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FEATURED ARTICLE

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PPI and CPI seasonal adjustment during the COVID-19 pandemic

The U.S. Bureau of Labor Statistics publishes seasonally adjusted Consumer Price Index (CPI) and Producer Price Index (PPI) data monthly. Seasonal adjustment removes within-year seasonal patterns from data. To seasonally adjust data and estimate seasonal patterns of time series, the CPI and PPI use a filter-based approach that employs moving averages of historical data. In 2020, many PPIs and CPIs experienced extreme movements because of the coronavirus disease 2019 (COVID-19) pandemic. For example, the PPI and CPI for gasoline decreased 53.0 percent and 16.5 percent in April 2020, respectively. Because the CPI and PPI use historical data to estimate seasonal patterns, the extreme price movements in 2020 could have adversely affected the capability of the two price programs to accurately estimate seasonally adjusted data. This article explains how the CPI and PPI mitigated the effects of the COVID-19 pandemic on their seasonally adjusted price indexes. Mitigation steps included identifying price indexes whose movements were affected by the pandemic, estimating time series models to quantify these effects, and removing pandemic-related price movements from the data before estimating seasonal patterns.

The U.S. Bureau of Labor Statistics (BLS) publishes seasonally adjusted Consumer Price Index (CPI) and Producer Price Index (PPI) time-series data monthly. Seasonal adjustment removes within-year seasonal patterns from index data, which have demonstrated regularly occurring within-year patterns over many years. In the case of price indexes, these within-year patterns may result from changing of seasons, production cycles, model changeovers, holidays, and sales. Seasonally adjusted data are usually preferred for short-term price analysis because they allow for comparability across months without the influence of normal seasonal fluctuations. To seasonally adjust data, the CPI and PPI use the U.S. Census Bureau's X-13ARIMA-SEATS software to implement a filter-based approach that employs moving averages of historical data to estimate the seasonal pattern of a time series.¹ After BLS staff members estimate the seasonal pattern, the data are seasonally adjusted by removing the within-year seasonal movements from the time series.

In 2020, multiple PPI and CPI series measured extreme price movements because of the coronavirus disease 2019 (COVID-19) pandemic. For example, in April 2020, the unadjusted PPI and CPI for gasoline decreased 53.0 and 16.5 percent, respectively. Because the PPI and CPI use historical data to estimate seasonal patterns, extreme price movements in 2020 may have adversely affected seasonal adjustment. This article explains how BLS mitigated the effects of the COVID-19 pandemic on seasonally adjusted price indexes. In particular, it outlines how BLS greatly increased the scope of intervention modeling for both the PPI and CPI in 2021 and how this strategy was effective in mitigating the effects of the COVID-19 pandemic on seasonal adjustment. As a result of this increase in intervention work, revisions to the all-items CPI and the PPI for final demand during the 2020 seasonal revision (which occurred in January 2021) were similar in magnitude to previous revisions. Throughout this article, an annual seasonal revision is referred to by the most recent year of data revised, not by the calendar year in which the revision occurred. For example, the 2020 annual seasonal revision refers to updating seasonally adjusted indexes from 2016 to 2020. The 2020 seasonal revision actually occurred in calendar year 2021.

This article describes in detail seasonal adjustment methods used. It also summarizes the areas within the PPI and CPI most affected by the COVID-19 pandemic. Next, it provides several examples of time series whose seasonal adjustments would have been less accurate relative to prior revisions if no steps were taken to mitigate the effects of the COVID-19 pandemic. Then, the article describes how BLS mitigated the effects of COVID-19 on seasonal adjustment. The final section summarizes the results.

PPI and CPI seasonal methodology

For both the PPI and the CPI, BLS uses direct and indirect seasonal adjustment methods. To do direct seasonal adjustments, BLS applies seasonal factors to unadjusted data to remove within-year seasonal patterns. Indirect adjustment is a method of seasonal adjustment used for aggregate series. In this method, two or more directly adjusted component indexes are combined into higher level time series. Seasonal factors

are not estimated for or applied to indirectly adjusted series. In the PPI, commodity-based indexes and Final Demand–Intermediate Demand (FD–ID) aggregation system indexes are eligible for seasonal adjustment. Most of the PPI commodity data that receive seasonal adjustment are directly adjusted. By contrast, BLS seasonally adjusts all its FD–ID PPIs using an indirect method. FD–ID PPIs are constructed by using a census value of shipments and revenue data along with U.S. Bureau of Economic Analysis input–output data to combine lower level commodity PPIs. Meanwhile, in the CPI, 330 national-level published series are eligible for direct seasonal adjustment and 65 series receive indirect seasonal adjustment. (CPI directly seasonally adjusts 167.) BLS periodically identifies a set of component CPI series for seasonal aggregation that are mutually exclusive and represent the complete weight of all items in the CPI. BLS selects this component series set to maximize the percentage of weight of the all-items index that receives seasonal adjustment. Therefore, BLS uses direct adjustment for its lower level CPIs (at the seasonal component-level and below) and indirect adjustment for all upper level aggregate indexes. Lower level indexes track price changes for specific goods and services over time, whereas upper level indexes track price changes for groupings of lower-level commodity indexes. Upper level CPIs are constructed by BLS using consumer expenditure weight data to combine lower level indexes.

Direct adjustment

BLS tests all PPI and CPI series that are eligible for direct adjustment for seasonality, and if seasonality is found, the series are seasonally adjusted. Using X-13ARIMA-SEATS,² a software program published by the U.S. Census Bureau, BLS tests both seasonality and direct seasonal adjustment. Seasonal adjustments are based on the X-11 variant of the Census II seasonal adjustment method. X-11 is a filter-based approach that employs moving averages to estimate trend and seasonal components in turn. Components are refined through several iterations of weighted moving averages. For both the PPI and CPI, BLS uses a multiplicative time-series decomposition model by default, calculated as

$$Y_t = T_t * S_t * I_t.$$

In this model, Y_t is the value of the observed series at time t , T_t represents the trend-cycle component at time t , S_t is the seasonal

component at time t , and I_t is the irregular component at time t . The multiplicative model is appropriate when a series has changing variation with time, as is often seen with PPI and CPI series. To enable the use of symmetric moving-average filters on a series, X-13 ARIMA-SEATS uses an ARIMA (Auto-Regressive Integrated Moving Average) modeling facility to forecast and backcast observations past the endpoints of the data.

F -tests are among the many diagnostics that are available for assessing the quality and stability of seasonal adjustments. F -tests look for the presence of stable and moving seasonality and quality control (QC) statistics from X-11.³ BLS uses three primary measures to determine whether a particular PPI or CPI should be seasonally adjusted: $F(s)$, $M7$, and Q . $F(s)$ is a measure of stable seasonality, $M7$ determines the amount of moving seasonality relative to the amount of stable seasonality, and Q is a weighted average of several diagnostic statistics. In general, for a series to be deemed seasonal, it must meet the following QC thresholds: $F(s) \geq 7$, $M7 < 1$, $Q < 1$.

Lower level CPIs and commodity PPIs that are found to exhibit a level of seasonality warranting adjustment (on the basis of meeting the QC thresholds) are directly adjusted by applying a seasonal factor to the unadjusted index according to

$$I_t^s = I_t^u / F_t * 100,$$

where I_t^s is the seasonal index value at time t , I_t^u is the unadjusted index value at time t , and F_t is the seasonal factor (the estimate of seasonal component from the previous equation) at time t . Seasonal factors indicate the seasonal pattern of a time series and are derived from historical unadjusted data. Seasonal factors are relatively stable over time. BLS typically uses 8 years of unadjusted monthly data to develop factors and test seasonality for both sets of indexes.

Intervention analysis

Nonseasonal events, such as natural disasters, pandemics, or wars, can distort the underlying seasonal pattern of an index. Intervention analysis entails estimating and removing the one-off effects of these events from indexes before they are tested for seasonality and before seasonal factors are developed. The goals of intervention analysis are to determine whether a seasonal pattern exists and to correctly estimate seasonal factors despite any distortion that might arise in the pattern. BLS applies intervention analysis to selected directly adjusted PPIs and CPIs. To conduct both CPI and PPI intervention analysis, BLS uses X-13ARIMA-SEATS. Using this method (X-13), BLS estimates ARIMA models that include prespecified intervention variables for a time series. These variables are used to identify the statistical significance and relative effects of nonseasonal events on time series. In cases in which a nonseasonal event (such as the COVID-19 pandemic) is found to significantly affect a time series, the effects of the event can be removed from the original time series by using the estimated coefficients from the ARIMA model. Three types of intervention variables are employed: outliers, level shifts, and ramps. (Ramps allow for a linear increase or

decrease in the level of a series over a specified time interval.) After nonseasonal effects are removed from the original time series, standard direct seasonal adjustment methods, as described earlier, are applied to the indexes to test for seasonality and to develop seasonal factors.

More than 1,500 PPIs and CPIs are currently eligible for direct seasonal adjustment. Conducting intervention modeling on this entire set of indexes is not feasible because of resource constraints. Consequently, BLS performs intervention modeling on only a relatively small set of PPIs and CPIs, referred to as intervention candidates. For a PPI to be an intervention candidate, the index must comprise at least 1 percent of a major FD-ID index. The major FDs-IDs indexes include goods for final demand, services for final demand, processed goods for intermediate demand, unprocessed goods for intermediate demand, and services for intermediate demand. Likewise, for a CPI series to be an intervention candidate, the index must account for at least 0.5 percent of the all-items CPI or be a subset of an already qualifying component series. Each year, BLS examines all intervention candidates for price index series to determine whether intervention modeling will improve seasonal adjustment of the series and performs intervention modeling if it leads to a more accurate seasonal adjustment. In 2020, these criteria were relaxed to address widespread extreme price movements resulting from the COVID-19 pandemic. (See section “Mitigating the effects of the COVID-19 pandemic,” in this article.)

Indirect adjustment

High-level indexes, such as the PPI for final demand and the CPI for all items, are indirectly seasonally adjusted by aggregating lower level series that are components of higher level indexes. Seasonally adjusted components are used when available (that is, when the lower level index received a seasonal adjustment); otherwise, unadjusted indexes are used. BLS indirectly adjusts all its FD-ID indexes, as well as any indexes that are aggregates of intervention indexes. In this manner, interventions estimated for lower level indexes are indirectly included in aggregate indexes. BLS indirectly seasonally adjusts the all-items CPI and 65 other aggregate series.

Yearly revisions and projected factors

Each year, with the release of the January data, the PPI and CPI seasonal factors are recalculated to reflect price movements that occurred during the just-completed calendar year. Seasonal factors are recalculated 5 years back, and all seasonally adjusted data are updated on the basis of these new factors. For example, in January 2021, factors were recalculated from 2013 to 2020 data and seasonal data from 2016 to 2020 were updated according to the new set of factors. After the yearly revision, the PPI and the CPI for the upcoming year are calculated with the previous year’s set of seasonal factors. For instance, the 2020 factors are used to calculate indexes throughout 2021.

Prices most affected by the COVID-19 pandemic

The COVID-19 pandemic affected both producer and consumer prices for a wide variety of products. This section provides an overview of products whose prices were most affected by the pandemic. This summary, however, does not document all product prices that were affected by the COVID-19 pandemic. It only highlights some areas in which prices and, consequently, seasonal adjustment were severely affected. As such, the summary will focus on prices for food, petroleum products, leisure and hospitality services, and automobile sales.

The COVID-19 pandemic substantially affected domestic producer and consumer prices for foods because stay-at-home orders and other pandemic-related policies affected both purchase and production patterns for food. In general, a notable decrease occurred in demand for food from restaurants, hotels, and institutional customers (primarily schools and universities). In addition, several supply disruptions occurred at food processing plants.⁴

Foods

The PPI for final-demand foods increased 1.5 percent between March and the end of 2020. (See table 1.) This relatively modest yearly increase does not, however, reflect the underlying volatility within the index, because the index swung significantly throughout the year. In May, the PPI for final-demand foods increased 6.4 percent, before declining 4.7 percent and 1.2 percent in June and July. Prices then rebounded in September and rose through November. Consumer food prices were also affected by the COVID-19 pandemic in 2020, because food-at-home prices typically rose and food-away-from-home prices became more volatile. (See table 1.) Prices for food at home during the year increased the most from March through June, rising 0.5, 2.7, 0.8, and 0.5 percent, respectively. Changes in both the PPI for final-demand foods and the CPI for food at home were driven by high volatility in prices for meat, dairy, eggs, and corn.

Table 1. Producer price and consumer price indexes for selected foods, monthly percent changes, not seasonally adjusted, January to December 2020

Category	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Producer price index												
Final demand foods	0.1	-1.8	0.1	-0.2	6.4	-4.7	-1.2	-0.4	1.3	1.8	0.1	-1.2
Slaughter livestock	3.7	-2.3	-5.1	-6.6	14.8	-10.9	-6.4	7.4	3.8	5.2	-0.5	-4.1
Meats	-1.9	-2.8	-0.6	6.1	43.0	-26.8	-11.6	0.8	3.4	1.1	1.7	-1.4
Raw milk	-5.3	-3.5	-4.8	-20.0	-5.6	33	13.3	-8.3	-4.7	12.8	5.5	-13.2
Eggs for fresh use	-35.2	33.4	26.4	31.8	-44.6	-12.7	6.2	-9.9	16.7	25.5	-2.8	-24.9
Corn	4.7	-1.8	-0.6	-18.4	-2.3	4.1	-0.7	-5.5	16.9	8.2	9.6	2.5
Consumer price index												
Food at home	0.6	0.4	0.5	2.7	0.8	0.5	-1.0	-0.1	-0.4	0.2	-0.6	0.3
Meats, poultry, fish, and eggs	0.0	0.2	0.5	4.5	3.4	2.1	-3.6	-1.5	-0.6	0.2	-0.2	-0.3
Beef and veal	-0.1	0.2	0.6	4.2	10.9	5.5	-8.2	-4.6	-1.4	-0.3	-0.1	-0.4
Eggs	-2.2	0.3	1.7	15.0	-8.0	-4.9	-3.9	-2.3	0.8	1.4	1.4	0.7
Dairy and related products	0.5	0.6	0.5	1.4	0.6	-0.8	-0.6	1.8	-0.2	-0.7	0.2	1.0
Source: U.S. Bureau of Labor Statistics.												

Meat prices were affected by low demand from restaurant and institutional customers and by supply shortages. Many meat processing plants were forced to close because of worker illness, and most plants modified production processes to protect workers once the plants reopened.⁵ Likewise, COVID-19-related lockdowns substantially decreased demand for dairy products from schools and university dining facilities. Notably, these decreases in demand from institutional customers who purchase milk in bulk quantities lowered producer prices. Dairy farmers who normally sell milk to bulk-packaging customers were forced to dump substantial amounts of their product.⁶ Egg prices were affected by COVID-19-related lockdowns in relation to Easter. Both the CPI and PPI for eggs rose in April 2020 because of increased consumer demand resulting from Easter. Before Easter, there was an excess of eggs, and because of the lack of restaurant and institutional demand, these eggs were sold mainly to grocery stores, which caused prices to decline.⁷ Finally, corn prices were affected by the pandemic and by a crude petroleum price war between Russia and Saudi Arabia that drove crude petroleum prices and, subsequently, corn prices lower. Corn is used to manufacture ethanol, which is typically added to gasoline. Ethanol and gasoline are, therefore, complementary goods whose prices often move in tandem. Throughout 2020, the activity in the ethanol market dominated price movements for corn. (See table 1 for a summary of PPI and CPI food price changes during 2020.)

Petroleum products

Prices for crude petroleum products were affected by the COVID-19 pandemic. Initially, they plummeted as worldwide demand for petroleum decreased and supplies remained high, and then later, they rebounded. Price changes for crude petroleum were passed through to refined petroleum prices, which also experienced substantial volatility during 2020.⁸

As the pandemic began, crude oil prices collapsed in tandem with slowing economic activity across the globe. China (the top oil importer) —having passed the United States in 2016—kicked off the collapse as the first country to undergo COVID-19.⁹ In response to this massive shock, the Organization of the Petroleum Exporting Countries (OPEC) pushed its members and Russia to cut production. Russia, however, resisted the call, aiming to gain market share. OPEC, unable to convince Russia, reversed its decision and revamped production. Given that demand was already low, this move led to a near-record level stockpile of 535.2 million barrels of crude petroleum in the United States on May 1, 2020.¹⁰

In response to these events, the PPI for crude petroleum dropped 14.3, 34.0, and 48.8 percent in February, March, and April, respectively. (See table 2.) Consumer and producer prices for refined petroleum products also declined considerably over this period. Beginning in May, crude petroleum prices started rising as OPEC+ members agreed to record production cuts, and Russia also complied.¹¹ The agreement called for a composite cut of 9.7 million barrels per day through the end of June, the largest production cut ever.¹² Prices for refined petroleum products also began rising in either May or June. (See table 2 for a summary of petroleum product price changes during 2020.)

Table 2. Producer price and consumer price indexes for selected petroleum products, monthly percent changes, not seasonally adjusted, 2020

Category	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PPI crude petroleum	-2.5	-14.3	-34.0	-48.8	35.9	50.9	6.0	4.4	-3.2	1.7	3.9	14.8
PPI gasoline	2.3	-6.4	-20.2	-53.0	45.0	34.9	9.9	-0.8	-1.5	-0.2	-3.9	10.3
PPI jet fuel	4.6	-18.9	-14.5	-48.6	-6.8	47.6	13.7	4.8	-6.8	-2.5	4.9	22.7
PPI No. 2 diesel fuel	-7.2	-9.9	-12.2	-27.2	-12.4	27.2	30.0	6.6	-7.1	5.5	7.4	11.7
CPI gasoline, all types	-0.8	-3.8	-7.4	-16.5	-0.2	10.0	4.8	0.0	0.7	-1.6	-2.7	3.4
CPI other motor fuels	-0.6	-3.4	-5.4	-8.2	-3.2	0.2	0.1	-0.4	-0.3	-1.5	-0.2	4.3

Note: CPI = consumer price index, and PPI = producer price index.
Source: U.S. Bureau of Labor Statistics.

Leisure and hospitality services

The pandemic substantially decreased demand for leisure and hospitality services, which led to large price declines. In April 2020, on some days, the daily number of air passengers declined over 96 percent, compared with that of April 2019.¹³ Likewise, hotel occupancy rates for the month of April fell by almost 64 percentage points from the prior year.¹⁴ Table 3 shows large declines during 2020 in the PPI for guestroom rental in February and April and decreases in the CPI for other lodging (including hotels and motels) from March through April. Producer airline passenger services prices fell considerably from January through April 2020, and the CPI for airline fares decreased from March through May 2020.¹⁵

Hotel occupancy rates began to recover somewhat but were still over 28 percentage points lower in September 2020 than in September 2019.¹⁶ On October 18, 2020, the Transportation Security Administration screened over 1 million air travelers for the first time since the beginning of the pandemic, but that amount was only 40 percent of prior-year levels.¹⁷ As can be seen from the PPIs and CPIs in table 3, prices for hotel lodging and airline fares were relatively volatile for the rest of the year.

Table 3. Producer price and consumer price indexes for selected leisure and hospitality services, monthly percent changes, not seasonally adjusted, 2020

Category	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PPI guestroom rental	1.3	-3.8	1.4	-16.8	1.4	1.7	2.3	-1.4	-0.3	0.8	-4.1	1.5
PPI airline passenger services	-4.0	-1.8	-7.4	-10.0	8.3	6.1	-6.9	-6.8	-0.1	5.5	-4.3	-4.3
CPI other lodging away from home, including hotels and motels	4.6	6.7	-3.5	-7.0	1.5	2.2	1.2	-1.6	-2.9	-8.0	-2.0	-2.1
CPI airline fares	1.1	3.9	-12.5	-12.4	-0.8	2.2	-0.6	-2.6	-1.0	9.4	3.4	-7.8

Note: CPI = consumer price index, and PPI = producer price index.
Source: U.S. Bureau of Labor Statistics.

Automobiles

The COVID-19 pandemic affected the market for automobiles, particularly used automobiles. According to J.D. Power and Associates, production of new cars decreased during the pandemic because of factory shutdowns and supply chain issues,¹⁸ which drove up the price of new cars and reduced sales. As a result, trade-ins were fewer and the inventory of used cars was reduced. At the same time, economic hardship increased the demand for used cars relative to new cars. The combination of all these factors led to large price increases for used cars.¹⁹

Table 4 presents monthly percent changes in the PPI for automobile retailing and the CPI for used cars and trucks. Of note, the PPI for automobile retailing (which includes both new and used vehicles) measures trade margins, calculated as the sales price less the acquisition price.²⁰ By contrast, the CPI measures the final sales price of the car or truck. The measurement difference between the PPI and CPI stems from the PPI definition of retail trade, which defines retailers as suppliers of the service of reselling and, thereby, excludes the value of the manufactured product itself. Despite these methodological differences, the two indexes showed large increases in 2020. The PPI for automobile retailing jumped 12.5, 19.5, and 11.8 percent in May, June, and July, respectively. The CPI for used cars and trucks rose 3.3 percent in July and 5.8 percent in August.

Table 4. Producer price and consumer price indexes for selected automobile sales, monthly percent changes, not seasonally adjusted, 2020

Category	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
PPI for automobile retailing	3.5	−0.3	4.3	−13.6	12.5	19.5	11.8	−0.5	0.8	5.0	1.5	−6.9
CPI for used cars and trucks	−0.8	1.0	2.4	−0.9	−0.7	−1.1	3.3	5.8	2.1	1.0	−1.3	−0.9

Note: CPI = consumer price index, and PPI = producer price index.
Source: U.S. Bureau of Labor Statistics.

Potential negative effects of COVID-19 on seasonal adjustment

In many cases, the extreme price movements in 2020 (such as those outlined in the previous section) created substantial challenges for seasonal adjustment, making detection of seasonality more difficult and estimation of the seasonal patterns less accurate. For example, in many cases, COVID-19 impacts moved indexes in different directions or in different months than would have been historically expected, thereby reducing measured seasonality.

This section highlights the difficulties the COVID-19 pandemic has caused for accurately estimating seasonal data. It compares seasonality tests from 2020 with tests from earlier years for high-level CPIs and PPIs to show the general decline in detectable seasonality brought on by the COVID-19 pandemic. It then shows how both the PPI and CPI for airline fares seasonal patterns were disrupted by the COVID-19 pandemic. For airline fares, seasonality tests and seasonal factors estimated with pre-COVID data (2012 through 2019) are compared with those estimated with data from the COVID-19 pandemic period (2013 through 2020). The seasonal factors and seasonality tests conducted during the COVID-19 period include no action by BLS to mitigate the effects of the COVID-19 pandemic. They are presented to illustrate the difficulties BLS faced with seasonal adjustment for the CPI and PPI during 2020. The later section on mitigating the effects of the COVID-19 pandemic provides additional examples of series whose seasonal patterns were disrupted by the COVID-19 pandemic and also describes the efforts BLS took to mitigate the effects of the pandemic on seasonal adjustment.

