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Imputing for Late Reporting in the U.S. Current Employment Statistics Survey

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Surveys of economic conditions are often published monthly to provide up-to-date measures of the state of a country's economy. In establishment surveys, some sample units may not report in time to be included in the current month's estimates, but eventually do report data. This late reporting can lead to revisions of estimates as more sample data become available. To maintain credibility, it is important that the size of revisions be kept as small as possible. We study this issue using the U.S. Current Employment Statistics (CES) survey. A model-based view of the CES weighted link relative estimator is used to identify potential bias due to model misspecification. An alternative approach, involving imputation for missing data, is used in an attempt to reduce the magnitude of revisions between preliminary and final estimates of employment for a month. The alternative, while not yielding statistically significant improvement in monthly revisions at the industry level, offers the potential for improved estimates for lower level aggregation.

Key words: Establishment survey; estimate revisions; nonignorable nonresponse; nonreporting; panel survey.

1. Introduction

Many economic surveys must strike a balance between timeliness and accuracy in the generation of estimates. Estimates are generally required to be published soon after the survey reference period in order to efficiently guide policy aimed at affecting the marketplace. Speedy delivery can adversely affect survey quality, however, as nonreporting will tend to be higher with shorter collection periods. Estimation methods developed for these surveys are intended to compensate for missing data so as to reduce the error due to nonreporting.

A portion of nonreporting within such a survey environment can often be viewed as temporal, with responses for some sample units becoming available subsequent to the prescribed collection period (referred to here as "late reporting"). The remaining portion of survey nonreporting reflects sample units that never report data for the reference period (referred to here as "nonresponse"). One approach commonly taken with economic data series is the issuance of preliminary estimates shortly after the reference period, based

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upon sample data received within the prescribed collection period (referred to here as "preliminary reporting"), and followed by one or more revised estimates based upon data from both preliminary and late reporters.

Despite the issuance of revised estimates, preliminary estimates are most critical for use and tend to receive the most visibility. Deviations between preliminary and revised estimates may be perceived as indicating an inability of the estimation methodology to appropriately correct for nonreporting. Although information on sampling and other errors associated with the preliminary estimates may be provided, and may indicate revisions are not outside the bounds of expected survey error, the perception of survey performance may still be tied to the nature of differences between preliminary and revised estimates. This is especially true when looking at revisions of period-to-period changes in the estimates, where a revision in a change may be larger than the preliminary estimate of change. The same size of revision between preliminary and revised estimates of level may be deemed inconsequential. Thus, one key objective for such surveys is reducing the potential for large differences between preliminary and revised estimates, in both monthly level and month-to-month change.

The U.S. Bureau of Labor Statistics' (BLS) Current Employment Statistics (CES) survey collects employment, hours, and earnings data monthly from a sample of over 300,000 United States (U.S.) establishments. To provide timely information, preliminary estimates are generated three to four weeks after the survey reference period (pay period containing the 12th of the month), resulting in a relatively large amount of late reporting. Final estimates are released two months later, incorporating late reports received after production of the preliminary estimates.

The estimate of change in employment is referred to as "new job creation," and is taken to be an important barometer of the health of the economy. New job creation is one item on a closely-watched list of economic statistics released by the U.S. government. Other important series are the consumer and producer price indexes, the average hourly wage series, and the unemployment rate. Relatively small deviations from economists' forecasts for these series can momentarily roil the U.S. stock and bond markets. Better-than-expected employment reports are interpreted as a sign that the economy is growing and that the Federal Reserve Board will raise short-term interest rates (see e.g., CNN 2005). In anticipation of higher interest rates, the prices of 10-year and 30-year bonds sold by the U.S. federal government typically drop. Stock prices tend to move in the opposite direction from bond prices, and a report on new jobs creation that falls below forecasts usually leads to a brief drop in the value of stocks (see e.g., CNN 2006).

Estimation methods attempt to lessen the effect of nonresponse and late reporting through the use of estimation cells defined by variables known for the population. To the extent late reporters differ from preliminary reporters on the variables of interest, final estimates may show large revisions of the preliminary estimates. The perception of survey performance is often based on the magnitude of the revisions.

If the employment estimate for a month is revised substantially, a false signal will have been sent to policy makers and analysts by the preliminary estimate. Although these revisions are often relatively small, there are exceptions. For example, the initial report for November, 2005, was that 215,000 jobs had been created in the U.S., but this was revised upward in December by 90,000 or 41 percent so that the final estimate for November was 305,000 (U.S. Bureau of Labor Statistics 2005, 2006).

Various alternatives are available to attempt to handle nonreporting. One is double sampling with intensive follow-up of nonrespondents. Deming (1953) and Hansen and Hurwitz (1958) are two early papers that propose this type of approach. Another approach is imputation (see, e.g., Rubin 1987). In the current CES procedure, data for late reporters are not explicitly imputed; rather, late reporters, nonsample, and nonreporters are all assumed to have the same growth rate as early reporters. Lahiri and Li (2005) discuss an approach for the CES survey based upon modeling differences between preliminary and revised estimates; however, their results are limited to one month and thus do not tell us anything about effect on month-to-month change.

We develop and examine an alternative approach for CES estimation, involving imputation for missing data assuming nonignorable nonresponse. Revisions from this alternative approach will be compared to those of the current estimator (see Copeland 2004 for additional details on this research).

2. CES Sample Design and Data Collection

The CES survey is a monthly survey of establishments in the United States collecting information on employment, hours, and earnings. The primary statistics of interest for the CES survey are the total nonfarm payroll employment in the U.S. and the change in total nonfarm payroll employment from the prior month. In order to provide timely information, estimates are generated three to four weeks after the survey reference period. Estimates are revised each of the next two months to incorporate late reporting (referred to as second and third closing estimates), and are subsequently revised on an annual basis to incorporate the most recent benchmark population information (referred to as benchmark revisions). The reader is referred to U.S. Bureau of Labor Statistics (2001, 2004a, 2004b) and Werking (1997) for broader and more detailed descriptions of the CES survey.

The population for the CES survey consists of over 8 million nonfarm business establishments (defined as economic units which produce goods or services) in the United States. The sampling frame is derived from the BLS's ES-202 program, a federal/State cooperative between the BLS and State Employment Security Agencies (SESA's). The ES-202 program collects information on businesses covered by State unemployment insurance (UI) laws and Federal agencies covered by the Unemployment Compensation for Federal Employees (UCFE) program. The main exclusions from this population are small agricultural employers and nonprofit organizations, and selected classes of workers (self-employed, domestic help, railroad workers, and State and local government elected officials).

