ARTICLE

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U.S. labor market shows improvement in 2021, but the COVID-19 pandemic continues to weigh on the economy

The U.S. labor market continued to recover in 2021 from the recession caused by the coronavirus disease 2019 pandemic. Both the number of people who were unemployed and the unemployment rate decreased over the year. Although both measures are still above their prepandemic levels, the number of unemployed fell by 4.1 million over the year, to 6.8 million, and the unemployment rate decreased by 2.6 percentage points, averaging 4.2 percent in the fourth quarter of 2021. The employment–population ratio increased by 1.8 percentage points, to 59.2 percent, while the labor force participation rate showed more modest improvement, increasing by 0.3 percentage point during the year, to 61.8 percent in the fourth quarter. The numbers of unemployed on temporary layoff and those unemployed for 27 weeks or longer decreased over the year, but both measures are still above their prepandemic levels. The number of people working part time for economic reasons returned to its prepandemic level, and the number of self-employed increased by 7.8 percent in 2021.

The recession induced by the coronavirus disease 2019 (COVID-19) pandemic resulted in steep job losses, pushed the unemployment rate to a high of 13.0 percent in the second quarter of 2020, and caused many people to leave the labor force.[1] By the end of 2021, even after substantial strides were made in combating the COVID-19 pandemic, the labor market still had not fully recovered.[2] The jobless rate continued to trend downward, and by the fourth quarter of 2021, it was 4.2 percent, 2.6 percentage points below the rate from the prior year.[3] The number of unemployed, at 6.8 million in the fourth quarter of 2021, decreased by 4.1 million over the year.[4]

Total employment, as measured by the Current Population Survey (CPS), rose by 5.4 million over the year, to 155.2 million, which was well below its prepandemic level of 158.5 million in the fourth quarter of 2019.[5] The employment–population ratio increased by 1.8 percentage points, to 59.2 percent. The labor force participation rate (the percentage of the population ages 16 years and older who are either employed or actively seeking employment) rose by 0.3 percentage point over the year, to 61.8 percent.

This article highlights a broad range of economic indicators from the CPS to provide a picture of labor market performance in 2021, both overall and for various demographic groups. The article also summarizes the number of people who, because of the COVID-19 pandemic, teleworked, were unable to work or worked reduced hours, or were prevented from looking for work. These data were collected through supplemental questions that were added to the CPS in the early stages of the pandemic. This article also provides 2021 updates on the trends in usual weekly earnings, labor force status flows, and the number of self-employed people and summarizes recent changes in the employment situations of veterans, people with a disability, and the foreign born.

Both the number of unemployed and the unemployment rate declined for all major demographic groups, but both measures remained above their prepandemic levels

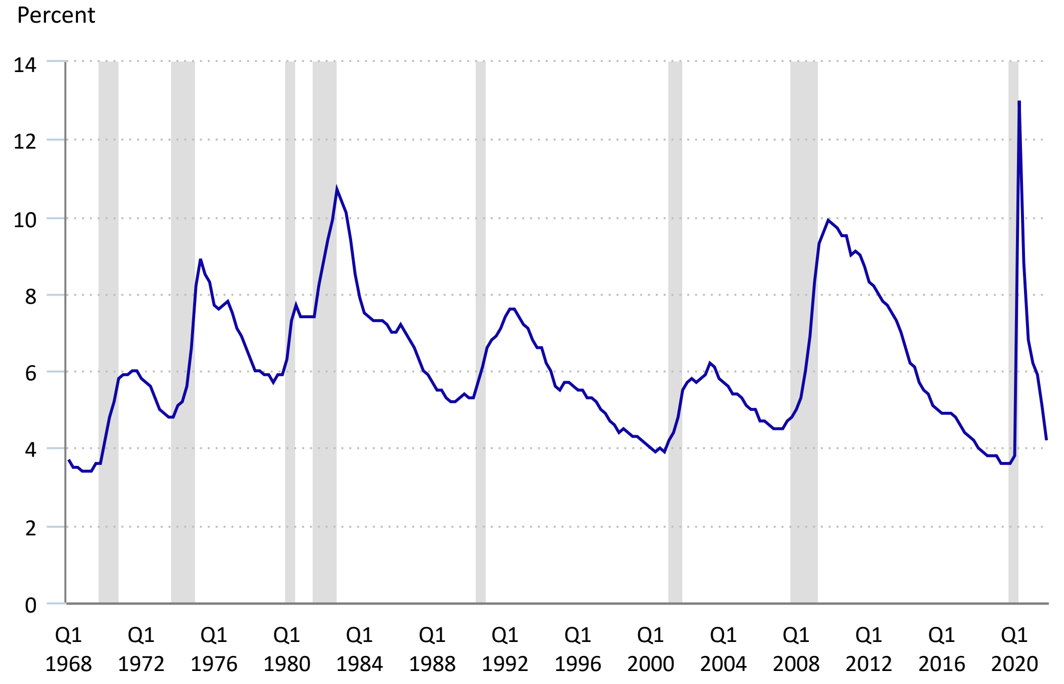
The number of unemployed people was 6.8 million in the fourth quarter of 2021, a decrease of 4.1 million from a year earlier. Despite the large decline in 2021, however, the total number of unemployed was still 908,000 more than it was in the fourth quarter of 2019, before the pandemic began. The unemployment rate also declined in 2021. (See table 1.) The unemployment rate averaged 4.2 percent in the fourth quarter of 2021, which is 2.6 percentage points below the rate in the fourth quarter of 2020. Even with this improvement, the unemployment rate remained above the rate of 3.6 percent in the fourth quarter of 2019. (See chart 1.)

Table 1. Employment status of the civilian noninstitutional population 16 years and older, by gender, race, and Hispanic or Latino ethnicity, quarterly averages, seasonally adjusted, 2020–21 (levels in thousands)

Characteristics	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Total, 16 years and older						
Civilian labor force	160,681	160,391	160,964	161,451	162,010	1,329
Participation rate	61.5	61.5	61.6	61.7	61.8	0.3
Employed	149,788	150,437	151,474	153,226	155,178	5,390
Employment–population ratio	57.4	57.7	58.0	58.6	59.2	1.8
Unemployed	10,894	9,954	9,491	8,225	6,832	-4,062
Unemployment rate	6.8	6.2	5.9	5.1	4.2	-2.6
Men, 16 years and older						
Civilian labor force	85,285	85,108	85,389	85,654	85,870	585
Participation rate	67.5	67.4	67.6	67.7	67.7	0.2
Employed	79,391	79,738	80,188	81,128	82,258	2,867
Employment–population ratio	62.9	63.2	63.5	64.1	64.9	2.0
Unemployed	5,894	5,370	5,200	4,526	3,611	-2,283
Unemployment rate	6.9	6.3	6.1	5.3	4.2	-2.7
Women, 16 years and older						
Civilian labor force	75,396	75,283	75,575	75,796	76,140	744
Participation rate	55.9	55.9	56.0	56.1	56.3	0.4
Employed	70,397	70,698	71,285	72,098	72,919	2,522
Employment–population ratio	52.2	52.5	52.9	53.4	53.9	1.7
Unemployed	4,999	4,585	4,290	3,699	3,221	-1,778
Unemployment rate	6.6	6.1	5.7	4.9	4.2	-2.4
White						
Civilian labor force	124,316	123,832	123,938	124,235	124,579	263
Participation rate	61.6	61.4	61.4	61.5	61.6	0.0
Employed	116,835	116,982	117,487	118,624	120,070	3,235
Employment–population ratio	57.9	58.0	58.2	58.7	59.4	1.5
Unemployed	7,481	6,850	6,451	5,611	4,509	-2,972
Unemployment rate	6.0	5.5	5.2	4.5	3.6	-2.4
Black or African American						
Civilian labor force	20,149	20,232	20,568	20,579	20,516	367
Participation rate	60.2	60.4	61.3	61.2	60.8	0.6
Employed	18,043	18,311	18,646	18,887	19,054	1,011
Employment–population ratio	53.9	54.6	55.5	56.1	56.5	2.6
Unemployed	2,106	1,920	1,921	1,692	1,462	-644
Unemployment rate	10.5	9.5	9.3	8.2	7.1	-3.4
Asian						
Civilian labor force	10,345	10,353	10,423	10,638	10,763	418
Participation rate	62.5	62.7	63.2	64.3	65.1	2.6
Employed	9,638	9,747	9,836	10,147	10,333	695
Employment–population ratio	58.2	59.0	59.6	61.4	62.5	4.3
Unemployed	707	607	587	491	430	-277
Unemployment rate	6.8	5.9	5.6	4.6	4.0	-2.8
Hispanic or Latino ethnicity						
Civilian labor force	29,155	29,087	29,207	29,511	29,842	687
Participation rate	65.4	65.2	65.2	65.6	66.0	0.6
Employed	26,541	26,704	27,061	27,672	28,274	1,733
Employment–population ratio	59.6	59.9	60.4	61.5	62.5	2.9
Unemployed	2,613	2,383	2,146	1,839	1,568	-1,045
Unemployment rate	9.0	8.2	7.3	6.2	5.3	-3.7

Note: Estimates for the race groups (White, Black or African American, and Asian) do not sum to totals because data are not presented for all races. People whose ethnicity is identified as Hispanic or Latino may be of any race. Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Chart 1. Unemployment rate for people 16 years and older, quarterly averages, seasonally adjusted, 1968–2021



Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

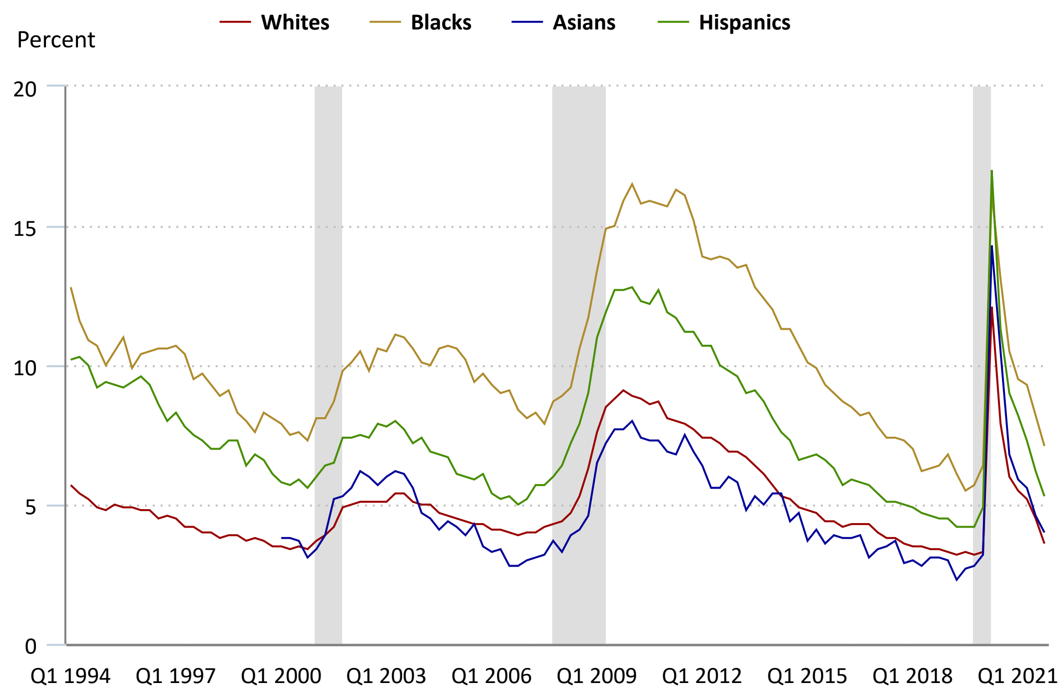
View Chart Data

Unemployment declined among both men and women in 2021. The jobless rate for men fell by 2.7 percentage points over the year, to 4.2 percent in the fourth quarter, and by 2.4 percentage points for women, to 4.2 percent. Although the unemployment rates for men and women declined in 2021, they remained above their prepandemic levels, when the rates for both men and women were 3.6 percent in the fourth quarter of 2019. (See table 1.)

Unemployment rates declined over the year for all demographic groups

The unemployment rates for all race and ethnicity groups declined in 2021, with the rate for Hispanics showing the largest over-the-year decrease. The jobless rate for Hispanics fell by 3.7 percentage points, to 5.3 percent, and the rate for Blacks fell by 3.4 percentage points, to 7.1 percent. The jobless rate for Asians declined by 2.8 percentage points, to 4.0 percent, and the rate for Whites fell by 2.4 percentage points, to 3.6 percent. Even with these improvements, the unemployment rates for Blacks and Hispanics remained considerably higher than the rates for Asians and Whites. Despite substantial improvements in 2021, particularly in the second half of the year, they were not enough to make up for the steep increases that occurred in the second quarter of 2020, when the rates for Whites, Asians, and Hispanics reached historic highs. (See chart 2.)

Chart 2. Unemployment rates, by race and Hispanic or Latino ethnicity, quarterly averages, seasonally adjusted, 1994–2021



Click legend items to change data display. Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Data for Asians are not available before 2000 and are not seasonally adjusted before 2010. People of Hispanic or Latino ethnicity may be of any race. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Jobless rates for younger workers declined more than the rates for older workers

The unemployment rate for 16- to 24-year-olds decreased by 3.6 percentage points over the year, to 8.4 percent in the fourth quarter of 2021. Within this age group, the jobless rate for teenagers (ages 16 to 19) fell by 3.3 percentage points over the year, to 11.2 percent in the fourth quarter of 2021. The rate for teenagers was well below its high of 28.4 percent in the second quarter of 2020 and lower than it had been before the pandemic (12.3 percent in the fourth quarter of 2019). The jobless rate for people ages 20 to 24 declined by 3.8 percentage points in 2021, to 7.2 percent, down from its high of 22.6 percent in the second quarter of 2020 but slightly above its prepandemic rate. Although unemployment rates rose sharply at the onset of the pandemic for all age groups, the increase was greatest among younger workers. A reverse pattern occurred in 2021, when younger workers experienced larger decreases in their jobless rates than did older workers. (See table 2.)

After hitting double digits (11.3 percent) in the second quarter of 2020, the unemployment rate for people in the prime working ages of 25 to 54 averaged 3.8 percent in the fourth quarter of 2021. This represents a decline of 2.4 percentage points over the year. The unemployment rates for both men and women of prime working age declined over the year, although these measures are still above the rates seen in the fourth quarter of 2019.

Table 2. Employment status of the civilian noninstitutional population 16 years and older, by age and gender, quarterly averages, seasonally adjusted, 2020–21 (levels in thousands)

Characteristics	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Total, 16 to 24 years						
Civilian labor force	20,704	20,615	20,672	20,605	20,847	143
Participation rate	55.3	55.2	55.5	55.3	56.0	0.7
Employed	18,218	18,336	18,578	18,675	19,103	885
Employment–population ratio	48.6	49.1	49.8	50.1	51.3	2.7
Unemployed	2,486	2,278	2,093	1,930	1,743	-743
Unemployment rate	12.0	11.1	10.1	9.4	8.4	-3.6
Total, 16 to 19 years						
Civilian labor force	5,942	5,948	5,991	5,948	5,966	24
Participation rate	35.9	36.1	36.4	36.2	36.3	0.4
Employed	5,080	5,131	5,342	5,286	5,300	220
Employment–population ratio	30.7	31.2	32.5	32.1	32.2	1.5
Unemployed	862	817	649	662	667	-195
Unemployment rate	14.5	13.7	10.8	11.1	11.2	-3.3
Total, 20 to 24 years						
Civilian labor force	14,761	14,667	14,681	14,657	14,881	120
Participation rate	70.5	70.3	70.5	70.5	71.7	1.2
Employed	13,137	13,205	13,236	13,389	13,804	667
Employment–population ratio	62.8	63.3	63.5	64.4	66.5	3.7
Unemployed	1,624	1,462	1,445	1,268	1,077	-547
Unemployment rate	11.0	10.0	9.8	8.7	7.2	-3.8
Total, 25 to 54 years						
Civilian labor force	102,211	102,366	102,751	103,110	103,217	1,006
Participation rate	81.0	81.2	81.5	81.8	81.8	0.8
Employed	95,924	96,597	97,230	98,326	99,310	3,386
Employment–population ratio	76.1	76.6	77.1	78.0	78.7	2.6
Unemployed	6,286	5,769	5,522	4,784	3,907	-2,379
Unemployment rate	6.2	5.6	5.4	4.6	3.8	-2.4
Men, 25 to 54 years						
Civilian labor force	54,506	54,544	54,781	54,988	54,933	427
Participation rate	87.5	87.6	88.0	88.3	88.1	0.6
Employed	51,090	51,482	51,745	52,353	52,868	1,778
Employment–population ratio	82.0	82.7	83.1	84.0	84.8	2.8
Unemployed	3,416	3,062	3,036	2,634	2,065	-1,351
Unemployment rate	6.3	5.6	5.5	4.8	3.8	-2.5
Women, 25 to 54 years						
Civilian labor force	47,704	47,822	47,970	48,122	48,285	581
Participation rate	74.7	75.0	75.2	75.4	75.7	1.0
Employed	44,834	45,115	45,485	45,973	46,442	1,608
Employment–population ratio	70.2	70.7	71.3	72.1	72.8	2.6
Unemployed	2,870	2,707	2,485	2,149	1,842	-1,028
Unemployment rate	6.0	5.7	5.2	4.5	3.8	-2.2
Total, 55 years and older						
Civilian labor force	37,737	37,323	37,544	37,816	37,914	177
Participation rate	38.7	38.3	38.4	38.5	38.4	-0.3
Employed	35,545	35,438	35,713	36,333	36,674	1,129
Employment–population ratio	36.5	36.3	36.5	37.0	37.2	0.7
Unemployed	2,192	1,885	1,831	1,483	1,240	-952
Unemployment rate	5.8	5.1	4.9	3.9	3.3	-2.5
Men, 55 years and older						
Civilian labor force	20,165	19,977	20,072	20,218	20,221	56
Participation rate	44.6	44.2	44.2	44.4	44.2	-0.4
Employed	19,027	18,939	19,093	19,415	19,605	578
Employment–population ratio	42.1	41.9	42.1	42.6	42.8	0.7
Unemployed	1,138	1,038	979	804	617	-521