Reduction in observed seasonality in aggregate indexes

In general, the extreme price movements resulting from the COVID-19 pandemic are expected to inhibit the typical seasonal signal observed in CPI and PPI data. Table 5 presents QC (quality control) statistics from seasonality tests conducted on high-level CPI and PPI series. Tests were conducted with the use of 8 years of data, ending with the years listed in the table. For example, 2019 tests were conducted with data from 2012 to 2019. If COVID-19-related price movements made detection of seasonality more difficult in PPI and CPI data, a decline in the seasonality test statistics would be expected when 2020 data are included. For all indexes in table 5, tests indicate a decrease in seasonality when 2020 data are included. The all-items CPI $F(s)$ falls from over 43 to approximately 17 when 2020 data are included in the tests and the all-items less food and energy CPI $F(s)$ experiences similar results. Likewise, for PPI, $F(s)$ falls across all categories when 2020 data are included in the tests. (Recall, values of $F(s) \geq 7$, $M7 < 1$ and $Q < 1$ indicate seasonality.)

Table 5. Quality control statistics for high-level producer price index and consumer price index data, 2018–2020 annual seasonal revisions

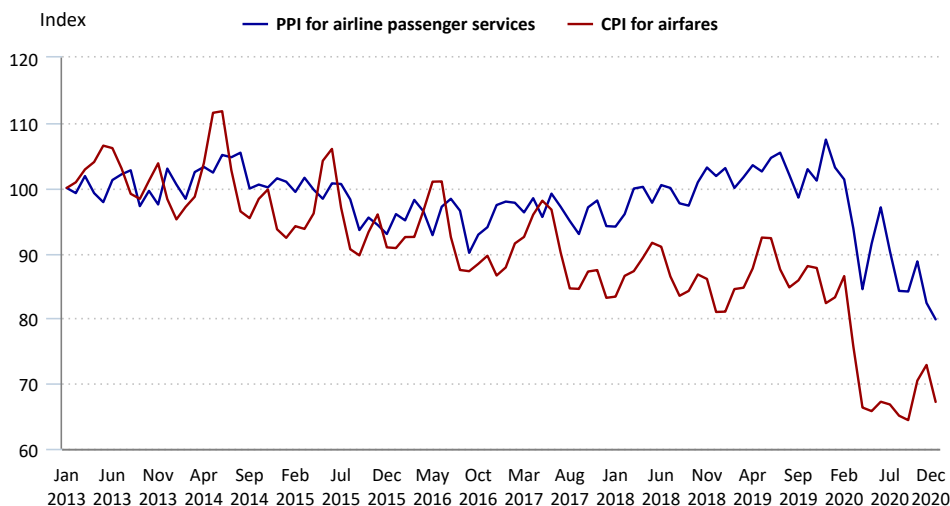
Index	<i>F(s)</i>	<i>M7</i>	<i>Q</i>
CPI all items			
2020	16.95	0.84	0.67
2019	43.45	0.45	0.39
2018	37.91	0.47	0.33
CPI all items less food and energy			
2020	11.44	0.79	0.55
2019	66.84	0.29	0.26
2018	68.97	0.31	0.27
PPI final demand			
2020	9.04	0.75	0.61
2019	21.95	0.49	0.37
2018	15.58	0.54	0.37
PPI processed goods for intermediate demand			
2020	9.90	0.98	0.80
2019	15.50	0.77	0.42
2018	15.29	0.70	0.42
PPI unprocessed goods for intermediate demand			
2020	1.20	2.47	1.35
2019	5.25	1.19	0.67
2018	5.00	1.32	0.71
PPI services for intermediate demand			
2020	2.81	1.99	1.00
2019	6.99	1.02	0.57
2018	7.66	1.02	0.58
Note: <i>F(s)</i> is a measure of stable seasonality, <i>M7</i> determines the amount of moving seasonality relative to the amount of stable seasonality, and <i>Q</i> is a weighted average of several diagnostic statistics. CPI = consumer price index, and PPI = producer price index. Source: U.S. Bureau of Labor Statistics.			

Airlines

High-level testing indicates a decrease in observable seasonality in 2020. For one to understand the underlying causes of this general decline, a detailed example of airline services prices is presented. The example shows how extreme price movements reduced the amount of detectable seasonality for airline services and distorted the normally observed seasonal patterns. The airline example indicates what occurred for many price indexes in 2020.

Chart 1 presents the PPI for airline passenger services and the CPI for airfares from January 2013 through December 2020. Both indexes experienced declines in the beginning of 2020. From December 2019 through April 2020, the PPI for airline passenger services fell approximately 21 percent. The CPI for airfares decreased approximately 24 percent from February 2020 through May 2020. The PPI then jumped almost 15 percent from April to June and then decreased for most of the remaining the year. The CPI increased in June and then again from October to November, but ultimately, the unadjusted index fell approximately 18 percent from December 2019 to December 2020.

Chart 1. Producer price index and consumer price index levels for airline services, January 2013–December 2020



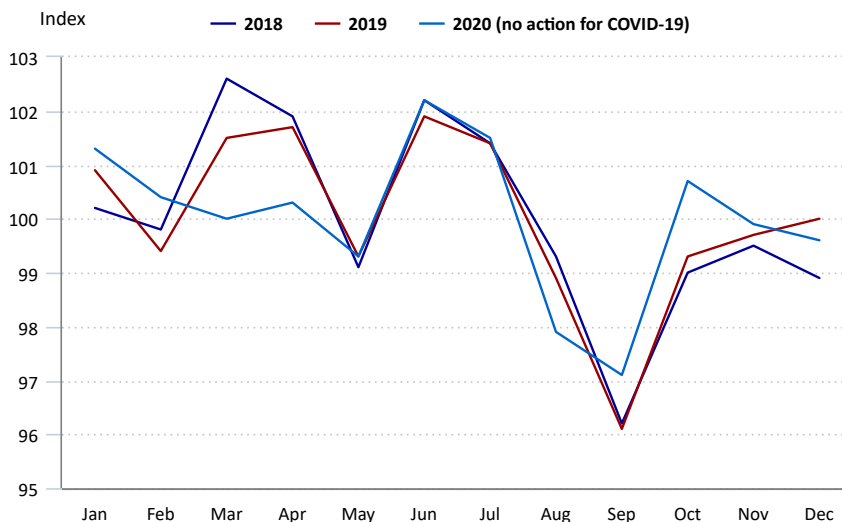
Click legend items to change data display. Hover over chart to view data.
 Note: CPI = consumer price index, and PPI = producer price index.
 Source: U.S. Bureau of Labor Statistics.



[View Chart Data](#)

To show how these extreme price movements affected seasonality, charts 2 and 3 compare seasonal factors for airline passenger services estimated with data from two pre-COVID-19 periods (2011–18 and 2012–19) with those estimated with data from the COVID-19 period (2013–20). The factors presented are from the final year of the estimation period. As can be seen, the seasonal patterns for both CPI and PPI estimated with pre-COVID-19 data differ from those estimated with data during the COVID-19 period. For PPI, the pre-COVID-19 factors (estimated from the 2019 annual seasonal revision) project prices to rise approximately 2.3 percent from February to April, while the factors estimated during the COVID-19 period anticipate prices will fall 1.1 percent over this same period. (See chart 2.) For CPI, the factors estimated without COVID-19 period data range from 95.3 to 107.0, whereas the factors estimated with the included 2020 data only range from 98.4 to 100.4. (See chart 3.) For both series, the large declines in airline prices in the early part of 2020 clearly affected seasonal factors.

Chart 2. Producer price index for airline passenger services, seasonal factors, 2018–20 annual seasonal revisions

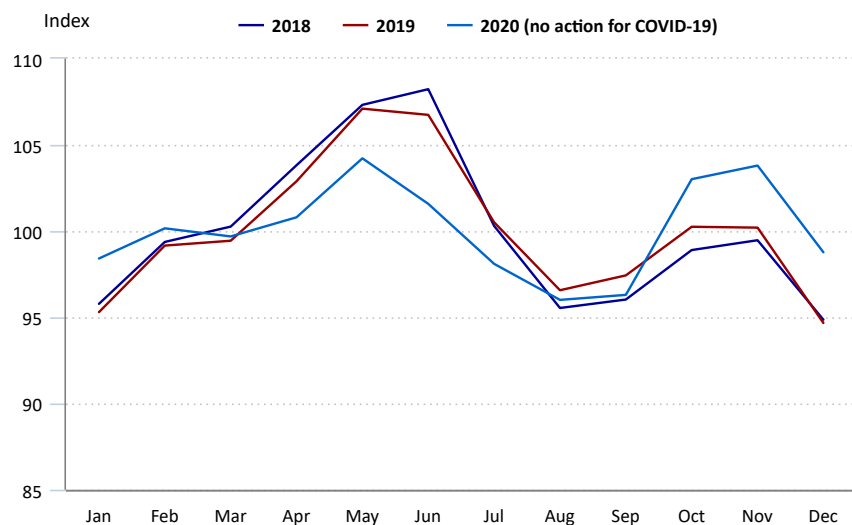


Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.



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Chart 3. Consumer price indexes for airline fares, seasonal factors, 2018–20 annual seasonal revisions



Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.

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Depicting seasonality tests, table 6 compares QC statistics estimated with data from 2012 to 2019 with those estimated with data from 2013 to 2020. The pre-COVID-19 QC statistics for both PPI and CPI indicate that airline passenger services are seasonal ($F(s) \geq 7$, $M7 < 1$ and $Q < 1$). The inclusion of 2020 data substantially changes the seasonality test results for airline passenger services. For PPI, $F(s)$ declines approximately 10 points and no longer indicates seasonality. For CPI, the pre-COVID-19 QC statistics indicate far more seasonality in airline fares than the QC statistics that are estimated, including 2020 data, with $F(s)$ falling close to 60 points when 2020 data are included. (See table 6.)

Table 6. Quality control statistics for producer price index and consumer price index airline services, 2019 and 2020 annual seasonal revisions

Index	$F(s)$	$M7$	Q
PPI 2020	3.91	1.30	0.99
PPI 2019	13.25	0.62	0.75
CPI 2020	9.90	0.83	0.64
CPI 2019	68.42	0.37	0.43

Note: $F(s)$ is a measure of stable seasonality, $M7$ determines the amount of moving seasonality relative to the amount of stable seasonality, and Q is a weighted average of several diagnostic statistics. CPI = consumer price index, and PPI = producer price index.

Source: U.S. Bureau of Labor Statistics.

Mitigating the effects of the COVID-19 pandemic on seasonal adjustment

BLS expanded the scope of intervention analysis on 2020 data used in the computation of seasonal factors. These factors were then used to seasonally adjust 2021 price indexes as forward factors and to recalculate seasonal data from previous years. For a PPI to be an intervention candidate, the index must comprise at least 1.0 percent of a major FD-ID index. And for a CPI to be an intervention candidate, the index must account for at least 0.5 percent of the all-items CPI weight or be a subset of an already qualifying component series. In 2020, both the CPI and PPI relaxed their relative importance rules for intervention candidates and expanded the number of series for which they conducted intervention analysis. The goal of this increased scope for intervention work was to mitigate the effects the COVID-19 pandemic on seasonal adjustment.

BLS began by extensively investigating PPI and CPI series whose seasonal adjustment may have been affected by the COVID-19 pandemic. In particular, economists evaluated each series that was seasonally adjusted in 2019 by visually examining it for extreme price movements in 2020. They then generated QC statistics with data from 2013 to 2020 and compared them with those generated with data from 2012 to 2019. Next, they generated seasonal factors with data from 2013 to 2020 and compared them with those generated with data from 2012 to 2019. They then ran automatic outlier detection and manually searched for outliers during the COVID-19 period. Finally, they consulted expert industry and commodity analysts.

Generally, the COVID-19 pandemic was deemed to adversely affect seasonal adjustment of a series relative to prior revisions when some combination of the following occurred:

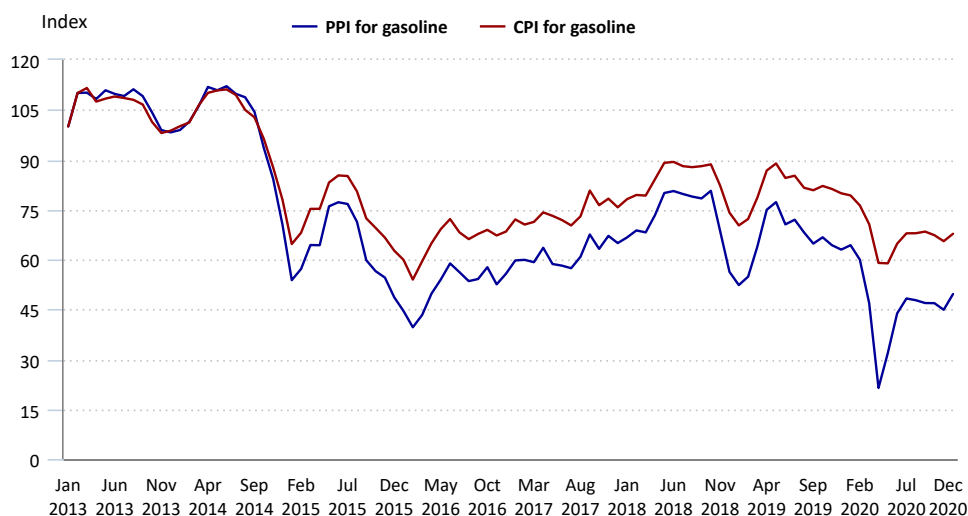
- Extreme price movements occurred in 2020.
- QC statistics changed substantially when COVID-19 period data were included in their estimation.
- Seasonal factors changed substantially when COVID-period data were included in their estimation.
- Auto-outlier and manual searches detected outlier points in 2020.
- Expert industry and commodity analysts indicated that COVID-19 was interfering with the typical seasonal pattern observed in the data.

In cases in which this testing indicated that COVID-19-related price movements would adversely affect seasonal adjustment of a series, the series was included as an intervention series for 2020. For series that were added because of the impact of COVID, only interventions during 2020 were included in their models. Several examples of the procedures that BLS took are presented in the following subsections.

Gasoline

Chart 4 presents the unadjusted PPI and CPI for gasoline from January 2013 through December 2020. Although gasoline prices are generally volatile, COVID-19-related shocks appeared to cause more extreme price movements in 2020. Both the PPI and CPI for gasoline fell sharply from February through April and then rebounded later in the spring.

Chart 4. Producer price index and consumer price index levels for gasoline, January 2013–December 2020



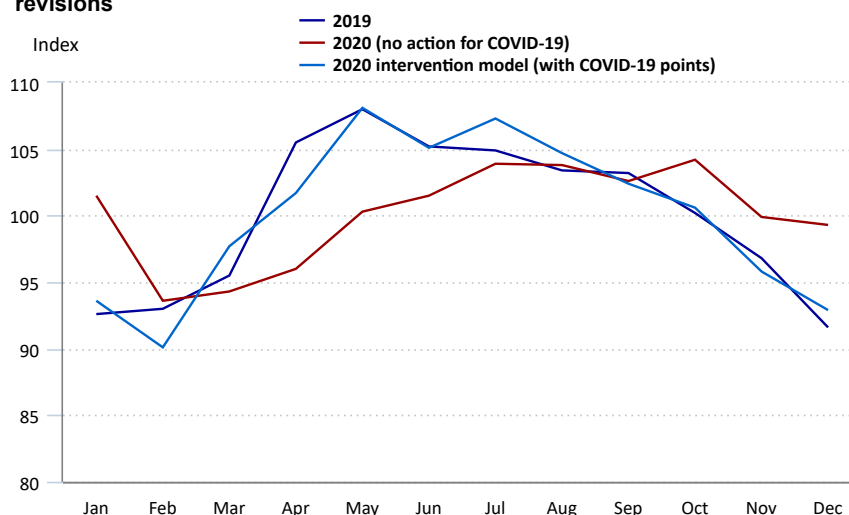
Click legend items to change data display. Hover over chart to view data.
Note: COVID-19 = coronavirus disease 2019.
Source: U.S. Bureau of Labor Statistics.



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To show the effect that the COVID-19 pandemic had on measurement of seasonality for gasoline, charts 5 and 6 compare seasonal factors for gasoline estimated with the 2012–19 data with those estimated with data from 2013 to 2020. The factors presented are from the final year of the estimation period. As can be seen, the factors estimated with 2020 data (without COVID-19 action) are substantially different from those estimated without 2020 data.²¹ For PPI, the factors estimated with 2020 data expect a large seasonal decline from January to February, while the factors estimated without 2020 data expect a small increase over the same period. The 2020 factors also expect a much smaller increase from March to April than the 2019 factors. The CPI seasonal factors show milder differences between 2019 and 2020 than those for PPI. For CPI, the second quarter 2019 factors expect a larger seasonal increase as compared with the 2020 factors. However, the remainder of the factors in 2020 aligns more closely.

Chart 5. Producer price index for unleaded regular gasoline, seasonal factors, with and without COVID-19 2020 action, 2019–20 annual seasonal revisions

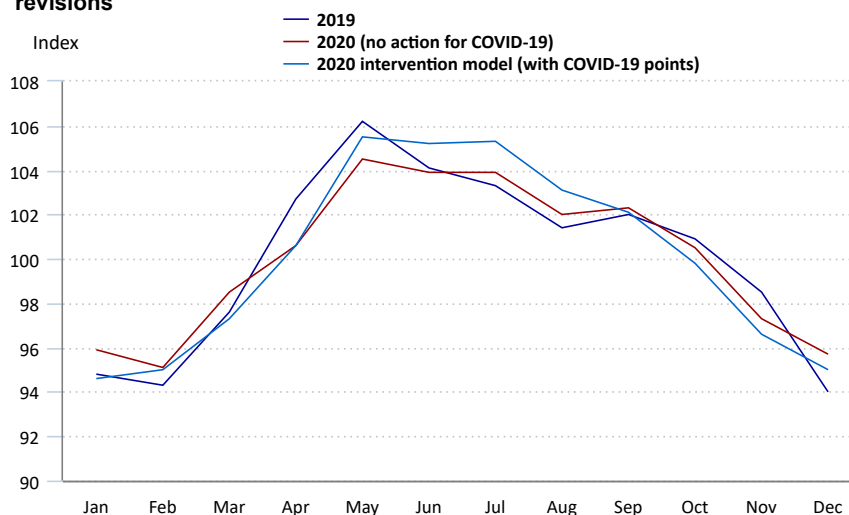


Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.

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Chart 6. Consumer price index for gasoline (all types), seasonal factors, with and without COVID-19 2020 action, 2019–20 annual seasonal revisions



Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.

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Table 7 compares QC statistics estimated with data from 2012 to 2019 with those estimated with data from 2013 to 2020. Because BLS regularly conducts intervention work on PPI and CPI gasoline prices, the 2019 intervention model was used for estimating both sets of QC statistics. Doing so minimizes differences between the two sets of QC statistics, which isolates the effects of COVID-19-related price movements. The QC statistics generated with data through 2019 clearly indicate seasonality in both the PPI and CPI for gasoline. For PPI, after 2020 data are added, $F(s)$ falls well below the threshold that would indicate seasonality. This result implies that the extreme price movements in 2020 likely made detecting seasonality in gasoline prices more difficult. For CPI, a similar although less pronounced trend occurred. The QC statistics for 2020 imply statistically significant seasonality but with a notable deterioration from the previous year's test statistics. The greater difference between 2019 and 2020 models in PPI than CPI is most likely due to more extreme price movements in the PPI in 2020.

Table 7. Quality control statistics for producer price index and consumer price index gasoline, 2019 and 2020 annual seasonal revisions

Indexes	<i>F(s)</i>	<i>M7</i>	<i>Q</i>
PPI 2019	17.84	0.58	0.64
PPI 2020 (no COVID-19 interventions)	3.10	1.39	1.02
PPI 2020 after modeling	13.87	0.60	0.64
CPI 2019	17.13	0.56	0.59
CPI 2020 (no COVID-19 interventions)	8.62	0.70	0.73
CPI 2020 after modeling	18.11	0.51	0.73
Note: <i>F(s)</i> is a measure of stable seasonality, <i>M7</i> determines the amount of moving seasonality relative to the amount of stable seasonality, and <i>Q</i> is a weighted average of several diagnostic statistics. COVID-19 = coronavirus disease 2019, CPI = consumer price index, and PPI = producer price index. Source: U.S. Bureau of Labor Statistics.			

Examination of price movements, QC statistics, and seasonal factors indicate that COVID-19-driven price movements could negatively affect seasonal adjustment of the CPI and PPI for gasoline. For these reasons, BLS developed intervention models for gasoline that included variables to offset the effects of COVID-19-related price movements. The intervention model for PPI included ramps from February 2020 through April 2020 and April 2020 through June 2020. For CPI, the intervention model included a level shift in April 2020. Table 8 presents coefficients, standard errors, and *t*-statistics from these intervention models.²²

Table 8. Intervention models conducted on producer price and consumer price indexes for gasoline, for the 2020 annual seasonal revision

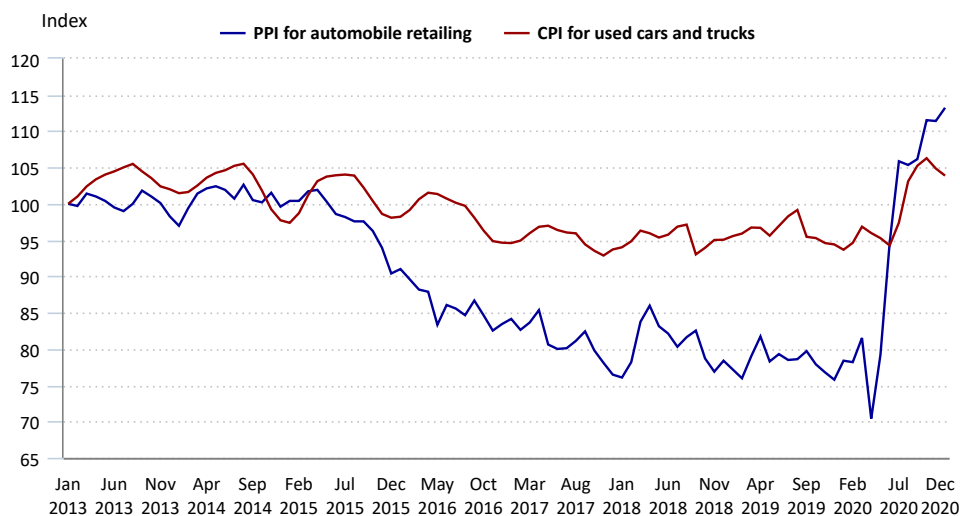
Variable	Coefficient	Standard error	<i>t</i> -value
PPI for gasoline: intervention model			
Level shift 2015.09	−0.19	0.08	−2.41
Ramp 2020.02 to 2020.04	−0.58	0.05	−11.24
Ramp 2020.04 to 2020.06	0.32	0.05	6.27
CPI for gasoline (all types): intervention model			
Ramp 2014.11 to 2015.01	−0.14	0.04	−3.76
Level shift 2020.04	−0.18	0.05	−3.92
Note: CPI = consumer price index, and PPI = producer price index. Source: U.S. Bureau of Labor Statistics.			