The sample design is a stratified, simple random sample. In most cases, the units are single establishments, but in some instances establishments are clustered by UI account. Strata are defined by state, industry (based upon North American Industry Classification System (NAICS) categories), and employment size (defined as the maximum employment across the most recent 12-month period). Sampling rates for each stratum are determined through optimum allocation. During the first quarter of each year, a new sample is drawn, with selected units remaining in the sample a minimum of two years. While the sample is generally selected to guarantee a large overlap, sample rotation is built into the design for strata with smaller sampling rates. During the third quarter of each year, an update is performed to select new establishments into the sample. Approximately 68% of the sample establishments from private industry, the sector we study here, overlap from year to year.

The BLS cooperates with the SESA's to collect the variables of interest from sample establishments. The reference period for a given month is defined as the pay period that includes the 12th day of the month. The primary variable of interest for the CES survey is total employees, defined as persons on an establishment's payroll who received pay for any part of the pay period that includes the 12th day of the month. Other variables collected are the number of nonsupervisory/production/construction (depending upon the industry) employees included in the total employee count, associated payroll and commission hours and overtime hours for total employees and for nonsupervisory/production/construction employees, and gross monthly earnings associated with total employees.

All data must be reported within a two- to three-week period, the cutoff date depending upon the day of the week the 12th falls on and the number of days in the month, for inclusion in the initial published estimates for the month, which are generally released the first Friday of the following month. For example, data for July 2004 (for which the 12th was the second Monday of the month) had to be reported by the cutoff date of July 30 (resulting in a reporting period of 14 weekdays from the 12th) to be included in the estimates published August 6.

Not all sample establishments report by the cutoff date for the month. Additional responses are received after the close of the collection period for the month. Initial estimates for a given month (referred to as first closing estimates) are revised the subsequent two months, incorporating data from late reporters (sample establishments reporting after the cutoff date for the month) into the survey estimates. These revisions are referred to as second and third closing estimates (see Copeland 2003a, b for more details).

3. CES Estimation Methodology

CES survey estimates of total employment are generated through use of what BLS refers to as a *weighted link relative estimator*. This estimator uses a weighted sample trend (the *weighted link relative*) within an estimation cell to move forward the prior month's weighted link relative estimate of employment for that cell. The current CES weighted link relative estimator of the total of all employees for a given closing, $k(= 1, 2, 3)$, for month t is defined as

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

where y_{tci} represents total month t employment reported by sample establishment i in estimation cell c

$c(= 1, \ldots, C)$ refers to estimation cell (defined by industry (3-, 4-, 5-, and/or 6- digit NAICS level) and, for selected industries, region)

w_{ci} represents the sampling weight for sample establishment i in estimation cell c

$s_{t,(t-1)c|k}$ represents the set of sample units that reported data for both months t and $t-1$ as of the cutoff date for closing $k\ [=1,2,3]$ of month t

$\hat{Y}^{(k+1)}_{(t-1)c}$ represents the prior month, $t-1$, weighted link relative estimate for estimation cell c based upon data reported as of the cutoff date for closing $k+1$ of month $t-1$ (which corresponds to closing k of month t). (Note that the maximum value for $k+1$ is 3)

$LR^{(k)}_{t,(t-1)c} = \sum_{i=s_{t,(t-1)c|k}} w_{ci}y_{tci} / \sum_{i=s_{t,(t-1)c|k}} w_{ci}y_{(t-1)ci}$ represents the weighted link relative for estimation cell c for month t based upon data reported as of the cutoff date for closing k of month t, and is a ratio estimate of change.

The corresponding estimator for month-to-month change in all employees is

$$\Delta^{(k)}_{t,(t-1)} = \hat{Y}^{(k)}_t - \hat{Y}^{(k+1)}_{(t-1)} \tag{2}$$

On an annual basis, estimates are revised to reflect incorporation of ES-202 population data from March of the prior calendar year. These revisions are referred to as benchmark estimates. In addition, sample replacement occurs during benchmark estimation.

The CES estimator can thus be viewed as being initialized at month t_B by using the most recently available March data from the ES-202. The estimator for the k^{th} closing can be rewritten as the product of link relatives

$$\hat{Y}^{(k)}_t = \sum_c \left[\left(LR^{(k)}_{t,(t-1)c} LR^{(k+1)}_{t-1,(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c} \right) Y_{t_B c} \right] \tag{3}$$

where $Y_{t_B c}$ represents the benchmark total employment from the ES-202 for cell c.

The first two terms in the equation for $\hat{Y}^{(k)}_t$ represent the k^{th} and $(k+1)^{th}$ closing weighted link relatives for months t and $t-1$, respectively. These terms will differ between the closing estimates for month t. All other terms represent the 3rd closing weighted link relatives for their respective months, which will not change.

CES survey estimates are also adjusted to account for business births (new establishments) and deaths (closed establishments). Business deaths are excluded from the CES weighted link relative; however, the prior month employment for such establishments is implicitly carried forward to the current month, thus overstating employment. This overstatement is offset by an understatement of the employment due to business births. As employment associated with business births will not equal the carried forward employment associated with business deaths, the residual employment due to the net effect of business births and deaths is estimated through use of a model-based approach. We do not consider this complication here.

CES survey estimates are seasonally adjusted to stabilize trends and enable better estimation of month-to-month changes in employment. Seasonal factors are calculated twice a year using multiplicative models in X-12 ARIMA (Kropf et al. 2002), and revisions are made annually in conjunction with the benchmark revision process.

Variance estimation for the CES survey is carried out using Fay's method for variance estimation under balanced repeated replication – BRR (Judkins 1990) using a total of 80 balanced half-samples. Variance estimates represent sampling variance and, implicitly, response variance, and do not reflect other nonsampling errors, such as measurement error and nonresponse bias.

Both monthly level and month-to-month change estimates from the CES survey are of interest to data users. Indirect measures of the accuracy of CES estimates are visible through the estimate revision process. Revisions from 1st to 3rd closing estimates are solely due to the effect of late reporting, while benchmark revisions are the result of the combined effects of sampling, nonresponse, and measurement error.

4. A Model-based View of the CES Estimator

The model that yields the weighted link relative, $LR^{(k)}_{t,(t-1)c}$, as a maximum likelihood estimator (MLE) is a weighted proportional regression model, in which the current month's value is assumed proportional to the prior month's value (West et al. 1989) with the proportionality factor assumed to vary by estimation cell, $c(= 1, \ldots, C)$, and month. Conditional on the month $t-1$ data, the model is

$$\text{Model 0}: Y_{tci} = \rho_{tc} Y_{(t-1)ci} + k_{tci} \tag{4}$$

$$k_{tci} \overset{ind}{\sim} N\left(0, \frac{\sigma_k^2 Y_{(t-1)ci}}{w_{ci}}\right)$$

where ρ_{tc} is the model parameter describing the month t expected growth rate for cell c.