Note: Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Characteristics	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Unemployment rate	5.6	5.2	4.9	4.0	3.0	-2.6
Women, 55 years and older						
Civilian labor force	17,560	17,365	17,486	17,580	17,678	118
Participation rate	33.6	33.2	33.3	33.4	33.4	-0.2
Employed	16,518	16,499	16,620	16,918	17,069	551
Employment–population ratio	31.6	31.5	31.7	32.1	32.3	0.7
Unemployed	1,042	866	866	662	609	-433
Unemployment rate	5.9	5.0	5.0	3.8	3.4	-2.5

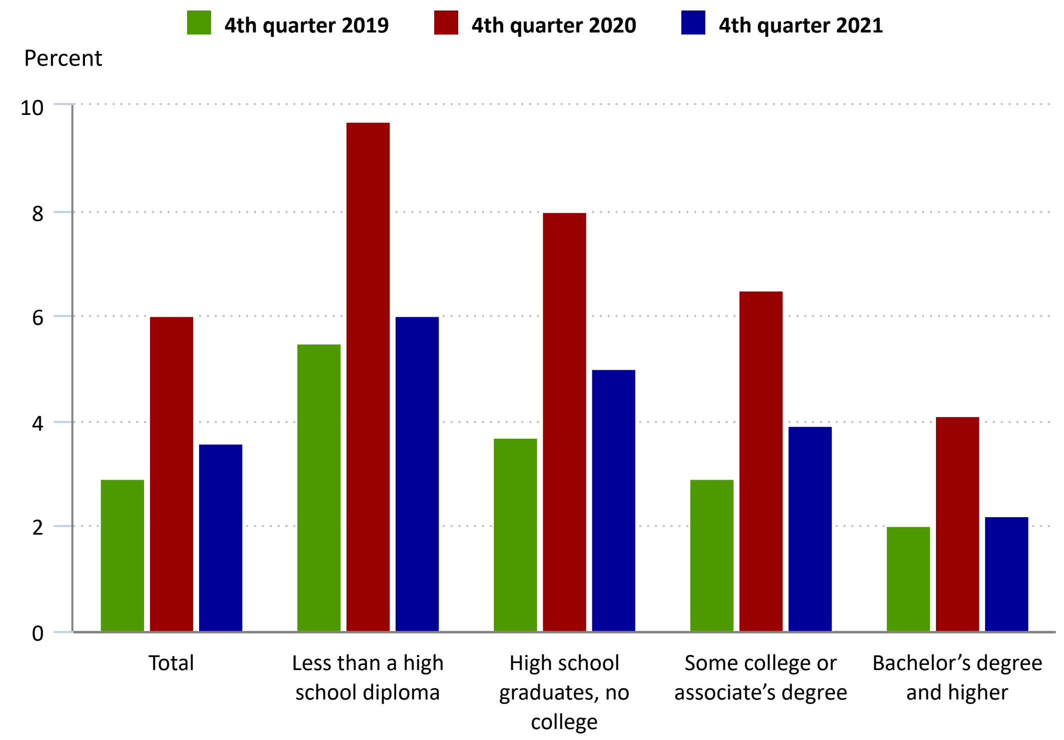
Note: Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Among workers ages 55 years and older, the unemployment rate was 3.3 percent in the fourth quarter of 2021, down by 2.5 percentage points over the year. The jobless rates for men and women in this age group had similar over-the-year declines: 2.6 percentage points for men and 2.5 percentage points for women. The rates for both groups remained above the levels seen in the fourth quarter of 2019.

Jobless rates declined for people of all education levels

Among workers ages 25 years and older, jobless rates across all education levels declined in 2021, although they remained higher than they were in the fourth quarter of 2019, before the pandemic. The unemployment rate for people with less than a high school diploma declined by 3.7 percentage points in 2021, to 6.0 percent in the fourth quarter, the steepest drop among the educational attainment categories. Still, the jobless rate for this group remained 0.5 percentage point higher than its rate in the fourth quarter of 2019, when it was 5.5 percent. The rate for high school graduates with no college fell by 3.0 percentage points over the year, to 5.0 percent by the end of 2021. The jobless rate for people with some college or an associate's degree, at 3.9 percent, decreased by 2.6 percentage points over the year. The jobless rate for people with a bachelor's degree and higher, at 2.2 percent in the fourth quarter of 2021, was 1.9 percentage points lower than it was a year earlier and 0.2 percentage point higher than it was in the fourth quarter of 2019. The rates for both those with less than a high school diploma and those with a bachelor's degree and higher have nearly returned to their prepandemic levels. As in the past, jobless rates in 2021 were much lower for people with higher levels of education than for those with less education. (See chart 3 and table 3.)

Chart 3. Unemployment rates for people 25 years and older, by educational attainment, seasonally adjusted, fourth quarter 2019–21



Click legend items to change data display. Hover over chart to view data.
Note: The category "High school graduates, no college" includes people with a high school diploma or equivalent. The category "Bachelor's degree and higher" includes people with bachelor's, master's, professional, and doctoral degrees.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Table 3. Employment status of the civilian noninstitutional population 25 years and older, by educational attainment, quarterly averages, seasonally adjusted, 2020–21 (levels in thousands)

Characteristics	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Less than a high school diploma						
Civilian labor force	9,208	9,026	8,970	9,188	8,843	-365
Participation rate	45.6	45.1	43.6	46.0	45.5	-0.1
Employed	8,316	8,205	8,114	8,426	8,309	-7
Employment–population ratio	41.2	41.0	39.5	42.1	42.7	1.5
Unemployed	893	822	857	763	534	-359
Unemployment rate	9.7	9.1	9.6	8.3	6.0	-3.7
High school graduates, no college[1]						
Civilian labor force	35,156	34,360	34,926	35,143	35,518	362
Participation rate	55.5	54.8	55.7	55.4	55.5	0.0
Employed	32,338	31,970	32,511	33,061	33,733	1,395
Employment–population ratio	51.0	51.0	51.8	52.1	52.7	1.7
Unemployed	2,818	2,390	2,415	2,082	1,786	-1,032
Unemployment rate	8.0	7.0	6.9	5.9	5.0	-3.0
Some college or associate’s degree						
Civilian labor force	35,770	35,587	35,892	35,805	35,430	-340
Participation rate	62.5	62.8	63.3	63.1	62.7	0.2
Employed	33,430	33,469	33,783	34,107	34,057	627
Employment–population ratio	58.5	59.1	59.5	60.1	60.3	1.8
Unemployed	2,341	2,118	2,110	1,699	1,372	-969
Unemployment rate	6.5	6.0	5.9	4.7	3.9	-2.6
Bachelor’s degree and higher[2]						
Civilian labor force	59,702	60,690	60,641	60,835	61,134	1,432
Participation rate	72.0	72.0	72.3	72.3	72.1	0.1
Employed	57,265	58,353	58,603	59,141	59,758	2,493
Employment–population ratio	69.1	69.3	69.9	70.2	70.4	1.3
Unemployed	2,437	2,337	2,038	1,694	1,375	-1,062
Unemployment rate	4.1	3.9	3.4	2.8	2.2	-1.9

[1] This category includes people with a high school diploma or equivalent.

[2] This category includes people with bachelor’s, master’s, professional, and doctoral degrees.

Note: Updated population controls are introduced annually with the release of January data.

Source: U.S. Bureau of Labor Statistics, Current Population Survey.

About 1 in 3 unemployed people had been jobless for 27 weeks or longer

As unemployment surged following the onset of the COVID-19 pandemic, there was an increase in the number of people who were newly unemployed—that is, those unemployed for less than 5 weeks—but that number began to decrease as people either returned to work, stopped looking, or moved into the longer duration categories.[6] In 2021, the number of short-term unemployed decreased by 615,000, or 23.5 percent, to 2.0 million in the fourth quarter. This group accounted for 29.5 percent of the total number of unemployed in the fourth quarter of 2021. (See table 4.)

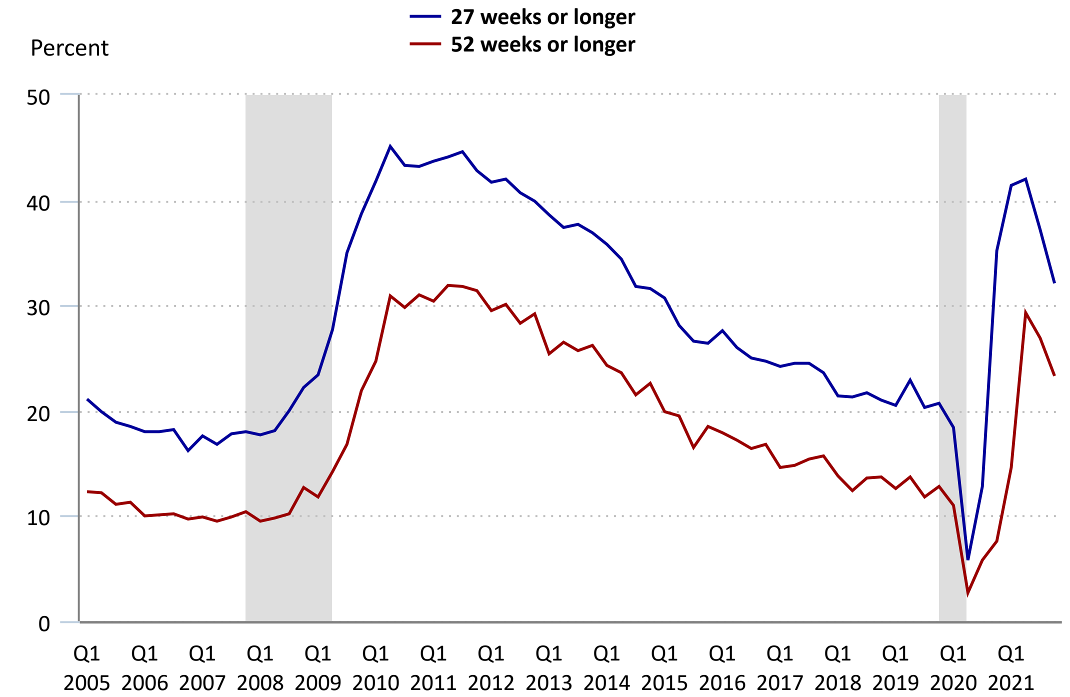
Table 4. Unemployed people, by reason and duration of unemployment, quarterly averages, seasonally adjusted, 2020–21 (levels in thousands)

Characteristics	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Reason for unemployment						
Job losers and people who completed temporary jobs	7,517	6,611	5,940	4,450	3,388	-4,129
On temporary layoff	3,040	2,351	1,903	1,167	909	-2,131
Not on temporary layoff	4,477	4,260	4,037	3,283	2,478	-1,999
Permanent job losers	3,600	3,471	3,262	2,553	1,903	-1,697
People who completed temporary jobs	877	789	775	730	575	-302
Job leavers	736	709	849	850	802	66
Reentrants	2,088	2,128	2,197	2,336	2,133	45
New entrants	532	541	540	491	501	-31
Percent distribution						
Job losers and people who completed temporary jobs	69.1	66.2	62.4	54.8	49.7	-19.4
On temporary layoff	28.0	23.5	20.0	14.4	13.3	-14.7
Not on temporary layoff	41.2	42.6	42.4	40.4	36.3	-4.9
Job leavers	6.8	7.1	8.9	10.5	11.8	5.0
Reentrants	19.2	21.3	23.1	28.8	31.3	12.1
New entrants	4.9	5.4	5.7	6.0	7.3	2.4
Duration of unemployment						
Less than 5 weeks	2,619	2,248	2,115	2,194	2,004	-615
5 to 14 weeks	2,375	2,230	2,127	1,816	1,717	-658
15 weeks or longer	5,854	5,498	5,218	4,226	3,064	-2,790
15 to 26 weeks	2,030	1,364	1,243	1,166	884	-1,146
27 weeks or longer	3,824	4,134	3,975	3,060	2,180	-1,644
Average (mean) duration in weeks	23.1	27.8	29.8	29.0	28.2	5.1
Median duration, in weeks	18.9	17.7	19.4	14.1	13.1	-5.8
Percent distribution						
Less than 5 weeks	24.1	22.5	22.4	26.6	29.5	5.4
5 to 14 weeks	21.9	22.4	22.5	22.0	25.3	3.4
15 weeks or longer	54.0	55.1	55.2	51.3	45.2	-8.8
15 to 26 weeks	18.7	13.7	13.1	14.2	13.0	-5.7
27 weeks or longer	35.2	41.4	42.0	37.2	32.1	-3.1

Note: Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

The number of long-term unemployed (people who were jobless for 27 weeks or longer) had been declining for about a decade prior to the onset of the pandemic. This measure rose to 4.1 million in the first quarter of 2021 but declined to 2.2 million by the end of the year. The number of long-term unemployed declined by 43.0 percent over the year. This group accounted for 32.1 percent of the total unemployed in the fourth quarter of 2021, down from 35.2 percent in the fourth quarter of 2020.[7] Both measures, the number of long-term unemployed and their share of total unemployment, remained well above the levels seen before the pandemic.[8] (See chart 4.)

Chart 4. Long-term unemployed as a percentage of total unemployed, quarterly averages, 2005–21



Click legend items to change data display Hover over chart to view data.
Note: Shaded regions represent recessions as designated by the National Bureau of Economic Research. Data for 27 weeks or longer are seasonally adjusted, and data for 52 weeks or longer are not seasonally adjusted. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

After reaching a record high of 4.5 million (not seasonally adjusted) in the second quarter of 2010, the number of people unemployed for a year or longer (those jobless for 52 weeks or more) declined for nearly a decade. At the time of the surge in unemployment in the second quarter of 2020, the number of people unemployed for 52 weeks or longer, at 556,000, was the lowest level it had been since 2003. The initial surge in unemployment continued to move through the longer duration categories for the remainder of 2020 and into 2021. Those unemployed for 52 weeks or more rose to 2.7 million in the second quarter of 2021, before declining to 1.5 million in the fourth quarter of 2021. Their share of total unemployment spiked to 29.3 percent in the second quarter of 2021, before falling to 23.3 percent in the fourth quarter of 2021.

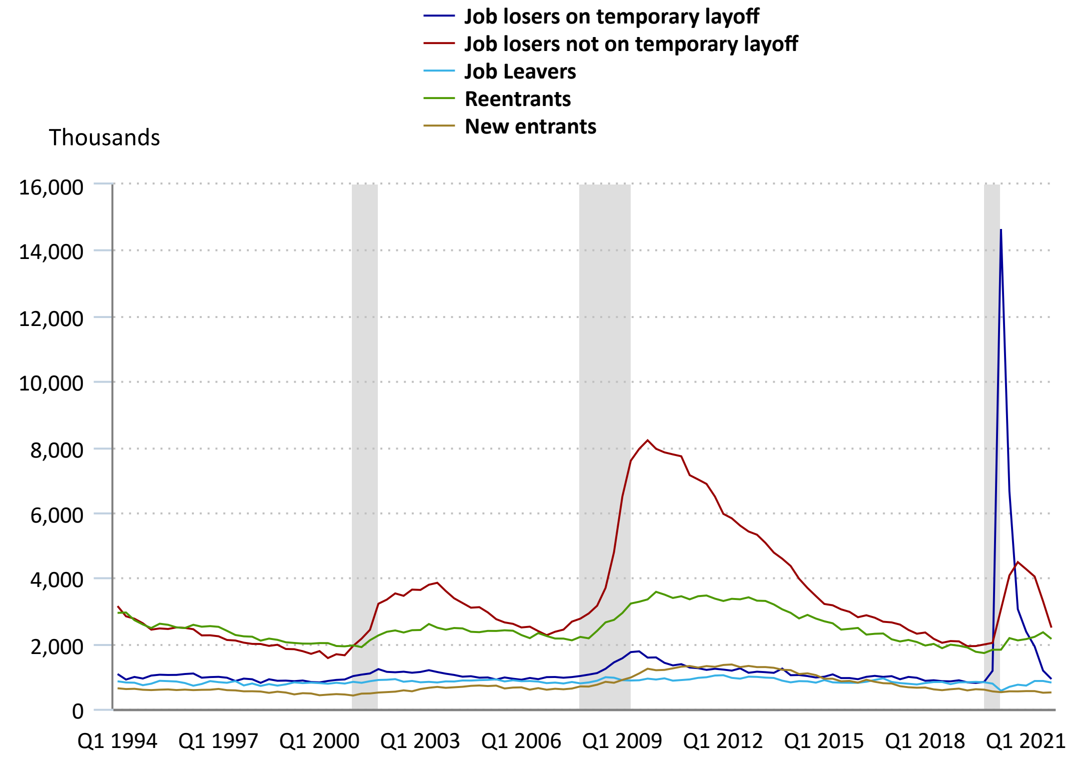
Number of people unemployed because they lost their job continued to decline

Unemployed people are grouped by their reasons for unemployment. People are unemployed because they either (1) were on temporary layoff, permanently lost their job, or completed a temporary job (referred to as job losers); (2) voluntarily left their job (job leavers); (3) reentered the labor force (reentrants); or (4) entered the labor force for the first time (new entrants).

