Recent Developments in Current Employment Statistics

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Abstract

The Current Employment Statistics (CES) program produces some of the timeliest, most valued monthly economic data, based on a large survey of businesses, reporting information on nonfarm payroll employment, hours, and earnings. In the 2020s, CES has faced lower response rates than before, while revisions have led to criticism from some data users. This paper presents a view of some of the challenges CES faces, how the program has adapted, and improvements CES is currently investigating and pursuing.

[1] Any opinions expressed in this paper are those of the authors and do not constitute policy of the Bureau of Labor Statistics.

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Introduction

The Current Employment Statistics (CES) program collects payroll data from a selected sample of nonfarm establishments to produce one of the 7 Principle Federal Economic Indicators published by the Bureau of Labor Statistics (BLS).[2,3] At the beginning of every month, BLS publishes national-level CES estimates for employment, hours, and earnings for the prior month alongside the unemployment rate from the Current Population Survey in the Employment Situation news release.[4] Together, data from these surveys are among the earliest indicators of current economic health; in particular, over-the-month changes in CES national-level employment signal underlying strength or weakness in the labor market.

The CES mission is to deliver timely, accurate, objective, and reliable data on nonfarm payroll employment, hours, and earnings across detailed industries for the nation, states, and metropolitan areas. The task is complex. The U.S. economy – the largest in the world[5] – is influenced by forces such as the supply and demand of labor, the surplus or shortage of workers, seasonal changes, cyclical changes, technological changes, and policy changes, making it

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[2] The monthly CES survey (also known as the payroll survey or the establishment survey) covers approximately 119,000 businesses and government agencies representing approximately 622,000 worksites throughout the United States. CES estimates represent information reported by survey respondents for their pay periods that include the 12th of the month. For more information on the program's concepts and methodology, see "Current Employment Statistics–National," in "Handbook of Methods," (U.S. Bureau of Labor Statistics), https://www.bls.gov/opub/hom/ces/. To access CES national-level data, see "Current Employment Statistics–CES (National)," https://www.bls.gov/ces.

[3] Principal federal economic indicators are the major statistical series that describe the current condition of the economy, as designated by the U.S. Office of Management and Budget (OMB). The indicators are compiled, released, and periodically evaluated in accordance with procedures established in OMB Statistical Policy Directive No. 3.

[4] Statistics on the employment status of the population are compiled from the Current Population Survey, which is administered by the US Census Bureau for the BLS. Respondents are interviewed to obtain the employment status of each member of the household 16 years of age and older. The inquiry relates to activities that occurred during the calendar week, Sunday through Saturday that includes the 12th of the month (the reference week.) The field interviews are conducted the following week, which is known as the survey week. For more information about the CPS program is available at http://www.bls.gov/cps/.

[5] The United States has the largest economy in the world by nominal Gross Domestic Product (GDP), valued at approximately $32.38 trillion as of 2026.

difficult to measure at a single point in time. Every month millions of jobs are added or lost and CES is tasked with measuring the net change, making it difficult to measure perfectly at a single point in time. Adding to the complexity are methodological challenges inherent to the survey, such as tradeoffs in the timeliness of publication vs the accuracy of the estimates, the inability to capture business openings and closings in real time, shifting seasonality, and an increasing reluctance to respond to surveys in general. CES constantly evaluates all aspects of the survey methodology for potential improvements and takes action to make those improvements when possible.

Current CES Challenges

Timeliness. As some of the timeliest economic indicators available on a monthly basis, there is a very short window to collect the data and then produce and publish initial CES estimates. According to the Office of Management and Budget, Statistical Policy Directive No. 3, "the interval between the period to which the data or estimates refer and the date when the data or estimates are released to the public shall be as short as practicable".[6] Typically, the Employment Situation news release is published on the third Friday after the conclusion of the survey reference week[7]—the week that includes the 12th day of the month. This means there are

[6] Statistical Policy Directive No. 3

[7] The reference week is the pay period that includes the 12th of the month. CES survey respondents report by pay periods (which are specific to each establishment and may or may not reflect the Sunday-to-Saturday calendar week) that include the 12th of the month, regardless of the length of the pay period. Establishments have a range of payroll frequencies (weekly, bi-weekly, semi-monthly, and monthly). Respondents report pay period length to CES, but they do not report the start and end dates of their pay periods. CES normalizes all hours and earnings data to a weekly basis so that data from establishments with pay periods of differing lengths reflect a weekly value.
Generally, the Employment Situation publication date is the third Friday after the week that includes the 12th. This usually results in the release being scheduled for the first Friday of the month following the reference month. However, when the 12th of the month falls on a Sunday and there are 30 days or less in the month, the release date will be the second Friday of the month. In addition, if the third Friday after the December reference period falls on January 1–3, the release date will be the second Friday of the month.
If the normal release day Friday happens to be a federal holiday, such as July 4th, the release date will be the Thursday immediately preceding the holiday. The Employment Situation release dates are adjusted only for designated federal holidays.

generally 9-16 days to collect data before processing initial estimates. This short collection cycle prevents some survey respondents from reporting their payroll information in time to be used in these initial estimates; for example, some respondents may have longer pay periods that are not complete in time for the first published estimates. In addition, when processing for initial estimates begins prior to the 1st of the following month, some large, centrally-collected firms can miss the initial deadline.

After the first preliminary deadline and publication of the initial estimates, CES sample responses for the reference month continue to be collected for 6 additional weeks and are incorporated into the second preliminary estimates and the final-sample based estimates published in the 2 subsequent months. These additional or corrected sample responses after the initial collection cycle and the calculation of new seasonal adjustment factors each month are the source of CES sample-based employment revisions. [8] While the first published estimates are some of the most widely anticipated and analyzed economic indicators each month, this process of refinement enhances accuracy of the estimates over time and is considered a strength rather than a deficiency.