Under this model the maximum likelihood estimator (MLE) for ρ_{tc} is

$$\hat{\rho}_{tc} = \frac{\sum_{i \in s_c} w_{ci} Y_{tci}}{\sum_{i \in s_c} w_{ci} Y_{(t-1)ci}} \tag{5}$$

where s_c represents the sample from estimation cell c. This estimator can also be derived using the pseudolikelihood approach (see, e.g., Binder 1983). This is the complete response form of the current CES weighted link relative. An estimate of current month employment can be written as

$$\hat{Y}_t = \sum_c \hat{\rho}_{tc} Y_{(t-1)c}$$

In practice, population totals, $Y_{(t-1)c}$, are unknown at the time of estimation, and estimation is complicated by the presence of late reporting and nonresponse. The weighted link relative used for CES is a variant of the MLE taking these situations into account by ignoring late reporting and nonresponse and by utilizing only sample units which report data in both months t and $t-1$. Estimated employment is obtained by linking back to the most recently available benchmark totals, $Y_{t_B c}$ (assumed to be fixed quantities), through the monthly weighted link relatives. Thus, the k^{th} closing estimator for month t may be written as the product of weighted link relatives back to t_B and the benchmark totals as shown in (3).

Under Model 0 it can be seen that, for all revisions, the expected value of the weighted link relative for month t, conditioned on $\boldsymbol{Y}_{(t-1)} = (Y_{(t-1)1}, \ldots, Y_{(t-1)C})$, is the month t proportionality factor for the estimation cell, i.e.,

$$E\left(LR^{(k)}_{t,(t-1)c} | \text{Model } 0\right) = \rho_{tc} \tag{6}$$

Correspondingly, the model-expected value of the estimated employment for month t under Model 0, conditioned on the benchmark population values $\boldsymbol{Y}_{t_B} = (Y_{t_B 1}, \ldots, Y_{t_B C})$, is equal to the expected population total for month t. This result is derived through a series of conditional expectations based on each population total prior to month t.

$$\begin{aligned}
E\left(\hat{Y}^{(k)}_t | \text{Model} 0\right) &= \sum_c E\left(\left[Y_{t_B c} LR^{(k)}_{t,(t-1)c} LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model} 0\right) \\
&= \sum_c E \ldots E\left(\left[Y_{t_B c} LR^{(k)}_{t,(t-1)c} LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model} 0, Y_{(t_B+1)c}, \ldots, Y_{(t-1)c}\right) \\
&= \sum_c E \ldots E\left(\left[Y_{t_B c} \rho_{tc} LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model} 0, Y_{(t_B+1)c}, \ldots, Y_{(t-2)c}\right) \\
&= \ldots = \sum_c \left(Y_{t_B c} \prod_{t^*=t_B+1}^{t} \rho_{t^* c}\right) = E(Y_t | \text{Model} 0, \boldsymbol{Y}_{t_B})
\end{aligned} \tag{7}$$

An implicit assumption of the current weighted link relative is that, within an estimation cell, establishments not reporting data for both months t and $t-1$ have the same expected growth rate as establishments reporting data, i.e., they all follow Model 0. The nonreporters include nonsampled units, and late reporting and nonresponse units in month t, as well as preliminary reporting units in month t for which data were not reported in month $t-1$.

A more reasonable assumption may be that the proportionality factor varies not only by the static characteristics currently used to define estimation cells, but also by dynamic characteristics related to recent employment information for the establishment. If, instead of Model 0, suppose that proportionality factors vary across classifications of establishments within estimation cell, as in

$$\text{Model } 1: \; E(Y_{tcgi} | Y_{(t-1)cgi}) = \rho_{tcg} Y_{(t-1)cgi} \tag{8}$$

where g represents some further classification of establishments within estimation cell c and ρ_{tcg} is the model parameter describing the month t expected growth rate for class g within cell c.

Then, the expected value under this model of the current weighted link relative no longer equals the expected value of the population total. This can be shown by first writing the deviation of the ρ_{tcg} from ρ_{tc} as

$$\rho_{tcg} = \rho_{tc} + \delta_{tcg}$$

The expected value of the current weighted link relative under Model 1 is then

$$\begin{aligned} E\left(LR^{(k)}_{t,(t-1)c} | \text{Model } 1, \boldsymbol{Y}_{t-1}\right) &= \frac{\sum_g \sum_{i \in s_{t,(t-1)cg|k}} w_{cgi} \rho_{tcg} Y_{(t-1)cgi}}{\sum_g \sum_{i \in s_{t,(t-1)cg|k}} w_{cgi} Y_{(t-1)cgi}} \\ &= \frac{\sum_g (\rho_{tc} + \delta_{tcg}) \sum_{i \in s_{t,(t-1)cg|k}} w_{cgi} Y_{(t-1)cgi}}{\sum_g \sum_{i \in s_{t,(t-1)cg|k}} w_{cgi} Y_{(t-1)cgi}} = \rho_{tc} + \sum_g \delta_{tcg} \hat{p}^{(k)}_{(t-1)cg} \equiv \rho_{tc} + \Psi^{(k)}_{tc} \end{aligned} \tag{9}$$

where $\Psi^{(k)}_{tc}$ is defined by the last equality and $\hat{p}^{(k)}_{(t-1)cg} = \sum_{i \in s_{(t,t-1)cg|k}} w_{cgi} Y_{(t-1)cgi} / \sum_g \sum_{i \in s_{t,(t-1)cg|k}} w_{cgi} Y_{(t-1)cgi}$ is an estimate as of revision k of $p_{(t-1)cg} = \sum_{i \in U_{(t-1)cg}} Y_{(t-1)cgi} / \sum_g \sum_{i \in U_{(t-1)cg}} Y_{(t-1)cgi}$, the proportion of the $U_{(t-1)cg}$ population total for estimation cell c contained within class g for month $t-1$.

Thus, if subdivisions, g, below the estimation cell level, c, have different growth rates, the current weighted link relative may be model-biased. In particular, if the deviations from the overall cell growth rate do not net out (i.e., $\Psi^{(k)}_{tc} \neq 0$), the current weighted link relative will be biased under Model 1. Empirical information on these components is provided in Section 5. Note that, under Model 1, with complete response the design-expectation of $\hat{p}^{(k)}_{(t-1)cg}$ is $p_{(t-1)cg}$, which implies that the design-expectation for $\Psi^{(k)}_{tc}$ is 0. Therefore, the weighted link relative is unbiased under Model 1 when repeated sampling is also considered.