Charts 5 and 6 compare seasonal factors for gasoline products estimated with the 2012–19 data with those estimated with data from 2013–20 (both with the intervention models presented earlier and without the intervention models). As the charts show, without the intervention models, the 2020 factors deviate considerably from the 2019 factors, which is undesirable because factors should be relatively stable across years. For PPI and CPI, the interventions included to offset COVID-19-related price movements clearly result in factors more similar to those estimated in 2019. For both CPI and PPI, all QC statistics indicate seasonality after modeling for COVID-19. These examples underscore the need for intervention modeling to mitigate the effects of the COVID-19 pandemic on seasonal adjustment.

Automobiles

Chart 7 presents the CPI for used cars and trucks and the PPI for automobile retailing from January 2013 through December 2020. Recall, the PPI for automobile retailing measures trade margins, calculated as the sales price less the acquisition price, whereas the CPI measures the final sales price of the car or truck. Despite these methodological differences, both indexes appear to have been affected by COVID-19-related shocks. The CPI for used cars and trucks rose rapidly from June through September 2020, and margins for automobile retailing jumped from April through July 2020 and then again later in 2020.

Chart 7. Producer price index and consumer price index levels for automobile sales, January 2013–December 2020



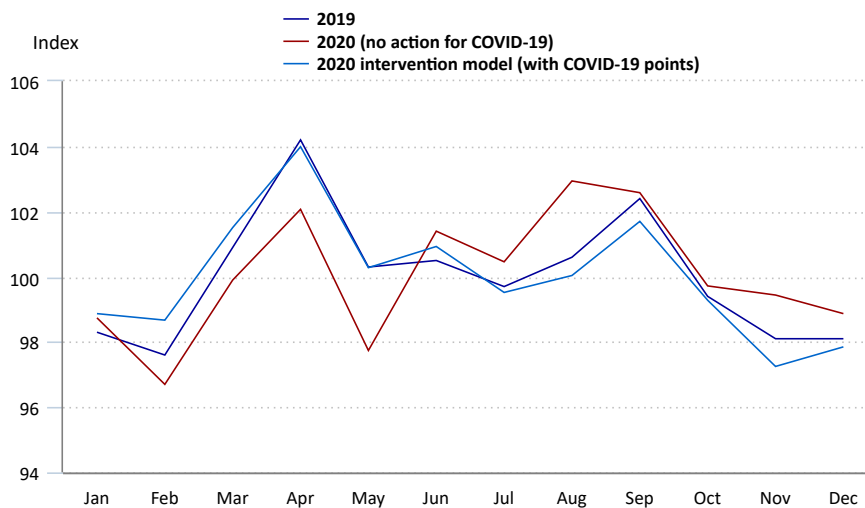
Click legend items to change data display. Hover over chart to view data.
 Note: CPI = consumer price index, and PPI = producer price index.
 Source: U.S. Bureau of Labor Statistics.



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As with gasoline, seasonal factors estimated with data from 2012 to 2019 are compared with factors estimated with data from 2013 to 2020.²³ (See charts 8 and 9, PPI for automobile retailing and CPI for used cars and trucks, respectively.) The seasonal factors estimated including data from 2020 (without COVID-19 action) differ substantially from those estimated with pre-COVID-19 data. For PPI, the 2020 factors expect an increase from May to June, which is not expected in the 2019 factors. Likewise, for CPI, the trend of the seasonal factors diverged from May to June after adding 2020 data. The seasonal factors had a more positive slope when 2020 data were included in their estimation, as compared with those estimated with data from 2012 to 2019.

Chart 8. Producer price index for automobile retailing, seasonal factors, with and without COVID-19 2020 action, 2019–20 annual seasonal revisions

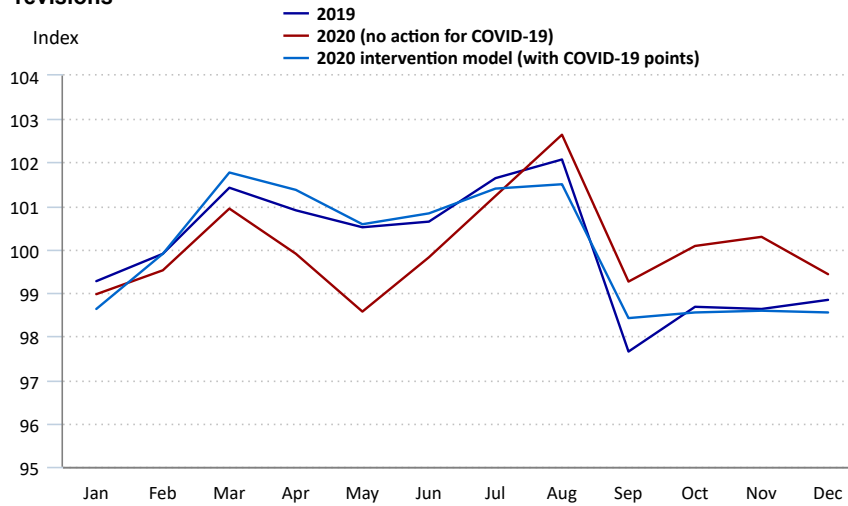


Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.



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Chart 9. Consumer price index for used cars and trucks, seasonal factors, with and without COVID-19 2020 action, 2019–20 annual seasonal revisions



Click legend items to change data display. Hover over chart to view data.
 Note: COVID-19 = coronavirus disease 2019.
 Source: U.S. Bureau of Labor Statistics.

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QC statistics estimated with data from 2012 to 2019 are compared with those estimated with data from 2013 to 2020. The QC statistics indicate a clear decline in detectable seasonality for both PPI and CPI from 2019 to 2020. For PPI, $F(s)$ fell almost 8 points after 2020 data were included in the tests and no longer indicated seasonality in 2020. For CPI, a similar trend happened. The $F(s)$ for used cars and trucks fell more than 17 points after including 2020 data, suggesting that seasonality was strongly attenuated by the COVID-19 pandemic. (See table 9.)

Table 9. Quality control statistics for automobiles conducted on producer price and consumer price indexes, 2019 and 2020 annual seasonal revisions

Index	$F(s)$	$M7$	Q
PPI 2019	9.66	0.93	0.65
PPI 2020 (no COVID interventions)	1.73	2.34	1.00
PPI 2020 after intervention modeling	9.97	0.94	0.68
CPI 2019	21.74	0.52	0.48
CPI 2020 (no COVID interventions)	4.41	1.54	0.91
CPI 2020 after intervention modeling	53.31	0.36	0.19

Note: $F(s)$ is a measure of stable seasonality, $M7$ determines the amount of moving seasonality relative to the amount of stable seasonality, and Q is a weighted average of several diagnostic statistics. COVID-19 = coronavirus disease 2019, CPI = consumer price index, and PPI = producer price index.
 Source: U.S. Bureau of Labor Statistics.

Intervention modeling was used to offset the effects of the COVID-19 pandemic on seasonal adjustment of both the PPI for automobile retailing and the CPI for used cars and trucks. For PPI, the intervention model included ramps from March 2020 through April 2020 and from April 2020 through July 2020, as well as an outlier in November 2020. For CPI, the intervention model consisted of a ramp from June 2020 through September 2020. Table 10 illustrates the intervention models employed for the automobile PPI and CPI.

Table 10. Intervention models conducted on producer price and consumer price indexes for automobiles, for the 2020 annual seasonal revision

Variable	Coefficient	Standard error	t-value
PPI for automobile retailing: intervention model			
Ramp 2020.03 to 2020.04	−0.16	0.02	−9.13
Ramp 2020.04 to 2020.07	0.15	0.01	14.32
Level shift 2020.11	0.06	0.02	3.23
CPI for used cars and trucks: intervention model			
Ramp 2020.06 to 2020.09	0.05	0.01	7.83
Note: CPI = consumer price index, and PPI = producer price index. Source: U.S. Bureau of Labor Statistics.			

Charts 8 and 9 compare seasonal factors for automobile sales estimated with 2012–19 data with those estimated with data from 2013 to 2020, employing the intervention models presented earlier. For both PPI and CPI, the interventions included to offset COVID-19-related price movements clearly result in factors more similar to those estimated in 2019, which again highlights the need for intervention modeling to mitigate the effects of the COVID-19 pandemic on seasonal adjustment. Table 9 presents QC statistics for automobiles generated with the intervention models included. For both CPI and PPI, the QC statistics indicate seasonality after controlling for the effects of COVID-19.

Scope of intervention modeling expansion and outcome

After considerable analysis for both the CPI and PPI, BLS expanded the scope of intervention work in 2020 to offset the effects of the COVID-19 pandemic on the seasonal factors used for seasonal adjustment in 2021. Economists applied intervention analysis on 68 CPIs in 2020, as compared with 32 in 2019. Of the 68 series that received intervention analysis, 47 were added to mitigate COVID-19 effects on seasonal adjustment. For these 47 newly added series, clear intervention events occurred related to COVID-19 during 2020. The other 21 series would have received intervention analysis even without COVID-19 effects. For CPI, the total number of interventions increased about 70 percent from 2019 to 2020. Economists applied intervention analysis on 76 PPI series in 2020, as compared with 41 in 2019. Of the 76 series, 36 series were added strictly to mitigate COVID-19 effects on seasonal adjustment and, thereby, only contained interventions in 2020. The total number of interventions for PPI increased 64 percent from 2019 to 2020.

Seasonal revisions

To measure whether its efforts to offset the effects of the COVID-19 pandemic on seasonal adjustment were effective, BLS compared revisions in top-level indexes resulting from the 2020 revision with those from previous revisions. In cases in which the revisions from 2020 data were similar to those from the previous three periods, efforts to offset the COVID-19 pandemic on seasonal adjustment could be inferred as effective, because adding the 2020 data to the estimation of factors did not result in large revisions. Table 11 compares average seasonal revisions to index percent changes based on the 2020 seasonal revision with those of the previous three seasonal revisions. The average annual seasonal revisions to both the PPI for final demand and the all-items CPI were similar in 2020 to those in the previous 3 years.

Table 11. Average seasonal revisions compared with monthly index percent changes of final demand and all items, 2017–2020

Year	PPI final demand	CPI all items
2017	0.075	0.055
2018	0.046	0.058
2019	0.058	0.046
2020	0.042	0.059
Note: CPI = consumer price index, and PPI = producer price index. Source: U.S. Bureau of Labor Statistics.		

Conclusion

The COVID-19 pandemic caused extreme movements in many PPIs and CPIs in 2020. Because BLS uses historical data to estimate seasonal factors, the extreme price movements resulting from the COVID-19 pandemic created difficulties in estimating seasonal data. To overcome these difficulties, BLS expanded the scope of intervention modeling for the CPI and the PPI in 2020. The number of series on which PPI conducted intervention analysis rose by more than 85 percent from 2019 to 2020 (from 41 to 76), and CPI intervention series rose by 113 percent over the same period (from 32 to 68). Likewise, the total number of interventions in the PPI increased by approximately 64 percent

from 2019 to 2020 (from 172 to 282) and those in the CPI rose 70 percent (from 64 to 109). As a result of this additional intervention modeling, the seasonal revisions to historical data seen in 2020 for both data products were in line with previous revisions, indicating that BLS successfully mitigated the effects of the COVID-19 pandemic on the CPI and PPI seasonally adjusted data.

SUGGESTED CITATION:

Blake Hoarty, Steven M. Muri, Daniel J. Pallotta, Marie Rogers, Jonathan C. Weinhausen, and Jeffrey S. Wilson, "PPI and CPI seasonal adjustment during the COVID-19 pandemic," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, May 2022, <https://doi.org/10.21916/mlr.2022.13>

Notes

¹ For more information on the X-13ARIMA-SEATS software, see https://www.census.gov/data/software/x13as>About_X-13.html.

² Ibid.

³ Julius Shiskin, Allan H. Young, and John C. Musgrave, "The X-11 variant of the Census method II seasonal adjustment program," Technical Paper 15 (U.S. Bureau of the Census, February 1967), [The X-11 Variant of the Census Method II Seasonal Adjustment Program \(Technical Paper 15\)](#).

⁴ The analysis on the food prices in this section draws heavily from another *Monthly Labor Review* article. See Dave Mead, Karen Ransom, Stephen B. Reed, and Scott Sager, "The impact of the COVID-19 pandemic on food price indexes and data collection," *Monthly Labor Review*, August 2020, <https://doi.org/10.21916/mlr.2020.18>.

⁵ Dee-Ann Durbin, "Where's the beef? Production shutdown leads to shortages," *The Associated Press*, May 5, 2020, <https://apnews.com/1ace47a100d73ce690990d73e597db22>.

⁶ Ashley, "Dairy farmers are dumping thousands of gallons of milk due to coronavirus," *CDL Life News*, April 6, 2020, <https://cdllife.com/2020/dairy-farmers-are-dumping-thousands-of-gallons-of-milk-due-to-coronavirus/>.

⁷ Krissa Welshans, "New egg industry report tackles COVID-19 impact," *Feedstuffs*, May 19, 2020, <https://www.feedstuffs.com/markets/new-egg-industry-report-tackles-covid-19-impact>.

⁸ The analysis of this section on petroleum products is largely based on Kevin M. Camp and colleagues' article. See Kevin M. Camp, David Mead, Stephen B. Reed, Christopher Sitter, and Derek Wasilewski, "From the barrel to the pump: the impact of the COVID-19 pandemic on prices for petroleum products," *Monthly Labor Review*, October 2020, <https://doi.org/10.21916/mlr.2020.24>.

⁹ Meng Meng and Florence Tan, "China overtakes U.S. again as world's top crude importer," *Reuters*, October 12, 2016, <https://www.reuters.com/article/us-china-economy-trade-crude/china-overtakes-u-s-again-as-worlds-top-crude-importer-idUSKCN12D0A9>.

¹⁰ Grant Smith, Nayla Razzouk, and Matthew Martin, "OPEC tries to force Russia into deeper cuts as oil price slumps," *Bloomberg*, March 5, 2020, <https://www.bloomberg.com/news/articles/2020-03-05/opec-meets-in-effort-to-bridge-saudi-russia-divide-on-oil-cuts>.

¹¹ The "+," or "plus," includes several non-OPEC (Organization of the Petroleum Exporting Countries) members that also participate in the organization's initiatives. These OPEC+ include Azerbaijan, Bahrain, Brunei, Kazakhstan, Malaysia, Mexico, Oman, Russia, Sudan, and South Sudan. For more information, see *Wikipedia: The Free Encyclopedia*, "OPEC," https://en.wikipedia.org/wiki/OPEC#cite_note-opec-8.

¹² Javier Blas, "Trump's oil deal: the inside story of how a price war ended," *Bloomberg*, March 13, 2020, <https://www.bloomberg.com/news/articles/2020-04-13/trump-s-oil-deal-the-inside-story-of-how-the-price-war-ended>.

¹³ Air passenger traffic is based on the number of security screenings at Transportation Security Administration (TSA) checkpoints. For more information see "TSA checkpoint travel numbers (current year versus prior year(s)/same weekday)" (TSA, updated daily), <https://www.tsa.gov/coronavirus/passenger-throughput?page=0>. Hotel occupancy rates are based on data from STR. For more information, see "STR: U.S. hotel performance for April 2020," *CoStar*, May 20, 2020, <https://www.hotelnewsnow.com/Articles/302776/STR-US-hotel-performance-for-April-2020>.

¹⁴ STR: U.S. hotel performance for April 2020.

¹⁵ The analysis from this section on leisure and hospitality services is largely based on the Sarah Eian and Brett Matsumoto's article. See Sarah Eian and Brett Matsumoto, "The impact of the COVID-19 pandemic on the input and output prices of the airline and hotel industries: insights from new BLS data," *Beyond the Numbers*, vol. 10, no. 3, February 2021, <https://www.bls.gov/opub/btn/volume-10/impact-of-covid-19-pandemic-on-input-and-output.htm>.

¹⁶ STR: U.S. hotel performance for April 2020.

¹⁷ "TSA screens over 1M passengers on a single day for the first time since March," National Press Release (TSA, October 19, 2020), <https://www.tsa.gov/news/press/releases/2020/10/19/tsa-screens-over-1m-passengers-single-day-first-time-march>.

¹⁸ Dustin Hawley, "Why are used cars so expensive?" *J.D. Power* (J.D. Power and Associates, March 3, 2021), <https://www.jdpower.com/cars/shopping-guides/why-are-used-cars-so-expensive>.

¹⁹ Ibid.

²⁰ For more information on margin pricing in PPI, see "Producer Price Indexes" (U.S. Bureau of Labor Statistics, updated periodically),

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MAY 2022

Comparing the euro area and U.S. labor market recoveries during COVID-19

Summary written by: [Demetrio Scopelliti](#)

In “[How Have the Euro Area and U.S. Labor Market Recoveries Differed?](#)” author Thomas Klitgaard (Liberty Street Economics, Federal Reserve Bank of New York, March 2022) evaluates labor markets for both the euro area and the United States during the initial phase of the pandemic and discusses how job retention strategies in the euro area during that period likely contributed to greater job stability relative to the United States.

In comparing labor market conditions during the initial phase of the pandemic, Klitgaard indicates that the U.S. unemployment rate rose from 3.5 percent in February 2020 to 14.7 percent in April 2020, while the unemployment rate for the euro area remained near 7.5 percent through May 2020 and rose to 8.6 percent in August 2020. He also cites differences in employment, as U.S. jobs decreased 12 percent from the fourth quarter of 2019 to the second quarter of 2020, while euro area employment decreased 3 percent over the same period. The author argues that relative to the United States, the euro area unemployment rates and job levels were more stable because of the implementation of job retention strategies that encouraged employers to retain staff. These strategies included governments subsidizing wages and employees accepting a cut in compensation and work hours. While hours worked in the United States dropped 13 percent from the fourth quarter of 2019 to the second quarter of 2020, hours worked in the euro area dropped by 17 percent. By the third quarter of 2020, hours worked in the euro area were only 5 percent lower than they had been when the pandemic started.

Although unemployment rates for both regions are near prepandemic levels 2 years following the onset of the pandemic, Klitgaard asserts that U.S. employment is down by three million from the fourth quarter of 2019 to the fourth quarter of 2021, compared with an increase of 600,000 for the euro area over that same period. He attributes the U.S. decrease to three industries: accommodation and food services; local government; and nursing/elderly care facilities. Although the euro area also experienced substantial job losses in accommodation and food services, the author indicates that these losses were more modest than those in the United States. In contrast to the United States, where government jobs (federal, state, and local) decreased by 600,000, public-sector jobs in the euro area (including public administration, education, and social work) increased by 1.3 million.

The author acknowledges that it is difficult to assess whether the shortfall in U.S. employment relative to prepandemic levels is due to decreased demand for labor or a decrease in labor force participation. Citing a lower number of job openings in state and local government relative to accommodation and food services, Klitgaard suggests that reduced demand for labor would explain the shortfall in government jobs while the shortfall in employment in accommodation and food services is due to the reluctance of workers to take on or resume employment in that industry.

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MAY 2022

Workers are less likely to work as much following the COVID-19 pandemic

Summary written by: [Lisa N. Huynh](#)

As employment is recovering from the onset of the coronavirus disease 2019 (COVID-19) pandemic, overall employment and willingness to work have decreased. In the working paper, “[Has the willingness to work fallen during the COVID pandemic?](#)” (National Bureau of Economic Research, Working Paper 29784, February 2022), authors R. Jason Faberman, Andreas I. Mueller, and Ayşegül Şahin analyze how much willingness to work has declined since the start of the COVID-19 pandemic.

Designed by the Federal Reserve Bank of New York, the Job Search Supplement of the Survey of Consumer Expectations (SCE) provides details on individuals’ desired work hours from 2013–21. The SCE collect information on people’s employment situations, work preferences, and job search behavior. This survey provides a measure to identify changes over time in people’s willingness to work and shows how the COVID-19 pandemic could affect decisions relating to people’s job searches and labor market participation.

Using data from the SCE and workers’ actual labor market participation, Faberman, Mueller, and Şahin construct a labor market underutilization measure called the aggregate hours gap (AHG). These data are used to identify the difference between desired hours worked and what is available within the labor market. Specifically, the AHG measures underutilization by looking at the difference between the desired work hours and actual hours worked by workers, regardless of employment status. According to the authors, AHG has a stronger relationship with nominal wage growth than other more traditional metrics (for example, the unemployment rate) do, since AHG can address the unique labor market brought on by the COVID-19 pandemic.

Faberman, Mueller, and Şahin note that the labor market is tighter than what the unemployment rate would suggest. This tightness is due to the individuals not in the labor force and part-time workers who reported a lower willingness to work many hours or participate in the labor market altogether. Between 2013 and 2021, the decline in desired hours worked was 4.6 percent; meanwhile, the decline in labor force participation rate was 2.3 percent.

The unemployment rate and AHG have displayed a diverging pattern following the recession caused by the COVID-19 pandemic. The authors don’t find evidence that the contraction in labor supply is due to women responding to childcare demands. Rather, the contraction is consistent across most demographic groups, with a larger decline among those with less than a college degree. The disinclination to work has reduced the labor supply, and this reduction has been persistent throughout the pandemic.

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BOOK REVIEW

MAY 2022

How can data science help address workforce challenges in the public sector?

Data Science in the Public Interest: Improving Government Performance in the Workforce. By Joshua D. Hawley. Kalamazoo, MI: W. E. Upjohn Institute for Employment Research, 2020, 152 pp., <https://doi.org/10.17848/9780880996754>.

Recent developments in web and mobile technologies have led to an explosion of big data, which are characterized by the so-called three Vs: volume (amount), variety (diversity), and veracity (accuracy). Because data can provide an efficient, fact-based means to identifying labor supply and demand, they can help governments allocate resources more effectively and prospective workers choose careers that are both profitable and beneficial to the overall economy. In *Data Science in the Public Interest: Improving Government Performance in the Workforce*, author Joshua D. Hawley examines how, by improving the quality, accuracy, and breadth of data within the public sector, data science can inform government workforce decisions. The author identifies several main workforce problems that guide the discussion.

One key problem is the long-term health of the workforce, which depends on the existence and maintenance of a mature workforce data system. In the 1960s and 1970s, the U.S. Department of Labor (DOL) and the U.S. Census Bureau developed longitudinal data systems to help federal and state governments make better decisions. Government researchers began to use these systems to study changes in employment and labor mobility, developing techniques for linking longitudinal data to decision making. Since the 1970s, however, many state governments have not updated their data systems. Hawley observes that some state governments still run their unemployment insurance programs on old computer systems that use outdated software written in Common Business-Oriented Language (COBOL), and there have been media reports that, during the coronavirus disease 2019 (COVID-19) pandemic, some jurisdictions recruited COBOL developers. As one example of a solution to this problem, the author frequently brings up Ohio's longitudinal data system (developed jointly with DOL) as a paradigm of successful implementation of data analytics and machine learning in public policy. The system, which links information about K–12 and higher education with workforce development data, provides critical performance metrics that have helped Ohio launch effective responses to health and economic crises. These responses have ranged from analyzing and addressing surges in state unemployment to targeting food aid across local school districts.