Business openings and closings. Another challenge for CES is the inability to capture business openings and closings in real time. The CES sample alone does not provide an adequate estimate of total employment because each month new firms generate employment change that cannot be immediately captured through existing sample. There is an unavoidable lag between a firm opening for business and its appearance on the CES sample frame, which is constructed from

[8] Revisions are calculated by comparing each month's second preliminary over-the-month change (OTMC) to the first preliminary change, the final sample-based OTMC to the second preliminary change, and the final sample-based OTMC to the first preliminary change, all on a seasonally adjusted basis.

quarterly Unemployment Insurance (UI) tax records.[9] These records cover virtually all U.S. employers and include newly established businesses, but they only become available on the CES sample frame 7 to 9 months after the reference month. Once these newly established businesses appear on the frame, additional time is required for sampling, contacting, and soliciting cooperation from the new firm and then verifying the initial data provided. In practice, it takes at least a full year to sample and collect data from new firms.

Similarly, there are challenges in identifying employment loss resulting from business closures during monthly sample collection. Businesses that have closed are unlikely to respond to the survey, and it may not be possible for data collectors to confirm closures until after the monthly collection period has ended. As with business openings, definitive information about business closures eventually becomes available only through delayed UI tax records.

Difficulty in capturing information from business birth and death units is not unique to the CES; virtually all current business surveys face these limitations. But, unlike many other surveys, CES explicitly adjusts for business births and deaths using statistical modeling techniques. Because the objective of the CES program is to estimate the change in employment each month – and the significance of business openings and closings in these calculations – CES applies a model-based adjustment in conjunction with reported sample. While the net birth-death adjustment has limitations, the CES nonfarm payroll employment estimates would be considerably less accurate without it.[10]

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[9] The universe of UI tax records serves as the sampling frame and primary benchmarking source for CES. Employment counts from these administrative records are published by the BLS Quarterly Census of Employment and Wages (QCEW).

[10] *More information about the CES net birth-death model is available on the CES Birth-Death Frequently Asked Questions page or in the Business births and deaths section of the CES Handbook of Methods. Current net birth-death contributions to the CES employment estimates are available on the CES Net Birth-Death page.*

Shifting seasonality. CES data users are mainly interested in seasonally adjusted over-the-month employment changes as a primary measure of overall national economic trends. Most series published by CES program have a regularly recurring seasonal movement that can be measured from past data. Seasonal adjustment eliminates the part of the change attributable to the normal seasonal variation and makes it possible to observe the cyclical and other nonseasonal movements in CES series. While seasonally adjusted series go through several monthly revisions and an annual benchmark revision before they are finalized, the first published estimates are the most widely anticipated and analyzed. In 2003 the survey converted from forecasted seasonal factors to concurrent seasonal adjustment in part to help adapt to shifting seasonal patterns more quickly. Under the concurrent methodology, new seasonal factors are calculated monthly, using all relevant data up to and including the current month.

Despite the improvements, sudden structural changes or economic shocks can break historical patterns, causing standard models to misidentify shifting seasonal peaks as real trend-cycle movements or irregular noise. For example, seasonal hiring in winter industries can be earlier or later than normal based on weather, school years may end later or start earlier than typical, factory shutdowns may be shorter in length or smaller than normal, and, after the COVID-19 pandemic, it took many industries years to return to their normal, or close to their normal seasonal hiring plans. In addition, when employment growth is accelerating (or decelerating), concurrent seasonal adjustment tends to revise that strength (or weakness) back through the prior 2 months. When events such as these occur at the end point of a time series, it may be difficult to determine whether an unusual data point reflects changing seasonality or other underlying patterns such as a cyclical or trend change.

Data collection. An increasingly challenging data collection environment is also becoming a challenge for the CES program. For the first 70 years of the survey, employers manually entered employment, hours, and earnings data on a survey form and mailed them to their State Employment Security Agencies (SESA). These State agencies would then forward the form to the Bureau of Labor Statistics (BLS) national office in Washington, D.C. From month-to-month, the form was shuttled back and forth between the employer, the SESA, and the BLS. This "shuttle" process resulted in low collection rates for the first and second releases of estimates for any given month. In the mid-1980s, the CES program began transitioning to automated data collection methods, and over the next 30 years, CES saw collection rates rise as more respondents transitioned to one of several automated collection methods. However, since 2019, the data collection environment has become more challenging, as it has for all statistical agencies, as respondents experience survey fatigue and a declining public willingness to participate in government surveys. This was exacerbated by the COVID-19 pandemic and subsequent lockdowns in 2020, resulting in CES collection rates dipping below 50 percent for initial estimates for the first time since early 2002. While collection rates have improved in recent years from the pandemic-related lows, they still have not returned to pre-pandemic levels, and the challenging data collection environment remains.[11]

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[11] *A variety of collection methods—mail, fax, touchtone data entry (TDE), computer-assisted telephone interviewing (CATI), electronic data interchange (EDI), and the web—better suit the individual preferences of respondents, thereby encouraging participation in the survey. By 2000, TDE had replaced mail as the most popular form of data collection, decreasing the lag time between the reference pay period and transmission to the BLS. The introduction and widespread use of automated systems such as CATI allowed for timelier and more accurate sample data than ever before as basic edits were performed at the time the data were collected. In recent years, reporting through the EDI method has become popular with large firms who pass on payroll data for multiple worksites across several states, if not nationwide. The newest data collection method, web-based reporting, allows for almost instantaneous transmission of data at minimal expense. Only a small percentage of sample units still report by mail.*

Recent methodological improvements (last 15 years):