The expected value of the month t estimated employment under Model 1 is

$$\begin{aligned} E\left(\hat{Y}^{(k)}_t | \text{Model } 1\right) &= \sum_c E\left(\left[Y_{t_B c} LR^{(k)}_{t,(t-1)c} LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model } 1\right) \\ &= \sum_c E \ldots E\left(\left[Y_{t_B c} LR^{(k)}_{t,(t-1)c} LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model } 1, Y_{(t_B+1)c}, \ldots, Y_{(t-1)c}\right) \\ &= \sum_c E \ldots E\left(\left[Y_{t_B c}\left(\rho_{tc} + \Psi^{(k)}_{tc}\right) LR^{(k+1)}_{(t-1),(t-2)c} \prod_{t^*=t_B+1}^{t-2} LR^{(3)}_{t^*,(t^*-1)c}\right] | \text{Model } 1, Y_{(t_B+1)c}, \ldots, Y_{(t-2)c}\right) \\ &= \ldots = \sum_c \left(Y_{t_B c}\left(\rho_{tc} + \Psi^{(k)}_{tc}\right)\left(\rho_{(t-1)c} + \Psi^{(k+1)}_{(t-1)c}\right) \prod_{t^*=t_B+1}^{t-2} \left(\rho_{t^* c} + \Psi^{(3)}_{t^* c}\right)\right) \equiv \sum_c Y_{t_B c} A_{tc} \end{aligned}$$

where A_{tc} is defined recursively as

$$A_{tc}=\prod_{t^*=t_B+1}^{t}\left(\rho_{t^*c}+\Psi_{t^*c}^{(K)}\right)$$

$$=\prod_{t^*=t_B+1}^{t}\rho_{t^*c}+\Psi_{(t_B+1)c}^{(3)}\prod_{t^*=t_B+2}^{t}\rho_{t^*c}+\Psi_{(t_B+2)c}^{(3)}A_{(t_B+1)c}\prod_{t^*=t_B+3}^{t}\rho_{t^*c}$$

$$+\ldots+\Psi_{(t-2)c}^{(3)}A_{(t-3)c}\prod_{t^*=t-1}^{t}\rho_{t^*c}+\Psi_{(t-1)c}^{(k+1)}A_{(t-2)c}\rho_{tc}+\Psi_{tc}^{(k)}A_{(t-1)c}$$

$$=\prod_{t^*=t_B+1}^{t}\rho_{t^*c}+B_{tc}$$

and B_{tc} is defined by the last equality. In the first line of the expression for A_{tc}, $K=k$ when $t^*=t$, $K=\min(k+1,3)$ when $t^*=t-1$, and $K=3$ when $t_B+1\leq t^*\leq t-2$. Any product in A_{tc} where the lower limit is greater than the upper limit for a particular t is understood to be zero and, by definition, $A_{t_Bc}=0$. Thus, we have

$$E\left(\hat{Y}_t^{(k)}|\text{Model 1}\right)=E(Y_t|\text{Model 0})+\sum_c Y_{t_Bc}B_{tc} \tag{10}$$

This calculation assumes the number of sample units in $s_{t,(t-1)c|k}$ is sufficiently large so the expectation of the product of ratios is approximately equal to the product of the expectations of the ratios. Again, under complete response, the design expectation of $\Psi_{t^*c}^{(K)}$ is zero, and the estimated employment is approximately design-model unbiased under Model 1.

Assuming ρ_{t^*c} and $\Psi_{t^*c}^{(k)}$ are relatively stable across time, replacing them with their mean values, $\bar{\rho}_c$ and $\overline{\Psi}_c$, and applying the binomial expansion, yields

$$E\left(\hat{Y}_t^{(k)}|\text{Model 1}\right) = E(Y_t|\text{Model 0}) + \sum_c Y_{t_Bc}(\bar{\rho}_c + \overline{\Psi}_c)^{t-t_B}$$

$$= E(Y_t|\text{Model 0}) + \sum_c\left\{Y_{t_Bc}\left[(t-t_B)\overline{\Psi}_c\bar{\rho}_c^{\,t-t_B-1} + \ldots + (t-t_B)\overline{\Psi}_c^{\,t-t_B-1}\bar{\rho}_c + \overline{\Psi}_c^{\,t-t_B}\right]\right\} \tag{11}$$

Further, assuming $\overline{\Psi}_c$ is small relative to $\bar{\rho}_c$ (if $\bar{\rho}_c$ is around 1.0, say $\overline{\Psi}_c < 0.001$), then terms involving 2nd and higher order values for $\overline{\Psi}_c$ may reasonably be ignored, leaving

$$E(\hat{Y}_t|\text{Model 1}) \cong E(Y_t|\text{Model 0}) + \sum_c\left[Y_{t_Bc}(t-t_B)\overline{\Psi}_c\bar{\rho}_c^{\,t-t_B-1}\right] \tag{12}$$

This result shows the bias in $\hat{Y}_t$ due to model misspecification increases with the number of months from the last benchmark date, assuming $\overline{\Psi}_c$ is nonzero. This provides the motivation for carrying out benchmark updates on a frequent basis. For the CES survey, the number of months from the last benchmark ranges from 11 to 23. Thus, even if biases on the monthly link relatives are less than one-tenth of one percentage point, the cumulative bias on the monthly employment estimate could be on the order of one percent of the population value after 11 or more months.

Given incomplete reporting, the expected value of the weighted link relative under Model 1 will vary between the preliminary and the final due to the inclusion of late reporters. The expected difference can be written as

$$E\left(LR^{(3)}_{t,(t-1)c} - LR^{(1)}_{t,(t-1)c}\right) = \left(\rho_{tc} + \sum_g \delta_{tcg}\hat{p}^{(3)}_{(t-1)cg}\right) - \left(\rho_{tc} + \sum_g \delta_{tcg}\hat{p}^{(1)}_{(t-1)cg}\right)$$

$$= \sum_g \delta_{tcg}\left(\hat{p}^{(3)}_{(t-1)cg} - \hat{p}^{(1)}_{(t-1)cg}\right) \tag{13}$$

To the extent the estimated relative sizes of the population in estimation cell c contained within class g vary between 1st and 3rd closings, the 1st and 3rd closing link relatives will differ. Empirical information on these values is provided in Section 5. One approach to generation of a 1st closing estimate subject to less revision would be to use the sample that can later be included as late reporters, thereby reducing differences between the $\hat{p}^{(1)}_{(t-1)cg}$ and $\hat{p}^{(3)}_{(t-1)cg}$. This is the approach developed in Section 6.

