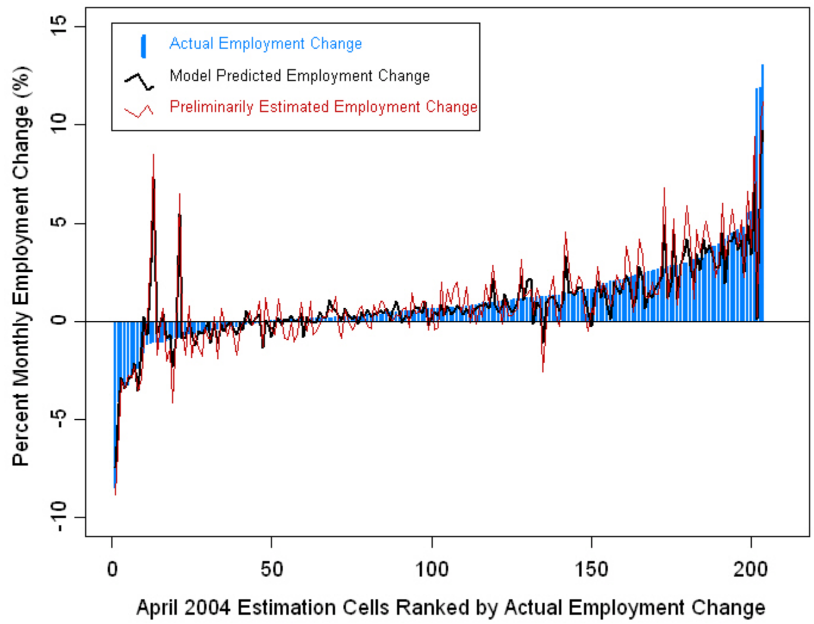

Table 1: Improvement of preliminary estimates at various aggregate levels

Percent Reduction in Monthly Employment Revision by EBP Estimator (%)

		Maximun	Average	1st Quartile	Median	3rd. Quartile
Industry	Mining	24.120	9.192	2.756	6.128	9.536
	Construction	42.230	20.400	10.992	23.588	36.480
	Manufacturing	26.120	16.544	4.980	9.816	19.456
	Wholesale Trade	46.040	31.776	12.612	20.244	44.280
State	Alabama	38.080	18.064	4.916	12.040	25.192
	Alaska	47.840	37.720	20.868	33.680	45.520
	Arizona	24.720	16.888	4.648	19.568	22.804
	……	……	……	……	……	……
	West Virginia	25.876	10.944	4.164	7.548	14.328
	Wisconsin	46.880	19.380	7.180	14.704	26.904
	Wyoming	34.840	20.508	8.300	13.044	25.252
All	***April 2003***	***47.840***	***28.976***	***5.328***	***29.372***	***39.128***

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