Despite current CES challenges, several of which are detailed above, CES constantly evaluates all aspects of the program for potential improvements. This includes research on relevance, estimators, seasonal adjustment, and procedures. Recent program improvements include:

a. In 2011, CES began publication of all employee average hourly and weekly earnings, a broader measurement of earnings including managers, executives and their staff, and salaried officials, that is also used as an input into preliminary estimates of personal income by the Bureau of Economic Analysis.
b. In 2011, BLS began updating the business net birth-death model on a quarterly basis instead of annually.
c. In 2014, sample rotation changed from annual to quarterly to parallel the solicitation of new sample. This efficiency enabled CES to incorporate additional units quicker, while also improving response rates and estimates.
d. In 2015, CES transitioned from using X-12-ARIMA to X-13ARIMA-SEATS to produce seasonally adjusted series and net birth-death forecasts.
e. From March 2020 to October 2021, CES implemented temporary adjustments to better capture unprecedented employment changes during the COVID-19 pandemic.
f. Also during the pandemic, many respondents were very difficult to reach because of a large increase in telework. CES introduced flexibility for a subset of respondents who had historically reported via a telephone interview, allowing or even encouraging

them to report via the web at their convenience instead of waiting to be called. Those who didn't report via the web by a certain time each month were then called, as usual. This proved to be successful during the pandemic and BLS has continued this process post pandemic.

g. CES adjusted the birth-death model for the months immediately following the March 2024 benchmark (April to October 2024) and the months immediately following the March 2025 benchmark (April 2025 forward) to increase its sensitivity to more current economic changes.

How is CES addressing our current challenges?

Timeliness. While the process of revising the initial estimates makes them more accurate, the revisions should have certain properties. Aruoba (2008) provides a framework to assess revisions to macroeconomic time series:

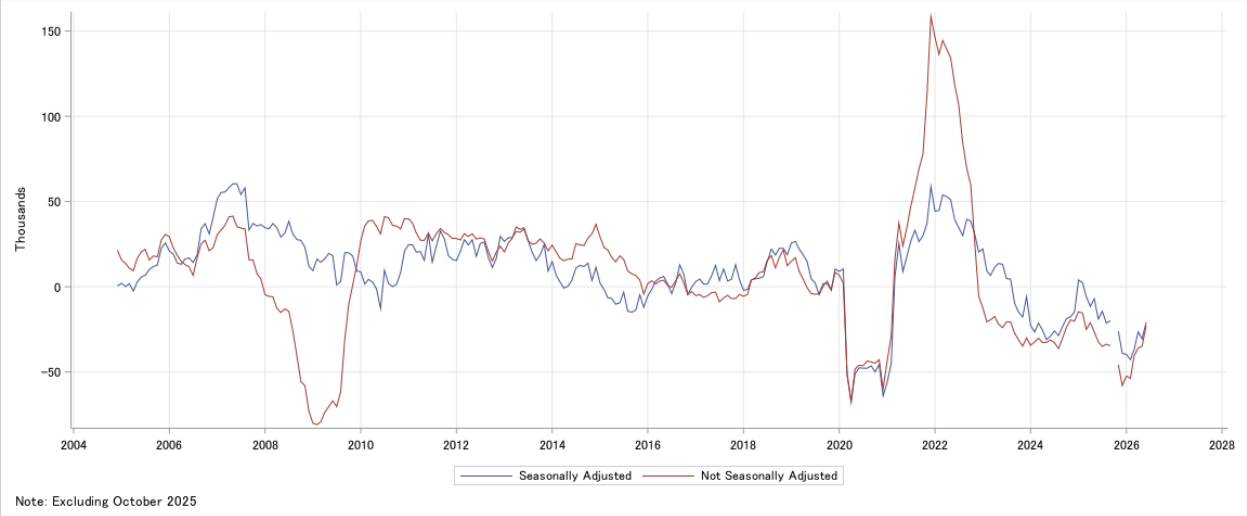
1. Their long-run average (mean) should be zero
2. Their variance should be small
3. They should not be predictable given the information available at the time of initial publication.

If revisions follow these properties, it implies the initial estimates are an unbiased, optimal forecast of the final estimate.

With each monthly publication, CES revises the prior two months of not seasonally adjusted estimates and seasonal factors. First (initial), second, and third (final) sample-based estimates,

and the revisions between these vintages, are reported on the BLS website.[12] (CES also revises at least 5 years of data with an annual benchmark revision, published with January estimates.) The long-run revision (from January 2003 – June 2026) to the CES initial to final over-the-month change is somewhat positive: +7,000 seasonally adjusted (+8,000 not seasonally adjusted). Figure 1 shows the 12-month trailing average of initial to final revisions at the total nonfarm level. For example, each December data point represents the average revision for the calendar year. The seasonally adjusted revisions (blue line) show a cyclical pattern: generally negative during the Great Recession (December 2007 – June 2009), positive during the early years of the recovery; then, negative in 2020, in part due to methodological changes made in March 2020 to capture business closures tied to the COVID-19 pandemic, and then positive during the subsequent recovery (averaging +159,000 across 2021). Although revisions have been positive on average since 2003, these values can diverge well from zero, and it is difficult to make good use of this long-run revision in developing employment estimates.

Figure 1. Initial-to-Final Sample-Based Over-the-Month Change Revision, 12-month trailing average