5. Empirical Data Related to Potential Bias in the Link Relative

Analyses used CES sample data for the period January 2000 through December 2002, along with ES-202 population totals for March 2001 and 2002, for establishments from the four industries – Construction, Manufacturing, Mining, and Wholesale Trade – which had transitioned to a probability sample design as of March 2001. A total of 60,944 sample establishments met the inclusion criteria.

Two sets of characteristics were hypothesized to be related to employment growth rate for month t: prior month employment size and prior month employment change. Employment size was considered because: 1) growth rate experience may reasonably be expected to differ for small and large establishments; and 2) growth rates are inherently more unstable for establishments with smaller employment in month $t-1$ (i.e., an employment change of 1 for an establishment with month $t-1$ employment of 5 represents a 20% change). Prior month employment change was considered since employment change for the current period could vary based upon the direction and magnitude of recent employment trends for an establishment.

Employment change can be viewed in actual $(Y_{(t-1)i} - Y_{(t-2)i})$ or relative $(Y_{(t-1)i}/Y_{(t-2)i})$ terms. For smaller establishments, actual employment change provides a more stable measure than does relative employment change, while the opposite is true for larger establishments. Therefore, the approach was developed to use actual change for smaller establishments and relative change for larger establishments.

Rank ordered prior month employment changes (both actual and relative) for each month were separated into three sets of units for purposes of defining prior month employment change classes within an industry, with each set containing the same number of sample establishments. Establishments within the first set were designated as low prior month employment change, those within the second set were designated as mid, and those within the third set were designated as high. Those units for which prior employment change was not known (i.e., unit did not report for month $t-2$) were designated as unknown.

The class used for an establishment was determined based upon the establishment's employment level for month $t-1$ (the base month for the employment change to be estimated by the model). For establishments classified as small employment level (<50) for month $t-1$, the actual prior month employment change class was used; for establishments classified as large employment level for month $t-1$, the relative prior month employment change class was used.

Averages of the monthly values for δ_{tcg} and $\hat{p}^{(3)}_{(t-1)cg}$ for the period March 2000–December 2002, for classes defined by prior month employment and prior month employment change within industry, were calculated using the 3rd closing reported sample (see Table 1). These results indicate that for smaller establishments (prior month employment <10), those with prior month employment change classified as low or high deviate noticeably from the industry level growth rate, and in opposite directions. Establishments with prior month employment of 10–19 and 20–49 showed some tendencies in this same direction, but not to the extent seen for the smallest size class. Where deviations occurred, establishments with low prior month employment change experienced growth rates larger than those for the industry as a whole, while establishments with high prior month employment change experienced growth rates smaller than those for the industry as a whole.

An illustration shows the degree of deviation from Model 0 for selected classes. Figure 1 presents a graph of link relatives for reporting establishments with prior month employment <10 for Construction plotted against the weighted link relatives for the industry as a whole. Different symbols are used for the three prior month employment change classes (Low, Mid, High). If Model 0 fit for all classes the observations would be on the 45-degree line denoted as "Linear (Model 0 Fit)."

For establishments in the Low prior month employment change class, the link relatives for the industry as a whole are well below the actual link relatives, while for establishments in the High prior month employment change class the link relatives for the industry as a whole tend to be above the actual link relatives. Results for the Mid prior month employment change class are fairly consistent with those for the industry as a whole. These results suggest that Model 1 (prior month employment size crossed with prior month employment change), at least for one or several smaller size classes, could better explain employment growth rates for potential late reporters than Model 0.

Based upon the preceding information, rough estimates of the potential bias in the current CES weighted link relative estimator and revisions between 1st and 3rd closing under Model 1 were estimated and are presented in Table 2. Potential bias and revisions were derived using average values of δ_{tcg}, $\hat{p}^{(1)}_{(t-1)cg}$, and $\hat{p}^{(3)}_{(t-1)cg}$ from Table 1, in conjunction with Formulae (12) and (13).

Results indicate small estimated biases for a monthly link relative based on the average values of δ_{tcg}, $\hat{p}^{(1)}_{(t-1)cg}$, and $\hat{p}^{(3)}_{(t-1)cg}$. Nevertheless, since the estimate for a given month is linked to the benchmark through 11 to 23 months and the bias is cumulative, the estimated bias for a monthly employment estimate could be on the order of several tenths of a percentage point (and more than one percentage point for Mining). However, examination of the estimated biases resulting from the individual month values, from which Table 1

Table 1. Components of Potential Model Misspecification Error: Prior Month Employment Size × Prior Month Employment Change for March 2002–December 2002

Industry	Prior month employment size	Prior month employment change							
		Low	Mid	High	Unk	Low	Mid	High	Unk
		Average values for δ_{tcg}				Average values for $\hat{p}^{(3)}_{(t-1)cg}$			
Construction	< 10	0.105	0.010	−0.031	0.029	0.028	0.102	0.031	0.007
	10–19	0.028	−0.006	−0.021	−0.004	0.035	0.049	0.041	0.004
	20–49	0.003	−0.007	0.001	−0.012	0.058	0.073	0.071	0.006
	50–99	−0.014	−0.005	0.005	−0.002	0.044	0.054	0.055	0.004
	100–249	−0.020	−0.005	0.007	0.001	0.053	0.060	0.072	0.005
	250 +	−0.016	−0.004	−0.003	−0.019	0.036	0.054	0.052	0.006
Manufacturing	< 10	0.093	0.004	−0.035	0.036	0.003	0.016	0.003	0.001
	10–19	0.024	−0.002	−0.012	0.005	0.007	0.015	0.007	0.001
	20–49	0.011	−0.003	−0.004	0.007	0.023	0.025	0.023	0.002
	50–99	0.000	−0.003	0.002	0.005	0.030	0.032	0.033	0.003
	100–249	0.003	−0.002	0.002	−0.006	0.072	0.062	0.077	0.004
	250 +	−0.006	−0.001	0.004	−0.005	0.144	0.229	0.169	0.019
Mining	< 10	0.183	0.001	0.002	0.076	0.009	0.051	0.009	0.003
	10–19	0.017	−0.017	−0.044	−0.018	0.016	0.033	0.018	0.002
	20–49	0.008	−0.005	−0.017	0.035	0.034	0.054	0.042	0.003
	50–99	0.002	−0.005	0.002	−0.037	0.027	0.032	0.034	0.002
	100–249	0.005	−0.004	0.015	0.016	0.046	0.035	0.049	0.003
	250 +	−0.008	0.003	−0.006	−0.092	0.147	0.191	0.147	0.014
Wholesale trade	< 10	0.056	0.002	−0.024	0.019	0.013	0.108	0.012	0.006
	10–19	0.017	−0.001	−0.015	0.018	0.020	0.062	0.021	0.004
	20–49	0.010	−0.003	−0.007	−0.005	0.048	0.071	0.049	0.007
	50–99	0.001	−0.001	−0.004	−0.003	0.043	0.049	0.050	0.005
	100–249	0.001	0.001	−0.002	−0.012	0.058	0.060	0.066	0.008
	250 +	−0.005	0.000	0.002	−0.003	0.070	0.079	0.069	0.021