The number of job losers and those who completed temporary jobs rose to an unprecedented level during the COVID-19 pandemic, to 17.7 million in the second quarter of 2020. (This was the highest quarterly average in the history of the data series, which began in 1967.) This number declined during the remainder of 2020 and through 2021. The number of job losers averaged 3.4 million in the fourth quarter of 2021. Virtually all of the increase in the number of job losers in the second quarter of 2020 consisted of people on temporary layoff.[9] However, the composition of unemployed job losers shifted to people not on temporary layoff in 2021. The number of unemployed people not on temporary layoff, which is made up mostly of permanent job losers, was 2.5 million at the end of 2021, accounting for 36.3 percent of the total unemployed. This represented an increase of 21.5 percentage points from the second quarter of 2020.

Among those unemployed who were not on temporary layoff, the number of people who permanently lost their jobs, at 1.9 million, decreased by 1.7 million over the year, but the number remained above its prepandemic level. (See table 4 and chart 5.)

Chart 5. Unemployed people, by reasons for unemployment, quarterly averages, seasonally adjusted, 1994–2021



Click legend items to change data display. Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

The number of unemployed reentrants to the labor force, at 2.1 million in the fourth quarter of 2021, changed little over the year. Reentrants are people who had been in the labor force previously, had spent time out of the labor force, and were actively seeking work once again. Reentrants accounted for 31.3 percent of unemployed people at the end of 2021.[10]

The number of unemployed job leavers—that is, people who voluntarily left their jobs—changed little over the year, averaging 802,000 in the fourth quarter of 2021. The number of new entrants to the labor force was essentially unchanged over the year, at 501,000.

The sharpest decline in unemployment occurred in service occupations

After rising with the onset of the COVID-19 pandemic in 2020, the unemployment rate decreased for all five major occupational categories from 2020 to 2021.[11] (Data are annual averages.) The jobless rate for service occupations had the sharpest decrease, declining by 5.2 percentage points, to 7.8 percent in 2021. Within this category, food preparation and serving-related occupations, with a jobless rate of 10.3 percent, and personal care and service occupations, with a jobless rate of 8.3 percent, had the largest declines in 2021. Even with the sharp declines in 2021, the jobless rate in service occupations was still well above its prepandemic level at the end of the year. Most notably, the rate for personal care and service occupations was twice as high as the rate in 2019. The jobless rates also declined in 2021 for production, transportation, and material-moving occupations (7.1 percent); natural resources, construction, and maintenance occupations (6.6 percent); sales and office occupations (5.3 percent); and management, professional, and related occupations (2.8 percent). The unemployment rates for all of the major occupational categories remained above their prepandemic values.

Unemployment rates decreased more for women than for men in four of the five major occupational categories from 2020 to 2021. For service occupations, the over-the-year decline in the unemployment rate was 4.7 percentage points for men and 5.6 percentage points for women. (See table 5.)

Table 5. Unemployment rates, by occupational group and gender, annual averages, not seasonally adjusted, 2020–21 (in percent)

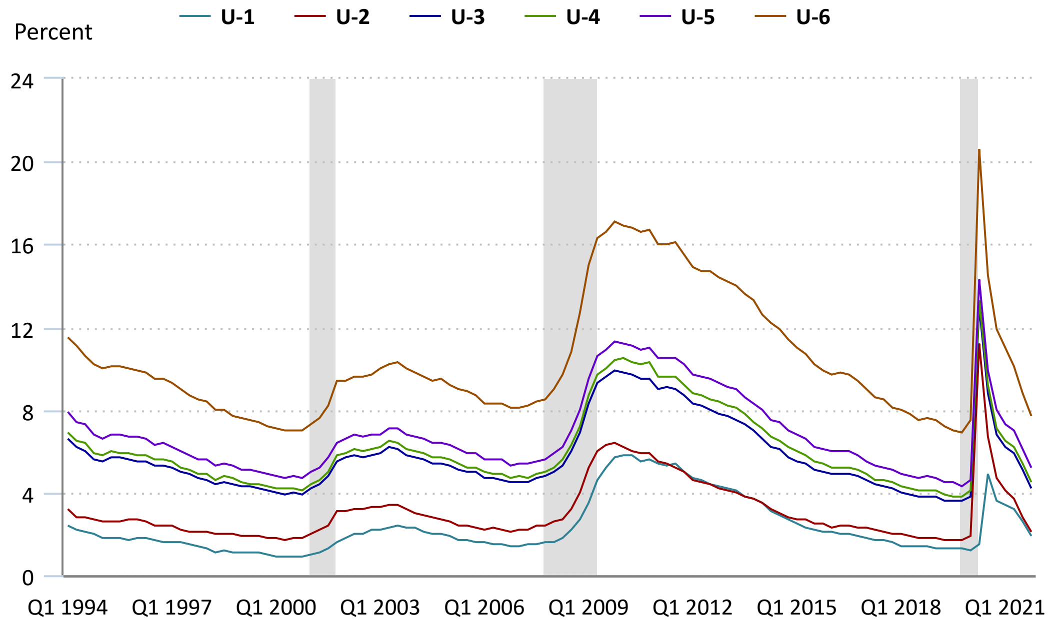
Occupational group	Total			Men			Women		
	2020	2021	Change, 2020–21	2020	2021	Change, 2020–21	2020	2021	Change, 2020–21
Management, professional, and related occupations	4.5	2.8	-1.7	4.2	2.8	-1.4	4.9	2.9	-2.0
Management, business, and financial operations occupations	4.1	2.8	-1.3	3.8	2.7	-1.1	4.4	3.0	-1.4
Professional and related occupations	4.9	2.8	-2.1	4.6	2.9	-1.7	5.1	2.8	-2.3
Service occupations	13.0	7.8	-5.2	12.6	7.9	-4.7	13.3	7.7	-5.6
Healthcare support occupations	7.3	5.9	-1.4	7.5	5.3	-2.2	7.3	6.0	-1.3
Protective service occupations	5.1	3.9	-1.2	3.9	3.6	-0.3	8.7	4.8	-3.9
Food preparation and serving-related occupations	19.6	10.3	-9.3	20.8	11.1	-9.7	18.5	9.7	-8.8
Building and grounds cleaning and maintenance occupations	10.9	7.5	-3.4	9.4	6.6	-2.8	13.1	8.8	-4.3
Personal care and service occupations	16.0	8.3	-7.7	17.5	12.5	-5.0	15.5	7.1	-8.4
Sales and office occupations	8.0	5.3	-2.7	7.2	4.9	-2.3	8.5	5.5	-3.0
Sales and related occupations	8.8	5.6	-3.2	6.9	4.6	-2.3	10.8	6.6	-4.2
Office and administrative support occupations	7.3	5.0	-2.3	7.9	5.5	-2.4	7.1	4.8	-2.3
Natural resources, construction, and maintenance occupations	8.9	6.6	-2.3	8.6	6.4	-2.2	12.5	9.1	-3.4
Farming, fishing, and forestry occupations	10.3	8.9	-1.4	8.4	8.3	-0.1	15.7	10.9	-4.8
Construction and extraction occupations	10.1	7.8	-2.3	10.0	7.7	-2.3	10.6	11.0	0.4
Installation, maintenance, and repair occupations	6.4	3.9	-2.5	6.2	4.0	-2.2	10.9	3.7	-7.2
Production, transportation, and material moving occupations	10.2	7.1	-3.1	9.8	6.9	-2.9	11.6	7.6	-4.0
Production occupations	9.0	5.8	-3.2	8.5	5.5	-3.0	10.0	6.3	-3.7
Transportation and material moving occupations	11.1	8.0	-3.1	10.6	7.8	-2.8	13.2	8.8	-4.4

Note: The unemployed are classified by occupation according to their last job, which may or may not be similar to the job they are currently seeking. Updated population controls are introduced annually with the release of January data. Effective with January 2020 data, occupations reflect the introduction of the 2018 Census occupational classification system into the Current Population Survey, or household survey. This classification system is derived from the 2018 Standard Occupational Classification. No historical data have been revised. Data for 2020 are not strictly comparable with earlier years.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

All six alternative measures of labor underutilization declined over the year

The U.S. Bureau of Labor Statistics (BLS) uses CPS data to construct six alternative measures of labor underutilization.[12] Known as U-1 through U-6 (U-3 is the official unemployment rate), these measures tend to show similar cyclical patterns, but they provide additional insight into the degree to which labor resources are being underutilized. Each of the six measures decreased in 2021, but they all remained above their prepandemic levels. U-3 decreased by 2.6 percentage points, to 4.2 percent in the fourth quarter of 2021. All six measures continued to trend down since reaching highs early in the COVID-19 pandemic. (See chart 6.) (See the box that follows for more information about the six measures of labor underutilization.)

Chart 6. Alternative measures of labor underutilization, quarterly averages, seasonally adjusted, 1994–2021



Click legend items to change data display. Hover over chart to view data.
Note: Shaded regions represent recessions as designated by the National Bureau of Economic Research (NBER). Turning points are quarterly. Measures of labor underutilization are defined as follows: U-1 = people unemployed 15 weeks or longer, as a percentage of the civilian labor force; U-2 = job losers and people who completed temporary jobs, as a percentage of the civilian labor force; U-3 = total unemployed, as a percentage of the civilian labor force (official unemployment rate); U-4 = total unemployed plus discouraged workers, as a percentage of the civilian labor force plus discouraged workers; U-5 = total unemployed, plus discouraged workers, plus all other marginally attached workers, as a percentage of the civilian labor force plus all marginally attached workers; U-6 = total unemployed, plus all marginally attached workers, plus total employed part time for economic reasons, as a percentage of the civilian labor force plus all marginally attached workers. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Alternative measures of labor underutilization

Six alternative measures of labor underutilization have long been available on a monthly basis from the Current Population Survey (CPS) for the United States as a whole. The official concept of unemployment (as measured in the CPS by U-3 in the U-1 to U-6 range of alternative measures) includes all jobless people who are available to take a job and have actively sought work in the past 4 weeks. The other measures encompass concepts both narrower (U-1 and U-2) and broader (U-4 through U-6) than the official concept of unemployment. The six measures are defined as follows:

- U-1: people unemployed 15 weeks or longer, as a percent of the civilian labor force;
- U-2: job losers and people who completed temporary jobs, as a percent of the civilian labor force;
- U-3: total unemployed, as a percent of the civilian labor force (this is the definition used for the official unemployment rate);
- U-4: total unemployed plus discouraged workers, as a percent of the civilian labor force plus discouraged workers;
- U-5: total unemployed, plus discouraged workers, plus all other marginally attached workers, as a percent of the civilian labor force plus all marginally attached workers;
- U-6: total unemployed, plus all marginally attached workers, plus total employed part time for economic reasons, as a percent of the civilian labor force plus all marginally attached workers.

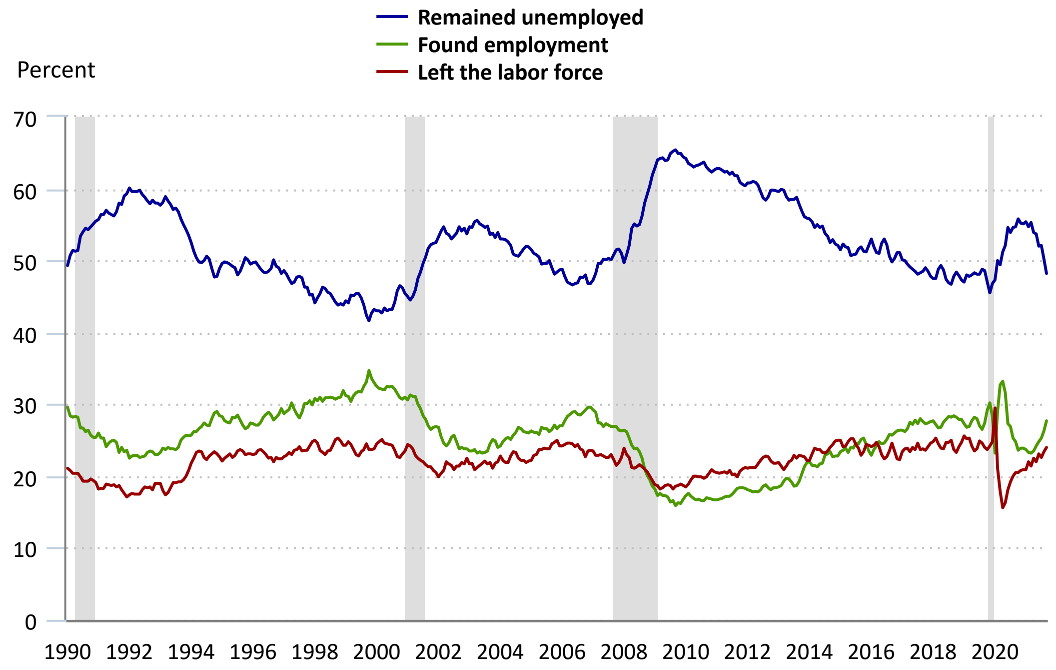
Discouraged workers (included in the U-4, U-5, and U-6 measures) are people who are not in the labor force, want and are available for work, and had looked for a job sometime in the prior 12 months. They are not counted as unemployed because they had not actively searched for work in the 4 weeks preceding the survey. Discouraged workers are not currently looking for work specifically because they believe no jobs are available for them or there are none for which they are qualified. The marginally attached (included in the U-5 and U-6 measures) category includes discouraged workers. The criteria for the marginally attached are the same as for discouraged workers, with the exception that any reason can be cited for the lack of active job search in the prior 4 weeks. People at work part time for economic reasons (included in the U-6 measure) are those working less than 35 hours per week who want to work full time, are available to do so, and give an economic reason for working part time (for example, their hours had been cut back or they were unable to find a full-time job). These individuals are sometimes referred to as involuntary part-time workers.

Improvements in unemployment were also reflected in labor force status flows

Each month, BLS reports on the number of people who are employed, unemployed, and not in the labor force, as measured by the CPS. A great deal of underlying movement contributes to the relatively small over-the-month net changes that typically occur in the different labor force statuses. These gross movements are captured by labor force status flows data, which show that millions of people move between employment and unemployment each month, while millions of others leave or enter the labor force.[13] In 2021, 17.2 million people, or 6.6 percent of the population, changed their labor force status in an average month. Examining the current status (employed, unemployed, or not in the labor force) of people who were unemployed in the previous month provides a greater understanding of unemployment in 2021.

Historically, unemployed people are more likely to remain unemployed from one month to the next than to either find employment or leave the labor force. The likelihood of unemployed people remaining unemployed tends to increase during labor market downturns, as it did after the onset of the COVID-19 pandemic. The share of unemployed people who remained unemployed declined in 2021; at about 50 percent in December 2021 (calculated as a 3-month moving average), the share is roughly comparable with its value at the end of 2019. The likelihood of unemployed people finding employment edged up over the year, and the percentage who stopped looking and left the labor force increased in 2021. In December 2021, 27.7 percent of people who were unemployed a month earlier found work, while 24.0 percent stopped looking for work and left the labor force. (See chart 7.)

Chart 7. Percentage of the unemployed who remained unemployed, found employment, or left the labor force, 3-month moving average, seasonally adjusted, April 1990–December 2021



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are monthly.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Number of people not in the labor force who wanted a job continued to trend down

People who are neither employed nor unemployed are classified as not in the labor force.[14] In 2021, the number of people not in the labor force decreased by 385,000, reaching 100.0 million by the end of the year. Although most people who are not in the labor force do not want a job (about 95 percent at the end of 2021), the number of people not in the labor force who indicated that they did want a job fell by 1.2 million, to 5.8 million at the end of 2021.[15] The measure remains above its prepandemic level of 4.8 million in the fourth quarter of 2019. The remaining people not in the labor force, numbering 94.2 million in the fourth quarter of 2021, did not want a job. (See table 6.)