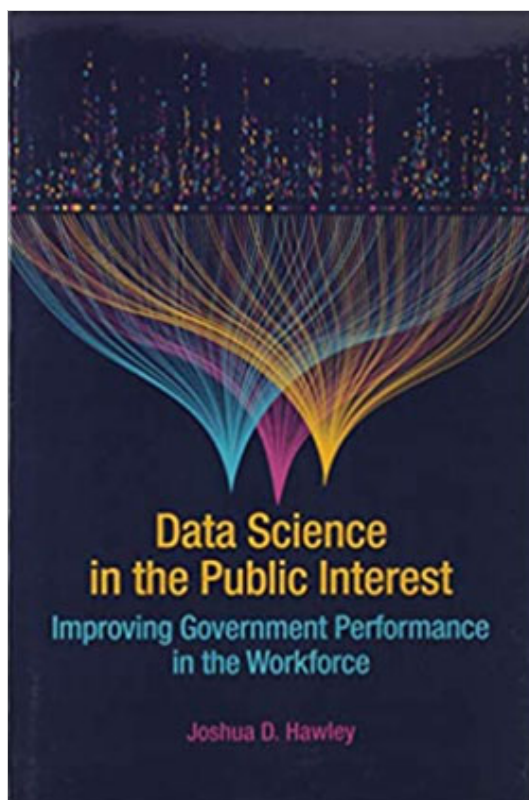
Another workforce problem identified by Hawley is automation, which, according to one source cited in the book, will replace 73 million U.S. jobs by 2030. The fear of automation is widespread: workers, particularly those performing routine tasks, fear that they will lose their jobs; employers worry that they will struggle to find workers who can use modern technology; and governments are concerned about automation's economic and fiscal impact on their communities. To address these concerns, governments have turned to big data for solutions. For example, states are increasingly using administrative data to design and build data systems that contain and track information on student outcomes, human services, workforce development, and employment. In 2014, the federal government outlined, for the first time, a common set of national performance standards in the Workforce Innovation and Opportunity Act (WIOA), and these standards have informed initiatives for providing and funding career and technical education, adult education, and temporary cash assistance for families in need. Some states and counties have incorporated WIOA performance standards into their economic development strategies, using online tools, such as dashboards, to monitor and measure the success of their workforce programs and systems.

A third problem discussed in the book revolves around the federal minimum wage, which has failed to keep up with increases in the cost of living. As seen during the 2007–09 Great Recession, which left many people unemployed, the problem of stagnating earnings was particularly stark among workers lacking the education or skills necessary to meet the demands of the changing nature of work. According to Hawley, one potential solution to this problem is government regulatory intervention through minimum-wage laws; another involves improving the skills of workers left on the sidelines by providing them with job training or subsidized postsecondary education. The author suggests that data systems can be particularly useful in informing these efforts, because they can help identify job skills that are in high demand. While the

federal government has overseen vocational training for adults, states have shown renewed interest in funding specific workforce development programs, such as the Registered Apprenticeship Program and career and technical education programs for high school students.

Finally, Hawley turns to the problem of state governments being slow to learn from past successes and setbacks. According to the author, data on prior experiences with workforce development programs can be used to improve the performance of ongoing and future programs. One example given in the book involves Ohio's Comprehensive Case Management and Employment program, which was rolled out in 2015 and required significant changes to the organization and delivery of local education and employment services to eligible youth. The state collected data on how counties changed their institutional structure to comply with state laws and implement the program, but it did not build the systems necessary to capture lessons learned from these changes. Thus, it became difficult to adjust program design, revise the curricula of the programs, or know whether program performance can be improved. Eventually, Ohio did build a dashboard using big data to create a set of standardized metrics for assessing program performance and presenting program outcomes. It is these lessons learned, captured in data, that could inform workforce development initiatives in the future.

While workforce data systems have continued to evolve since the 1980s, change has been slow. In 2010, in an effort to strengthen longitudinal data systems in state government, DOL launched the Workforce Data Quality Initiative, which has encouraged states to use data more actively in their workforce programs. While such initiatives are steps in the right direction, their success is not guaranteed. Convincing states to take the lead on developing workforce data systems and ensuring their interoperability may require a cultural change.



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MAY 2022

Do pricier hospitals lead to better care?

Summary written by: [Eleni X. Karageorge](#)

The belief that patients receive better quality care when they are treated at higher priced hospitals is examined in a recent study. In “[Do higher-priced hospitals deliver higher-quality care?](#),” authors Zack Cooper, Joseph J. Doyle Jr., John A. Graves, and Jonathan Gruber analyze whether receiving higher priced hospital care results in higher quality care.

To understand the perceived correlation between hospital prices and patient health outcomes, the authors gathered insurance claims data from the Health Care Cost Institute between June 2007 and June 2014 on individuals ages 18 through 64 who had employer-sponsored health insurance. To overcome selection challenges, they used data on patients who were taken by ambulance to high- and low-priced hospitals. Ambulances are selected randomly to respond to emergency calls. The authors found that patients receiving care from higher priced hospitals reduces in-hospital mortality by about 35 percent. However, this finding between higher prices and lower mortality only exists at hospitals in less concentrated markets where hospitals face more competition. By contrast, patients receiving care from expensive hospitals in concentrated markets spend substantially more for the care with no noticeable effect on their mortality.

The authors discovered that, in both concentrated and unconcentrated hospital markets, receiving care from high-priced hospitals increased health costs by approximately 52 percent. When patients went to pricier hospitals in concentrated markets, their costs went up, but health outcomes did not improve. In unconcentrated or more competitive markets, patients who were treated at a higher priced hospital led to higher spending, but it also reduced mortality by 47 percent for time-sensitive conditions such as heart attacks. In other words, in these competitive markets, patients spend 52 percent more, but they are 47 percent less likely to die.

In their sample, Cooper and colleagues applied the Herfindahl-Hirschman Index (HHI) that measures the market concentration of hospitals. The mean hospital HHI in the study was 4,327. Ultimately, they found that in markets with an HHI of less than 4,000, receiving care from pricier hospitals resulted in just over a 1-percentage-point reduction in in-hospital mortality. For each life saved, the cost was an additional \$1 million in health spending, leading the researchers to suggest that saving lives in higher priced hospitals likely saves costs. Receiving care from similarly pricier hospitals, however, with HHIs greater than or equal to 4,000 had no effect on mortality. Although care from these hospitals generated additional spending, it did not change patient health outcomes.

Evidence shows that in these concentrated hospital markets, higher prices may not reflect higher quality of care but instead a lack of alternative options. The authors suggest that policymakers should consider regulating prices at hospitals in concentrated markets, which may help protect patients against higher prices when their care options are limited.

In addition, the authors find that seeking care at pricier hospitals will not necessarily improve patient health outcomes. Instead,

health outcomes may improve if the hospital is in a less concentrated market with more competition or in a concentrated market with heavy consolidation.

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FEATURED ARTICLE

MAY 2022

The challenges of seasonal adjustment for the Current Employment Statistics survey during the COVID-19 pandemic

For its seasonally adjusted data, the Bureau of Labor Statistics (BLS) seeks to remove all fluctuations that are caused by the yearly cycle of seasons. The coronavirus 2019 pandemic posed a challenge to this task, because its effect was strong, across the entire economy, and lasted for at least several months. To ensure that the effects of the pandemic were not being incorporated into the seasonal adjustment factors, the Current Employment Statistics program took additional actions such as splitting the seasonal adjustment into two runs (prepandemic and postpandemic) and incorporating additional types of outliers into its models.

Most series published by the Current Employment Statistics (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 to help provide a better interpretation of trends without the influence of regularly occurring seasonal patterns. Previous publications from the U.S. Bureau of Labor Statistics (BLS) have discussed the challenges of seasonal adjustment during the coronavirus disease 2019 (COVID-19) pandemic. Those publications focused on the approaches BLS has taken to mitigate the effects of the pandemic on the real-time seasonal factors BLS uses to produce the seasonally adjusted series.¹ Those discussions address how we use outlier detection, our most commonly used tool, to intervene in realtime when we estimate seasonal factors each month.

COVID-19 had a dramatic effect on the labor market. Unlike a strike or weather event, the effect was nationwide and, for some industries, sustained over a long period. BLS needed to carefully construct its seasonal adjustment models to ensure that the effect of the pandemic did not get incorporated into the models as a normal seasonal fluctuation. This article addresses how the CES program seeks to mitigate the effects of the pandemic on the 5 years of historical seasonal factors that are revised annually for the CES program. To preserve the accuracy of the historical seasonally adjusted data in response to the effects of COVID-19, BLS combined a sequence of two runs (prepandemic and postpandemic) as an additional intervention, along with the normal outlier-detection treatment, to produce the revised series for the 2020 annual review. Since the time of the 2020 annual review, BLS time-series researchers have developed responses that provide a more standardized approach to mitigating the effects of the pandemic. This article also addresses the procedure used during the 2021 annual review, which includes the use of additional outlier types discussed in the responses developed by these researchers.

Background

The CES program is a monthly survey conducted by the Bureau of Labor Statistics. The program provides employment, hours, and earnings estimates based on payroll records of business establishments. Data produced from the CES survey include nonfarm employment series for all employees, production and nonsupervisory employees, and women employees, as well as average hourly earnings, average weekly hours, and average weekly overtime hours (in manufacturing industries) for both all employees and production and nonsupervisory employees.

Each year, BLS examines and revises the previous 5 years of seasonal factors and seasonally adjusted data that were originally calculated in realtime. The CES program uses 10 years of original data to produce seasonally adjusted data. Once a year, the CES program selects new model specifications and recalculates the previous 5 years of seasonally adjusted data using the new model specifications.² The model specifications selected annually are not changed until the next annual review. After 5 years, the CES program no longer revises the seasonally adjusted series, unless there is a change to the industry that requires a reconstruction of the time series.³

How the seasonal adjustment process works

[illegible]

The COVID-19 pandemic is an event that has affected just about every part of the economy to such a degree that we now define many aspects of what we do into a prepandemic (prior to February 2020) and postpandemic (March 2020 forward) time frame. Given the pandemic, the CES program had to determine how best to maintain the integrity of the seasonally adjusted history prior to the pandemic. This task was particularly challenging in that the effects of the pandemic should not influence the seasonal adjustment model used to generate the seasonal factors that are prior to the pandemic. Ordinarily, outlier detection alone is used to prevent extreme values from affecting the calculation of the seasonal factors. However, additional intervention was necessary because of the extreme, pandemic-induced fluctuations in the estimates and the extended time frame over which the pandemic has occurred. The results provided show that, even with the outlier detection used as part of the normal treatment process, there were larger than normal revisions to the historical time series and unexpected changes to the historical normal seasonal movements.

Seasonal adjustment for postpandemic period																		
2011	2012	2013	2014	2015	2016	2017	2018	2019	2020									
									Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Seasonal adjustment for prepandemic period																		
2011	2012	2013	2014	2015	2016	2017	2018	2019	2020									
									Jan	Feb								
5-year seasonally adjusted revision																		
									2020		2020							
									Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Prepandemic period									Postpandemic period									

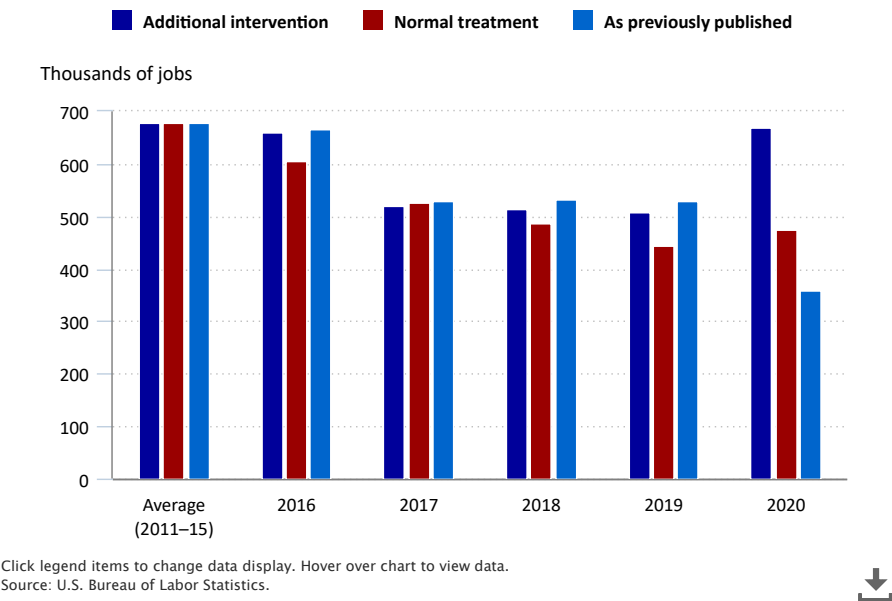
To better understand historical seasonal patterns, it is useful to view the normal seasonal movement in a series over time. The normal seasonal movement is calculated as the difference between the month-to-month change in the original, not seasonally adjusted series minus the month-to-month change in the seasonally adjusted series:

The normal seasonal movement is useful for analyzing historical seasonal patterns because it provides a rough estimate of the strength of the

seasonal effect over time. The normal seasonal movements of the total employment series using the normal treatment are compared to the normal seasonal movements of the published total employment series using the additional intervention to show the effects of using the additional intervention as compared to the normal treatment.

Chart 1 highlights the normal seasonal movements of total nonfarm employment over time for March, one the months hit hardest, economically, by the pandemic. The rightmost bar in each year shows the normal seasonal movements as previously published before the annual review. In March of each year from 2011 to 2019, employment has increased by approximately 500,000–600,000 on account of the normal seasonal movement. In contrast, the previously published normal seasonal movement for March 2020 was 360,000, much lower than normal. This weakness comes from the effects of the pandemic without any additional intervention to mitigate them. The middle bar of the chart shows a similar pattern in the normal seasonal movements calculated with the normal treatment. As a result of the revision, the weakness from the effects of the pandemic is spread over the previous 5 years in addition to March 2020. The leftmost bar in each year of chart shows the normal seasonal movements revised 5 years using the additional intervention. The normal seasonal movements with the additional intervention are more stable and consistent with the history prior to the influence of the pandemic. Next, the results for the prepandemic period and the postpandemic period are discussed to explain the effects of the additional intervention compared with the normal treatment in more detail.

Chart 1. Normal seasonal movement of total nonfarm employment for March from 2011 to 2020



[View Chart Data](#)

Prepandemic period

The normal seasonal movements in the prepandemic period, from January 2016 to February 2020, show that the additional intervention provides more consistency and smaller revisions compared with the results from the normal treatment. This is especially visible in the history of the series in the months of March and April. Without the additional intervention, the historical normal seasonal movements show a weaker seasonal increase than the previously published data. This weakening is due to the seasonal adjustment process factoring the effects of the pandemic into the history. The normal seasonal movements resulting from the additional intervention are more consistent with the previously published historical seasonal movements.

Postpandemic period

In the first month of the postpandemic period, March 2020, the expected seasonal increase made using the normal treatment appears to have been weakened by the effects of the pandemic. Using the additional intervention shows a larger revision more in line with the previously published data compared to the normal treatment, which appears to have shifted the weakness from the pandemic back into the historical normal seasonal movement. The estimates for the remainder of the postpandemic period from April 2020 forward are the same between the normal treatment and the additional intervention because all 10 years of data through October 2020 were used to calculate the seasonal factors for both approaches.

Additional intervention for the 2021 review

The two-step approach used during the 2020 annual review addressed the need to mitigate the effects of the pandemic in realtime with a limited amount of data. Now that we have more data available and additional guidance on using outlier intervention options within the X-13

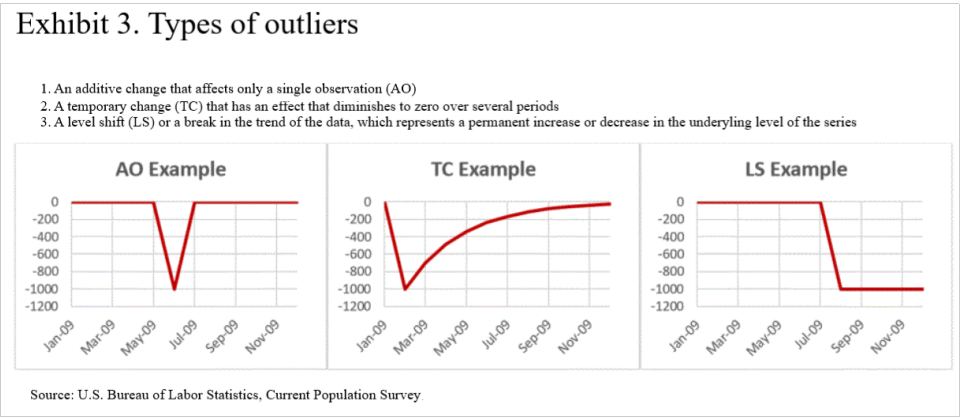
ARIMA-SEATS software, CES has moved toward using a more standardized approach.

As the COVID-19 pandemic unfolded, BLS time-series researchers developed several responses to the challenges. They found that using additional outlier types could provide a more parsimonious outlier set for the pandemic period.⁵ Using additional outlier types provides users the simplest model with the least variables and greatest explanatory power. Additionally, there are a number of CES series with complex movements during the pandemic period that could not be adequately adjusted by using the additive outlier types only.

For 2021's annual review, two approaches were evaluated:

- 1. Traditional outlier treatment—using additive outliers (AOs) only.
- 2. Additional outlier treatment—using all outlier types: additive (AO), level shifts (LS), and temporary changes (TC)

Exhibit 3 provides details on the different outlier types:



To compare model fits, the CES program uses a version of the Akaike information criterion (AIC). From Rebecca Bevans of Scribbr, "The Akaike information criterion is a mathematical method for evaluating how well a model fits the data it was generated from. In statistics, AIC is used to compare different possible models and determine which one is the best fit for the data. AIC is calculated from:

- the number of independent variables used to build the model.
- the maximum likelihood estimate of the model (how well the model reproduces the data).

The best-fit model according to AICc is the one that explains the greatest amount of variation using the fewest possible independent variables."⁶

The CES program uses the AIC corrected for small sample sizes, the AICc. As such, the AICc is used here to determine which outlier treatment provides the best model fit. Like the AIC value, a lower AICc value is an indicator of a better fit model. Table 1 provides a comparison of the number of series with a lower AICc from the model using the normal treatment with AOs only against those of the additional-treatment model using all outlier types.

Table 1. Comparison of the number of series with lower AICc for models with all outlier types and AO-only outlier types

CES series	AICc lower (better model fit)				
	All outlier types		AO only		Total number of series
	Number of series with better fit	Percentage of series with better fit	Number of series with better fit	Percent of series with better fit	
Total	2,363	48	2,555	52	4,918
All employees	571	68	263	32	834
Average weekly hours for all employees	233	37	404	63	637
Average hourly earnings for all employees	215	34	422	66	637
Average weekly overtime hour for all employees	43	35	79	65	122
Production employees	435	68	202	32	637
Average weekly hours for production employees	218	34	419	66	637
Average hourly earnings for production employees	201	32	436	68	637
Average weekly overtime hours for production employees	40	33	82	67	122
Women employees	407	62	248	38	655
Note: AO = Additive outliers. AICc = Akaike's information criterion (corrected for small sample size). CES = Current Employment Statistics. Source: U.S. Bureau of Labor Statistics.					

We found that, overall, the number of series with a better model fit when we used all outlier types (48 percent of series) is approximately the same as those with a better model fit when we used the AO-only outlier types (52 percent). However, there are substantial differences in these numbers by data series type. For the employment series, the model using all outlier types provided a better fit for most series: all employees (68 percent of series), production employees (68 percent), and women employees (62 percent). The pandemic most strongly complicated the behavior of the employment series, which required additional outlier types to fully adjust. For the hours and earnings series, the model using AO-only outliers provided a better fit for most series. The impact from the pandemic on the hours and earnings series were less substantial in most cases and do not require the additional outlier types to provide a better model fit. The model with the lower AICc was used to produce the seasonally adjusted data for each series. Additionally, CES analysts performed a review of the series on a case-by-case basis to validate the seasonally adjusted series as part of the usual annual review procedure.

Prepandemic period

The normal seasonal movements in the prepandemic period, from January 2017 to February 2020, show that including the additional outlier types provides more consistency and smaller revisions compared with the normal treatment that uses the AOs only. The smaller revisions are broadly visible throughout the history of the series. Without the use of the additional outlier types, the historical normal seasonal movements show a weaker seasonal increase than those previously published. This weakening is due to the seasonal adjustment process incorrectly factoring the effects of the pandemic into the history as normal seasonal movement. The normal seasonal movements calculated with the additional outlier types are more consistent with the previously published historical seasonal movements.

Postpandemic period

The normal seasonal movements in the postpandemic period, from March 2020 to October 2021, show that including the additional outlier types provides more consistency and smaller revisions compared with the normal treatment that uses the AOs only. In the first month of the postpandemic period, March 2020, and in the following March 2021, the expected seasonal increase calculated with the AOs only appears to have been weakened by the effects of the pandemic. Using the additional outlier types shows a normal seasonal movement more in line with the previously published history compared with the results from the AOs only model, which appears to have shifted the weakness from the pandemic back into the historical normal seasonal movement. The revisions to March 2020 through the remainder of the postpandemic period are consistently smaller when including the additional outlier types.

Conclusion

The COVID-19 pandemic is unusual in its severity and duration when compared with other shocks to the economy. As a result, additional intervention was required to preserve the accuracy of the historical seasonally adjusted series. The results show that the effects of the

pandemic were not completely removed from the seasonal factors as part of the normal treatment in which we used additive outlier detection alone. As part of the 2020 annual review, additional intervention and a sequence of two runs (prepandemic and postpandemic) was used to mitigate the impact of the pandemic on the historical seasonal factors. The additional intervention is an extension of the normal outlier-detection treatment and is an additional step towards effectively isolating the prepandemic period. The point of the additional intervention is to ensure that the postpandemic period does not influence the seasonal model prior to the pandemic—so that we preserve the historical seasonal patterns. The results show that the historical normal seasonal movements calculated with the the additional intervention are more in line with the expected normal seasonal movement—especially in the months in which the pandemic had its largest economic effect (March and April 2020). This approach provided the most accurate revisions to the seasonally adjusted data in realtime with the limited amount of postpandemic-period data available during the 2020 annual review just after the start of the pandemic. As the pandemic unfolded, BLS time-series researchers were able to develop a more standardized approach to mitigating the effects of the pandemic. In lieu of using the two-step approach used during the 2020 review, CES incorporated the use of additional outlier types available in the X-13 ARIMA-SEATS software as part of the most recent annual review to mitigate the effects of the pandemic. The models available by the use of the additional outlier types provide a better fit and allow better adjustments for the complex movements in the CES series that are due to the pandemic. These new models result in the calculation of more stable seasonal factors used to produce the seasonally adjusted series.

Appendix

2020 annual review

The appendix provides the components used to calculate the normal seasonal movement for total nonfarm employment for the following:

- Table A-1: Not seasonally adjusted series;
- Table A-2: Revised seasonally adjusted series using the normal treatment;
- Table A-3: Revised seasonally adjusted series using the additional intervention;
- Table A-4: Seasonally adjusted series as previously published prior to revision.