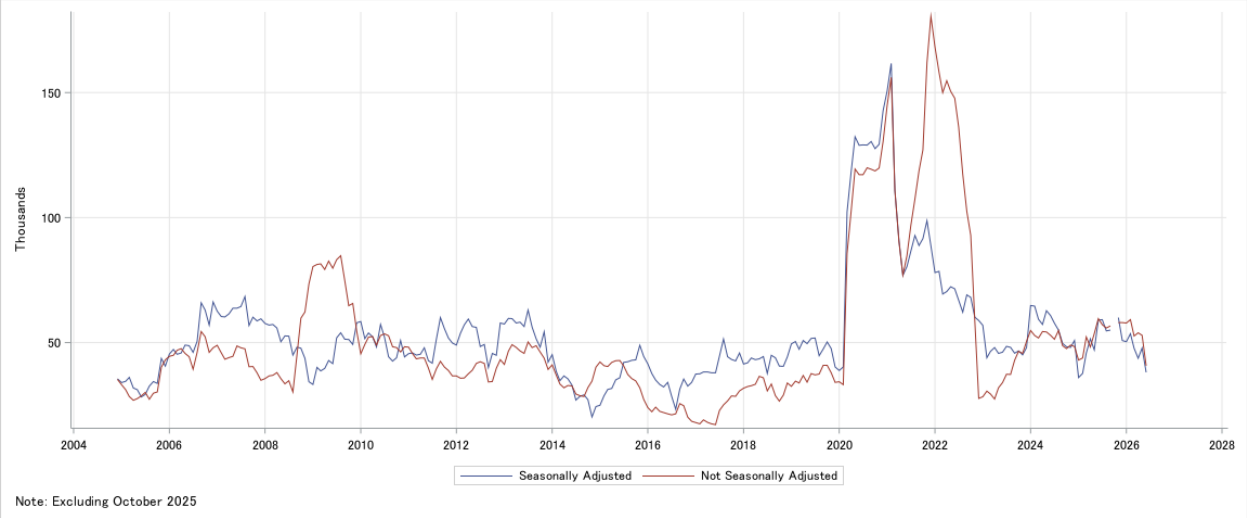


[12] Nonfarm Payroll Employment: Revisions between over-the-month estimates, 1979-present

The revisions to not seasonally adjusted data (red line) do not show such a pronounced pattern, indicating that much of the cyclicality comes from concurrent seasonal adjustment process. Not seasonally adjusted revisions in 2021 were generally positive, but less so (averaging +59,000). Notably, revisions to not seasonally adjusted data during the Great Recession were still generally positive.

Is the variance of the revisions small? Since 2005, absolute initial-to-final revisions have averaged 51,000 seasonally adjusted (53,000 not seasonally adjusted).[13] Figure 2 shows the 12-month trailing average of absolute revisions. In this plot, the December data point represents the average absolute revision for the calendar year. The size of seasonally adjusted revisions (blue line) also appears to be more cyclical, with a clear increase during the Great Recession and especially during the pandemic recession and recovery.

Figure 2. Initial-to-Final Sample-Based Over-the-Month Change Absolute Revision, 12-month trailing average



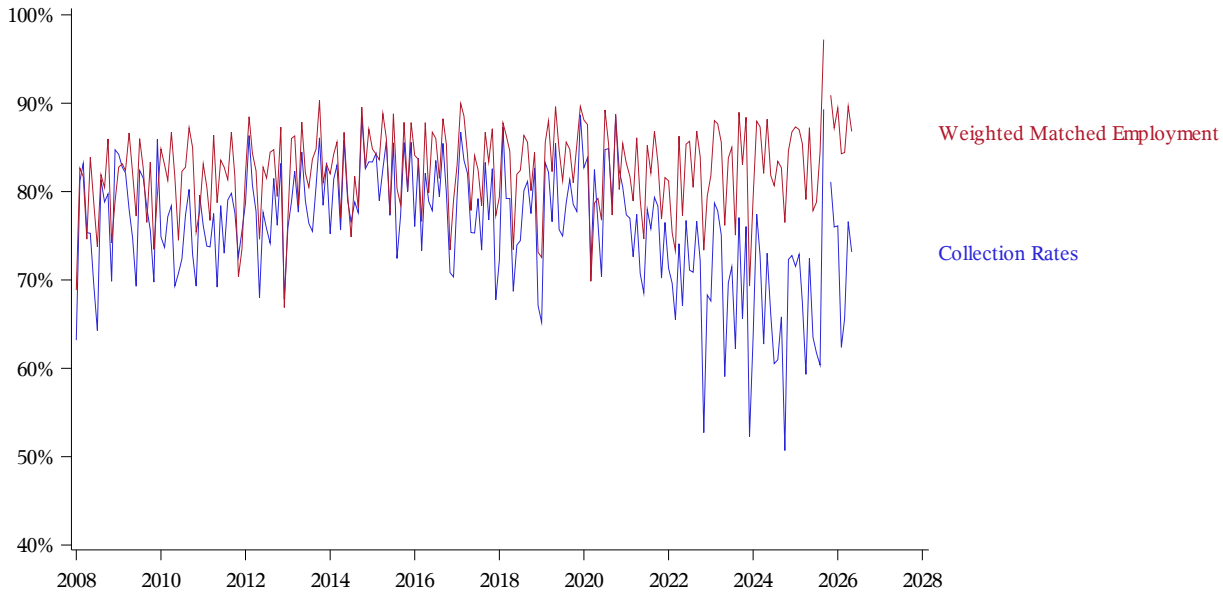
Overall, revisions have been slightly larger in the most-recent years (2023-2026) than they were in the recovery/expansion 2010s, but not above their long-run average since 2003. Wilcox (2025)

[13] As a point of comparison, the standard error of a 1-month change in total nonfarm employment is 74,000 as of 2026.

presents as a puzzle that the average size of revisions in relative terms post-pandemic has been similar to the 2005-2013 time period despite a much larger gap between initial and final collection rates, which would indicate a greater disparity in the sample information used to produce the initial and final estimates, and suggests the collection rate may be a noisy measure of the amount of information obtained in the CES survey. In researching this issue, CES calculated an alternative collection measure by summing survey weighted employment for all matched responding establishments and taking the ratio between first and third closing[14]. Figure 3 compares this alternative measure of weighted matched employment against the ratio of initial and final collection rates (expressed as percentages). Both ratios average around 80 percent in the 2010s, with the annual average weighted matched ratio 2 to 7 percentage points higher than the annual average collection rate ratio in those years. After 2020, the weighted matched employment ratio remains (red line) above 80 percent on average each year, while the collection rate ratio (blue line) drops noticeably, averaging around 69 percent from January 2023 - June 2026.