Table 6. Number of people not in the labor force, quarterly averages, seasonally adjusted, 2020–21 (in thousands)

Category	Fourth quarter 2020	2021 First quarter 2021	2021 Second quarter 2021	2021 Third quarter 2021	2021 Fourth quarter 2021	Change, fourth quarter 2020–21
Total not in the labor force	100,399	100,533	100,253	100,165	100,014	-385
People who currently want a job	7,027	6,900	6,545	6,049	5,822	-1,205
Marginally attached to the labor force [1]	2,074	1,882	1,874	1,727	1,645	-429
Discouraged workers[2]	633	553	586	446	456	-177

[1] This category includes people who want a job, have searched for work during the prior 12 months, and were available to take a job during the reference week but had not looked for work in the 4 weeks prior to the survey.

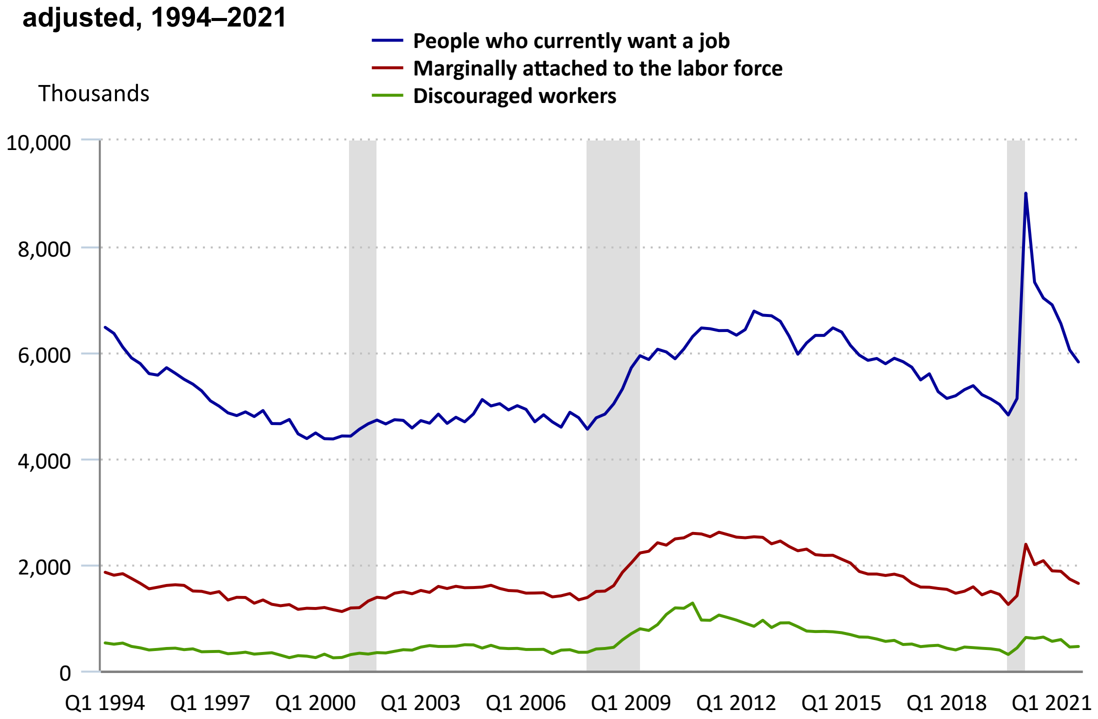
[2] This category includes people who did not actively look for work in the 4 weeks prior to the survey for reasons such as thinks no work available, could not find work, lacks schooling or training, employer thinks too young or old, and other types of discrimination.

Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Among people not in the labor force who currently want a job, the number defined as marginally attached to the labor force, at 1.6 million in the fourth quarter of 2021, fell by 429,000 over the year. These individuals wanted a job, had searched for work sometime in the previous year, and were available to work if a job had been offered to them. Still, they are not counted as unemployed because they had not actively searched for work in the 4 weeks preceding the survey.

In addition to declining unemployment and increasing employment, another measure that reflected the improvement in the labor market in 2021 is the number of discouraged workers. Among the marginally attached, people currently not looking for work specifically because they felt that no jobs were available for them are defined as discouraged workers. The number of discouraged workers declined by 177,000 over the year, to 456,000 in the fourth quarter of 2021. (See chart 8.)

Chart 8. People not in the labor force, quarterly averages, not seasonally adjusted, 1994–2021



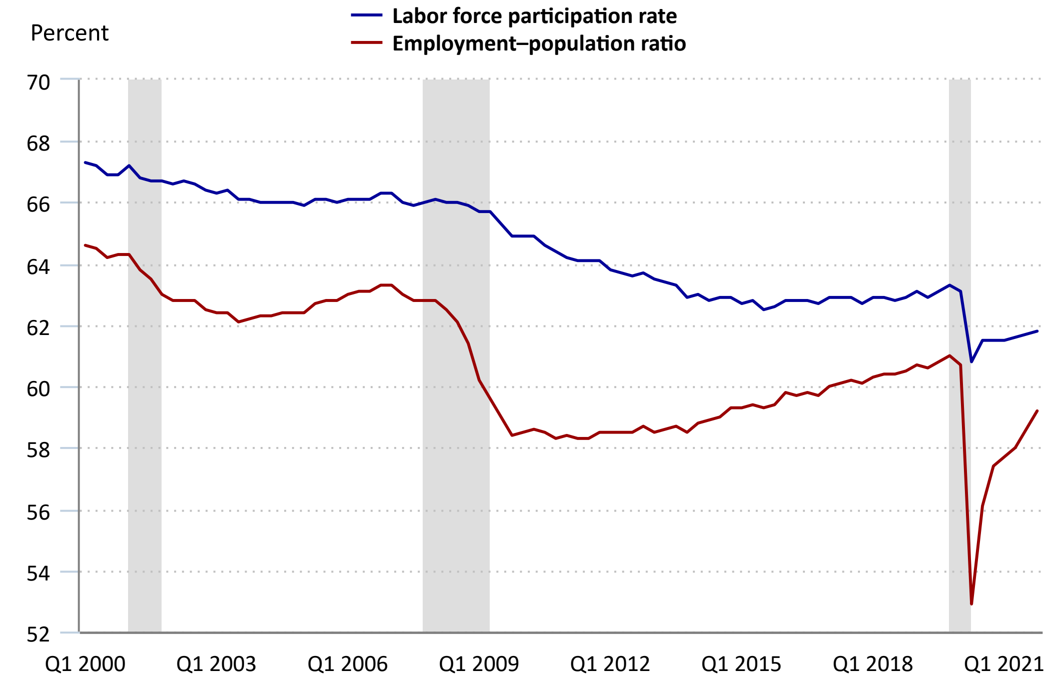
Click legend items to change data display. Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Employment continued to trend up in 2021

After falling by 20.1 million in the second quarter of 2020 following the onset of the COVID-19 pandemic, employment growth recovered more than half (12.2 million) of those losses in the second half of that year. Employment growth continued in 2021, and by the fourth quarter, the number of people employed averaged 155.2 million, up by 5.4 million from the previous year. The employment–population ratio (the percentage of the population ages 16 years and older who are employed) also increased in 2021. This ratio increased by 1.8 percentage points over the year, to 59.2 percent, but it remains 1.8 percentage points below its level in the fourth quarter of 2019. (See table 1 and chart 9.)

Chart 9. Labor force participation rate and employment–population ratio, quarterly averages, seasonally adjusted, 2000–21



Click legend items to change data display. Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Labor market conditions improved for both women and men in 2021. From the fourth quarter of 2020 to the fourth quarter of 2021, employment increased by 2.5 million for women and by 2.9 million for men. The employment–population ratio increased by 1.7 percentage points for women, compared with 2.0 percentage points for men. (See table 1.)

Employment–population ratios increased for all race and ethnicity groups

Employment rose for all race and ethnicity groups, and this was reflected in their employment–population ratios. The over-the-year increase in the employment–population ratio was greatest for Asians, followed by Hispanics, Blacks, and Whites.

The employment–population ratio for Asians rose by 4.3 percentage points, to 62.5 percent in 2021.[16] The ratio is essentially the same as the prepandemic figure of 62.6 percent in the fourth quarter of 2019. The employment–population ratio for Hispanics, at 62.5 percent in the fourth quarter of 2021, increased by 2.9 percentage points over the year. The employment–population ratio for Blacks increased by 2.6 percentage points, to 56.5 percent, after having fallen below 50.0 percent in the second quarter of 2020. (See table 1.) The employment–population ratio for Whites, at 59.4 percent in the fourth quarter of 2021, rose by 1.5 percentage points over the year. The ratios for Whites, Blacks, and Hispanics were still below the ratios seen before the COVID-19 pandemic.

People ages 16 to 24 did well in the labor market in 2021

Among people ages 16 to 24, employment rose over the year by 885,000, or 4.9 percent. Much of that rise in employment occurred in the 20- to-24-year age group, which accounted for 75.4 percent of the increase. The employment–population ratio for people ages 16 to 24 was 51.3 percent in the fourth quarter of 2021, 2.7 percentage points higher than it was a year earlier, and essentially the same as in the fourth quarter of 2019 (51.4 percent). (See table 2.)

The number of employed people ages 25 to 54 rose by 3.4 million, or 3.5 percent, from the fourth quarter of 2020 to the fourth quarter of 2021. The employment–population ratio rose by 2.6 percentage points over the year, to 78.7 percent. Both measures are still below their prepandemic levels.

Employment among people ages 55 years and older increased by 1.1 million, or 3.2 percent, in 2021. The employment–population ratio for older workers, at 37.2 percent in the fourth quarter of 2021, rose by 0.7 percentage point over the year. Despite these increases, both measures remained below their prepandemic levels at the end of 2021.

Employment growth was strongest for people with more education

For people ages 25 years and older, employment among those with less than a high school diploma, at 8.3 million, was essentially unchanged from the fourth quarter of 2020 to the fourth quarter of 2021. However, the employment–population ratio for this group rose by 1.5 percentage points, to 42.7 percent in 2021. Employment increased by 4.3 percent over the year for high school graduates with no college, raising the level to 33.7 million. The employment–population ratio for this group increased by 1.7 percentage points over the year, to 52.7 percent. Employment among people with some college or an associate's degree increased by 1.9 percent in 2021, to 34.1 million. The employment–population ratio for this group rose 1.8 percentage points, to 60.3 percent. Employment among people with a bachelor's degree and higher increased 4.4 percent over the year, rising to 59.8 million in the fourth quarter of 2021. The employment–population ratio for this group rose 1.3 percentage points, to 70.4 percent. Nevertheless, both measures remained below their prepandemic levels. (See table 3.)

Labor force participation rates increased slightly over the year for most race and ethnicity groups, with Asians showing the most improvement

Even as the unemployment rate declined to a level that is relatively low by historical standards and employment continued to grow, the net effect was a moderate increase in the labor force.[17] The labor force participation rate increased by 0.3 percentage point over the year, to 61.8 percent in the fourth quarter of 2021; the rate was 63.3 percent in the fourth quarter of 2019, before the pandemic. The labor force participation rate increased for men by 0.2 percentage point, to 67.7 percent, and for women by 0.4 percentage point, to 56.3 percent. (See table 1 and chart 9.)

The labor force participation rate for Asians increased by 2.6 percentage points over the year, to 65.1 percent, slightly higher than the prepandemic rate of 64.4 percent. Labor force participation rates for Blacks and Hispanics edged up by 0.6 percentage point each in 2021. The rate for Blacks was 60.8 percent in the fourth quarter, while the rate for Hispanics was 66.0 percent. Hispanics had the highest participation rate among the major race and ethnicity groups. However, the rates for Blacks and Hispanics are still below their prepandemic levels. The labor force participation rate for Whites was unchanged over the year, at 61.6 percent, and remained below the prepandemic rate of 63.2 percent in the fourth quarter of 2019. (See table 1.)

Recent improvements in relation to the effects of the COVID-19 pandemic and in labor market conditions have narrowed the differences in the labor force participation rates among demographic groups. However, other factors help explain the relatively moderate increase in the labor force participation rate in 2021, such as people choosing not to work because of health risks, early retirements, and family-care duties.[18]

Growth in labor force participation rates was similar for young people and those of prime working age

The labor force participation rate for prime-working-age people, those ages 25 to 54, rose by 0.8 percentage point over the year, to 81.8 percent in the fourth quarter of 2021. Among people ages 16 to 24, the rate increased by 0.7 percentage point, to 56.0 percent. Within this group, the labor force participation rate for those ages 20 to 24 increased by 1.2 percentage points in 2021, to 71.7 percent. Although labor force participation rates for young workers have historically been lower than the rates for older age groups, they have rebounded more quickly than those of the other age groups since the COVID-19 pandemic began.[19] The labor force participation rate for people ages 55 years and older was 38.4 percent in the fourth quarter of 2021, compared with 40.3 percent in the fourth quarter of 2019. Some researchers have suggested that this decline may reflect an increase in the number of early retirements, what has sometimes been called the “Great Resignation,” which could be dragging down the overall labor force participation rate.[20] (See table 2.)

Labor force participation rates changed little across different educational groups

For workers ages 25 years and older with less than a high school diploma, the labor force participation rate was 45.5 percent in the fourth quarter of 2021, essentially unchanged from the fourth quarter of 2020. (See table 3.) Although this rate is 0.9 percentage point below the rate for the fourth quarter of 2019, before the pandemic, it is closer to the prepandemic rate than are the comparable rates for other educational attainment groups.[21]

The labor force participation rate for high school graduates with no college, at 55.5 percent in the fourth quarter of 2021, was unchanged over the year but down by 2.4 percentage points from its prepandemic level. The rate for workers with some college or an associate’s degree, at 62.7 percent, was little changed from a year earlier and down by 2.0 percentage points from the fourth quarter of 2019. The labor force participation rate for people with higher levels of education—those with a bachelor’s degree and higher—at 72.1 percent in the fourth quarter of 2021, was also little changed from the prior year. The 2021 rate for this group was 1.7 percentage points below the prepandemic rate.

Employment rose substantially in all major occupation groups

Of the major occupation groups, the largest employment growth in 2021 occurred in service occupations, with an increase of 1.6 million workers, or 6.8 percent. (These are annual averages.) Service occupations saw the sharpest decline in employment at the onset of the COVID-19 pandemic, in early 2020. Within this occupational group, employment in food preparation and serving-related occupations rose sharply over the year. (See table 7.)

Table 7. Employment, by occupational group and gender, annual averages, 2020–21 (in thousands)

Occupational group	Total			Men			Women		
	2020	2021	Change, 2020–21	2020	2021	Change, 2020–21	2020	2021	Change, 2020–21
Total, 16 years and older	147,795	152,581	4,786	78,560	80,829	2,269	69,234	71,752	2,518
Management, professional, and related occupations	63,644	64,744	1,100	30,734	31,109	375	32,910	33,636	726
Management, business, and financial operations occupations	27,143	27,864	721	15,028	15,231	203	12,114	12,633	519
Professional and related occupations	36,502	36,880	378	15,706	15,878	172	20,796	21,003	207
Service occupations	22,853	24,403	1,550	9,820	10,328	508	13,033	14,075	1,042
Healthcare support occupations	4,790	4,887	97	703	728	25	4,087	4,158	71
Protective service occupations	3,024	2,987	-37	2,310	2,276	-34	714	711	-3
Food preparation and serving related occupations	6,556	7,370	814	2,989	3,343	354	3,566	4,027	461
Building and grounds cleaning and maintenance occupations	5,084	5,482	398	3,036	3,198	162	2,048	2,285	237
Personal care and service occupations	3,399	3,676	277	781	783	2	2,618	2,893	275
Sales and office occupations	29,726	30,166	440	11,506	11,604	98	18,221	18,563	342
Sales and related occupations	14,168	14,369	201	7,261	7,219	-42	6,907	7,150	243
Office and administrative support occupations	15,558	15,797	239	4,244	4,384	140	11,314	11,413	99
Natural resources, construction, and maintenance occupations	13,357	13,959	602	12,607	13,181	574	750	778	28
Farming, fishing, and forestry occupations	1,045	1,061	16	793	804	11	252	257	5
Construction and extraction occupations	7,710	8,057	347	7,402	7,746	344	308	311	3
Installation, maintenance, and repair occupations	4,602	4,840	238	4,411	4,630	219	190	210	20
Production, transportation, and material moving occupations	18,215	19,309	1,094	13,894	14,608	714	4,321	4,700	379
Production occupations	7,590	7,950	360	5,443	5,703	260	2,147	2,247	100
Transportation and material moving occupations	10,625	11,359	734	8,451	8,906	455	2,174	2,453	279

Note: Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Management, professional, and related occupations is the largest of the major occupational groups, accounting for about 42.4 percent of the total number of employed people in 2021. Employment in this group grew by 1.1 million from 2020 to 2021, or 1.7 percent. This occupational group had the smallest decline in employment at the onset of the pandemic. Within this group, employment in management, business, and financial operations expanded by 721,000 in 2021, and the number of workers in professional and related occupations was little changed.