Tables A-5 through A-7 provide the normal seasonal movements calculated using the components from Tables A-1 through A-4. The difference in the normal seasonal movement between the normal treatment and the additional intervention is provided in table A8. The difference between the normal seasonal movement as previously published and the revised normal seasonal movement calculated by means of the normal treatment and the additional intervention is provided in tables A-9 and A-10, respectively. Some months are affected by the variable survey week adjustment, sometimes referred to as the 4- versus 5-week effect.⁷

Table A-1. month-to-month change, not seasonally adjusted, in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	-2,863	814	906	1,217 ^[1]	684	489 ^[1]	-1,274	275	746 ^[1]	923	335	-175 ^[1]
2012	-2,606	954 ^[1]	904	883	814	337 ^[1]	-1,209	379 ^[1]	628	847	389 ^[1]	-75
2013	-2,882	1,038 ^[1]	799	1,005	893 ^[1]	409	-1,174	437 ^[1]	608	922	525 ^[1]	-251
2014	-2,804 ^[1]	740	958	1,138	912 ^[1]	587	-1,079	380 ^[1]	686	1,054 ^[1]	465	-4
2015	-2,815 ^[1]	831	757	1,183 ^[1]	942	475	-952 ^[1]	192	558	1,148 ^[1]	421	-2
2016	-2,974 ^[1]	831	895	1,094 ^[1]	649	664 ^[1]	-973	253	666 ^[1]	882	432	-212 ^[1]
2017	-2,876	1,029 ^[1]	656	1,024	839	643 ^[1]	-1,103	317	388 ^[1]	1,013	574 ^[1]	-247
2018	-3,098	1,237 ^[1]	703	977	935	666 ^[1]	-1,164	470 ^[1]	312	1,003	481 ^[1]	-200
2019	-2,953	805 ^[1]	675	1,062	673 ^[1]	622	-1,058	436 ^[1]	417	989	595 ^[1]	-249
2020	-2,791 ^[1]	913	-1,016	-19,701 ^[1]	3,168	5,082	606 ^[1]	1,621	1,218	1,622 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-2. Revised month-to-month change, seasonally adjusted (additive outlier only), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	19	212	235	314 ^[1]	101	236 ^[1]	60	126	233 ^[1]	204	132	202 ^[1]
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	67 ^[1]	192	292	207 ^[1]	51	255 ^[1]	383	151	287 ^[1]	92	115	190 ^[1]
2017	212	200 ^[1]	132	236	161	212 ^[1]	242	205	27 ^[1]	210	169 ^[1]	152
2018	85	389 ^[1]	220	183	288	224 ^[1]	166	226 ^[1]	84	176	52 ^[1]	203
2019	229	-41 ^[1]	233	263	88 ^[1]	193	205	188 ^[1]	184	147	182 ^[1]	119
2020	260 ^[1]	244	-1,487	-20,679 ^[1]	2,833	4,846	1,726 ^[1]	1,583	716	680 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-3. Revised month-to-month change, seasonally adjusted (all outlier types), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	19	212	235	314 ^[1]	101	236 ^[1]	60	126	233 ^[1]	204	132	202 ^[1]
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	108 ^[1]	212	237	197 ^[1]	41	258 ^[1]	371	143	289 ^[1]	118	130	214 ^[1]
2017	197	183 ^[1]	139	220	141	211 ^[1]	228	190	42 ^[1]	249	196 ^[1]	179
2018	81	378 ^[1]	195	153	270	214 ^[1]	149	229 ^[1]	105	212	92 ^[1]	240
2019	237	-50 ^[1]	168	219	63 ^[1]	175	193	195 ^[1]	221	195	234 ^[1]	161
2020	315 ^[1]	289	-1,683	-20,679 ^[1]	2,833	4,846	1,726 ^[1]	1,583	716	680 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-4. month-to-month change, seasonally adjusted (as previously published), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	19	212	235	314 ^[1]	101	236 ^[1]	60	126	233 ^[1]	204	132	202 ^[1]
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	73 ^[1]	263	229	187 ^[1]	42	267 ^[1]	354	135	269 ^[1]	145	151	230 ^[1]
2017	185	188 ^[1]	129	197	155	216 ^[1]	215	184	18 ^[1]	267	225 ^[1]	130
2018	121	406 ^[1]	176	137	278	219 ^[1]	136	244 ^[1]	80	201	134 ^[1]	182
2019	269	1 ^[1]	147	210	85 ^[1]	182	194	207 ^[1]	208	185	261 ^[1]	184
2020	214 ^[1]	251	-1,373	-20,787 ^[1]	2,725	4,781	1,761 ^[1]	1,493	711	654 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-5. Revised normal seasonal movement (additive outlier only) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	^[2]	602	671	903 ^[1]	583	253 ^[1]	-1,334	149	513 ^[1]	719	203	-377 ^[1]
2012	-2,960	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,041 ^[1]	639	603	887 ^[1]	598	409 ^[1]	-1,356	102	379 ^[1]	790	317	-402 ^[1]
2017	-3,088	829 ^[1]	524	788	678	431 ^[1]	-1,345	112	361 ^[1]	803	405 ^[1]	-399
2018	-3,183	848 ^[1]	483	794	647	442 ^[1]	-1,330	244 ^[1]	228	827	429 ^[1]	-403
2019	-3,182	846 ^[1]	442	799	585 ^[1]	429	-1,263	248 ^[1]	233	842	413 ^[1]	-368
2020	-3,051 ^[1]	669	471	978 ^[1]	335	236	-1,120 ^[1]	38	502	942 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A6. Revised normal seasonal movement (all outlier types) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	[2]	602	671	903 ^[1]	583	253 ^[1]	-1,334	149	513 ^[1]	719	203	-377 ^[1]
2012	-2,960	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,082 ^[1]	619	658	897 ^[1]	608	406 ^[1]	-1,344	110	377 ^[1]	764	302	-426 ^[1]
2017	-3,073	846 ^[1]	517	804	698	432 ^[1]	-1,331	127	346 ^[1]	764	378 ^[1]	-426
2018	-3,179	859 ^[1]	508	824	665	452 ^[1]	-1,313	241 ^[1]	207	791	389 ^[1]	-440
2019	-3,190	855 ^[1]	507	843	610 ^[1]	447	-1,251	241 ^[1]	196	794	361 ^[1]	-410
2020	-3,106 ^[1]	624	667	978 ^[1]	335	236	-1,120 ^[1]	38	502	942 ^[1]	[2]	[2]

Note:

[1] These values come from a 5-week survey interval.

[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-7. Normal seasonal movement (as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	-2,882	602	671	903 ^[1]	583	253 ^[1]	-1,334	149	513 ^[1]	719	203	-377 ^[1]
2012	-2,960	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,047 ^[1]	568	666	907 ^[1]	607	397 ^[1]	-1,327	118	397 ^[1]	737	281	-442 ^[1]
2017	-3,061	841 ^[1]	527	827	684	427 ^[1]	-1,318	133	370 ^[1]	746	349 ^[1]	-377
2018	-3,219	831 ^[1]	527	840	657	447 ^[1]	-1,300	226 ^[1]	232	802	347 ^[1]	-382
2019	-3,222	804 ^[1]	528	852	588 ^[1]	440	-1,252	229 ^[1]	209	804	334 ^[1]	-433
2020	-3,005 ^[1]	662	357	1,086 ^[1]	443	301	-1,155 ^[1]	128	507	968 ^[1]	[2]	[2]

Note:

[1] These values come from a 5-week survey interval.

[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-8. Difference in normal seasonal movement (revised with additive outliers only versus revised with all outlier types) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	-41 ^[1]	-20	55	10 ^[1]	10	-3 ^[1]	12	8	-2 ^[1]	-26	-15	-24 ^[1]
2017	15	17 ^[1]	-7	16	20	1 ^[1]	14	15	-15 ^[1]	-39	-27 ^[1]	-27
2018	4	11 ^[1]	25	30	18	10 ^[1]	17	-3 ^[1]	-21	-36	-40 ^[1]	-37
2019	-8	9 ^[1]	65	44	25 ^[1]	18	12	-7 ^[1]	-37	-48	-52 ^[1]	-42
2020	-55 ^[1]	-45	196	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-9. Difference in normal seasonal movement (revised with additive outliers only versus as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	-6 ^[1]	-71	63	20 ^[1]	9	-12 ^[1]	29	16	18 ^[1]	-53	-36	-40 ^[1]
2017	27	12 ^[1]	3	39	6	-4 ^[1]	27	21	9 ^[1]	-57	-56 ^[1]	22
2018	-36	-17 ^[1]	44	46	10	5 ^[1]	30	-18 ^[1]	4	-25	-82 ^[1]	21
2019	-40	-42 ^[1]	86	53	3 ^[1]	11	11	-19 ^[1]	-24	-38	-79 ^[1]	-65
2020	46 ^[1]	-7	-114	108 ^[1]	108	65	-35 ^[1]	90	5	26 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table A-10. Difference in normal seasonal movement (revised with all outlier types versus as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2011	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	35 ^[1]	-51	8	10 ^[1]	-1	-9 ^[1]	17	8	20 ^[1]	-27	-21	-16 ^[1]
2017	12	-5 ^[1]	10	23	-14	-5 ^[1]	13	6	24 ^[1]	-18	-29 ^[1]	49
2018	-40	-28 ^[1]	19	16	-8	-5 ^[1]	13	-15 ^[1]	25	11	-42 ^[1]	58
2019	-32	-51 ^[1]	21	9	-22 ^[1]	-7	-1	-12 ^[1]	13	10	-27 ^[1]	-23
2020	101 ^[1]	38	-310	108 ^[1]	108	65	-35 ^[1]	90	5	26 ^[1]	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

2021 annual review

The appendix provides the components used to calculate the normal seasonal movement for total nonfarm employment for the following:

- Table-B1: Not seasonally adjusted series;
- Table B-2: Revised seasonally adjusted series using additive outliers only;
- Table B-3: Revised seasonally adjusted series using all outlier types;
- Table B-4: Seasonally adjusted series as previously published prior to revision.

Tables B-5 through B-7 provide the normal seasonal movements calculated using the components from tables B-1 through B-4. The difference in the normal seasonal movement between the additive outliers only and all outlier types is provided in table B-8. The difference between the normal seasonal movement as previously published and the revised normal seasonal movement calculated with the additive outliers only and all outlier types is provided in tables B-9 and B-10, respectively. Some months are affected by the variable survey week adjustment, sometimes referred to as the 4- versus 5-week effect.⁸

Table B-1. Month-to-month change, not seasonally adjusted, in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	-2,606	954 ^[1]	904	883	814	337 ^[1]	-1,209	379 ^[1]	628	847	389 ^[1]	-75
2013	-2,882	1,038 ^[1]	799	1,005	893 ^[1]	409	-1,174	437 ^[1]	608	922	525 ^[1]	-251
2014	-2,804 ^[1]	740	958	1,138	912 ^[1]	587	-1,079	380 ^[1]	686	1,054 ^[1]	465	-4
2015	-2,815 ^[1]	831	757	1183 ^[1]	942	475	-952 ^[1]	192	558	1,148 ^[1]	421	-2
2016	-2,974 ^[1]	831	895	1,094 ^[1]	649	664 ^[1]	-973	253	666 ^[1]	882	432	-212 ^[1]
2017	-2,876	1,029 ^[1]	656	1,024	839	643 ^[1]	-1,103	317	388 ^[1]	1,013	574 ^[1]	-247
2018	-3,098	1,237 ^[1]	703	977	935	666 ^[1]	-1,164	470 ^[1]	312	1,003	481 ^[1]	-200
2019	-2,953	805 ^[1]	675	1,062	673 ^[1]	622	-1,058	436 ^[1]	417	989	595 ^[1]	-249
2020	-2,791 ^[1]	913	-1,016	-19,699 ^[1]	3,169	5,085	598 ^[1]	1,622	1,231	1,607 ^[1]	550	-510
2021	-2,631 ^[1]	1,155	1,179	1,050 ^[1]	946	1,189	-41 ^[1]	495	704 ^[1]	1,659	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-2. Revised month-to-month change, seasonally adjusted (additive outlier only), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	108 ^[1]	212	237	197 ^[1]	41	258 ^[1]	371	143	289 ^[1]	118	130	214 ^[1]
2017	76	186 ^[1]	150	320	474	216 ^[1]	139	104	30 ^[1]	3	91 ^[1]	63
2018	84	431 ^[1]	315	408	694	232 ^[1]	-21	107 ^[1]	-117	-31	-79 ^[1]	115
2019	213	82 ^[1]	377	639	283 ^[1]	378	50	14 ^[1]	-103	-163	-3 ^[1]	89
2020	154 ^[1]	336	-1,119	-19,090 ^[1]	2,322	4,500	1,369 ^[1]	1,436	564	301 ^[1]	77	-177
2021	343 ^[1]	643	1,059	1,719 ^[1]	219	577	633 ^[1]	256	109 ^[1]	290	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-3. Revised month-to-month change, seasonally adjusted (all outlier types), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	108 ^[1]	212	237	197 ^[1]	41	258 ^[1]	371	143	289 ^[1]	118	130	214 ^[1]
2017	213	190 ^[1]	142	205	223	197 ^[1]	183	145	99 ^[1]	141	200 ^[1]	176
2018	133	402 ^[1]	225	179	333	183 ^[1]	66	219 ^[1]	57	145	102 ^[1]	248
2019	279	24 ^[1]	224	288	77 ^[1]	130	78	160 ^[1]	163	93	252 ^[1]	200
2020	339 ^[1]	376	-1,498	-20,493 ^[1]	2,642	4,505	1,388 ^[1]	1,665	919	647 ^[1]	333	-115
2021	520 ^[1]	710	704	263 ^[1]	447	557	689 ^[1]	517	424 ^[1]	677	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-4. Month-to-month change, seasonally adjusted (as previously published), in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	354	262 ^[1]	240	82	100	73 ^[1]	152	172 ^[1]	187	159	156 ^[1]	239
2013	191	278 ^[1]	139	191	222 ^[1]	181	112	242 ^[1]	187	225	264 ^[1]	69
2014	175 ^[1]	166	254	325	218 ^[1]	326	232	188 ^[1]	309	252 ^[1]	291	268
2015	191 ^[1]	271	71	284 ^[1]	331	174	302 ^[1]	125	155	306 ^[1]	237	273
2016	108 ^[1]	212	237	197 ^[1]	41	258 ^[1]	371	143	289 ^[1]	118	130	214 ^[1]
2017	197	183 ^[1]	139	220	141	211 ^[1]	228	190	42 ^[1]	249	196 ^[1]	179
2018	81	378 ^[1]	195	153	270	214 ^[1]	149	229 ^[1]	105	212	92 ^[1]	240
2019	237	-50 ^[1]	168	219	63 ^[1]	175	193	195 ^[1]	221	195	234 ^[1]	161
2020	315 ^[1]	289	-1,683	-20,679 ^[1]	2,833	4,846	1,726 ^[1]	1,583	716	680 ^[1]	264	-306
2021	233 ^[1]	536	785	269 ^[1]	614	962	1,091 ^[1]	483	379 ^[1]	648	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-5. Revised normal seasonal movement (additive outlier only) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	[2]	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,082 ^[1]	619	658	897 ^[1]	608	406 ^[1]	-1,344	110	377 ^[1]	764	302	-426 ^[1]
2017	-2,952	843 ^[1]	506	704	365	427 ^[1]	-1,242	213	358 ^[1]	1,010	483 ^[1]	-310
2018	-3,182	806 ^[1]	388	569	241	434 ^[1]	-1,143	363 ^[1]	429	1,034	560 ^[1]	-315
2019	-3,166	723 ^[1]	298	423	390 ^[1]	244	-1,108	422 ^[1]	520	1,152	598 ^[1]	-338
2020	-2,945 ^[1]	577	103	-609 ^[1]	847	585	-771 ^[1]	186	667	1,306 ^[1]	473	-333
2021	-2,974 ^[1]	512	120	-669 ^[1]	727	612	-674 ^[1]	239	595 ^[1]	1,369	[2]	[2]

Note:

[\[1\]](#) These values come from a 5-week survey interval.

[\[2\]](#) Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-6. Revised normal seasonal movement (all outlier types) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	[2]	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,082 ^[1]	619	658	897 ^[1]	608	406 ^[1]	-1,344	110	377 ^[1]	764	302	-426 ^[1]
2017	-3,089	839 ^[1]	514	819	616	446 ^[1]	-1,286	172	289 ^[1]	872	374 ^[1]	-423
2018	-3,231	835 ^[1]	478	798	602	483 ^[1]	-1,230	251 ^[1]	255	858	379 ^[1]	-448
2019	-3,232	781 ^[1]	451	774	596 ^[1]	492	-1,136	276 ^[1]	254	896	343 ^[1]	-449
2020	-3,130 ^[1]	537	482	794 ^[1]	527	580	-790 ^[1]	-43	312	960 ^[1]	217	-395
2021	-3,151 ^[1]	445	475	787 ^[1]	499	632	-730 ^[1]	-22	280 ^[1]	982	[2]	[2]

Note:

[\[1\]](#) These values come from a 5-week survey interval.

[\[2\]](#) Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-7. Normal seasonal movement (as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	-2,960	692 ^[1]	664	801	714	264 ^[1]	-1,361	207 ^[1]	441	688	233 ^[1]	-314
2013	-3,073	760 ^[1]	660	814	671 ^[1]	228	-1,286	195 ^[1]	421	697	261 ^[1]	-320
2014	-2,979 ^[1]	574	704	813	694 ^[1]	261	-1,311	192 ^[1]	377	802 ^[1]	174	-272
2015	-3,006 ^[1]	560	686	899 ^[1]	611	301	-1,254 ^[1]	67	403	842 ^[1]	184	-275
2016	-3,082 ^[1]	619	658	897 ^[1]	608	406 ^[1]	-1,344	110	377 ^[1]	764	302	-426 ^[1]
2017	-3,073	846 ^[1]	517	804	698	432 ^[1]	-1,331	127	346 ^[1]	764	378 ^[1]	-426
2018	-3,179	859 ^[1]	508	824	665	452 ^[1]	-1,313	241 ^[1]	207	791	389 ^[1]	-440
2019	-3,190	855 ^[1]	507	843	610 ^[1]	447	-1,251	241 ^[1]	196	794	361 ^[1]	-410
2020	-3,106 ^[1]	624	667	980 ^[1]	336	239	-1,128 ^[1]	39	515	927 ^[1]	286	-204
2021	-2,864 ^[1]	619	394	781 ^[1]	332	227	-1,132 ^[1]	12	325 ^[1]	1,011	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-8. Difference in normal seasonal movement (revised with additive outliers only versus revised with all outlier types) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2017	-137	-4 ^[1]	8	115	251	19 ^[1]	-44	-41	-69 ^[1]	-138	-109 ^[1]	-113
2018	-49	29 ^[1]	90	229	361	49 ^[1]	-87	-112 ^[1]	-174	-176	-181 ^[1]	-133
2019	-66	58 ^[1]	153	351	206 ^[1]	248	-28	-146 ^[1]	-266	-256	-255 ^[1]	-111
2020	-185 ^[1]	-40	379	1,403 ^[1]	-320	-5	-19 ^[1]	-229	-355	-346 ^[1]	-256	-62
2021	-177 ^[1]	-67	355	1,456 ^[1]	-228	20	-56 ^[1]	-261	-315 ^[1]	-387	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B-9. Difference in normal seasonal movement (revised with additive outliers only versus as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2017	-121	3 ^[1]	11	100	333	5 ^[1]	-89	-86	-12 ^[1]	-246	-105 ^[1]	-116
2018	3	53 ^[1]	120	255	424	18 ^[1]	-170	-122 ^[1]	-222	-243	-171 ^[1]	-125
2019	-24	132 ^[1]	209	420	220 ^[1]	203	-143	-181 ^[1]	-324	-358	-237 ^[1]	-72
2020	-161 ^[1]	47	564	1,589 ^[1]	-511	-346	-357 ^[1]	-147	-152	-379 ^[1]	-187	129
2021	110 ^[1]	107	274	1,450 ^[1]	-395	-385	-458 ^[1]	-227	-270 ^[1]	-358	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

Table B10. Difference in normal seasonal movement (revised with all outlier types versus as previously published) in total nonfarm employment (in thousands)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2012	0	0 ^[1]	0	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0
2013	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0
2014	0 ^[1]	0	0	0	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0
2015	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]	0	0
2016	0 ^[1]	0	0	0 ^[1]	0	0 ^[1]	0	0	0 ^[1]	0	0	0 ^[1]
2017	16	7 ^[1]	3	-15	82	-14 ^[1]	-45	-45	57 ^[1]	-108	4 ^[1]	-3
2018	52	24 ^[1]	30	26	63	-31 ^[1]	-83	-10 ^[1]	-48	-67	10 ^[1]	8
2019	42	74 ^[1]	56	69	14 ^[1]	-45	-115	-35 ^[1]	-58	-102	18 ^[1]	39
2020	24 ^[1]	87	185	186 ^[1]	-191	-341	-338 ^[1]	82	203	-33 ^[1]	69	191
2021	287 ^[1]	174	-81	-6 ^[1]	-167	-405	-402 ^[1]	34	45 ^[1]	29	^[2]	^[2]

Note:

^[1] These values come from a 5-week survey interval.

^[2] Not applicable at time of annual review.

Source: U.S. Bureau of Labor Statistics.

SUGGESTED CITATION:

Nicole Hudson, Jeannine Mercurio, and Jurgen Kropf, "The challenges of seasonal adjustment for the Current Employment Statistics survey during the COVID-19 pandemic," *Monthly Labor Review*, U.S. Bureau of Labor Statistics, May 2022

Notes

¹ For an example of one such publication, see "The challenges of seasonal adjustment during the COVID-19 pandemic" *Commissioner's Corner* (U.S.

Bureau of Labor Statistics, December 21, 2020), <https://blogs.bls.gov/blog/2020/12/21/the-challenges-of-seasonal-adjustment-during-the-covid-19-pandemic/>.

² For more information on seasonal adjustment, see "Technical notes for the Current Employment Statistics survey: seasonal adjustment" Current Employment Statistics—CES (national) (U.S. Bureau of Labor Statistics, February 4, 2022), <https://www.bls.gov/web/empst/cestn.htm#section6e>.

³ All CES series are evaluated annually for sample size, coverage, and response rates. Reconstruction of time series may result from a reevaluation of the sample and universe coverage for CES industries. In this case, seasonal adjustment is rerun for the entire history of the reconstructed time series.

⁴ X-13 ARIMA-SEATS is publicly available from the U.S. Census Bureau at <https://www.census.gov/data/software/x13as.html>.

⁵ Brian C. Monsell, "Time series responses to the COVID-19 pandemic at BLS for monthly and weekly series," Statistical Survey Paper (U.S. Bureau of Labor Statistics, December 2021), <https://www.bls.gov/osmr/research-papers/2021/pdf/st210040.pdf>.

⁶ Rebecca Bevans, "An introduction to the Akaike information criterion," *Scribbr*, March 26, 2020, <https://www.scribbr.com/statistics/akaike-information-criterion/>.