[14] These data are provided in the appendix.

Figure 3. Ratio of initial (1st) / final (3rd) values, collection rate and weighted matched sample



Are revisions predictable? If they are, that would suggest there is information CES could be taking advantage of to make a more accurate first closing estimate. To assess predictability, we conducted pseudo-out-of-sample forecasting exercises over the 2016-2025 time period comparing simple time series models against a baseline expectation of 0.

For the seasonally adjusted data, we fit an AR(3) model[15] to the total nonfarm revisions. The AR(3) forecast performed slightly better than the baseline forecast, but the gain was heavily concentrated in 2021, and not statistically significant at usual levels. While we find some serial correlation in the revisions, this information is not obviously usable in a simple way.

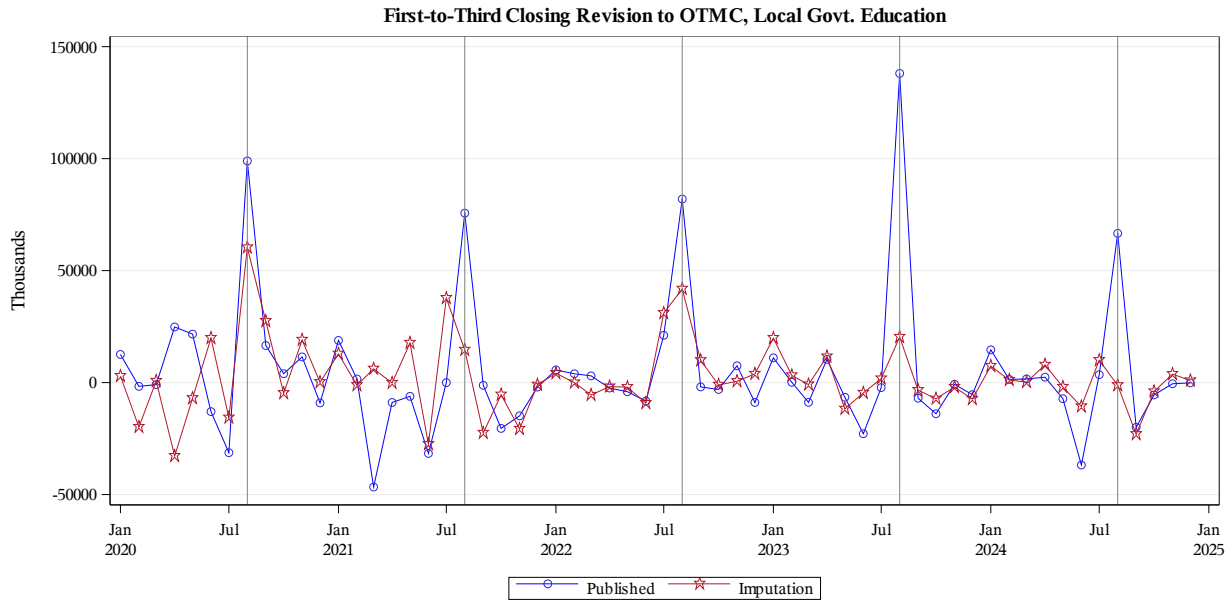
For the not seasonally adjusted data, we modeled revisions at the 3-digit NAICS level, covering 100 industries, using X-13ARIMA-SEATS, allowing the software's automatic ARIMA modeling and outlier identification procedures to select the models, potentially including an intercept to account for historical averages. CES already imputes for certainty units that subject

[15] This model was identified manually by examining the ACF and PACF of the revisions time series.

matter experts have identified as exhibiting predictable, seasonal differences from the rest of the population. We also calculated what the revisions would have been if CES had not made these imputations and assessed the predictability of those counterfactual revisions. Several industries showed clear evidence of predictability for the revisions without imputation, but no significant evidence of predictability with the imputations. This suggests that the imputations are helping to remediate the predictability of revisions from the first closing sample.

The only industry in this exercise that showed clear evidence of predictability in revision to its published data was *Local Government Education,* which for several Augusts in a row were above +50,000. To address this, CES built a RegARIMA model to predict the growth rate of the expected late sample conditional on the historical average growth rate of these school districts as well as the current and past values of the sample that has already responded at first closing. Applying this technique in a pseudo-out-of-sample comparison from 2015-2024, the average absolute revision in August would have been 29,000 instead of 62,000. Figure 4 shows the first-to-third closing revisions for this industry (blue line) as well as revisions had the imputed values been available and used (red line). These revisions would have still been generally positive in August, which suggests continued room for improvement. Imputation improved revisions to other months slightly, but the gain was small. Since August 2025, these RegARIMA predictions have been provided to CES analysts to assist in identifying and imputing for late sample that may exhibit different job growth than the 1st closing sample.

Figure 4. Initial-to-Final Revision, Local Government Education



Although the revisions in private sector industries are not easily predictable using simple time series approaches, there still may be room for improvement given the information contained in CES microdata. CES research has primarily focused on using imputation to predict late-responding sample, in part because revisions are disproportionately driven by large employers (certainty units in the CES sample), some of which have idiosyncratic job growth patterns that would not be well accounted for with alternatives such as weight calibration. CES has information derived from the frame on variables including detailed geography, size class, age of firm, and individual establishments' CES and administrative (UI tax) reported employment history.

We followed Czaplicki and Gonzalez (2019), who used RegARIMA models, with parameters estimated at the industry level, to impute for late response in the Census Bureau's Monthly Advance Retail Trade Survey. We also fit RegARIMA models directly for very large, individual respondents at an aggregated nationwide level.