Employment in production, transportation, and material-moving occupations increased by 6.0 percent over the year, to 19.3 million. Employment in this occupational group is up by 681,000 from its prepandemic level in 2019. Employment in sales and office occupations increased by 1.5 percent over the year, to 30.2 million. Employment in natural resources, construction, and maintenance occupations increased from 13.4 million in 2020 to 14.0 million in 2021, little changed from its prepandemic level of 14.3 million.

Number of self-employed workers continued to trend up

In general, during labor market downturns, employment drops, although the degree of the decline often varies by industry and occupation, depending on the underlying causes of the economic contraction. This was certainly the case during the recent recession caused by the COVID-19 pandemic. This procyclical response affects many of the self-employed, whose businesses often suffer from the drop in demand for their products and services, sometimes resulting in the failure of the business. At the same time, a countercyclical effect could result in a rise in self-employment, if laid-off wage and salary workers decide to start businesses of their own.

The number of nonagricultural self-employed workers whose businesses were unincorporated declined sharply at the onset of the pandemic but was essentially the same as its prepandemic level by the first quarter of 2021. During 2021, the total number of nonagricultural self-employed trended up, reaching 9.3 million in the fourth quarter, up by 678,000 over the year.[22] This amounts to an increase of 7.8 percent over the year, compared with a gain of 3.7 percent for total employment growth in nonagricultural industries. The increase coincides with complaints from many U.S. companies about not being able to find and retain enough employees in the aftermath of the pandemic.[23] (See table 8.)

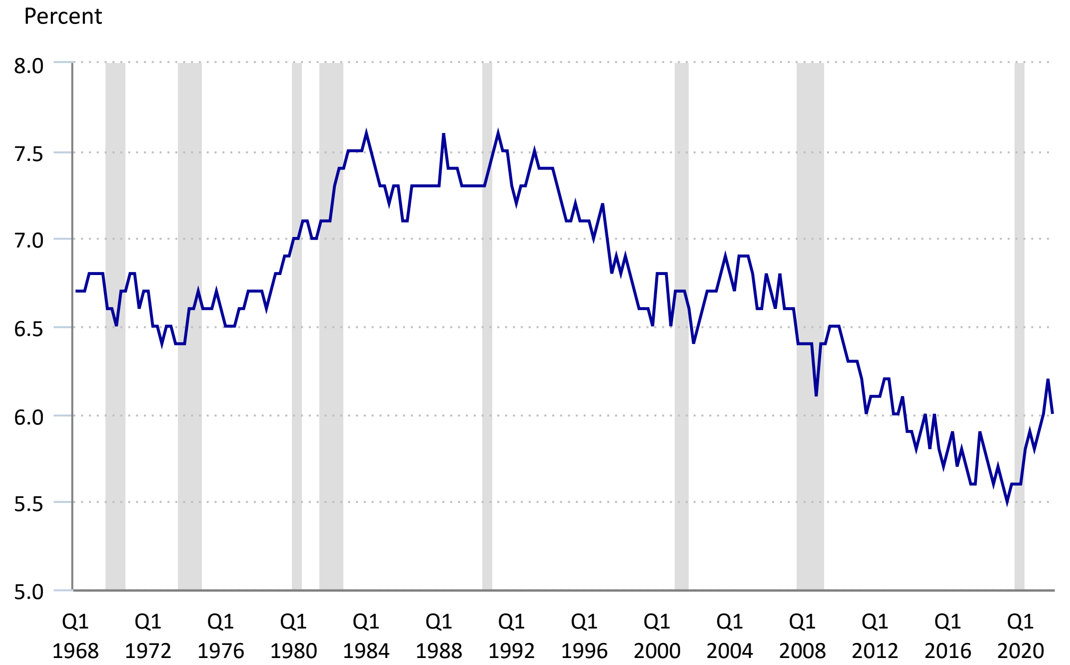
Table 8. Employed people, by class of worker, quarterly averages, seasonally adjusted, 2020–21 (in thousands)

Class of worker	Fourth quarter 2020	2021				Change, fourth quarter 2020–21
		First quarter	Second quarter	Third quarter	Fourth quarter	
Agriculture and related industries	2,464	2,329	2,292	2,281	2,272	-192
Wage and salary workers	1,576	1,537	1,551	1,547	1,471	-105
Self-employed workers, unincorporated	845	724	701	718	766	-79
Nonagricultural industries	147,218	147,947	149,308	151,110	152,804	5,586
Wage and salary workers	138,615	139,244	139,998	141,227	143,495	4,880
Self-employed workers, unincorporated	8,656	8,942	9,140	9,491	9,334	678

Note: Both agricultural and nonagricultural wage and salary workers include self-employed workers whose businesses are incorporated.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

The nonagricultural self-employment rate—the proportion of total nonagricultural employment made up of the self-employed—was 6.0 percent at the end of 2021, compared with its prepandemic level of 5.6 percent in the fourth quarter of 2019. (See chart 10.)

Chart 10. Nonagricultural self-employment rate, quarterly averages, 1968–2021



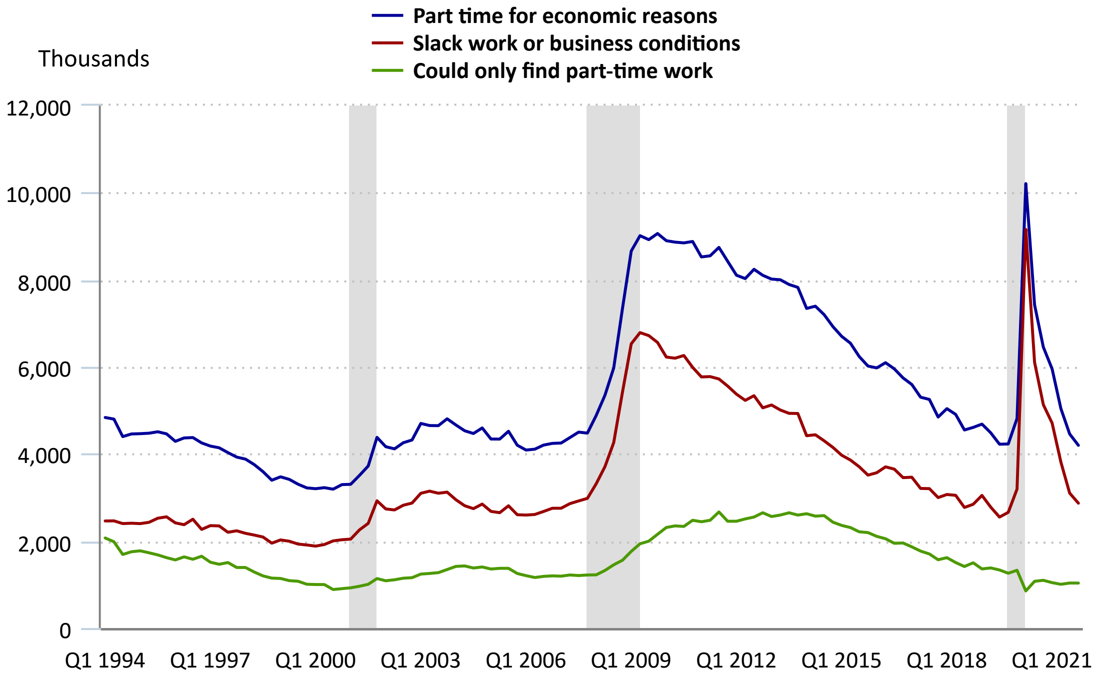
Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. The nonagricultural self-employment rate is the number of nonagricultural self-employed workers as a percentage of total nonagricultural employment. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Number of people employed part time for economic reasons declined over the year

Also referred to as involuntary part-time employment and thought of as one type of underemployment, the number of people who worked part time for economic reasons—those who worked less than 35 hours per week but would have preferred full-time employment—ended the fourth quarter of 2021 at 2.3 million lower than a year earlier, returning to prepandemic levels.[24] Historically, slack work or unfavorable business conditions, rather than an inability to find full-time work, have been the primary reason for working part time involuntarily. The number of involuntary part-time workers has been decreasing since it reached a high of 10.2 million in the second quarter of 2020. The number of people employed part time involuntarily, at 4.2 million in the fourth quarter of 2021, was little different from the level seen in 2019. (See chart 11.)

Chart 11. Number of people employed part time for economic reasons, quarterly averages, seasonally adjusted, 1994–2021



Click legend items to change data display. Hover over chart to view data.
Note: Shaded areas represent recessions as determined by the National Bureau of Economic Research. Turning points are quarterly. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

At the end of 2020, men continued to make up slightly more than half of all involuntary part-time workers. The number of men who worked part time for economic reasons decreased by 1.1 million, or 34.4 percent, from the fourth quarter of 2020 to the fourth quarter of 2021, ending the year at 2.2 million. Over the same period, the number of women working part time for economic reasons decreased by 1.1 million, or 36.7 percent, to 1.9 million. (These data are not seasonally adjusted.)

Unemployment rate for veterans remained lower than the rate for nonveterans

There were 18.0 million veterans ages 18 years and older in the civilian noninstitutional population in the fourth quarter of 2021. Veterans who served during World War II, the Korean War, and the Vietnam era account for the largest share of the veteran population, at 6.3 million, followed by veterans who served during Gulf War era II (4.6 million) and Gulf War era I (3.1 million). Nearly 3.9 million veterans served on active duty during “other service periods,” mainly between the Korean War and the Vietnam era and between the Vietnam era and Gulf War era I. Among veterans, women accounted for 10.7 percent of the total veteran population in the fourth quarter of 2021.

The unemployment rate for veterans was 3.6 percent in the fourth quarter of 2021 (not seasonally adjusted), down by 2.1 percentage points over the year. This rate is down by 6.2 percentage points from its peak in the second quarter of 2020, when it was 9.8 percent. The unemployment rate for nonveterans, at 3.9 percent in the fourth quarter of 2021, decreased by 2.6 percentage points over the year. The unemployment rate for male veterans, at 3.5 percent, decreased by 2.4 percentage points in 2021, while the jobless rate for female veterans, at 4.4 percent, changed little over the same period. The jobless rate for Gulf War-era II veterans (those who served from September 2001 to the present) decreased by 2.0 percentage points from a year earlier, to 4.1 percent. (See table 9.)

Table 9. Employment status of people 18 years and older, by veteran status, period of service, and gender, quarterly averages, not seasonally adjusted, 2020–21 (levels in thousands)

Employment status, veteran status, and period of service	Total			Men			Women		
	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21
Veterans, 18 years and older									
Civilian noninstitutional population	18,319	17,951	-368	16,411	16,029	-382	1,908	1,921	13
Civilian labor force	8,721	8,409	-312	7,607	7,247	-360	1,114	1,162	48
Participation rate	47.6	46.8	-0.8	46.4	45.2	-1.2	58.4	60.5	2.1
Employed	8,222	8,102	-120	7,161	6,991	-170	1,062	1,111	49
Employment–population ratio	44.9	45.1	0.2	43.6	43.6	0.0	55.6	57.8	2.2
Unemployed	499	307	-192	446	256	-190	52	51	-1
Unemployment rate	5.7	3.6	-2.1	5.9	3.5	-2.4	4.7	4.4	-0.3
Gulf War-era II veterans									
Civilian labor force	3,502	3,620	118	2,960	3,048	88	541	572	31
Participation rate	77.4	78.7	1.3	79.2	80.5	1.3	68.4	70.3	1.9
Employed	3,289	3,471	182	2,773	2,924	151	516	547	31
Employment–population ratio	72.7	75.5	2.8	74.2	77.2	3.0	65.2	67.3	2.1
Unemployed	213	149	-64	187	125	-62	26	25	-1
Unemployment rate	6.1	4.1	-2.0	6.3	4.1	-2.2	4.7	4.3	-0.4
Gulf War-era I veterans									
Civilian labor force	2,257	2,257	0	1,933	1,911	-22	324	346	22
Participation rate	73.2	71.7	-1.5	74.4	72.0	-2.4	67.0	70.2	3.2
Employed	2,148	2,194	46	1,837	1,861	24	310	333	23
Employment–population ratio	69.7	69.7	0.0	70.7	70.1	-0.6	64.1	67.6	3.5
Unemployed	109	62	-47	95	49	-46	14	13	-1
Unemployment rate	4.8	2.8	-2.0	4.9	2.6	-2.3	4.3	3.7	-0.6
World War II, Korean War, and Vietnam-era veterans									
Civilian labor force	1,167	1,011	-156	1135	960	-175	33	51	18
Participation rate	17.5	16.1	-1.4	17.6	15.8	-1.8	14.0	23.0	9.0
Employed	1,111	971	-140	1080	925	-155	31	46	15
Employment–population ratio	16.6	15.4	-1.2	16.8	15.2	-1.6	13.5	20.8	7.3
Unemployed	56	40	-16	55	35	-20	1	5	4
Unemployment rate	4.8	3.9	-0.9	4.8	3.6	-1.2	[1]	[1]	[1]
Veterans of other service periods									
Civilian labor force	1,795	1,521	-274	1,579	1,328	-251	216	193	-23
Participation rate	44.5	38.9	-5.6	43.5	37.8	-5.7	54.0	49.0	-5.0
Employed	1,675	1,466	-209	1,470	1,281	-189	204	185	-19
Employment–population ratio	41.5	37.5	-4.0	40.5	36.5	-4.0	51.1	47.0	-4.1
Unemployed	121	55	-66	109	47	-62	12	8	-4
Unemployment rate	6.7	3.6	-3.1	6.9	3.6	-3.3	5.4	4.1	-1.3
Nonveterans, 18 years and older									
Civilian noninstitutional population	233,980	235,053	1,073	105,461	106,245	784	128,519	128,808	289
Civilian labor force	149,779	151,277	1,498	76,442	77,328	886	73,337	73,949	612
Participation rate	64.0	64.4	0.4	72.5	72.8	0.3	57.1	57.4	0.3
Employed	140,099	145,399	5,300	71,356	74,289	2,933	68,743	71,110	2,367
Employment–population ratio	59.9	61.9	2.0	67.7	69.9	2.2	53.5	55.2	1.7
Unemployed	9,680	5,877	-3,803	5,086	3,039	-2,047	4,594	2,838	-1,756
Unemployment rate	6.5	3.9	-2.6	6.7	3.9	-2.8	6.3	3.8	-2.5

[1] No data available, data do not meet publication criteria, or base is less than 60,000.

Note: Veterans are men and women who previously served on active duty in the U.S. Armed Forces and were not on active duty at the time of the survey. Nonveterans never served on active duty in the U.S. Armed Forces. Veterans could have served anywhere in the world during these periods of service: Gulf War era II (September 2001–present), Gulf War era I (August 1990–August 2001), Vietnam era (August 1964–April 1975), Korean War (July 1950–January 1955), World War II (December 1941–December 1946), and other service periods (all other periods). Veterans are only counted in one period of service: their most recent wartime period. Veterans who served in both a wartime period and any other service period are classified in the wartime period.

Source: U.S. Bureau of Labor Statistics, Current Population Survey.

The labor force participation rate for veterans, at 46.8 percent in the fourth quarter of 2021, changed little over the year, while the rate for nonveterans increased by 0.4 percentage point, to 64.4 percent. Labor force participation rates are generally lower for older people than they are for people of prime working age. Thus, the labor force participation rate for those who served during World War II, the Korean War, and the Vietnam era—who are all over the age of 60 and accounted for 35.1 percent of the veteran population—was 16.1 percent in the fourth quarter of 2021, down by 1.4 percentage points over the year. By contrast, Gulf War-era II veterans, who tend to be younger, had a much higher participation rate, 78.7 percent, which was little changed from a year earlier. The employment–population ratio for veterans, at 45.1 percent, also changed little over the year, while the ratio for nonveterans rose by 2.0 percentage points, to reach 61.9 percent in the fourth quarter of 2021. The employment–population ratio for Gulf War-era II veterans increased by 2.8 percentage points over the year, to 75.5 percent in the fourth quarter of 2021.

Unemployment rate for people with a disability more than twice that of those with no disability

Many demographic groups faced challenging labor market conditions in 2021, including people with a disability. The unemployment rate for people with a disability, at 8.2 percent in the last quarter of 2021, was more than double the rate for those without a disability (3.7 percent). (Data are not seasonally adjusted.) The rate for people with a disability decreased by 3.3 percentage points in 2021, compared with a decrease of 2.6 percentage points for those without a disability.

Among the 31.9 million people ages 16 years and older with a disability in the fourth quarter of 2021, 7.2 million, or 22.7 percent, participated in the labor force. By contrast, the participation rate for people with no disability was 67.2 percent. The lower rate for people with a disability reflects, in part, the older age profile of those with a disability; older people, regardless of disability status, are less likely to be in the labor force. About half of all people with a disability were ages 65 years and older, nearly 3 times the share of those with no disability. (See table 10.)