NOTE: Unk refers to unknown prior month employment change, such as when as establishment did not report in both the prior months

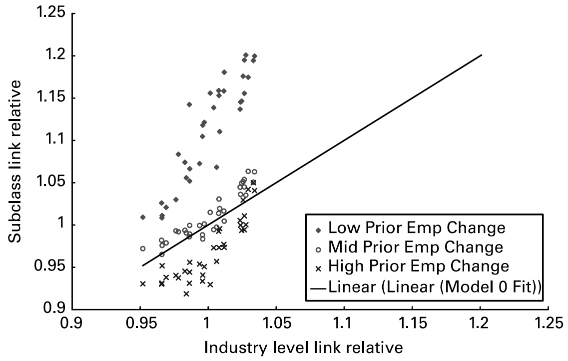

Fig. 1. Employment Change Subclass Link Relatives vs. Industry Level Link Relatives for Construction Establishments with Prior Month Employment < 10, March 2000–December 2002

was derived, indicated that the biases tend to be fairly evenly balanced around zero. This suggests the biases could have a tendency to net out over time. Should this not be the case – for example should the sample composition be skewed toward establishments with lower growth rates than for the industry as a whole – then there is the potential for biases on the order of a tenth of a percentage point or more on the estimated link relative in any given month.

The estimated bias for small establishments, however, appears much more pronounced. Using the same approach, the estimated bias was derived for establishments with prior month employment <10 (see Table 3). Average bias refers to the bias derived using average values of δ_{tcg} and $\hat{p}^{(3)}_{(t-1)cg}$. Minimum bias refers to the bias estimated using average values of δ_{tcg} with minimum values of $\hat{p}^{(3)}_{(t-1)cg}$ if δ_{tcg} is positive and with maximum values of $\hat{p}^{(3)}_{(t-1)cg}$ if δ_{tcg} is negative. Maximum bias refers to the bias estimated using average values of δ_{tcg} with maximum values of $\hat{p}^{(3)}_{(t-1)cg}$ if δ_{tcg} is positive and with minimum values of $\hat{p}^{(3)}_{(t-1)cg}$ if δ_{tcg} is negative. Average, minimum, and maximum values are derived across the period March 2000 through December 2002.

The results show that estimated bias in the link relative for such establishments could be more than one percentage point. In addition, minimum and maximum estimated biases are not balanced around zero, and thus would tend to cumulate across time. In the U.S., small establishments are often considered an important source of job creation, especially in technology industries where innovation is occurring. Thus, having good estimates for that segment of the population is important for some analyses.

Table 2. Potential Error Associated with Current Weighted Link Relative, Under Model 1 Based on Data from March 2000–December 2002

Industry	Potential bias	Potential revision
Construction	0.0001	−0.0002
Manufacturing	0.0000	−0.0001
Mining	−0.0019	0.0001
Wholesale trade	0.0001	−0.0001

NOTE: Potential Bias, Revision derived using average values of δ_{tcg}, $\hat{p}^{(1)}_{(t-1)cg}$, and $\hat{p}^{(3)}_{(t-1)cg}$ from Table 1

Table 3. Estimated Bias for Current Weighted Link Relative Under Model 1
Prior Month Employment < 10
Based on Data from March 2000–December 2002

Industry	Estimated bias		
	Average	Minimum	Maximum
Construction	0.0194	0.0172	0.0209
Manufacturing	0.0129	0.0118	0.0139
Mining	0.0260	0.0138	0.0374
Wholesale trade	0.0057	0.0054	0.0058

6. An Alternative Approach

The results in the prior section suggest that employment growth rate within industry may vary based upon prior month employment size and prior month employment change, at least for establishments with small prior month employment. In an attempt to reduce the revision between 1st and 3rd closings, imputation for missing month t data was carried out for sample units reporting for month $t-1$. While this results in the inclusion of sample units that do not subsequently become late reporters (i.e., that become nonresponders for month t), given that late reporters make up the majority ($\sim 75\%$) of these sample units, it was felt this approach may yield smaller differences between 1st and 3rd closing estimates.

Classification of units within industry was made based on prior month employment and prior month employment change.

Based on the results in Section 5, two sets of size classes were used in the evaluation: 1) <10 and $10+$ (recognizing the distinctions in deviations seen at the size class level) – Model 1A; and 2) <10, 10–19, 20–49, and $50+$ (recognizing potential additional distinctions in deviations seen at the size by employment growth class level) – Model 1B. Four prior employment change classes (Low, Mid, High, Unknown) were created for smaller size classes. For the large establishment size class, no further disaggregation by prior month employment change was made, given the results discussed previously. Growth rates were estimated using a maximum likelihood estimator like that given in (5).

One question is specification of the assumed distribution for units other than those reporting in month $t-1$ (i.e., other than constant reporters or units for which imputations are carried out). Pattern-mixture models (Little 1993) offer one approach. The population can be assumed to be divided into three groups:

- Units for which data for both months t and $t-1$ are available. These are the units currently used in the weighted link relative.
- Units for which data for only month $t-1$ are available. These are the units for which the alternative approach will derive imputed values for use in the weighted link relative.
- Units for which data for month $t-1$ are not available. These represent a combination of nonsampled, nonreporters for both months t and $t-1$, and units reporting for month t but not month $t-1$.

Each of these three groups of units is assumed to have a different missing data pattern. Under the pattern-mixture model approach, growth rate is assumed dependent upon missing data pattern, e.g.,

$$Y_{tMcgi} = \rho_{tMcg} Y_{(t-1)Mcgi} + k_{tMcgi}$$

$$k_{tcMgi} \overset{ind}{\sim} N\left(0, \frac{\sigma_k^2 Y_{(t-1)cMgi}}{w_{cMgi}}\right)$$

where M refers to missing data pattern as defined above.