⁷ See "Technical notes for the Current Employment Statistics survey: seasonal adjustment" Current Employment Statistics—CES (national) (U.S. Bureau of Labor Statistics, February 4, 2022), <https://www.bls.gov/web/empst/cestn.htm#section6e>.

⁸ See "Technical notes for the Current Employment Statistics survey: seasonal adjustment" Current Employment Statistics—CES (national) (U.S. Bureau of Labor Statistics, February 4, 2022), <https://www.bls.gov/web/empst/cestn.htm#section6e>.



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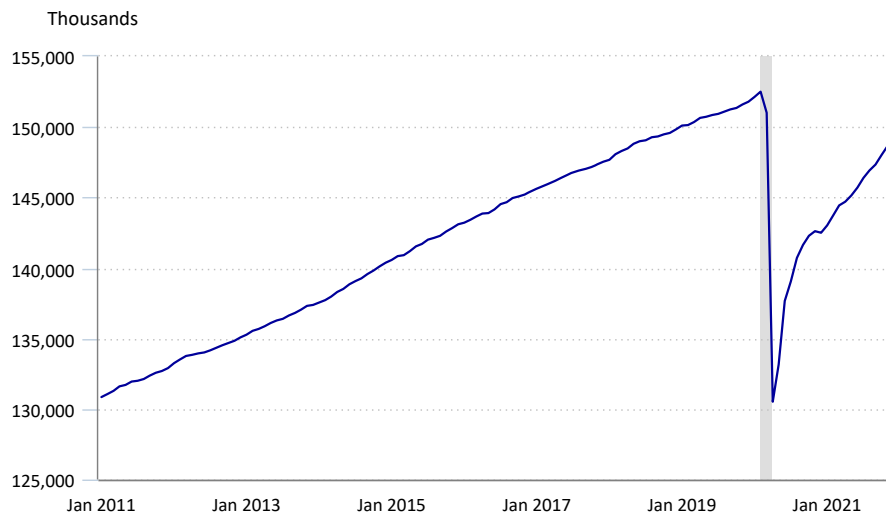
MAY 2022

Employment recovery continues in 2021, with some industries reaching or exceeding their prepandemic employment levels

Total nonfarm employment in the United States continued to recover in 2021, with some industries fully recovering and subsequently expanding amid the coronavirus disease 2019 pandemic. The leisure and hospitality industry and the professional and business services industry led the widespread employment gains over the year.

According to data from the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey, total nonfarm payroll employment in the United States continued to recover in 2021, moving further away from the widespread job losses caused by the coronavirus disease 2019 (COVID-19) pandemic in 2020. (See chart 1.) Employment rose by 6.7 million in 2021, the largest calendar-year gain in the history of the CES employment series (see chart 2) and the strongest relative gain (+4.7 percent) since 1978.

Chart 1. Total nonfarm employment, seasonally adjusted, January 2011–December 2021

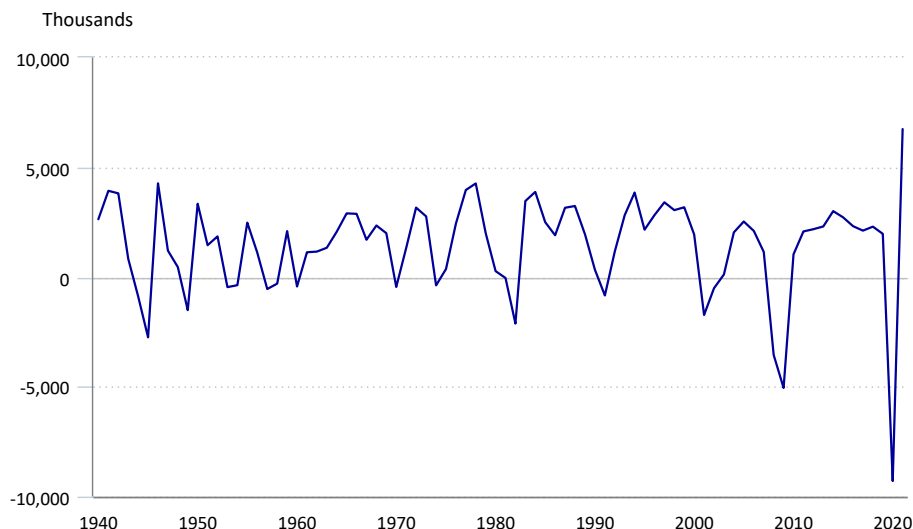


Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Chart 2. Over-the-year change in total nonfarm employment, seasonally adjusted, 1940–2021



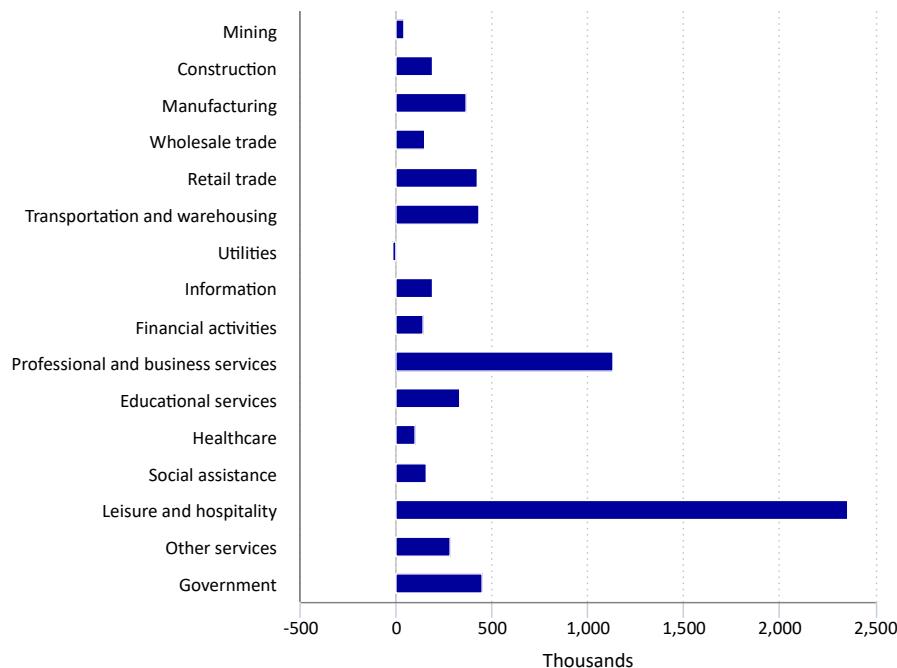
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Nearly all major industries experienced employment gains in 2021. (See chart 3.) Leisure and hospitality led these gains, adding 2.4 million jobs over the year, followed by professional and business services, which added 1.1 million jobs. Employment in transportation and warehousing continued to expand in 2021, after fully recovering in November 2020. Both financial activities and retail trade added jobs in 2021, essentially reaching their prepandemic (February 2020) employment levels.¹ (See chart 4.)

Chart 3. Over-the-year change in total nonfarm employment, by industry, seasonally adjusted, 2021

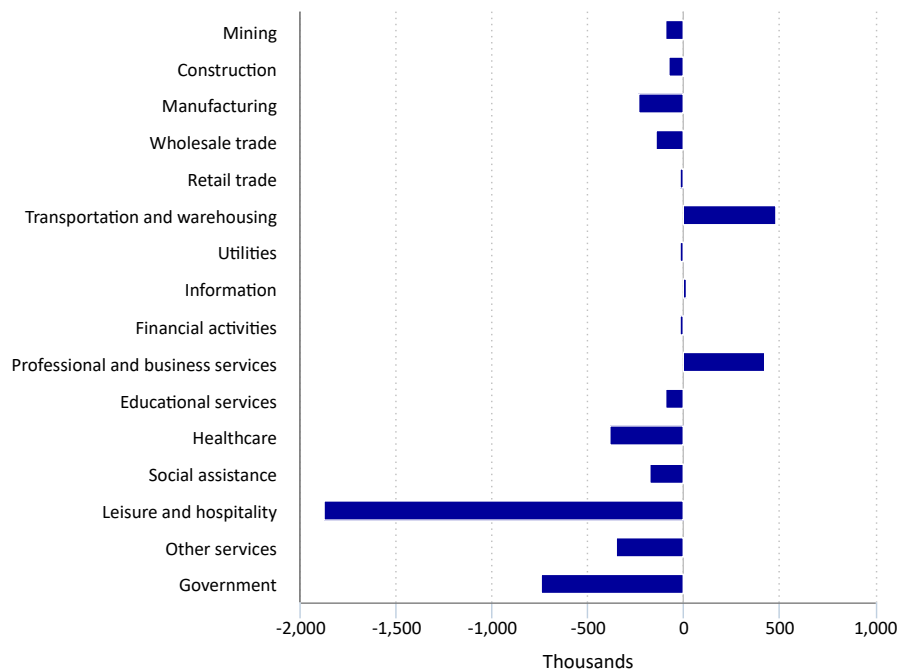


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Chart 4. Employment change in total nonfarm employment, by industry, seasonally adjusted, February 2020–December 2021



Hover over chart to view data.

Note: From February 2020 to December 2021, total nonfarm and total private employment declined by 3.3 million and 2.5 million, respectively.

Source: U.S. Bureau of Labor Statistics.



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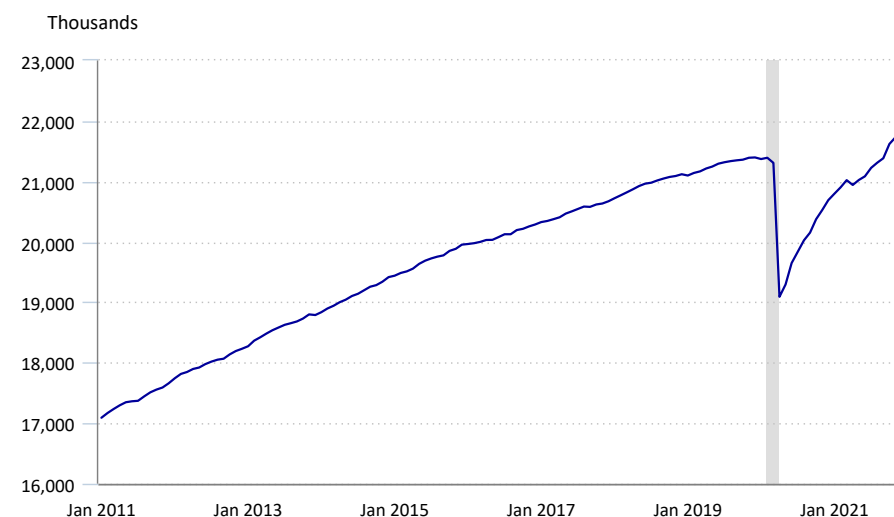
Employment recovery and expansion

After declining considerably in early 2020, employment in most industry sectors started to recover later that year and continued to increase in 2021. Three sectors—professional and business services, transportation and warehousing, and information—reached their prepandemic employment levels and then exceeded them in 2021.

Professional and business services

Employment in professional and business services grew by 1.1 million in 2021, exceeding its prepandemic level by 428,000 jobs. (See chart 5.) The expansion in this sector was concentrated in professional and technical services, in which employment had recovered in March 2021; over the year, this industry added 632,000 jobs. (See chart 6.) The 2021 job gains in professional and technical services were spread across component industries and driven by management and technical consulting services (+147,000) and computer systems design and related services (+146,000).

Chart 5. Employment in professional and business services, seasonally adjusted, January 2011–December 2021

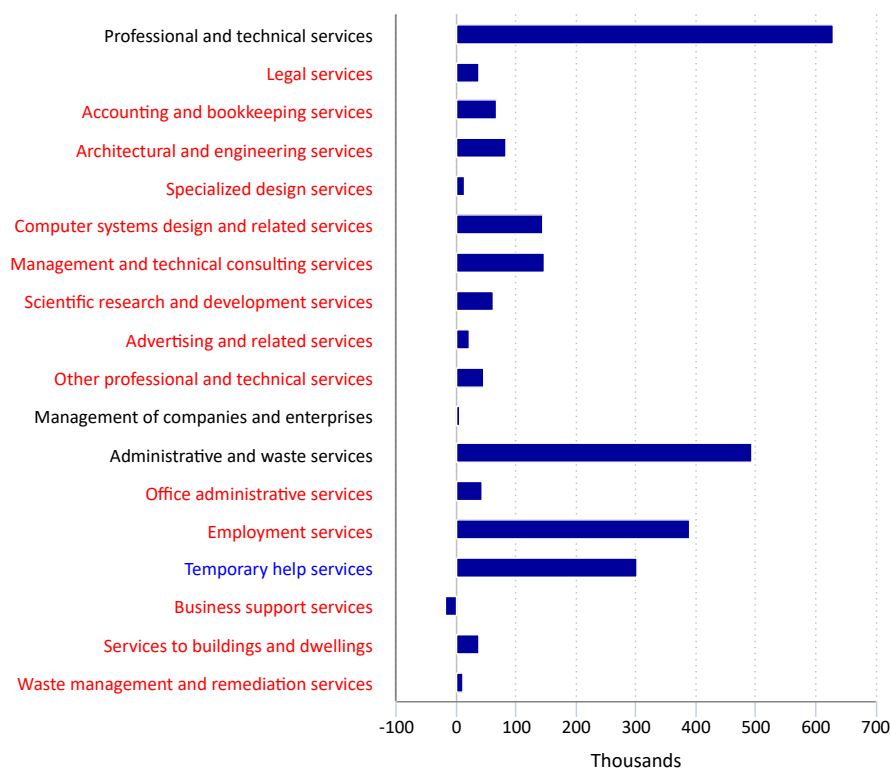


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Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Chart 6. Over-the-year employment change in professional and business services, by component industry, 2021



Hover over chart to view data.
Note: The waste management and remediation services industry includes additional component industries that are not shown separately. Levels of industry aggregation are indicated by color: black for level 1, red for level 2, and blue for level 3.
Source: U.S. Bureau of Labor Statistics.

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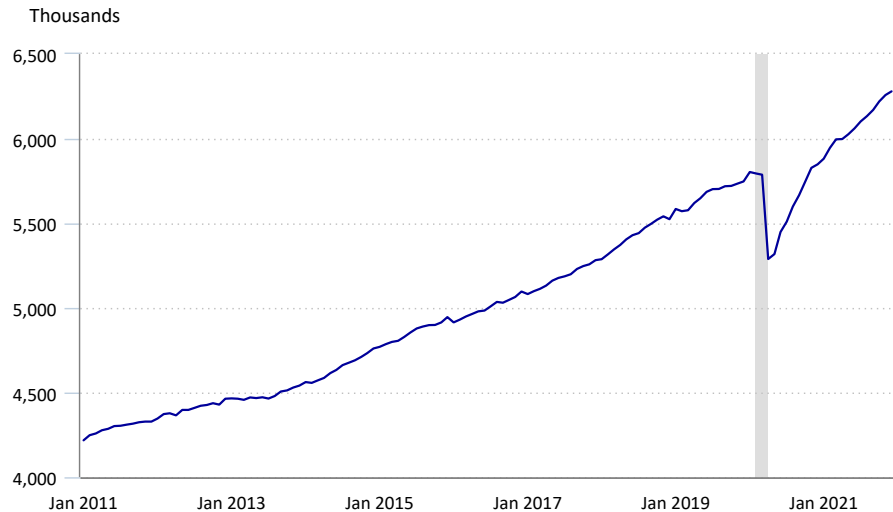


The administrative and waste services industry—another component industry of professional and business services—also added jobs over the year (+495,000), reaching its prepandemic employment level by December 2021. Within this industry, employment services added 392,000 jobs in 2021, with temporary help services accounting for 303,000 of these jobs (these gains coincided with a 19.5-percent increase in the American Staffing Association’s Staffing Index).² Employment in office administrative services and in services to buildings and dwellings rose at a more moderate pace in 2021, increasing by 43,000 and 38,000, respectively.

Transportation and warehousing

Transportation and warehousing added 432,000 jobs in 2021. (See chart 7.) Employment in this sector grew strongly before and after the 2020 recession and, after recovering in 2020, continued to expand in 2021, ending the year 485,000 above its prepandemic level. These gains were consistent with a 2021 increase (+7.7 percent) in the Cass Freight Index, which measures shipment volumes in the United States.³

Chart 7. Employment in transportation and warehousing, seasonally adjusted, January 2011–December 2021



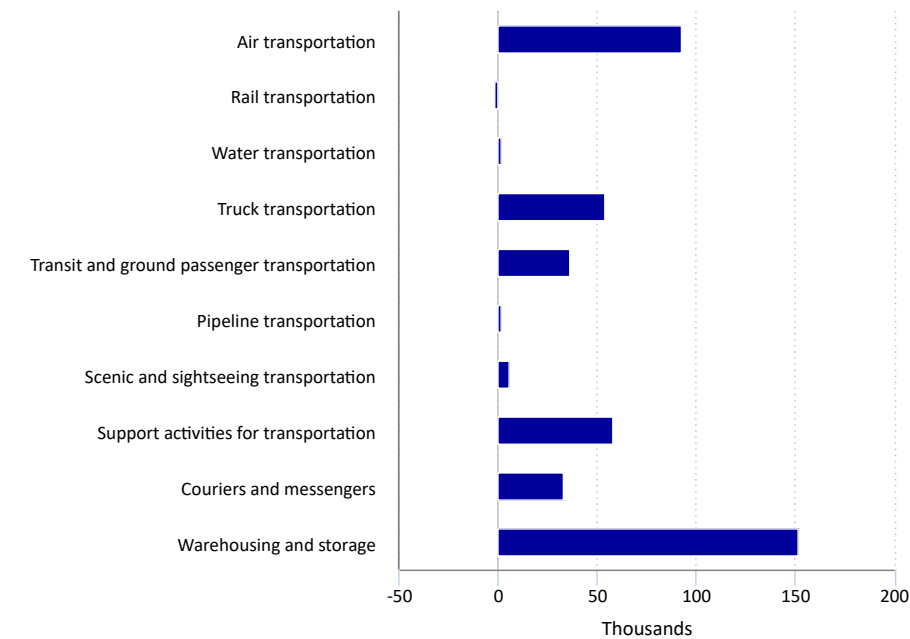
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Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Within transportation and warehousing, job gains in 2021 continued in warehousing and storage (+152,000) and couriers and messengers (+33,000). (See chart 8.) These gains coincided with a consumer behavioral shift toward online shopping and delivery services.⁴ Over the year, job growth also continued in air transportation (+93,000), truck transportation (+54,000), support activities for transportation (+58,000), and transit and ground passenger transportation (+36,000). Employment in air transportation experienced the largest percent increase (+21.9 percent) in the history of the series (since 1990), and employment in truck transportation experienced its largest percent increase (+3.7 percent) since 2011.

Chart 8. Over-the-year employment change in transportation and warehousing, by component industry, seasonally adjusted, 2021



Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.



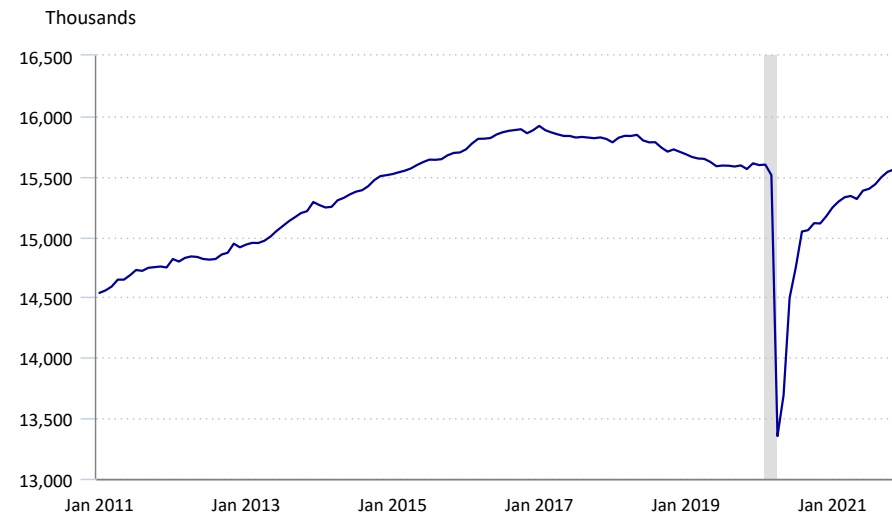
Information

Employment in the information sector increased by 194,000 in 2021, slightly exceeding (by 10,000 jobs) its February 2020 level. This increase was driven by gains in motion picture and sound recording industries (+129,000), with growth also occurring in other information services (+30,000) and publishing industries, except internet (+28,000).

Retail trade

Retail trade added 425,000 jobs in 2021, reaching its prepandemic employment level. (See chart 9.) This growth was concentrated in general merchandise stores (+115,000), clothing and clothing accessories stores (+102,000), health and personal care stores (+90,000), miscellaneous store retailers (+65,000), and nonstore retailers (+36,000). (See chart 10.) In contrast, after adding jobs for most of 2020 and reaching an employment peak in December of that year, building materials and garden supply stores shed 50,000 jobs in 2021. Employment in electronics and appliance stores changed little (+2,000) over the year.

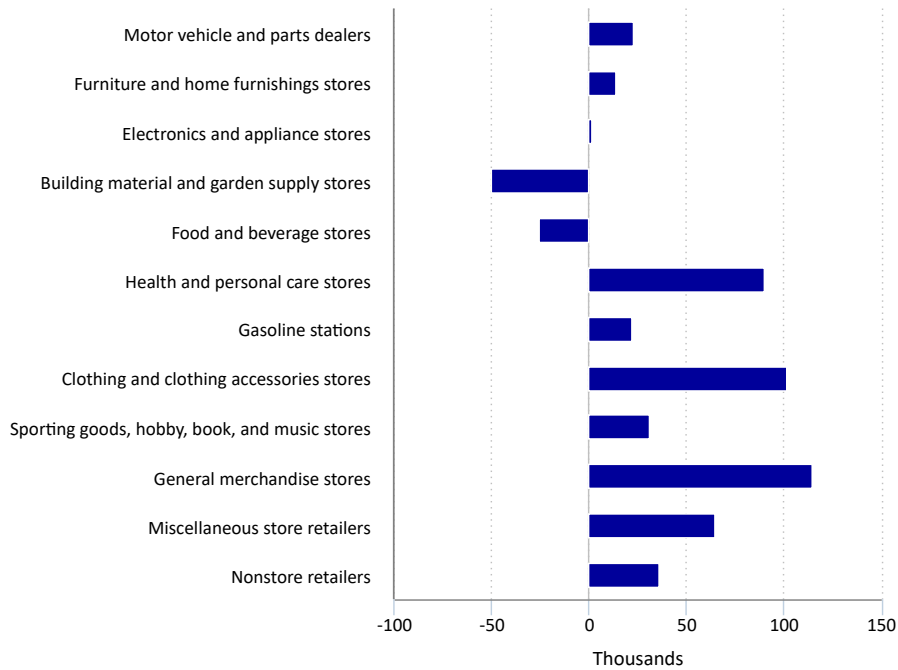
Chart 9. Employment in retail trade, seasonally adjusted, January 2011–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.