Table 10. Employment status of the civilian noninstitutional population, by gender, age, and disability status, quarterly averages, not seasonally adjusted, 2020–21 (levels in thousands)

Employment status, gender, and age	People with a disability			People with no disability		
	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21
Total, 16 years and older						
Civilian noninstitutional population	29,880	31,859	1,979	231,200	230,165	-1,035
Civilian labor force	6,078	7,229	1,151	154,434	154,657	223
Participation rate	20.3	22.7	2.4	66.8	67.2	0.4
Employed	5,381	6,634	1,253	144,702	148,865	4,163
Employment–population ratio	18.0	20.8	2.8	62.6	64.7	2.1
Unemployed	697	595	-102	9,732	5,792	-3,940
Unemployment rate	11.5	8.2	-3.3	6.3	3.7	-2.6
Men, 16 to 64 years						
Civilian labor force	2,651	3,018	367	76,445	76,510	65
Participation rate	35.0	38.3	3.3	81.5	82.0	0.5
Employed	2,342	2,748	406	71,392	73,573	2,181
Employment–population ratio	30.9	34.9	4.0	76.1	78.9	2.8
Unemployed	310	270	-40	5,053	2,937	-2,116
Unemployment rate	11.7	8.9	-2.8	6.6	3.8	-2.8
Women, 16 to 64 years						
Civilian labor force	2,344	2,904	560	68,389	68,490	101
Participation rate	31.7	35.9	4.2	70.5	71.4	0.9
Employed	2,037	2,652	615	64,221	65,905	1,684
Employment–population ratio	27.5	32.7	5.2	66.2	68.7	2.5
Unemployed	307	252	-55	4,168	2,585	-1,583
Unemployment rate	13.1	8.7	-4.4	6.1	3.8	-2.3
Total, 65 years and older						
Civilian noninstitutional population	14,907	15,887	980	40,429	41,006	577
Civilian labor force	1,083	1,306	223	9,600	9,657	57
Participation rate	7.3	8.2	0.9	23.7	23.6	-0.1
Employed	1,003	1,233	230	9,089	9,387	298
Employment–population ratio	6.7	7.8	1.1	22.5	22.9	0.4
Unemployed	80	73	-7	511	271	-240
Unemployment rate	7.4	5.6	-1.8	5.3	2.8	-2.5

Note: A person with a disability has at least one of the following conditions: is deaf or has serious difficulty hearing; is blind or has serious difficulty seeing even when wearing glasses; has serious difficulty concentrating, remembering, or making decisions because of a physical, mental, or emotional condition; has serious difficulty walking or climbing stairs; has difficulty dressing or bathing; or has difficulty doing errands alone such as visiting a doctor's office or shopping because of a physical, mental, or emotional condition. Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Unemployment rate for foreign-born workers differed little from that of native-born workers

The foreign born accounted for 17.8 percent of the U.S. civilian labor force ages 16 years and older in the fourth quarter of 2021, up from 17.0 percent a year earlier. For the past few years, the unemployment rate for the foreign born has been slightly lower than the jobless rate for the native born; however, after the rates for both groups peaked in the second quarter of 2020, the jobless rate for the foreign born remained slightly above the rate for the native born for the rest of 2020 and the first half of 2021. At the end of 2021, the jobless rate for the foreign born, at 3.9 percent, and the rate for the native born, at 4.0 percent, were nearly the same.

The unemployment rate for foreign-born people decreased more over the year (down by 3.3 percentage points) than did the rate for native-born people (down by 2.3 percentage points). The foreign-born jobless rate increased sharply in 2020, partly because of the relatively high concentration of foreign-born workers in the leisure and hospitality industry, which was hit particularly hard by the COVID-19 pandemic. This industry's strong (though incomplete) recovery in 2021 may help explain the larger decrease in the foreign-born unemployment rate.[25]

The employment–population ratio for the foreign born increased by 3.3 percentage points over the year, rising to 62.9 percent in the fourth quarter of 2021, while the ratio for the native born increased by 1.5 percentage points, reaching 58.6 percent. (See table 11.)

Table 11. Employment status of the foreign- and native-born populations, by gender, quarterly averages, not seasonally adjusted, 2020–21 (levels in thousands)

Employment status and nativity	Total			Men			Women		
	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21	Fourth quarter 2020	Fourth quarter 2021	Change, fourth quarter 2020–21
Foreign born, 16 years and older									
Civilian noninstitutional population	42,523	43,890	1,367	20,442	21,386	944	22,081	22,503	422
Civilian labor force	27,314	28,740	1,426	15,692	16,575	883	11,623	12,165	542
Participation rate	64.2	65.5	1.3	76.8	77.5	0.7	52.6	54.1	1.5
Employed	25,340	27,628	2,288	14,712	15,999	1,287	10,628	11,630	1,002
Employment–population ratio	59.6	62.9	3.3	72.0	74.8	2.8	48.1	51.7	3.6
Unemployed	1,974	1,112	-862	979	576	-403	995	535	-460
Unemployment rate	7.2	3.9	-3.3	6.2	3.5	-2.7	8.6	4.4	-4.2
Native born, 16 years and older									
Civilian noninstitutional population	218,557	218,134	-423	105,852	105,390	-462	112,705	112,744	39
Civilian labor force	133,198	133,146	-52	69,322	69,044	-278	63,876	64,102	226
Participation rate	60.9	61.0	0.1	65.5	65.5	0.0	56.7	56.9	0.2
Employed	124,743	127,870	3,127	64,634	66,222	1,588	60,109	61,648	1,539
Employment–population ratio	57.1	58.6	1.5	61.1	62.8	1.7	53.3	54.7	1.4
Unemployed	8,455	5,276	-3,179	4,688	2,822	-1,866	3,767	2,454	-1,313
Unemployment rate	6.3	4.0	-2.3	6.8	4.1	-2.7	5.9	3.8	-2.1

Note: The foreign born are people residing in the United States who were not U.S. citizens at birth. That is, they were born outside the United States or one of its outlying areas, such as Puerto Rico or Guam, to parents who were not U.S. citizens. This group includes legally admitted immigrants, refugees, students, temporary workers, and undocumented immigrants. The survey data, however, do not separately identify the number of people in these categories. The native born are people who were born in the United States or one of its outlying areas, such as Puerto Rico or Guam, or who were born abroad of at least one parent who was a U.S. citizen.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

The labor force participation rate increased for both the native born and the foreign born. Foreign-born people continued to have a higher labor force participation rate than native-born people. The rate for the foreign born, at 65.5 percent in the fourth quarter of 2021, increased by 1.3 percentage points over the year. By way of comparison, the rate for the native born was about unchanged over the year, at 61.0 percent.

Share of workers who teleworked because of the pandemic decreased over the year

In May 2020, new questions were added to the CPS to help measure the impact of the COVID-19 pandemic on the labor market.[26] The questions gathered information on whether people teleworked because of the pandemic, whether people were unable to work because their employer closed or lost business because of the pandemic, whether they received pay for the time they were unable to work, and whether people were unable to look for work because of the pandemic.[27] (These data are not seasonally adjusted and are available as monthly estimates.) The share of the employed who teleworked because of the COVID-19 pandemic trended downward during the second half of 2020 and throughout 2021. In December of 2021, 11.1 percent of employed people teleworked or worked from home because of the pandemic. (See table 12.)

Table 12. Percentage of people who teleworked, were prevented from working, were paid for hours not worked, and did not look for work because of the COVID-19 pandemic, not seasonally adjusted, January–December 2021

Month	Teleworked[1]	Prevented from working[2]	Paid for hours not worked[3]	Did not look for work[4]
January	23.2	5.7	12.7	4.6
February	22.7	5.1	10.5	4.1
March	21.0	4.4	10.2	3.7
April	18.3	3.6	9.3	2.8
May	16.6	3.0	9.3	2.5
June	14.4	2.4	10.0	1.6
July	13.2	2.0	9.1	1.6
August	13.4	2.2	13.9	1.5
September	13.2	1.9	15.5	1.6
October	11.6	1.5	13.3	1.3
November	11.3	1.4	15.8	1.2
December	11.1	1.2	15.9	1.1

[1] People who teleworked or worked from home because of the coronavirus disease 2019 (COVID-19) pandemic in the 4 weeks prior to the survey. Only employed people are asked this question. This group does not include people whose telework was not related to the pandemic.

[2] People who were unable to work during the 4 weeks prior to the survey because their employer closed or lost business as a result of the COVID-19 pandemic.

[3] People who received pay from their employer for hours not worked in the 4 weeks prior to the survey. The question is asked of people who were unable to work because of the COVID-19 pandemic.

[4] People who were prevented from looking for work during the 4 weeks prior to the survey because of the COVID-19 pandemic. The question is asked of people who were not in the labor force at the time of the survey.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

In December 2021, 3.3 percent of workers ages 16 to 24 had teleworked in the 4 weeks prior to the survey because of the COVID-19 pandemic, compared with 13.0 percent of workers ages 25 to 54 and 10.2 percent of workers ages 55 years and older. Although some workers were able to continue to work remotely in 2021, telework was not a viable option for people who work in food preparation and serving-related occupations (who tend to be younger), and this was reflected in the data on COVID-19 pandemic-related telework. (See table 13.)

Table 13. Employed people who teleworked or worked at home for pay at any time in the 4 weeks prior to the survey because of the COVID-19 pandemic, by selected characteristics, December 2021 (levels in thousands)

Characteristic	December 2021				
	Total employed	People who teleworked because of the COVID-19 pandemic		Percent distribution	
		Total	Percent of total employed	Total employed	People who teleworked because of the COVID-19 pandemic
Total, 16 years and over	155,732	17,358	11.1	100.0	100.0
16 to 24 years	18,825	620	3.3	12.1	3.6
25 to 54 years	100,016	12,988	13.0	64.2	74.8
55 years and over	36,891	3,750	10.2	23.7	21.6
Total, 25 years and over	136,907	16,738	12.2	100.0	100.0
Less than a high school diploma	8,271	80	1.0	6.0	0.5
High school graduates, no college[1]	34,154	1,184	3.5	24.9	7.1
Some college or associate's degree	34,335	2,566	7.5	25.1	15.3
Bachelor's degree and higher[2]	60,147	12,908	21.5	43.9	77.1
Bachelor's degree only	37,052	7,268	19.6	27.1	43.4
Advanced degree	23,096	5,639	24.4	16.9	33.7

[1] This category includes people with a high school diploma or equivalent.

[2] This category includes people with bachelor's, master's, professional, and doctoral degrees.
Note: People who teleworked because of the coronavirus disease 2019 (COVID-19) pandemic are those who teleworked or worked at home for pay specifically because of the pandemic. This does not include those whose telework was unrelated to the pandemic, such as those who worked entirely from home before the pandemic began. Data are not seasonally adjusted.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

People with higher levels of educational attainment were more likely to telework because of the COVID-19 pandemic than were those with less education. This largely reflects the occupational and industry differences among these workers. In December 2021, among workers ages 25 years and older, 24.4 percent of people with an advanced degree and 19.6 percent of those with only a bachelor's degree had teleworked or worked from home because of the pandemic in the 4 weeks prior to the survey. By contrast, only 1.0 percent of people with less than a high school diploma had teleworked in the prior 4 weeks because of the pandemic.

In May 2020, 49.8 million people (19.2 percent of the population) reported that at some point during the 4 weeks prior to the survey they were unable to work because their employer closed or lost business because of the COVID-19 pandemic. This measure includes people whose hours had been reduced and those who did not work at all. By December 2021, the number of people unable to work because of the pandemic had decreased considerably, to 3.1 million, or 1.2 percent of the population ages 16 years and older.

People who could not work because of the COVID-19 pandemic were asked if they had received any pay from their employer for hours they did not work in the 4 weeks prior to the survey. In May 2020, 17.6 percent of those unable to work because of the pandemic received at least some pay for the hours they did not work. This estimate was slightly lower in December 2021 (15.9 percent).

People who were not in the labor force were asked if the COVID-19 pandemic had prevented them from looking for work in the previous 4 weeks. In May 2020, 9.7 million people did not look for work because of the pandemic. In December 2021, 1.1 million were prevented from looking for work, down by 3.4 million from a year earlier.

Median weekly earnings for full-time wage and salary workers increased in 2021, but at a considerably slower pace than inflation

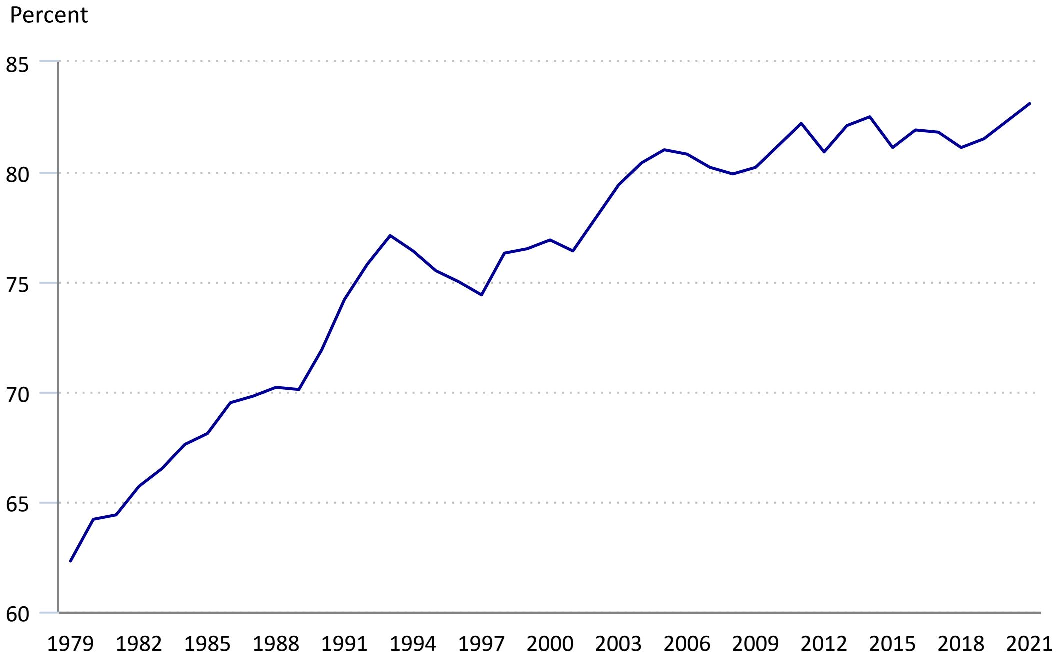
Median weekly earnings were $998 in 2021, up by 1.4 percent from 2020.[28] (Data are annual averages.) During the same period, inflation—as measured by the Consumer Price Index for All Urban Consumers (CPI-U)—increased by 4.7 percent. Real median usual weekly earnings (adjusted with the use of the CPI-U) showed a decline of 3.1 percent from 2020.[29] (See table 14.) Women's median weekly earnings increased more than those of men; however, changes in median weekly earnings during the year should be interpreted with caution because they continue to reflect the impact of the pandemic on the labor market.[30] Women's earnings increased by 2.4 percent over the year while men's earnings increased by 1.4 percent. The women's-to-men's earnings ratio edged up to 83.1 percent in 2021. In 1979, the first year for which comparable data on usual weekly earnings are available, women's earnings were 62.3 percent of men's earnings. (See chart 12.)