Growth rates for missing data patterns 2 and 3 cannot be estimated from the data. Therefore identifying restrictions linking the parameters for the models for missing data patterns 2 and 3 are linked to those for missing data pattern 1 so as to allow estimation of parameters. The identifying restrictions for missing data pattern 2 assume equivalence of growth rates within the redefined cells, i.e., $\rho_{t2cg} = \rho_{t1cg}$. This identifying restriction allows imputation of missing values based upon the estimated growth rates for a cell based upon constant reporters.

For missing data pattern 3, the intention is to use the weighted link relative within an industry based upon the set of constant reporters plus reporters for month $t-1$ with imputed values to estimate the link relative for the industry. This assumes that the identifying restriction for missing data pattern 3 links the growth for units in the missing data pattern at the industry level to the marginal (at the industry level) of the growth rates for missing data patterns 1 and 2, i.e., $\rho_{t3c} = \rho_{t.c}$

One could examine more elaborate alternatives, such as incorporation of additional characteristics (e.g., geography, metropolitan/nonmetropolitan area, and further breakdowns within industries). As expansion of the set of characteristics included in the model would greatly expand the number of parameters, use of regression techniques could be investigated. Regression would, in fact, be more flexible than the cell formation methods described above since main effects and subsets of interactions could be used rather than the full cross-classification of all variables. Exploration of such alternatives was not possible in this case because of limitations in the available data but is worthy of future research.

7. Empirical Analysis of the Alternative Approach

The data set used for the empirical analysis consisted of CES reports for four industries (Construction, Manufacturing, Mining, and Wholesale Trade) for the period January 2000–December 2002. Outliers, which are treated differently in the CES weighted link relative, were excluded for purposes of analysis.

Monthly estimates of employment were derived by utilizing March 2000 ES-202 data as the benchmark month, and moving the estimates forward by multiplying link relatives across months. Preliminary estimates were calculated as the preliminary link relative times the prior month's final estimate of employment.

Variance estimates for weighted link relative estimates were derived using the CES BRR method described previously. As discussed in Shao et al. (1998), imputing for missing values separately using only the data within each half-sample recovers variance due to imputation and produces consistent variance estimates for a class of estimators that are smooth functions of totals, which encompasses the weighted link relative estimator. This approach to variance estimation was carried out for the empirical analysis, with growth rates estimated separately for each half-sample.

For monthly estimates, the performance measure used is the relative revision between preliminary and final estimates

$$\mathrm{Rel\,Rev}\left(\hat{Y}_t^{(1)}\right) = \left(\hat{Y}_t^{(3)} - \hat{Y}_t^{(1)}\right) / \hat{Y}_t^{(1)}$$

The difference in absolute relative revisions between that for the current method and that for an alternative method provides an indication of the reduction in the magnitude of the revision. Table 4 provides summary information for the relative revisions across the period April 2000 through December 2002. Revisions for alternative methods are essentially the same as those for the current method, although the alternative methods achieved a slight reduction in the average revision. These results are consistent with the rough estimated revisions derived in Section 5.

It must be noted that variances associated with the link relatives dominate the size of the revisions. Whereas average absolute relative revisions are on the order of 0.1% to 0.3%, the standard errors on both preliminary and final weighted link relative estimates are roughly three to ten times that size, on the order of 0.3% to 1.3% (see Table 5). This relationship between standard errors and size of revisions will limit the conclusions that can be drawn from the analysis.

For estimates of month-to-month change, the performance measure used is the actual revision between preliminary and final estimates

$$\mathrm{Rev}\left(\hat{\Delta}_{t,(t-1)}^{(1)}\right) = \hat{\Delta}_{t,(t-1)}^{(3)} - \hat{\Delta}_{t,(t-1)}^{(1)}$$

For all industries, there is a reduction in the absolute revision of month-to-month change estimates, on average across the months, as seen in Table 6. This reduction, although less than 1,000 on average, does represent 6% – 8% of the average revision for the current method.

Table 4. Relative Revisions in Estimated Monthly Employment April 2000–December 2002

Industry	Metric	Current	Model 1A	Model 1B
Construction	Ave Revision	0.00%	0.01%	0.02%
	Ave Abs Revision	0.11%	0.10%	0.10%
	Ave Reduction in Abs Revision	–	0.01%	0.01%
Manufacturing	Ave Revision	−0.02%	−0.02%	−0.02%
	Ave Abs Revision	0.08%	0.08%	0.08%
	Ave Reduction in Abs Revision	–	0.01%	0.01%
Mining	Ave Revision	0.04%	0.05%	0.04%
	Ave Abs Revision	0.30%	0.30%	0.30%
	Ave Reduction in Abs Revision	–	0.00%	0.00%
Wholesale trade	Ave Revision	−0.02%	−0.01	0.00%
	Ave Abs Revision	0.08%	0.08%	0.08%
	Ave Reduction in Abs Revision	–	0.01%	0.00%

Table 5. Average Revisions, Standard Errors for Estimated Link Relatives April 2000-December 2002

Industry	Current			Model 1A			Model 1B		
	Average s.e.			Average s.e.			Average s.e.		
	Preliminary	Final	Average absolute revision	Preliminary	Final	Average absolute revision	Preliminary	Final	Average absolute revision
Construction	1.06%	1.07%	0.11%	1.06%	1.07%	0.10%	1.08%	1.08%	0.10%
Manufacturing	0.33%	0.33%	0.08%	0.33%	0.33%	0.08%	0.33%	0.33%	0.08%
Mining	1.42%	1.32%	0.30%	1.43%	1.30%	0.30%	1.41%	1.29%	0.30%
Wholesale trade	0.64%	0.55%	0.08%	0.65%	0.56%	0.08%	0.66%	0.56%	0.08%

Table 6. Absolute Revision in Estimated Month-to-Month Change in Employment May 2000-December 2002

Industry	Metric	Current	Model 1A		Model 1B	
Construction	Ave Abs Revision	6,506	6,006		6,095	
	Ave Reduction in Abs Revision	–	500	7.7%	411	6.3%
Manufacturing	Ave Abs Revision	11,540	10,824		10,702	
	Ave Reduction in Abs Revision	–	716	6.2%	837	7.3%
Mining	Ave Abs Revision	1,500	1,492		1,487	
	Ave Reduction in Abs Revision	–	7	0.5%	13	0.9%
Wholesale trade	Ave Abs Revision	3,603	3,362		3,476	
	Ave Reduction in Abs Revision	–	241	6.7%	128	3.6%