Chart 10. Over-the-year employment change in retail trade, by component industry, seasonally adjusted, 2021



Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

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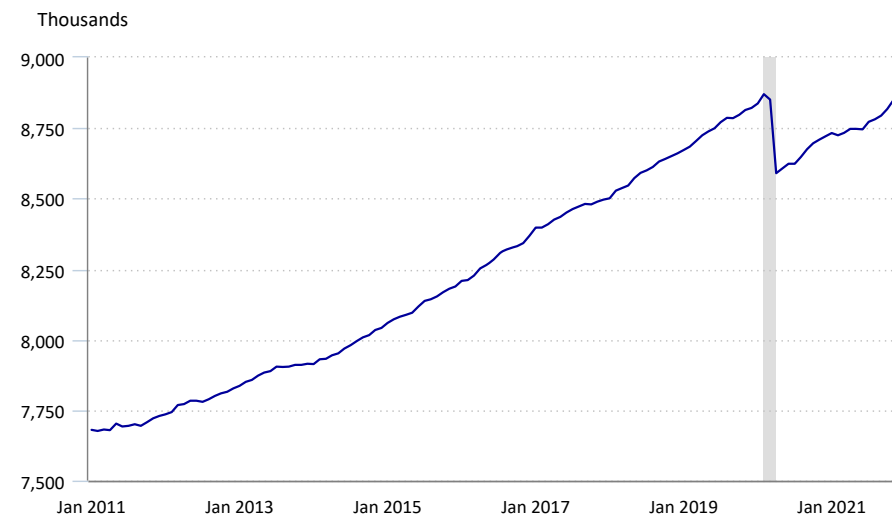


Consistent with the strength in retail trade employment, retail sales continued to expand in 2021.⁵ Likewise, the Consumer Confidence Index increased by 20.9 points over the year.⁶ However, despite these increases in retail sales and consumer confidence, high lumber prices, low inventories, and rising inflation in 2021 signaled potential employment weakness in some retail industries, especially building materials and garden supply stores.⁷

Financial activities

Employment in financial activities grew by 142,000 in 2021, ending the year just 7,000 below its prepandemic level. (See chart 11.) This growth was concentrated in real estate (+71,000); securities, commodity contracts, investments, and funds and trusts (+41,000); and rental and leasing (+36,000). (See chart 12.) On the other hand, employment in credit intermediation changed little over the year (+8,000). Within this component industry, nondepository credit intermediation and activities related to credit intermediation added jobs (+22,000 and +12,000, respectively), whereas commercial banking shed 33,000 jobs. The employment decline in commercial banking likely reflects the impact of growth in digital banking and the continuing effects of pandemic-related closures of bank branches.⁸

Chart 11. Employment in financial activities, seasonally adjusted, January 2011–December 2021

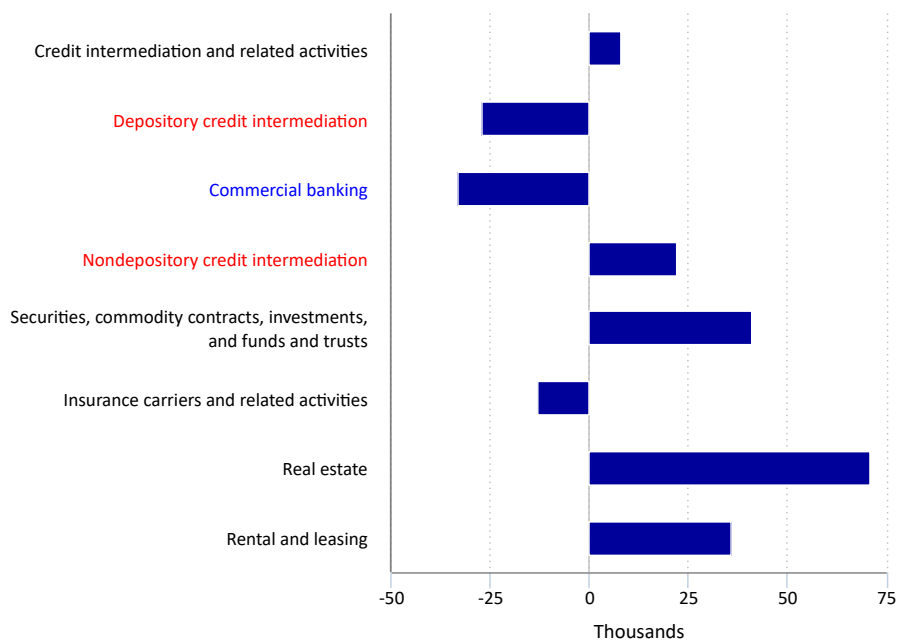


Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Chart 12. Over-the-year employment change in financial activities, by component industry, seasonally adjusted, 2021



Hover over chart to view data.
Note: Levels of industry aggregation are indicated by color: black for level 1, red for level 2, and blue for level 3.
Source: U.S. Bureau of Labor Statistics.

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Job growth in real estate and in nondepository credit intermediation was consistent with economic indicators for these industries in 2021. Although the federal funds rate remained low over the year, the 30-year fixed mortgage rate edged up by 0.44 percentage point; however, at 3.12 percent in December, the mortgage rate was still low by historical standards.⁹

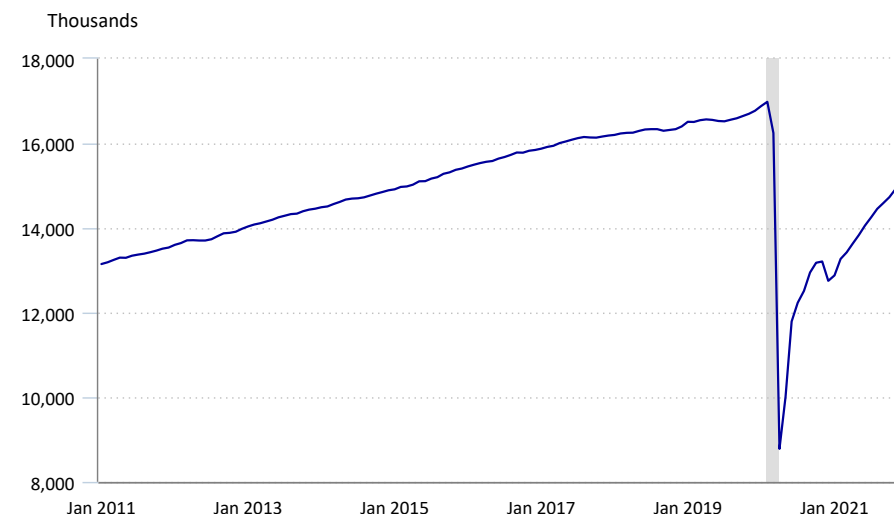
Continued employment recovery

Although supply shortages and business restrictions eased in 2021, some industries continued to suffer the effects of the COVID-19 pandemic. This section discusses the sectors that experienced job growth over the year but did not reach their prepandemic employment levels.

Leisure and hospitality

Leisure and hospitality added 2.4 million jobs in 2021 and, by December, had recovered 6.3 million of the 8.2 million jobs lost in March and April 2020. (See chart 13.) Within this sector, food services and drinking places experienced the largest employment gain in 2021, adding 1.6 million jobs over the year, an increase that helped the industry recover 4.9 million of the 6.0 million jobs lost in March and April 2020. (See chart 14.)

Chart 13. Employment in leisure and hospitality, seasonally adjusted, January 2011–December 2021

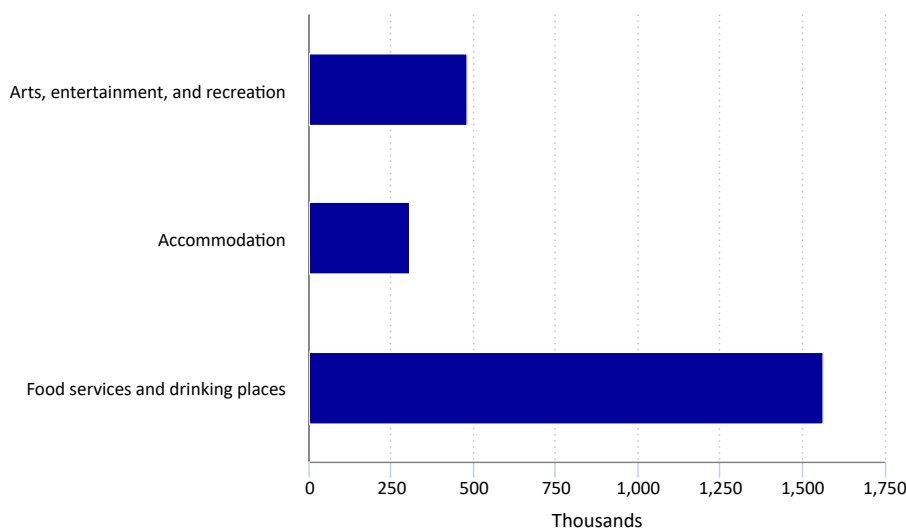


Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Chart 14. Over-the-year employment change in leisure and hospitality, by component industry, 2021



Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

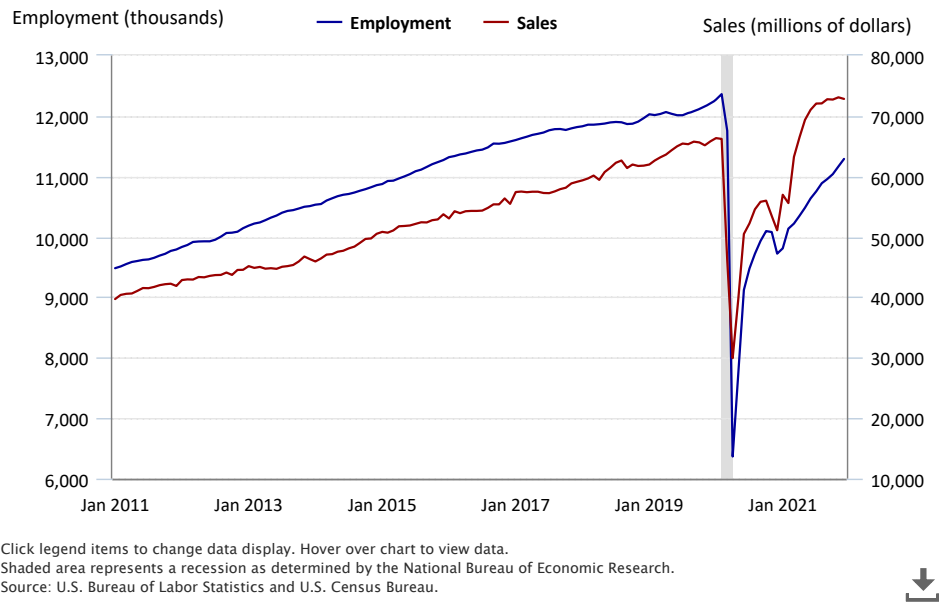
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Employment in food services and drinking places trended up at a steady pace in 2021, adding an average of 130,000 jobs per month. Monthly sales in this industry rose during the first half of the year, but they tapered off and changed little during the second half.¹⁰ (See chart 15.) Sales data suggest that the industry's weak employment recovery was likely due to surges in cases of the COVID-19 Delta and Omicron variants in 2021, which threatened the reopening and capacity expansion of dine-in restaurants. In addition, over the year, inflation rose to 7.1 percent (as measured by the Consumer Price Index for All Urban Consumers),¹¹ and this increase may also have affected consumption and contributed to some employment weakness. Another factor likely adding to employment weakness was a 9.8-percent over-the-year increase in the average Employer Costs for Employee Compensation for private sector workers in accommodation and food services.¹² According to data from the

CES survey, average hourly earnings of all employees in food services and drinking places rose sharply in 2021 (+14.9 percent), and this increase resulted in higher labor costs for employers.

Chart 15. Employment and monthly sales in food services and drinking places, seasonally adjusted, January 2011–December 2021



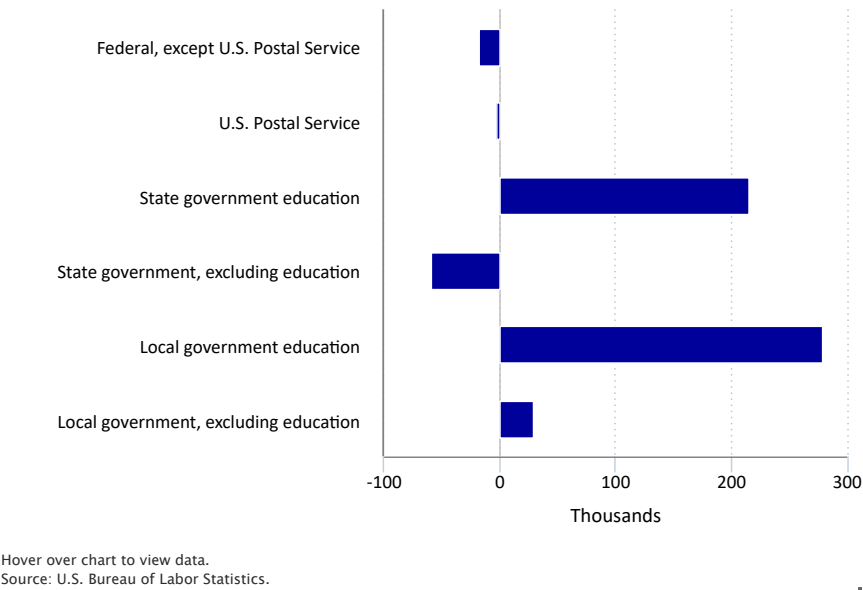
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Employment in arts, entertainment, and recreation increased by 483,000 in 2021. Similarly, employment in accommodation increased by 307,000 over the year.

Government

The government sector added 450,000 jobs in 2021 and, by December, had recovered 725,000 of the 1.5 million jobs lost between February and June 2020. Within this sector, state government education added 216,000 jobs in 2021, with employment in the industry ending the year just 10,000 below its February 2020 peak. (See chart 16.) Local government education added 279,000 jobs in 2021, but that industry’s employment level in December was still 387,000 below its prepandemic peak. In 2021, employment declined in federal government (except U.S. Postal Service) (–17,000) and in state government (excluding education) (–59,000).

Chart 16. Over-the-year employment change in government, by component industry, seasonally adjusted, 2021

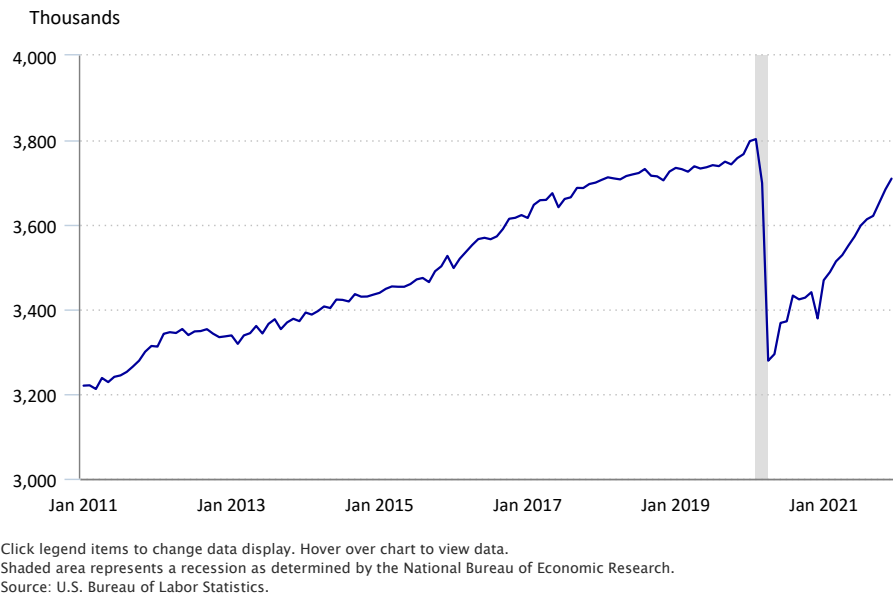


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Private education

Like public education, private educational services experienced employment gains in 2021, adding 331,000 jobs over the year, but the industry’s employment level in December was still 93,000 below its February 2020 peak. (See chart 17.)

Chart 17. Employment in private educational services, seasonally adjusted, January 2011–December 2021

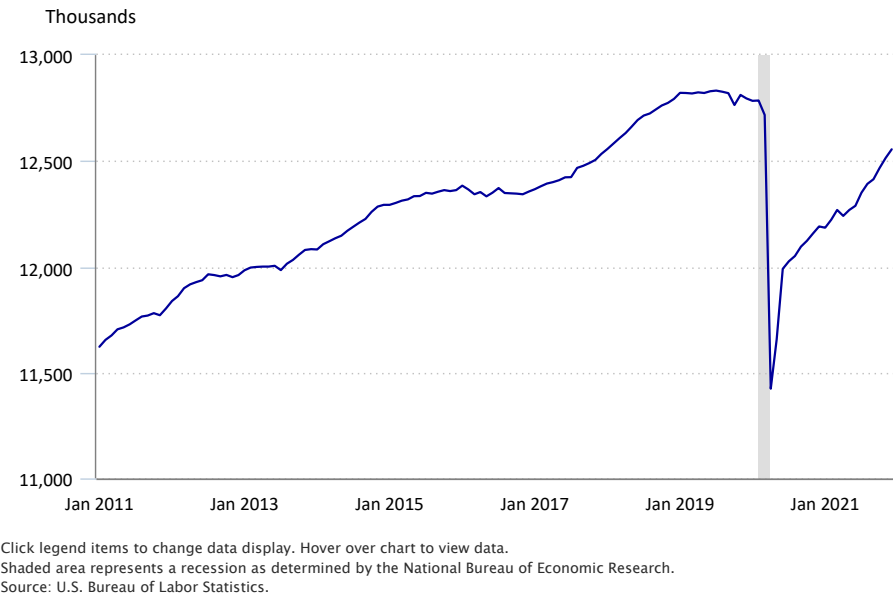


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Manufacturing

Employment in manufacturing grew by 365,000 in 2021, advancing in both durable goods manufacturing (+236,000) and nondurable goods manufacturing (+129,000). With these gains, the sector was able to recover 1.1 million of the 1.4 million jobs lost in early 2020. (See chart 18.)

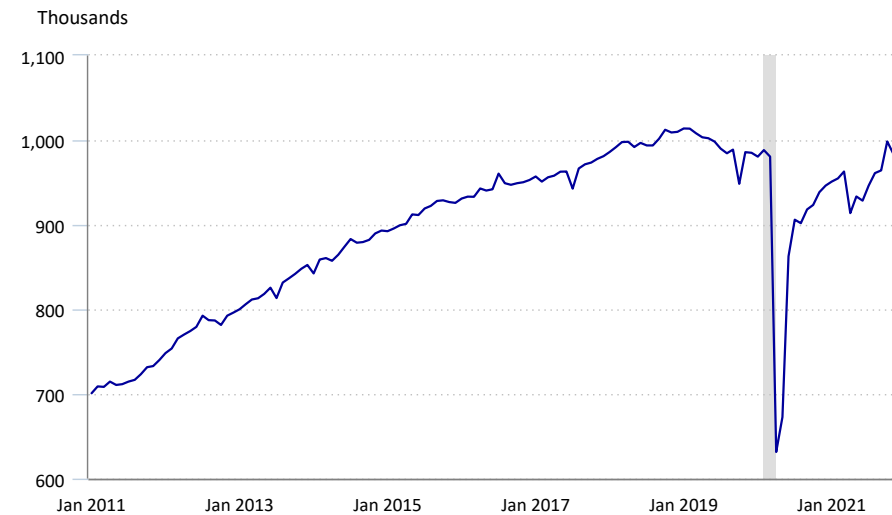
Chart 18. Employment in manufacturing, seasonally adjusted, January 2011–December 2022



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Driving the employment gains in durable goods manufacturing were transportation equipment (+50,000), fabricated metal products (+46,000), miscellaneous durable goods manufacturing (+32,000), and machinery (+28,000). Within transportation equipment, most of the employment gains were driven by motor vehicles and parts, which added 38,000 jobs over the year. (See chart 19.) Despite this increase, the global semiconductor shortage that began in early 2021 hampered automobile production and was further exacerbated by the automobile sector’s competition with the personal electronics sector, whose demand soared since March 2020 and into 2021.¹³

Chart 19. Employment in motor vehicles and parts, seasonally adjusted, January 2011–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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The employment strength in durable goods manufacturing was consistent with 2021 increases in new orders for manufactured durable goods.¹⁴ In December 2021, the Purchasing Managers' Index (PMI) of the Institute for Supply Management reached 58.7 percent, after expanding for 19 consecutive months since April 2020.¹⁵ A PMI greater than 50 percent indicates expansion in manufacturing activity. Employment gains in nondurable goods manufacturing were concentrated in miscellaneous nondurable goods manufacturing (+40,000), chemicals (+26,000), and plastics and rubber products (+20,000).

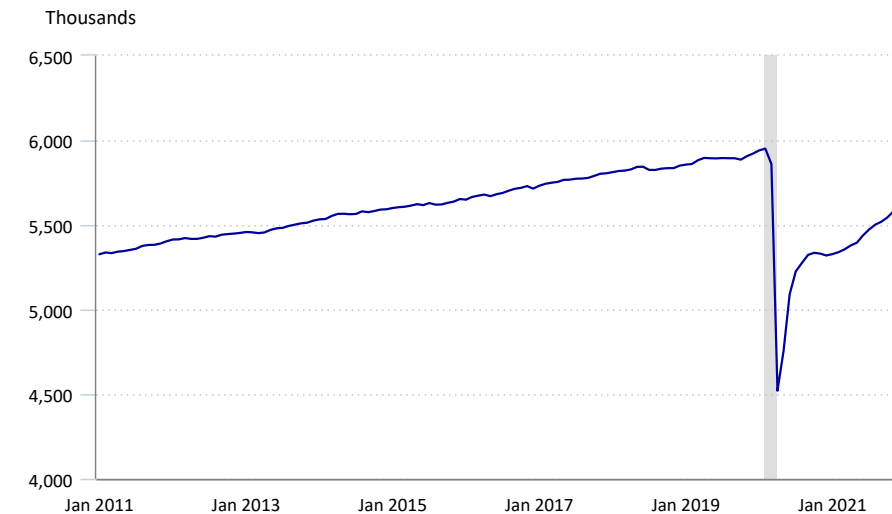
Wholesale trade

Employment in wholesale trade grew by 152,000 in 2021, contributing to the recovery of 262,000 of the 405,000 jobs lost in March and April 2020.

Other services

Other services added 285,000 jobs in 2021 and, by December, had recovered 1.1 million of the 1.4 million jobs lost in 2020. (See chart 20.) Personal and laundry services drove most of the sector's job growth in 2021, adding 144,000 jobs. Repair and maintenance also showed employment strength, adding 93,000 jobs over the year, followed by membership associations and organizations, which added 48,000 jobs.