Table 14. Median usual weekly earnings of full-time wage and salary workers, by selected characteristics, annual averages, 2020–21

Characteristic	Current dollars			Constant (1982–84) dollars		
	2020	2021	Percent change, 2020–21	2020	2021	Percent change, 2020–21
Total, 16 years and older	$984	$998	1.4	$380	$368	-3.1
Men	1,082	1,097	1.4	418	405	-3.2
Women	891	912	2.4	344	337	-2.2
White	1,003	1,018	1.5	388	376	-3.1
Men	1,110	1,125	1.4	429	415	-3.2
Women	905	925	2.2	350	341	-2.4
Black or African American	794	801	0.9	307	296	-3.6
Men	830	825	-0.6	321	304	-5.1
Women	764	776	1.6	295	286	-3.0
Asian	1,310	1,328	1.4	506	490	-3.2
Men	1,447	1,453	0.4	559	536	-4.1
Women	1,143	1,141	-0.2	442	421	-4.7
Hispanic or Latino ethnicity	758	777	2.5	293	287	-2.1
Men	797	820	2.9	308	303	-1.7
Women	705	718	1.8	272	265	-2.7
Total, 25 years and older	1,029	1,057	2.7	398	390	-1.9
Less than a high school diploma	619	626	1.1	239	231	-3.4
High school graduate, no college	781	809	3.6	302	299	-1.1
Some college or associate's degree	903	925	2.4	349	341	-2.2
Bachelor's degree or higher	1,421	1,452	2.2	549	536	-2.4

Note: The Consumer Price Index for All Urban Consumers is used to convert current dollars to constant (1982–84) dollars.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Chart 12. Women's median usual weekly earnings as a percentage of men's, full-time wage and salary workers, annual averages, 1979–2021

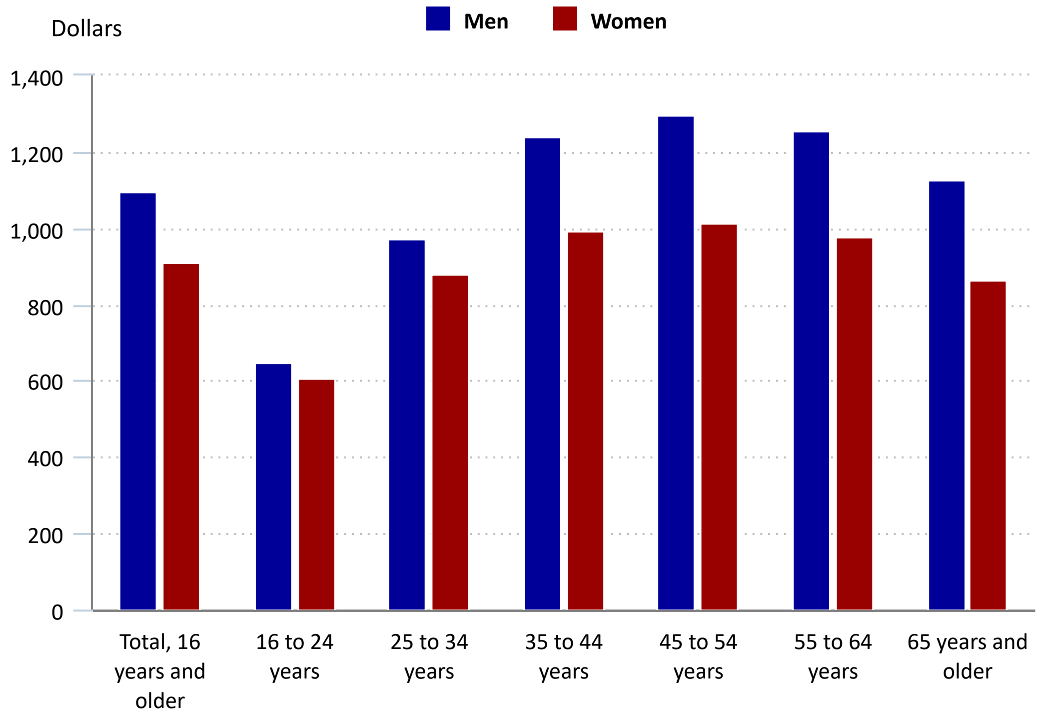


Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

For both men and women, earnings were lowest for those ages 16 to 24, followed by 25- to 34-year-olds. Median weekly earnings of those ages 35 to 64 ranged between $1,241 to $1,295 for men and $976 to $1,012 for women. The women's-to-men's earnings ratio was higher among younger workers than among older workers. For example, the ratio was 93.1 percent for 16- to 24-year-olds, compared with 78.1 percent among 45- to 54-year-olds. (See chart 13.)

Chart 13. Median usual weekly earnings of full-time wage and salary workers, by age and gender, annual averages, 2021



Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

View Chart Data

Among the major race and ethnicity groups, median weekly earnings increased for all groups. In 2021, earnings increased by 2.5 percent for Hispanics ($777), 1.5 percent for Whites ($1,018), 1.4 percent for Asians ($1,328), and 0.9 percent for Blacks ($801). The women's-to-men's earnings ratio varied by race and ethnicity; the ratio was higher among Blacks and Hispanics. White women earned 82.2 percent as much as their male counterparts, compared with 94.1 percent for Black women, 78.5 percent for Asian women, and 87.6 percent for Hispanic women.

Among workers ages 25 years and older, high school graduates with no college had the largest over-the-year increase in median weekly earnings compared with other educational attainment groups. Earnings for high school graduates rose by 3.6 percent, to $809 in 2021. (See table 14.)

Among the major occupational groups, people employed full time in management, professional, and related occupations had the highest median weekly earnings: $1,609 for men and $1,222 for women. As has historically been the case, men ($723) and women ($598) employed in service occupations earned the least in 2021. (See table 15.)

Table 15. Median usual weekly earnings of full-time wage and salary workers, by occupation and gender, annual averages, 2020–21

Occupation and gender	Number of workers (in thousands)		Median weekly earnings		
	2020	2021	2020	2021	Percent change, 2020–21
Total, 16 years and older	110,387	114,316	$984	$998	1.4
Management, professional, and related occupations	50,023	51,166	1,356	1,390	2.5
Management, business, and financial operations occupations	20,811	21,529	1,461	1,482	1.4
Professional and related occupations	29,213	29,637	1,270	1,335	5.1
Service occupations	13,771	14,630	621	644	3.7
Sales and office occupations	21,165	21,748	809	826	2.1
Sales and related occupations	8,958	9,281	880	887	0.8
Office and administrative support occupations	12,207	12,467	781	806	3.2
Natural resources, construction, and maintenance occupations	10,690	11,182	905	919	1.5
Farming, fishing, and forestry occupations	787	800	589	623	5.8
Construction and extraction occupations	5,826	6,171	906	904	-0.2
Installation, maintenance, and repair occupations	4,077	4,211	984	1,017	3.4
Production, transportation, and material moving occupations	14,738	15,590	746	774	3.8
Production occupations	6,820	7,107	775	809	4.4
Transportation and material moving occupations	7,917	8,483	719	738	2.6
Men, 16 years and older	60,911	62,928	1,082	1,097	1.4
Management, professional, and related occupations	24,090	24,561	1,578	1,609	2.0
Management, business, and financial operations occupations	11,082	11,231	1,667	1,672	0.3
Professional and related occupations	13,008	13,330	1,532	1,555	1.5
Service occupations	6,740	7,000	704	723	2.7
Sales and office occupations	8,435	8,677	956	970	1.5
Sales and related occupations	4,991	5,090	1,046	1,049	0.3
Office and administrative support occupations	3,445	3,587	868	899	3.6
Natural resources, construction, and maintenance occupations	10,152	10,635	917	930	1.4
Farming, fishing, and forestry occupations	600	651	608	637	4.8
Construction and extraction occupations	5,635	5,965	910	908	-0.2
Installation, maintenance, and repair occupations	3,917	4,019	991	1,023	3.2
Production, transportation, and material moving occupations	11,494	12,056	796	825	3.6
Production occupations	5,055	5,251	841	884	5.1
Transportation and material moving occupations	6,439	6,804	759	786	3.6
Women, 16 years and older	49,476	51,388	891	912	2.4
Management, professional, and related occupations	25,933	26,605	1,164	1,222	5.0
Management, business, and financial operations occupations	9,729	10,299	1,274	1,306	2.5
Professional and related occupations	16,204	16,306	1,121	1,167	4.1
Service occupations	7,032	7,630	574	598	4.2
Sales and office occupations	12,729	13,071	746	766	2.7
Sales and related occupations	3,967	4,191	715	720	0.7
Office and administrative support occupations	8,762	8,880	756	779	3.0
Natural resources, construction, and maintenance occupations	538	547	682	696	2.1
Farming, fishing, and forestry occupations	187	149	528	585	10.8
Construction and extraction occupations	191	207	796	720	-9.5
Installation, maintenance, and repair occupations	160	192	801	836	4.4
Production, transportation, and material moving occupations	3,243	3,535	614	638	3.9
Production occupations	1,765	1,856	630	653	3.7
Transportation and material moving occupations	1,478	1,679	600	624	4.0

Note: Updated population controls are introduced annually with the release of January data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey.

Summary

In summary, major employment and unemployment measures from the CPS continued to show improvement in 2021. The national unemployment rate trended down in each quarter of 2021, reaching 4.2 percent by the end of the year. The jobless rate decreased for men and women, as well as for all major race and ethnicity groups. The unemployment rate decreased among all occupations, with the sharpest decline in service occupations. The employment–population ratio increased by 1.8 percentage points, to 59.2 percent in the fourth quarter of 2021, while the labor force participation rate improved at a much slower pace, rising by 0.3 percentage point to reach 61.8 percent by the end of the year. The level of self-employment in nonagricultural industries increased throughout 2021. The percentage of people who teleworked because of the COVID-19 pandemic declined throughout 2021 and ended the year at 11.1 percent.

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Notes

[1] The Business Cycle Dating Committee of the National Bureau of Economic Research (NBER) is the official arbiter of the beginning and ending dates of recessions and expansions in the United States. According to NBER, the most recent economic peak occurred in February 2020, and a trough occurred in April 2020. Or, in terms of quarters, the economic peak occurred in the fourth quarter of 2019 and a trough occurred in the second quarter of 2020. For the quarterly analysis in this article, the NBER-designated quarterly dates are used. According to NBER, the "trough" of a recession marks the beginning of an expansion, and the "peak" of an expansion marks the beginning of a recession. The February–April 2020 recession was the shortest recession ever identified by NBER. For more information, see "U.S. business cycle expansions and contractions" (National Bureau of Economic Research, last updated July 19, 2021), https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions.

[2] For more information, see "Effects of COVID-19 pandemic on the Employment Situation news release and data" (U.S. Bureau of Labor Statistics, last modified January 7, 2022), https://www.bls.gov/covid19/effects-of-covid-19-pandemic-and-response-on-the-employment-situation-news-release.htm.

[3] Although data from the Current Population Survey (CPS) are published monthly, the data analyzed in this article are seasonally adjusted quarterly averages, and all over-the-year changes are comparisons of fourth-quarter 2020 data with fourth-quarter 2021 data, unless otherwise noted.

[4] In the CPS, unemployed people are defined as those ages 16 years and older who were not employed during the survey reference week, had actively searched for work during the 4 weeks prior to the survey, and were available for work. People who were on temporary layoff and available for work are counted as unemployed and do not have to have searched for work during the reference period.

[5] The U.S. Bureau of Labor Statistics (BLS) produces two sets of national employment estimates each month from two different surveys: the estimate of total nonfarm jobs, derived from the Current Employment Statistics survey, also known as the establishment or payroll survey; and the estimate of total civilian employment, based on the CPS, also called the household survey. The two surveys use different definitions of employment, as well as different survey and estimation methods. For more information on the two monthly employment measures, see "Comparing employment from the BLS household and payroll surveys," Labor Force Statistics from the Current Population Survey (U.S. Bureau of Labor Statistics, last modified February 4, 2022), https://www.bls.gov/web/empsit/ces_cps_trends.htm.

[6] The duration of joblessness is the length of time (through the current reference week) that people classified as unemployed have been looking for work. This measure refers to the duration of the current spell of unemployment, rather than to that of a completed spell. Data for 27 weeks or longer are seasonally adjusted. Data for 52 weeks or longer are not seasonally adjusted.

[7] Research suggests that, to some extent, the decrease in the number of long-term unemployed over the year can be explained by federal unemployment benefits that ended at the end of the third quarter of 2021, pushing down the number of long-term unemployed. For more information on the expiration of federal benefits, see Jim Tankersly and Ben Casselman, "Unemployment benefits expire for millions without pushback from Biden," *The New York Times*, September 6, 2021, https://www.nytimes.com/2021/09/06/business/economy/unemployment-benefits.html.

[8] For more information about duration of unemployment in 2020, see "36.9 percent of unemployed jobless 27 weeks or more as pandemic continues, November 2020," *The Economics Daily* (U.S. Bureau of Labor Statistics, December 9, 2020), www.bls.gov/opub/ted/2020/36-point-9-percent-of-unemployed-jobless-27-weeks-or-more-as-pandemic-continues-november-2020.htm.

[9] The CPS collects data on the different reasons that people are unemployed, including being on temporary layoff. Unemployed people on temporary layoff are those who (1) said they were laid off or were not at work during the survey reference week because of layoff (temporary or indefinite) or slack work or business conditions, (2) have been given a date to return or expect to be recalled within the next 6 months, and (3) could have returned to work if they had been recalled (except for those who had a temporary illness that prevented them from returning to work). Unlike other unemployed people, those on temporary layoff do not need to be actively looking for work to be classified as unemployed. Pay status is not part of the criteria for being classified as unemployed on temporary layoff. People absent from work because of temporary layoff are classified as unemployed on temporary layoff, whether or not they were paid during the time they were off work. Since March 2020, household survey interviewers have been instructed to classify employed people absent from work because of temporary, pandemic-related business closures or cutbacks as unemployed on temporary layoff. However, some workers affected by the pandemic who should have been classified as unemployed on temporary layoff were instead misclassified as employed but not at work. The share of responses that may have been misclassified was highest in the early months of the pandemic and has been considerably lower since. If the misclassified workers who were recorded as employed but not at work for the entire survey reference week had been classified as "unemployed on temporary layoff," the total number of unemployed people and the unemployment rate would have been higher than reported. For more information, see "Effects of COVID-19 pandemic on the Employment Situation news release and data," especially question 12, "Household survey: What is the misclassification issue?"

[10] Some research has suggested that the number of reentrants to the labor force will increase as the economy improves, as some workers who left the labor force during the coronavirus disease 2019 (COVID-19) pandemic may reenter the labor market. See, for example, Rakesh Kochhar and Jesse Bennett, "U.S. Labor market inches back from the COVID-19 shock, but recovery is far from complete" (Pew Research Center, April 14, 2021), https://www.pewresearch.org/fact-tank/2021/04/14/u-s-labor-market-inches-back-from-the-covid-19-shock-but-recovery-is-far-from-complete/.

[11] Beginning with data for January 2020, the CPS has classified occupations according to the 2018 Census occupational classification system, which is derived from the 2018 Standard Occupational Classification (SOC) system. The 2018 SOC system replaced the earlier 2010 Census occupational classification based on the 2010 SOC system, which was used in the CPS from January 2011 through December 2019. As a result of this change, CPS occupational data from January 2020 and later are not comparable with occupational data from earlier years. Although the names of the broad- and intermediate-level occupational groups in the 2018 SOC system remained the same, some detailed occupations were reclassified between the broader groups, which substantially affects data comparability over time. For example, within sales and office occupations, the office and administrative support occupations group is now smaller in scope. (The titles of the groups were unchanged.) Stock clerks and order fillers, which employed 1.5 million people in 2019, moved out of the broad group office and administrative support occupations and into transportation and material-moving occupations. Similarly, computer operators, which employed 72,000 people in 2019, moved out of office and administrative support occupations and into computer and mathematical occupations. In addition, within production, transportation, and material-moving occupations, the transportation and material-moving occupations group is now larger in scope because it includes stock clerks and order fillers. Finally, some detailed occupations were reclassified but remained in the same broad occupation category—within service occupations, for example, personal care aides, which employed 1.5 million people in 2019, moved from personal care and service occupations to healthcare support occupations. For more information, see "Industry and occupation classification" (U.S. Census Bureau, last revised October 8, 2021), https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/industry-and-occupation-classification.html.

[12] For more information, see Steven E. Haugen, "Measures of labor underutilization from the Current Population Survey," Working Paper 424 (U.S. Bureau of Labor Statistics, March 2009), https://www.bls.gov/osmr/research-papers/2009/pdf/ec090020.pdf. See also John E. Bregger and Steven E. Haugen, "BLS introduces new range of alternative unemployment measures," *Monthly Labor Review*, October 1995, https://www.bls.gov/opub/mlr/1995/10/art3full.pdf.

[13] For more information, see "Research series on labor force status flows from the Current Population Survey," Labor Force Statistics from the Current Population Survey (U.S. Bureau of Labor Statistics, last modified October 8, 2015), www.bls.gov/cps/cps_flows.htm.

[14] For more information, see Steven F. Hipple, "People who are not in the labor force: why aren't they working?" *Beyond the Numbers*, vol. 4, no. 15 (U.S. Bureau of Labor Statistics, December 2015), www.bls.gov/opub/btn/volume-4/people-who-are-not-in-the-labor-force-why-arent-they-working.htm.

[15] "People not in the labor force who want a job" is a measure of people who reported wanting a job without having necessarily looked for one; this group includes all people who responded "yes" to the question, "Do you currently want a job, either full or part time?"

[16] For more information on employment declines in the first year of the pandemic, see "Employment trends of Asians and Native Hawaiians and other Pacific Islanders," *Commissioner's Corner* (U.S. Bureau of Labor Statistics, May 24, 2021), https://blogs.bls.gov/blog/2021/05/24/employment-trends-of-asians-and-native-hawaiians-and-other-pacific-islanders/.

[17] For more information, see Alyssa Flowers and Andrew Van Dam, "The most unusual job market in modern American history, explained," *The Washington Post*, December 29, 2021, https://www.washingtonpost.com/business/2021/12/29/job-market-2021/.

[18] For more information, see Katia Dmitrieva and Jill R Shah, "These out-of-work Americans tell us job market turmoil is anything but transitory," *Bloomberg Businessweek*, October 14, 2021, https://www.bloomberg.com/news/features/2021-10-14/why-aren-t-out-of-work-americans-going-back-to-their-jobs.

[19] See Mark Wasson, "Rising wages draw teen workers across region," *West Central Tribune*, December 27, 2021, https://www.wctrib.com/business/rising-wages-draw-teen-workers-across-region.

[20] For more information on the "Great Resignation," see Andrew Van Dam "The latest twist in the 'Great Resignation': retiring but delaying Social Security," *The Washington Post*, November 1, 2021, https://www.washingtonpost.com/business/2021/11/01/latest-twist-great-resignation-retiring-delaying-social-security/. See also Peter Coy, "The pandemic prompted people to retire early. Will they return to work?," *The New York Times*, November 17, 2021, https://www.nytimes.com/2021/11/17/opinion/retirement-pandemic.html.