We used frame and historical information, along with time series forecasts, in a variety of modeling approaches using statistical models and machine learning techniques. While many approaches improve upon the implicit imputation done with the link relative estimator at the microdata level, we have yet to find an approach that generally improves upon current practice with respect to monthly revisions to the macro level estimates. Similarly, Copeland and Valliant (2007) developed imputations that improved prediction of late responding CES sample in some cases but also did not find statistically significant improvements to industry-level revisions. While we have yet to successfully find an approach that improves the private sector revisions, this remains an area of active research.

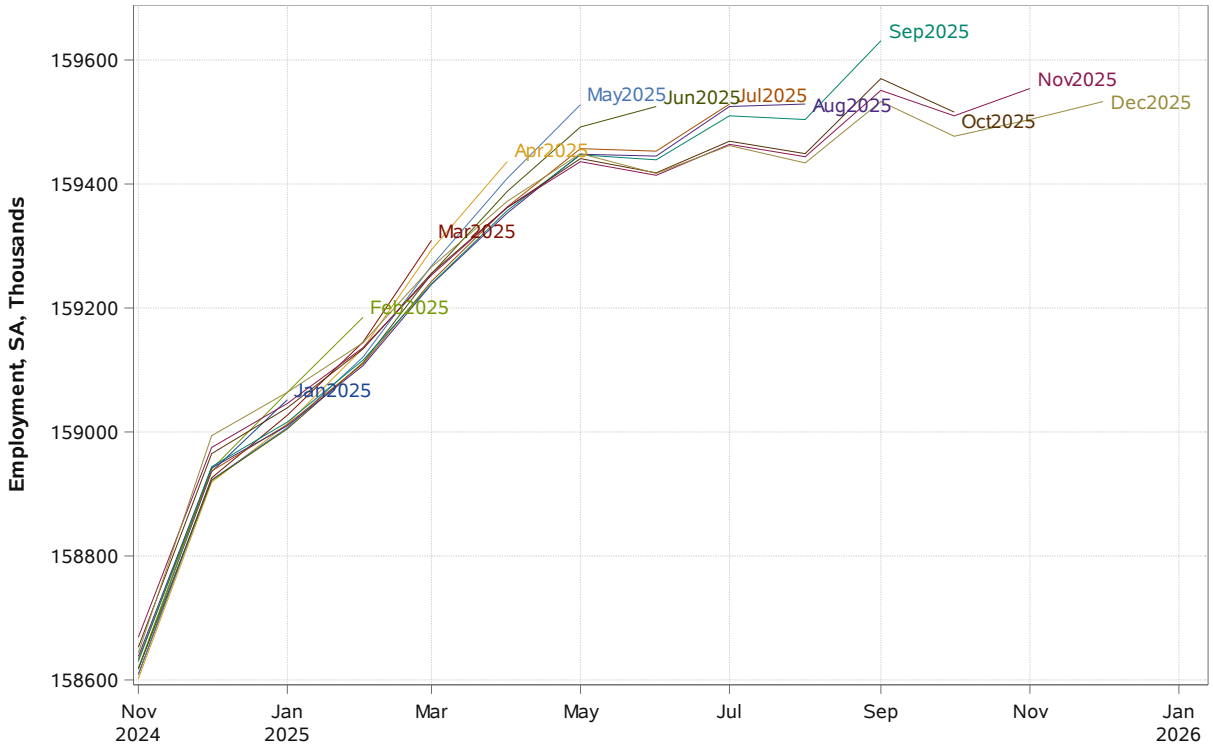
Seasonal Adjustment. The seasonal adjustment process aims to remove recurring seasonal variation from employment time series so that data users can better assess the underlying trend, cyclical change, and short-term nonseasonal variations. Seasonal adjustment at the endpoint of the time series is particularly challenging, and it is often difficult to determine if an unusual value at the end of a series is due to a changing seasonal pattern, which should be removed from the seasonally adjusted series, or a change in the trend-cycle component, which should remain. CES seasonal adjustment is performed using X-13ARIMA-SEATS software, which appends a RegARIMA forecast and backcast to the series before applying a series of moving averages to decompose it into trend-cycle, irregular, and seasonal components, the last of which is removed to produce the seasonally adjusted level[16]. Revisions to the seasonal factors contribute to the overall seasonal adjustment. Seasonal adjustment factors can revise from their initial to third (final sample-based estimate) values because of:

[16] Forecast extension was found in the 1970s to offer many improvements to the seasonal adjustment, which otherwise rely on heavily asymmetric filters that have many undesirable properties. While CES uses the X11-type of seasonal adjustment, SEATS is an alternative model-based signal extraction approach to seasonal adjustment available in the same software which CES is also exploring.

1. Revisions to the underlying not seasonally adjusted data
2. Forecast error – that is, the values observed 1-2 months ahead differ from values that were used in the forecast extensions
3. Changes associated with the annual processing – these would only cause difference between first and third closing factors for November and December.