Chart 20. Employment in other services, seasonally adjusted, January 2011–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

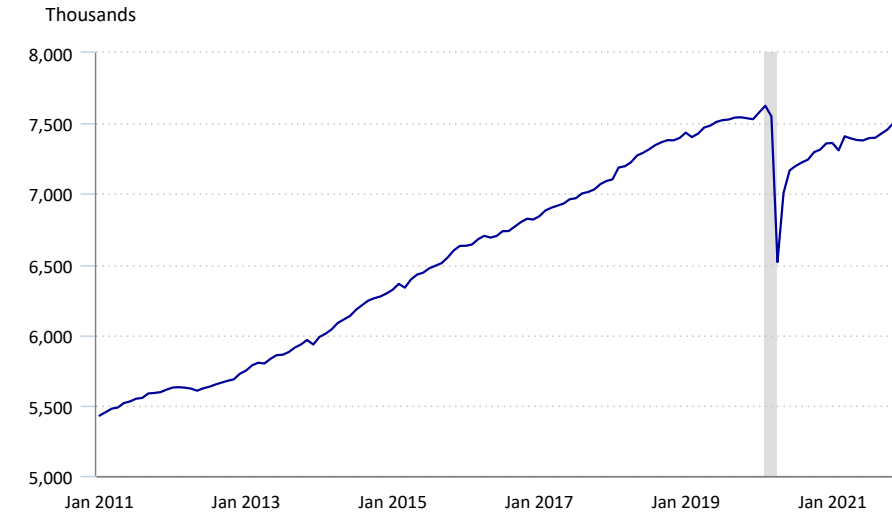


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Construction

In 2021, construction added 189,000 jobs and, by December, had recovered 1.0 million of the 1.1 million jobs lost in March and April 2020. (See chart 21.) The sector's job gains in 2021 were driven by employment advances in residential specialty trade contractors (+64,000), nonresidential specialty trade contractors (+49,000), and residential building (+44,000). (See chart 22.) Over the year, employment changed little in civil engineering construction (+21,000) and nonresidential building (+11,000).

Chart 21. Employment in construction, seasonally adjusted, January 2021–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.



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Chart 22. Over-the-year employment change in construction, by component industry, 2021



Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.



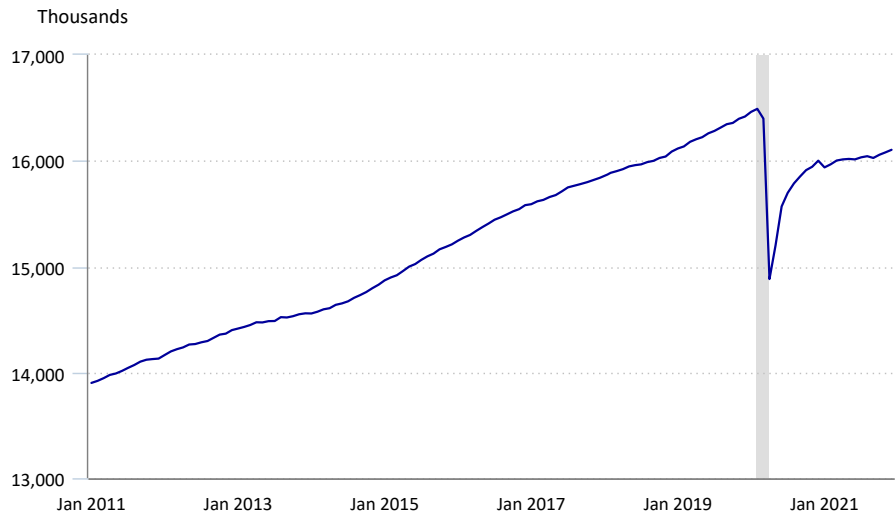
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In 2021, job growth in construction coincided with a relatively stable and low federal funds rate (0.08 percent in December) and a low 30-year fixed mortgage rate (3.12 percent in December).¹⁶ However, this growth was likely dampened by sharp and volatile increases in the prices of building materials over the year—increases measured by the Producer Price Index and reflected in the costs for new nonresidential building.¹⁷

Healthcare and social assistance

Healthcare added 103,000 jobs in 2021 and, by December, had recovered 1.2 million of the 1.6 million jobs lost in early 2020. (See chart 23.) The industry’s employment gains in 2021 were concentrated in ambulatory healthcare services, which added 274,000 jobs, an increase driven by offices of physicians (+89,000), offices of other health practitioners (+85,000), and offices of dentists (+48,000). (See chart 24.) In contrast, nursing and residential care facilities continued to lose jobs over the year (–139,000), with the industry shedding 410,000 jobs (nearly all since February 2020) after reaching an employment peak in July 2019. Hospital employment showed little net change (–32,000) in 2021.

Chart 23. Employment in healthcare, seasonally adjusted, January 2011–December 2021

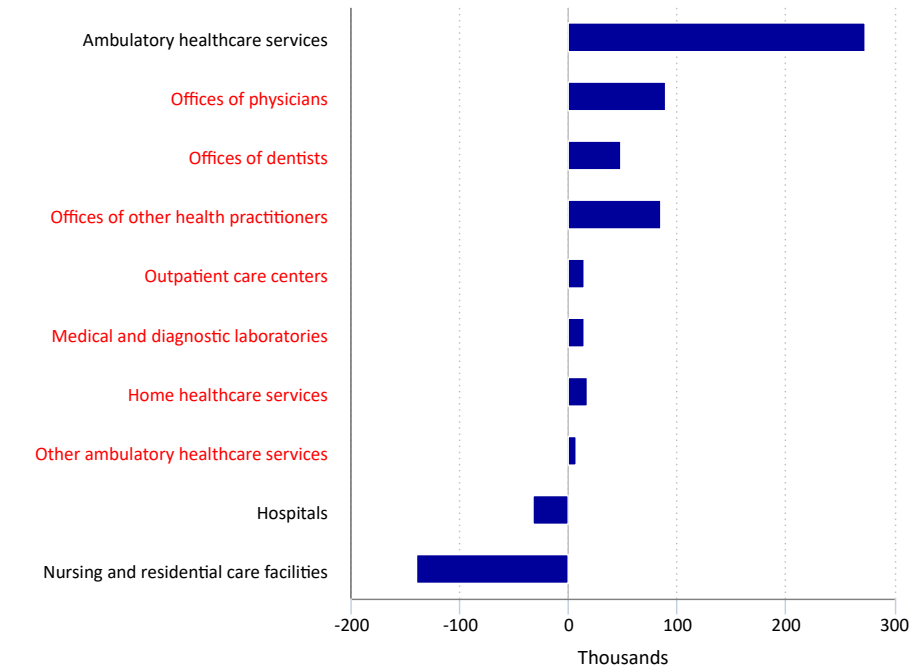


Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

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Chart 24. Over-the-year employment change in healthcare, by component industry, seasonally adjusted, 2021



Hover over chart to view data.
Note: Levels of industry aggregation are indicated by color: black for level 1 and red for level 2.
Source: U.S. Bureau of Labor Statistics.

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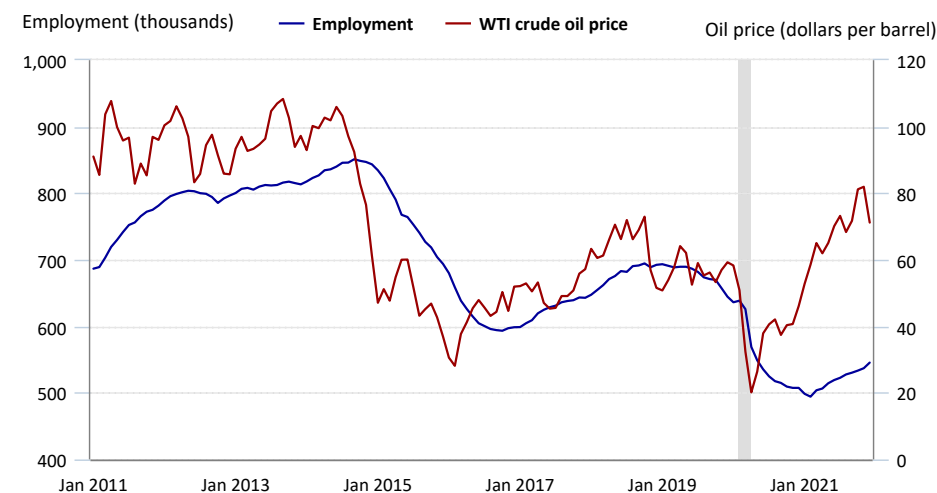


Employment in social assistance grew by 156,000 over the year, with individual and family services (+87,000) and child daycare services (+58,000) leading the gains.

Mining

Employment in mining rose by 38,000 in 2021, ending the year 93,000 below its February 2020 level. (See chart 25.) These gains were concentrated in support activities for mining, which added 37,000 jobs in 2021, mostly in support activities for oil and gas operations (+28,000). For most of the year, employment changed little in coal mining and in oil and gas extraction. Because mining employment is highly sensitive to fluctuations in oil prices, its gains in 2021 were likely driven by over-the-year increases in the price of crude oil (measured by the price of West Texas Intermediate crude oil).¹⁸

Chart 25. Employment in mining, seasonally adjusted, and West Texas Intermediate (WTI) crude oil price, not seasonally adjusted, January 2011–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics and U.S. Energy Information Administration.

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Utilities

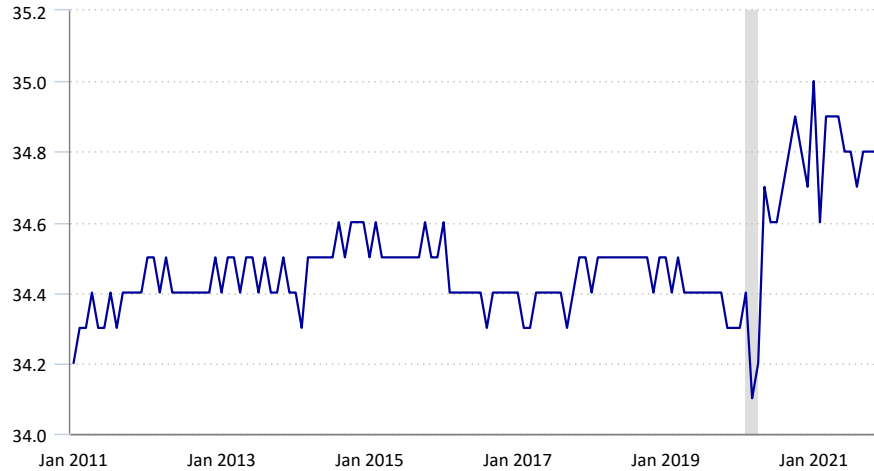
Employment in utilities changed little (−3,000) in 2021 and, by December, had fallen by 9,000 since February 2020.

Hours and earnings

In 2021, average weekly hours of all private sector employees rose by 0.1 hour, to 34.8 hours (see chart 26), whereas average weekly hours of production and nonsupervisory employees declined by 0.1 hour, to 34.1 hours. Combining employment gains with changes in the length of the workweek, the indexes of aggregate weekly hours for all employees and for production and nonsupervisory employees in the private sector increased by 5.8 and 5.5 points, respectively. In addition, in December 2021, the index for all employees was 0.9 point below its prepandemic level, while the index for production and nonsupervisory employees was 1.9 points lower.

Chart 26. Average weekly hours, all private sector employees, seasonally adjusted, January 2011–December 2021

Average weekly hours



Click legend items to change data display. Hover over chart to view data.
Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

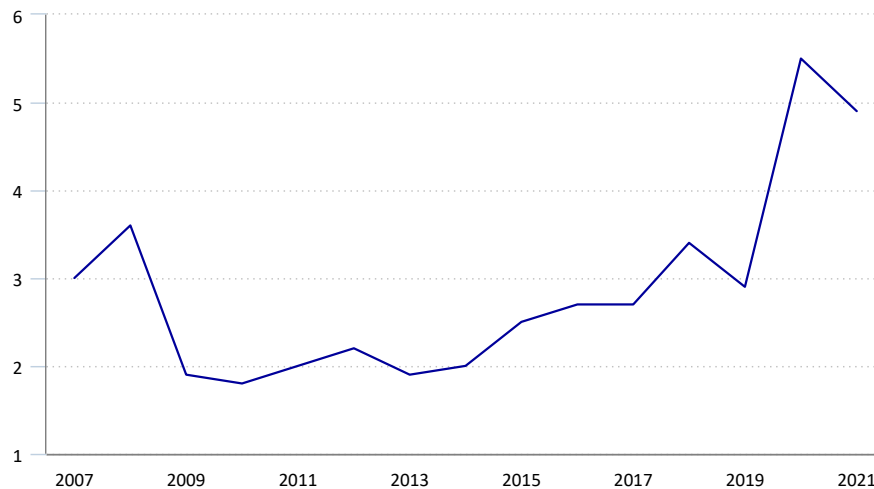
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In 2021, average hourly earnings of all private sector employees increased by 4.9 percent, the second-largest calendar-year gain since the series began in March 2006 (the largest gain, both relative and absolute, occurred in 2020). (See chart 27.) Average hourly earnings of production and nonsupervisory employees, which represent about 82 percent of all employees, increased by 6.2 percent over the year—the largest calendar-year gain since 1981, when hourly earnings rose by 7.2 percent. (See chart 28.) Relative earnings gains of all employees ranged from 1.5 percent in the information sector to a very strong 13.3 percent in leisure and hospitality. (See chart 29.)

Chart 27. Over-the-year percent change in average hourly earnings, all employees, seasonally adjusted, 2007–21

Percent

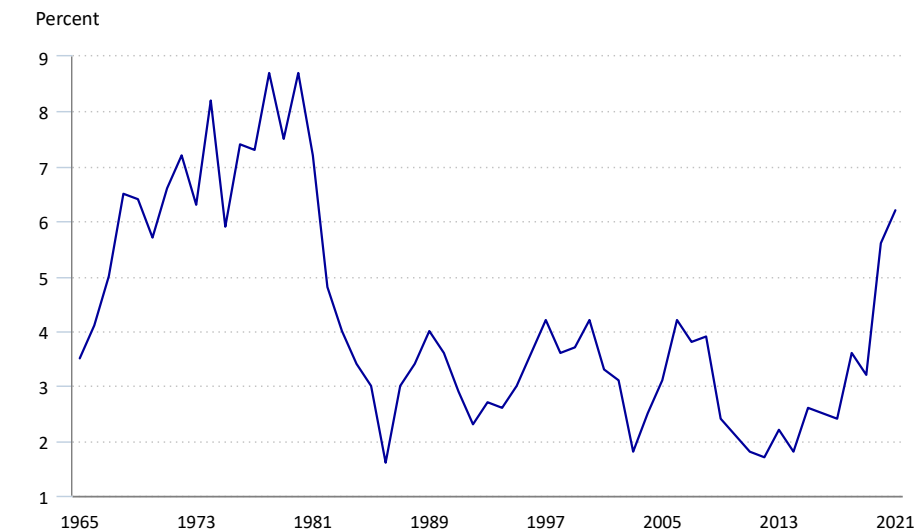


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Source: U.S. Bureau of Labor Statistics.

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Chart 28. Over-the-year percent change in average hourly earnings, production and nonsupervisory employees, seasonally adjusted, 1965–2021

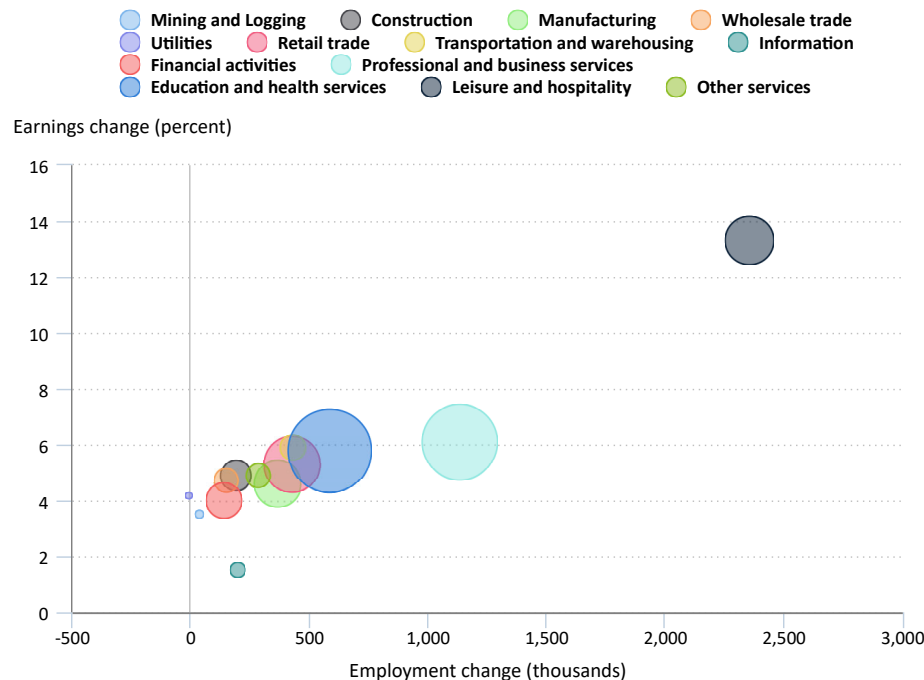


Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

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Chart 29. Employment change and average hourly earnings change, by industry, seasonally adjusted, December 2020–December 2021



Click legend items to change data display. Hover over chart to view data.
Note: Bubble size represents December 2020 employment level. In 2021, average hourly earnings of all private sector employees increased by 4.9 percent.
Source: U.S. Bureau of Labor Statistics.

[View Chart Data](#)



The substantial increase in average hourly earnings in 2020 resulted largely from changes in employment, because industries with lower hourly earnings lost more jobs. In 2021, the gains in average hourly earnings of all employees were due mainly to inflationary effects. Adjusted for inflation by using the Consumer Price Index for all Urban Consumers, real average hourly earnings for all employees declined by 2.1 percent over the year. Adjusted for price increases by the Consumer Price Index for Urban Wage Earners and Clerical Workers, real hourly earnings for production and nonsupervisory employees declined by 1.5 percent.

Conclusion

In 2021, total nonfarm employment rose by 6.7 million, continuing its recovery from the widespread declines in March and April 2020. Most

major industries added jobs over the year, with leisure and hospitality recording the largest employment gain. Employment in professional and business services reached and exceeded its prepandemic level, and employment in transportation and warehousing continued to expand. Average hourly earnings increased over the year, and average weekly hours edged up.

SUGGESTED CITATION:

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Notes

¹ Hereafter, the term "prepandemic" refers to industry employment levels for February 2020.

² "December staffing employment remains at record levels" (Alexandria, VA: American Staffing Association, December 21, 2021), <https://americanstaffing.net/posts/2021/12/21/december-staffing-employment-remains-at-record-levels/>.

³ "Cass Freight Index: shipments" (FRED, Federal Reserve Bank of St. Louis, March 2022), <https://fred.stlouisfed.org/series/FRGSHPU649NCIS>.

⁴ For data on retail e-commerce sales, see *Quarterly retail e-commerce sales: 4th quarter 2021*, CB22-23 (U.S. Census Bureau, February 18, 2022), https://www.census.gov/retail/mrts/www/data/pdf/ec_current.pdf.

⁵ "Advance retail sales: retail trade" (FRED, Federal Reserve Bank of St. Louis, March 2022), <https://fred.stlouisfed.org/series/RXFXS>.

⁶ "Consumer confidence improved again in December," press release (The Conference Board, December 22, 2021), <https://www.prnewswire.com/news-releases/consumer-confidence-improved-again-in-december-301449863.html>.

⁷ Ryan Dezember, "Sky-high lumber prices are back," *The Wall Street Journal*, December 19, 2021, <https://www.wsj.com/articles/sky-high-lumber-prices-are-back-11639842879>.

⁸ Imani Moise, Anirban Sen, and Anna Irrera, "Analysis: digital banks gain U.S. customers during pandemic, thanks to early deposits," *Reuters*, January 13, 2021, <https://www.reuters.com/business/finance/digital-banks-gain-us-customers-during-pandemic-thanks-early-deposits-2021-01-13/>; and Kimberly M. Kreiss, "Bank branches and COVID-19: where are banks closing branches during the pandemic?" *FEDS Notes* (Board of Governors of the Federal Reserve System, December 17, 2021), <https://doi.org/10.17016/2380-7172.3027>.

⁹ Data on the 30-year fixed-rate mortgage average in the United States are from Freddie Mac's Primary Mortgage Market Survey (<https://www.freddiemac.com/pmms>). Data capture rates including the 12th of the month.

¹⁰ "Advance retail sales: food services and drinking places" (FRED, Federal Reserve Bank of St. Louis, March 2022), <https://fred.stlouisfed.org/series/RSFSDP>.

¹¹ "All items in U.S. city average, all urban consumers, seasonally adjusted," series CUSR0000SA0 (U.S. Bureau of Labor Statistics), <https://www.bls.gov/cpi/>.

¹² "Total compensation cost per hour worked for private industry workers in accommodation and food services industries," series CMU201720000000D (U.S. Bureau of Labor Statistics), <https://www.bls.gov/ncs/ect/>.

¹³ Mark Ludiwowski and William Sjoberg, "Semiconductors shortage and the U.S. auto industry," *Reuters*, June 22, 2021, <https://www.reuters.com/legal/legalindustry/semiconductor-shortage-us-auto-industry-2021-06-22/>; and "U.S. consumer technology revenue sales end 2021 up 9%, following double digit growth in 2020" (Port Washington, NY: The NPD Group, January 6, 2022), <https://www.npd.com/news/press-releases/2022/us-consumer-technology-revenue-sales-end-2021-up-9-following-double-digit-growth-in-2020/>.

¹⁴ "Advance monthly manufacturers' shipments, inventories and orders" (U.S. Census Bureau, March 24, 2022), <https://www.census.gov/econ/currentdata/dbsearch?program=M3ADV&startYear=2011&endYear=2021&categories=MDM&dataType=NO&geoLevel=US&adjusted=1&submit=GET+DATA&releaseScheduleId=>.

¹⁵ "December 2021 ISM® Report On Business®: manufacturing" (Tempe, AZ: Institute for Supply Management, January 1, 2022), <https://www.ismworld.org/supply-management-news-and-reports/news-publications/inside-supply-management-magazine/2021--January-february-issue/manufacturing/>.

¹⁶ For data on the effective federal funds rate, see "Federal funds effective rate" (FRED, Federal Reserve Bank of St. Louis, March 2022), <https://fred.stlouisfed.org/series/DFE>. Data on the 30-year fixed-rate mortgage average in the United States are from Freddie Mac's Primary Mortgage Market Survey (<https://www.freddiemac.com/pmms>).

¹⁷ For data on building materials, see "PPI industry group data for building material and supplies dealers, not seasonally adjusted," series PCU44441—4441 (U.S. Bureau of Labor Statistics), <https://www.bls.gov/ppi/>. For data on new nonresidential building, see "PPI commodity data for construction (partial)—new nonresidential building construction, not seasonally adjusted," series WPU801 (U.S. Bureau of Labor Statistics), <https://www.bls.gov/ppi/>.

¹⁸ For data on the price of West Texas Intermediate crude oil, see "Crude oil prices: West Texas Intermediate (WTI)—Cushing, Oklahoma" (FRED, Federal Reserve Bank of St. Louis, March 2022), <https://fred.stlouisfed.org/series/DCOILWTICO#0>. Data capture rates including the 12th of the month.



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