At a more local level, the performance of the model can be evaluated by comparing imputed values to actual values for late reporters. Imputation error for a set of late reporters can be defined as

$$\mathrm{Rel\,Err(Method}\ \ m) = \frac{\sum_{i \in s_t^{LR}} \hat{Y}_{ti,m} - \sum_{i \in s_t^{LR}} Y_{ti}}{\sum_{i \in s_t^{LR}} Y_{ti}}$$

where Y_{ti} represents the reported employment for month t from sample establishment i

$\hat{Y}_{ti,m}$ represents the imputed employment for month t for sample establishment i, based on imputation method m

s_t^{LR} represents the set of late reporters for month t

Note that for the current weighted link relative estimator, the imputed employment for a sample establishment is equal to the prior month employment for that establishment times the 1st closing link relative for the corresponding estimation cell

$$\hat{Y}_{tci,m} = LR^{(1)}_{t,(t-1)c} Y_{(t-1)ci}$$

Tables 7 and 8 contain summary information on average relative errors by prior month size, and by prior month employment change within prior month size, for March 2000–December 2002. Both 10+ and 10–19, 20–49, 50+ size classes are shown, with the results for Model 1 based upon the corresponding Model 1A (10+) or Model 1B (10–19, 20–49, 50+).

These data show reduction in errors for establishments with prior month employment < 10, especially those with Low prior month employment change. These data also indicate that improvements due to use of Model 1 are fairly well restricted to establishments with prior month employment size < 10.

Table 7. Relative Errors in Predicting Employment for Late Reporters, March 2000–December 2002

Size Class	Metric	Construction		Manufacturing		Mining		Wholesale trade	
		Current	Model 1	Current	Model 1	Current	Model 1	Current	Model 1
< 10	Ave Rel Err	−5.5%	−3.3%	−5.5%	−3.9%	−7.8%	−5.9%	−1.0%	−0.3%
	Ave Abs (Rel Err)	5.6%	3.9%	5.7%	4.4%	9.8%	8.7%	1.4%	1.1%
	Ave Reduction in Abs (Rel Err)		1.7%		1.2%		1.2%		0.3%
10 +	Ave Rel Err	0.1%	−0.3%	0.0%	0.0%	−0.3%	−0.4%	0.1%	0.0%
	Ave Abs (Rel Err)	0.8%	0.08%	0.3%	0.3%	1.1%	1.2%	0.4%	0.4%
	Ave Reduction in Abs (Rel Err)		0.0%		0.0%		0.0%		0.0%
10–19	Ave Rel Err	−1.7%	−1.7%	−0.3%	0.0%	−0.3%	−1.4%	0.3%	0.5%
	Ave Abs (Rel Err)	2.2%	2.5%	1.8%	1.8%	3.9%	4.4%	1.2%	1.3%
	Ave Reduction in Abs (Rel Err)		−0.2%		0.0%		−0.5%		−0.1%
20–49	Ave Rel Err	−1.7%	−1.9%	−0.6%	−0.5%	0.3%	−0.2%	0.3%	0.2%
	Ave Abs (Rel Err)	2.0%	2.1%	1.1%	1.1%	2.0%	2.3%	0.9%	1.1%
	Ave Reduction in Abs (Rel Err)		−0.1%		0.0%		−0.3%		−0.2%
50 +	Ave Rel Err	0.3%	−0.3%	0.0%	0.0%	−0.3%	−0.2%	0.1%	−0.1%
	Ave Abs (Rel Err)	0.9%	0.9%	0.3%	0.3%	1.2%	1.4%	0.4%	0.5%
	Ave Reduction in Abs (Rel Err)		0.0%		0.0%		−0.2%		−0.1%

Table 8. Relative Errors in Predicting Employment for Late Reporters with Prior Month Employment Size < 10, March 2000–December 2002

Size class	Emp change class	Metric	Construction		Manufacturing		Mining		Wholesale trade	
			Current	Model 1	Current	Model 1	Current	Model 1	Current	Model 1
< 10	Low	Ave Rel Err	−13.6%	−5.1%	−12.1%	−4.8%	−12.7%	−1.5%	−5.4%	0.0%
		Ave Abs (Rel Err)	14.2%	7.3%	12.6%	10.1%	20.0%	21.5%	6.3%	5.1%
		Ave Reduction in Abs (Rel Err)		6.8%		2.6%		−1.5%		1.2%
	High	Ave Rel Err	3.7%	0.9%	−0.6%	−4.0%	−3.7%	−3.3%	2.9%	0.7%
		Ave Abs (Rel Err)	5.8%	4.7%	6.3%	6.8%	18.1%	22.7%	4.6%	4.7%
		Ave Reduction in Abs (Rel Err)		1.1%		−0.5%		−4.5		−0.2%
	Mid	Ave Rel Err	−4.5%	−3.3%	−3.2%	−2.7%	−4.7%	−4.9%	−0.7%	−0.4%
		Ave Abs (Rel Err)	5.0%	4.2%	3.9%	3.6%	8.2%	8.6%	1.3%	1.2%
		Ave Reduction in Abs (Rel Err)		0.9%		0.3%		−0.4%		0.1%

8. Implications

Late reporting is a common phenomenon in longitudinal surveys of establishments. If the late reporters have different characteristics than reporters used for initially published estimates, this can lead to bias. The U.S. Current Employment Statistics Survey is an example of this where monthly estimates are published on a regular schedule. As data for late reporters are received, revised estimates are released. A critical goal is to limit the size of these revisions since economic policy is affected by the estimates, and the credibility of the survey as useful policy input must be maintained. This issue is faced by other governmental surveys, such as the Survey of Employment, Payroll, and Hours (SEPH) in Canada, and the Monthly Retail Trade Survey in the U.S.

The current CES weighted link relative estimator of total employment will be biased if employment growth rates vary depending on characteristics not accounted for in estimation. We found that growth rates do vary by size of establishment and previously reported sizes of employment change. At the aggregate industry level, accounting for these variations through imputation did not yield significant improvement in the sizes of monthly revisions. However, for small establishments consistent improvement was achieved by imputing for nonreporters using a model that incorporates recent reported data, in addition to type of industry and size class, in the imputation model.

Although the improvements in this case were not statistically significant, growth rates for late reporters were clearly different from those other establishments. Adjusting for the small differences is important for surveys whose results, such as estimated numbers of jobs created or lost, are used in labor market policy analysis and are closely monitored by financial markets. Even though the adjustments themselves may be small, making them can be important for public perception of the quality of the survey.

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