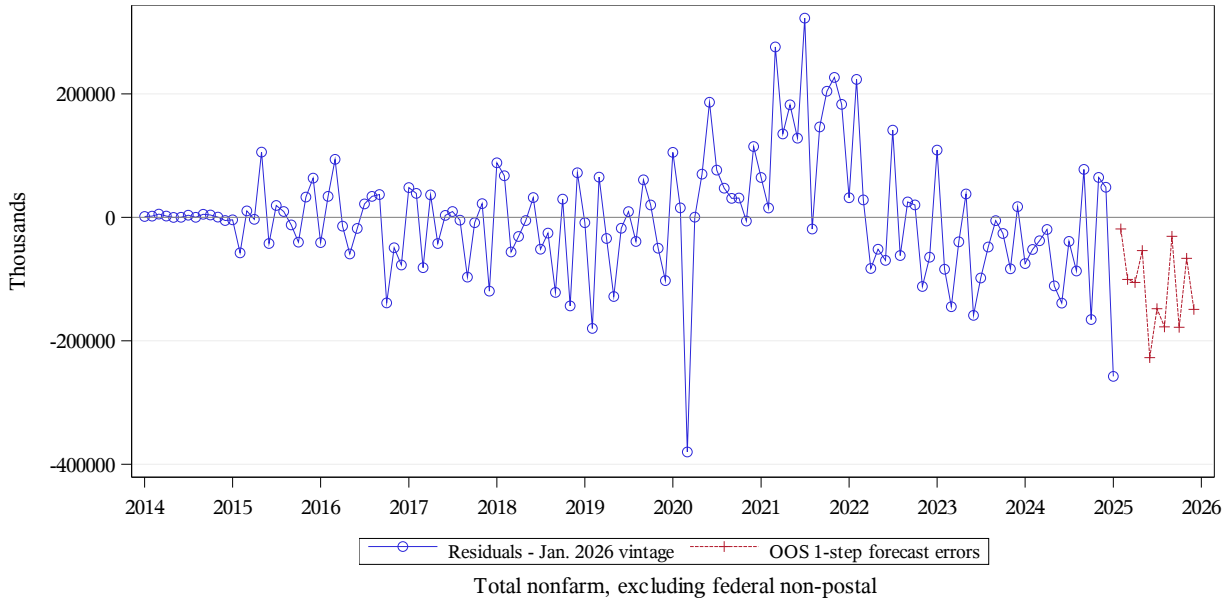
Forecasting is particularly challenging at turning points, and CES examined forecast error as a potential source of the apparent cyclicality in the seasonally adjusted revisions by running seasonal adjustment on employment series that are not themselves revised: for example, using January 2025 third closing as an end point, then February 2025 third closing, March 2025 third closing, etc. Figure 5 shows the output of this exercise for 2025. Every month from February – November 2025 revises downward from its concurrent value as the trend of employment growth slowed through the year. As of the December run of this simulation, the underlying seasonally adjusted levels for June, August, and September all were over 90,000 lower than their initial concurrent level.

Figure 5. Illustration of revisions to Total Nonfarm employment with no revisions to underlying employment series



This pattern suggests forecast error plays a significant role in the observed cyclicality of seasonally adjustment revisions. BLS plans to research improvements to the forecast extension for CES in 2027. At present, CES directly adjusts 148 series and aggregates them to total nonfarm. In aggregate, the residuals appear to exhibit some serial correlation, as shown in Figure 6, suggesting room for improvement in forecasting. Multivariate approaches may be able to take advantage of the structure of these residuals across series. Additionally, the out-of-sample forecast errors have not been centered on zero, suggesting the possibility for making intercept corrections to the forecasts, as in Castle et al. (2025). If improved forecasts can be developed, CES would explore appending them to the observed data and running that forecast-extended series in the seasonal adjustment software.

Figure 6. Aggregate model residuals (converted to additive levels) and one-step-ahead forecast errors from seasonal adjustment exercise using series without revisions to the not seasonally adjusted data



Data Collection - Nonresponse. Declining response rates lower the effective sample size of CES, which increases sampling error variance and variability of employment estimates. Of deeper concern is the potential for bias if relative job growth for nonrespondents differs systematically from respondents at the estimation cell level. The CES estimation cell structure is stratified at a detailed industry level and, in some cases, by Census region, which accounts for much heterogeneity in establishment job growth. Within these cells, CES assumes respondents and nonrespondents have similar job growth. CES has been researching the use of multivariate tree models to identify groups of establishments (by state and size class) that differ with respect to response rate and employment growth from other establishments in their estimating cells. This would allow for weight calibration to make the weighted responding sample better represent the selected sample. So far these techniques are in the research and development stage and have been applied with somewhat promising but preliminary results to a small number of industries that have appeared to have suffered from substantial nonresponse error.

Additionally, BLS has engaged with a contractor to produce a nonresponse bias analysis that can be reproduced periodically on an ongoing basis. This analysis relies on comparing the administrative employment values from the UI tax system of the selected and responding samples, examining their differences, based on relevant covariates. The analysis also examines characteristics of late CES responders with respect to their potential effect on monthly revisions. BLS plans to make the results of the study available to the public by the end of 2026.

Business Openings and Closings. CES first implemented its net-birth-death model with the probability sample re-design as outlined by Mueller (2006). The "actual" birth-death value can be thought of as the amount needed to offset the inability to capture business births and deaths in real time and can be derived from applying CES processes to the administrative UI universe data. From its introduction, CES used a seasonal ARIMA model to forecast birth-death that assumed actual birth-death values followed a seasonal pattern, and that recent deviations would tend to revert to the seasonal history. Battista (2013) first explored using concurrent information in a RegARIMA model to forecast birth-death, including the CES sample, and found some improvement over the Great Recession, when birth-death forecast error contributed to a large downward benchmark revision in March 2009.

With steep job loss in March 2020 came a surge in the number of CES respondents reporting zero employment, which challenged the assumption that birth-death values would follow their seasonal history, but also opened up the possibility that reported business deaths could be used in real time. CES adjusted its methodology to employ a version of the models developed by Battista (2013), which lowered the forecast values. In addition, CES used reported drops-to and returns-from zero employment in excess of their historical norm as part of the sample-based estimator. These reports are not typically included in the CES matched sample due to assumptions in the

birth-death model. Including the reported zeros helped CES track the effect of short-term business closures, which were eventually shown in the actual birth-death values, but required substantial changes in the assumptions behind the CES estimator and the derivation of actual birth-death. After the number of excess zeros became negligible in 2021, CES reverted to the ARIMA forecasting approach, and began research to find an approach that would work well in a wide range of business conditions without requiring major changes to methodology. Grieves et al. (2023) showed that birth-death could be predicted by exploiting the seasonal covariation between birth-death values and the sample link relative. These models showed continued good results in the post-pandemic period.

CES implemented RegARIMA models including sample information that closely matched the post-pandemic research models with the 2024 April-October post-benchmark values but continued to use the ARIMA forecasts for the following year due to production limitations. Beginning with the January 2026 estimates, CES began using the RegARIMA models on a monthly basis. CES plans to continue refining the models, examine how extreme events reported in the sample may help better inform the forecasts, and research improvements in how birth-death values are produced for detailed-industry values and allocated for use in state and local estimates.

Alternative Data. While CES faces several challenges, there are increasing opportunities to make use of alternative data. Decker (2026), in outlining potential methodological improvements for CES, discussed the possibility of using data obtained from payroll providers blended with the CES survey data. Along those lines, Cajner et al. (2022) showed how data from one large payroll processer could be used to construct timely, high-frequency measures of payroll employment

that policymakers found useful during the extreme economic changes associated with the COVID-19 pandemic.

CES has been involved in work with data from another large payroll provider, covering over 5 percent of private U.S. employment, to create a weekly employment indicator, as outlined by Bell, et al. (2026) that could complement official employment statistics with additional geographic detail, higher frequency, and increased timeliness. Previously, as detailed by Dunn et al. (2026), BLS worked with BEA and Census to demonstrate how these payroll provider data could be used in a model to expand the "accuracy-granularity frontier" of payroll employment estimates, potentially improving the capacity to produce sufficiently accurate and highly granular estimates (e.g., county-by-industry) that CES does not currently publish, but which would be of use to BEA.

Applied work with payroll provider data complements work being done by CES with other researchers at BLS in small area estimation and developing theoretical groundwork for combining probability samples with alternative, nonprobability data. Savitsky and Gershunskaya (2023) developed a Bayesian approach to co-model employment point estimates and their variances, which CES now uses to produce employment estimates for state and metropolitan area estimates with insufficient sample for reliable sample-based estimation. CES aims to explore using covariates derived from payroll provider information in these Bayesian models to investigate if the accuracy-granularity frontier can be expanded further still. Savitsky et al. (2023) developed a method to combine nonprobability (convenience) samples with probability survey data, including in circumstances where the overlap between samples is unknown, in order to increase effective sample size and reduce variability. Savitsky et al. (2025), found further improvements in accuracy developing a threshold for inclusion for the convenience samples, and

Beresovsky et al. (2026) extended these approaches under conditions of deterministic and probabilistic data linkage. These techniques may be of most use for CES in improving the accuracy of detailed industry-area domains or in supplementing survey data in strata where the convenience sample has particularly high coverage.

Still, there are practical considerations that must be addressed in using alternative data in official statistics. Abraham (2022) provides an overview the promises of using alternative data in statistical agencies but also examines several potential challenges with naturally occurring private data, including the representativeness of the sample, the quality of data elements that may be of little interest to the business that generated the data, comparability over time, documentation, and ownership of the data (i.e., there is a risk that statistical agencies' access to the data may lapse). In addition, alternative data sources may lack information needed to construct inclusion probabilities in order to develop weights so that the convenience sample may be treated like a "pseudo" random sample. Regardless, CES continues to research ways in which alternative data could be integrated into our production workflow in order to improve the accuracy of our estimates or potentially create new data products.

Conclusion

CES produces very timely data that is heavily relied upon by a wide array of data users to assess the state of the U.S. labor market in order to make business and policy decisions. As such, ensuring that CES continues to produce accurate, high-quality statistics is of paramount importance. Declines in survey participation and the timeliness of responses, as well as large data revisions, have led some data users to question the continued reliability of CES data. BLS continuously assesses and strives to improve the quality of CES data. In recent years, CES has implemented many process and methodological improvements including new data collection

methods, better approaches to account for businesses births and deaths, and more accurate small area models. The CES program is continuing to make efforts to assess and address late response and nonresponse to the survey and is working to identify ways to improve employment estimates with the use of alternative non-survey data. Challenges remain. However, CES data continue to provide critical information about the American economy and BLS strives to ensure their quality despite a changing survey landscape.

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Appendix – Percent of Weighted Matched Employment, Initial / Final Sample-Based

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2008	69%	83%	82%	75%	84%	79%	74%	82%	80%	86%	74%	79%
2009	83%	83%	82%	87%	82%	77%	86%	83%	77%	83%	73%	80%
2010	85%	83%	81%	87%	82%	74%	82%	83%	87%	85%	75%	78%
2011	83%	81%	77%	86%	79%	84%	83%	81%	87%	82%	70%	73%
2012	82%	88%	84%	82%	75%	83%	82%	84%	85%	79%	87%	67%
2013	77%	86%	86%	78%	88%	82%	80%	84%	85%	90%	81%	83%
2014	82%	84%	86%	77%	87%	80%	75%	82%	78%	90%	83%	87%
2015	85%	84%	84%	89%	86%	78%	89%	80%	79%	88%	80%	88%
2016	84%	84%	77%	88%	80%	87%	86%	81%	88%	85%	73%	79%
2017	83%	90%	89%	84%	78%	84%	82%	78%	87%	83%	87%	77%
2018	79%	88%	86%	85%	73%	82%	82%	86%	86%	80%	84%	73%
2019	73%	86%	88%	82%	90%	85%	81%	86%	85%	81%	85%	90%
2020	88%	88%	70%	79%	79%	77%	89%	85%	77%	89%	80%	85%
2021	83%	82%	79%	86%	79%	75%	85%	82%	87%	83%	77%	82%
2022	81%	75%	73%	86%	77%	85%	86%	80%	87%	84%	73%	80%
2023	82%	88%	88%	86%	76%	84%	85%	75%	89%	83%	88%	69%
2024	79%	88%	87%	82%	88%	82%	81%	83%	83%	77%	85%	87%
2025	87%	87%	85%	79%	87%	78%	79%	85%	97%	[17]	91%	87%
2026	89%	84%	84%	90%	87%							

[17] October 2025 data were not produced or published on their planned timeline due to a lapse in funding and therefore a comparable figure could not be provided.