[21] For more on this issue, see Jeanna Smialek and David McCabe, "The luckiest workers in America? Teenagers," *The New York Times*, May 30, 2021, https://www.nytimes.com/2021/05/30/business/economy/pandemic-jobs-teenagers.html.

[22] Since the late 1940s, data on self-employment have been collected regularly as part of the CPS. In addition to classifying employment by occupation and industry, the CPS subdivides the employed by "class of worker"—that is, wage and salary employees, self-employed, and unpaid family workers. In 1967, it became possible to identify another group of self-employed workers: those who reported in the CPS they were self-employed and had incorporated their businesses. Individuals choose to incorporate their businesses for several reasons, including legal and tax considerations. Since 1967, the official estimates of self-employment published by BLS have included only the unincorporated self-employed. Although it is possible to identify the incorporated self-employed separately, these individuals are counted as wage and salary workers in the official statistics because, from a legal standpoint, they are employees of their own businesses. For more information, see Steven F. Hipple and Laurel A. Hammond, "Self-employment in the United States," *Spotlight on Statistics* (U.S. Bureau of Labor Statistics, March 2016), https://www.bls.gov/spotlight/2016/self-employment-in-the-united-states/.

[23] See Josh Mitchell and Kathryn Dill, "Workers quit jobs in droves to become their own bosses," *The Wall Street Journal*, November 29, 2021, https://www.wsj.com/articles/workers-quit-jobs-in-droves-to-become-their-own-bosses-11638199199. See also Eric Morath, "Millions are unemployed. Why can't companies find workers?," *The Wall Street Journal*, May 6, 2021, https://www.wsj.com/articles/millions-are-unemployed-why-cant-companies-find-workers-11620302440.

[24] BLS produces measures of people at work part time for economic and noneconomic reasons from the CPS. People at work part time for economic reasons, also referred to as involuntary part-time workers, include those who gave an economic reason when asked why they worked 1 to 34 hours during the reference week (the week including the 12th of the month). Economic reasons include the following: slack work, unfavorable business conditions, inability to find full-time work, and seasonal declines in demand. People who usually work part time and were at work part time during the reference week must indicate that they wanted and were available for full-time work to be classified as part time for economic reasons.

[25] See Rakesh Kochhar and Jesse Bennett, "Immigrants in the U.S. experienced higher unemployment in the pandemic but have closed the gap" (Pew Research Center, July 26, 2021), https://www.pewresearch.org/fact-tank/2021/07/26/immigrants-in-u-s-experienced-higher-unemployment-in-the-pandemic-but-have-closed-the-gap/.

[26] For more information about the effects of the COVID-19 pandemic on the labor market, see "Supplemental data measuring the effects of the coronavirus (COVID-19) pandemic on the labor market," Labor Force Statistics from the Current Population Survey (U.S. Bureau of Labor Statistics, last modified April 22, 2022), https://www.bls.gov/cps/effects-of-the-coronavirus-covid-19-pandemic.htm.

[27] People did not have to telework for the entire time that they worked to be counted among those who telework. People whose telework was not related to the COVID-19 pandemic, such as those who worked entirely from home before the pandemic, are not included in this measure.

[28] Data are annual averages and are in current dollars. The CPS data on earnings represent earnings before taxes and other deductions and include any overtime pay, commissions, or tips typically received. For multiple jobholders, only earnings received at their main job are included. Earnings reported on a nonweekly basis are converted to a weekly equivalent. The term "usual" reflects each survey respondent's understanding of the term. If the respondent asks for a definition of "usual," interviewers are instructed to define the term as more than half the weeks worked during the past 4 or 5 months. Wage and salary workers are defined as those who receive wages, salaries, commissions, tips, payment in kind, or piece rates. This definition includes both public- and private-sector employees but excludes all self-employed people, regardless of whether their businesses are incorporated or unincorporated. Earnings comparisons made in this article are on a broad level and do not control for many factors that help explain earnings differences, such as job skills and responsibilities, work experience, and specialization. Finally, full-time workers are those who usually work 35 hours or more per week at their main job.

[29] An unusually large increase in median weekly earnings occurred in the second quarter of 2020, but that reflected the precipitous declines in employment among lower paid workers (who were disproportionately affected by job loss related to the pandemic) compared with higher paid workers. When lower paid workers lost their jobs, they dropped out of the distribution of earnings, and this put upward pressure on the median (the midpoint of the earnings distribution). This large and abrupt shift in the earnings distribution during the year led to an increase in earnings in 2020; however, the underlying rate of growth in worker's earnings is difficult to discern because of the sudden and dramatic shift in the earnings distribution.

[30] The composition of the labor force and base effects help explain wage growth after the economy lost millions of jobs in April 2020. For more information, see Chair Cecilia Rouse and Martha Gimbel, "The pandemic's effect on measured wage growth," Council of Economic Advisors (White House, April 19, 2021), https://www.whitehouse.gov/cea/written-materials/2021/04/19/the-pandemics-effect-on-measured-wage-growth/.

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Job openings and quits reach record highs in 2021, layoffs and discharges fall to record lows

Estimates from the Job Openings and Labor Turnover Survey (JOLTS) highlighted large increases in job openings and quits throughout 2021. Job openings reached a series high in December 2021 of 11.4 million, and quits reached a series high in November of 4.5 million. By contrast, layoffs and discharges trended lower throughout 2021, reaching a series low of 1.3 million in December. The series lows followed the large increase in layoffs and discharges that occurred at the onset of the COVID-19 pandemic, when this measure reached a series high of 13.0 million in March 2020. The movement in these JOLTS estimates signaled a stronger demand for labor in 2021, following the February–April 2020 pandemic-induced recession.

The Job Openings and Labor Turnover Survey (JOLTS) estimates showed large increases in job openings and quits throughout 2021, despite the surge of two coronavirus disease 2019 (COVID-19) variants, Delta in the summer and Omicron at the end of the year. Layoffs and discharges declined throughout the year and reached a series low at the end of 2021. This article reviews the JOLTS estimates for 2021 at the total nonfarm, industry, and regional levels.[1] (For definitions of JOLTS terms, see the box that follows.)

Definitions of JOLTS terms

Job openings

Job openings include all positions that are open on the last business day of the reference month. A job is open only if it meets the following three conditions: (1) a specific position exists and there is work available for that position; the position can be full time or part time, and it can be permanent, short term, or seasonal; (2) the job could start within 30 days, whether or not the employer can find a suitable candidate during that time; and (3) the employer is actively recruiting workers from outside the establishment to fill the position; active recruiting means that the establishment is taking steps to fill a position and may include advertising in newspapers, on television, or on the radio; posting Internet notices, posting "help wanted" signs, networking or making "word-of-mouth" announcements; accepting applications; interviewing candidates; contacting employment agencies; or soliciting employees at job fairs, state or local employment offices, or similar sources.

Excluded are positions open only to internal transfers, promotions or demotions, or recalls from layoffs. Also excluded are openings for positions with start dates more than 30 days in the future; positions for which employees have been hired but not yet reported for work; and positions to be filled by employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

Hires

Hires include all additions to the payroll during the entire reference month, including newly hired and rehired employees; full-time and part-time employees; permanent, short-term, and seasonal employees; employees who were recalled to a job at the location following a layoff (formal suspension from pay status) lasting more than 7 days; on-call or intermittent employees who returned to work after having been formally separated; workers who were hired and separated during the month; and transfers from other locations.

Excluded are transfers or promotions within the reporting location; employees returning from a strike; and employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

Separations

Separations include all separations from the payroll during the entire reference month and are reported by type of separation: quits, layoffs and discharges, and other separations. Quits include employees who left voluntarily, except for retirements or transfers to other locations. Layoffs and discharges include involuntary separations initiated by the employer, including layoffs with no intent to rehire; layoffs (formal suspensions from pay status) lasting or expected to last more than 7 days; discharges resulting from mergers, downsizing, or closings; firings or other discharges for cause; terminations of permanent or short-term employees; and terminations of seasonal employees (whether or not they are expected to return the next season). Other separations include retirements, transfers to other locations, separations due to employee disability, and deaths.

Excluded are transfers within the same location; employees on strike; and employees of temporary help agencies, employee leasing companies, outside contractors, or consultants.

Job openings

The job openings level is an indicator for the demand for labor between employers and potential employees. An increase in job openings signals that employers are in need of additional employees. This signal is further confirmed by the relationship between job openings and employment, as the two measures tend to increase and decrease together.

The job openings level can also be a sign of shifts in the economy and often increases when approaching an economic expansion or decreases when approaching an economic contraction.[2]

Over-the-month estimates show that job openings continued to increase throughout 2021 after the large decline in the spring of 2020 as a result of the February–April 2020 economic recession.[3] From December 2020 to December 2021, job openings increased by 67.0 percent to a not seasonally adjusted level of 10.4 million.[4] (See table 1.)

Table 1. Change in level and percentage of job openings, by industry and region, not seasonally adjusted, December 2019–December 2021 (levels in thousands)

Industry and region	Level by month and year			Change, December 2019–December 2021		Change, December 2019–December 2021	
	December 2019	December 2020	December 2021	Level	Percent	Level	Percent
Total nonfarm	6,060	6,204	10,353	144	2.4	4,149	66.9
Industry							
Total private	5346	5557	9313	211	3.9	3,756	67.6
Mining and logging	11	13	31	2	18.2	18	138.5
Construction	208	211	301	3	1.4	90	42.7
Manufacturing	353	443	725	90	25.5	282	63.7
Durable goods	211	261	413	50	23.7	152	58.2
Nondurable goods	143	183	313	40	28.0	130	71.0
Trade, transportation, and utilities	1,073	1,120	1,755	47	4.4	635	56.7
Wholesale trade	169	164	256	-5	-3.0	92	56.1
Retail trade	640	665	916	25	3.9	251	37.7
Transportation, warehousing, and utilities	264	291	583	27	10.2	292	100.3
Information	136	119	242	-17	-12.5	123	103.4
Financial activities	316	275	448	-41	-13.0	173	62.9
Finance and insurance	229	218	334	-11	-4.8	116	53.2
Real estate and rental and leasing	88	57	114	-31	-35.2	57	100.0
Professional and business services	1,056	1,356	1,863	300	28.4	507	37.4
Education and health services	1,188	1,217	2,083	29	2.4	866	71.2
Educational services	103	75	197	-28	-27.2	122	162.7
Healthcare and social assistance	1,085	1,142	1,886	57	5.3	744	65.1
Leisure and hospitality	748	609	1,516	-139	-18.6	907	148.9
Arts, entertainment, and recreation	108	50	144	-58	-53.7	94	188.0
Accommodation and food services	640	559	1,371	-81	-12.7	812	145.3
Other services	256	192	350	-64	-25.0	158	82.3
Government	714	647	1,040	-67	-9.4	393	60.7
Federal	85	87	153	2	2.4	66	75.9
State and local	629	561	887	-68	-10.8	326	58.1
Education	220	194	320	-26	-11.8	126	64.9
Excluding education	409	367	567	-42	-10.3	200	54.5
Region							
Northeast	1,064	1,027	1,817	-37	-3.5	790	76.9
South	2272	2,491	3,899	219	9.6	1,408	56.5
Midwest	1,258	1,333	2,264	75	6.0	931	69.8
West	1,467	1,353	2,374	-114	-7.8	1,021	75.5

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Job openings by industry

During 2021, the monthly job openings level for 16 of 19 industries reached an all-time series high. The three industries with the most job openings were professional and business services, at 2.0 million in October; healthcare and social assistance, at 2.0 million in December; and accommodation and food services, at 1.8 million in December. (See table 2.)

Table 2. Monthly series highs by industry and region, seasonally adjusted, 2021 (in thousands)

Data element	Industry and region	Month	Level
Industry			
Job openings	Durable goods	September	560
Job openings	Nondurable goods	October	394
Job openings	Wholesale trade	October	345
Job openings	Retail trade	August	1,177
Job openings	Transportation, warehousing, and utilities	December	611
Job openings	Information	December	232
Job openings	Finance and insurance	November	372
Job openings	Real estate and rental and leasing	July	192
Job openings	Professional and business services	October	2,043
Job openings	Educational services	December	217
Job openings	Healthcare and social assistance	December	1,970
Job openings	Arts, entertainment, and recreation	July	257
Job openings	Accommodation and food services	December	1,785
Job openings	Other services	May	466
Job openings	State and local government education	December	361
Job openings	State and local government, excluding education	September	580
Hires	Finance and insurance	September	224
Hires	Professional and business services	July	1,325
Hires	Educational services	January	125
Hires	State and local government education	June	211
Quits	Durable goods	November	185
Quits	Wholesale trade	August	145
Quits	Retail trade	December	786
Quits	Transportation, warehousing, and utilities	April	200
Quits	Professional and business services	November	834
Quits	Healthcare and social assistance	November	626
Quits	Accommodation and food services	November	813
Quits	State and local government, excluding education	November	119
Other separations	Finance and insurance	September	65
Other separations	Professional and business services	June	118
Region			
Job openings	Northeast	December	1,923
Job openings	South	December	4,330
Job openings	Midwest	December	2,530
Job openings	West	December	2,664
Quits	Northeast	November	608
Quits	South	November	1,883
Quits	Midwest	November	1,008
Quits	West	November	1,010

Source: U.S. Bureau of Labor Statistics.

Job openings increased over the year from December 2020 to December 2021 in all 19 JOLTS industrial supersectors and total nonfarm. The largest over-the-year increases in job openings occurred in arts, entertainment, and recreation (+188.0 percent); educational services (+162.7 percent); and accommodation and food services (+145.3 percent).

Job openings by region

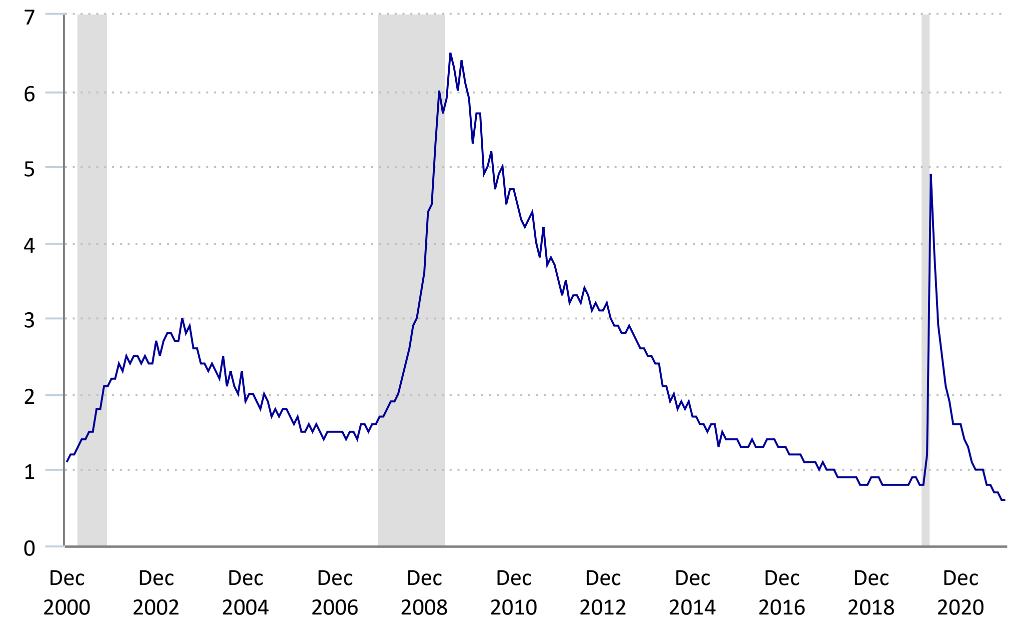
All four census regions reached series highs for job openings in December 2021. The Northeast series high was 2.0 million, the South was 4.3 million, the Midwest was 2.5 million, and the West was 2.7 million. (See table 2.) Comparing December 2020 and December 2021, job openings increased less in the South (+56.5 percent) than in the Midwest (+69.8 percent), the West (+75.5 percent), and the Northeast (+76.9 percent). (See table 1.)

Job openings and unemployment

One way to evaluate the number of job openings is to compare it with the number of unemployed people, published by the Current Population Survey. These measures tend to move in opposite directions. This relationship can be explored by dividing the number of unemployed by the number of job openings. This creates a measure referred to as the number of unemployed people per job openings ratio. If the resulting ratio is high, it indicates a high level of unemployed and a low level of job openings. The relationship between unemployed people and job openings is a useful comparison and can often signal times of economic expansion or contraction.

At the beginning of 2021, the unemployed people per job openings ratio was 1.4, continuing a decline that started after the recent high of 4.9 in April 2020. The ratio continued to steadily decline, falling to 1.0 in April 2021. The ratio remained unchanged until July before resuming the downward trend. Unemployed people per job opening fell to the lowest ratio in the history of the JOLTS series at 0.6 in November and December. The decline in the ratio reflects both the increase in job openings throughout the year and a decrease in the number of unemployed. (See chart 1.)

Chart 1. Ratio of unemployed persons to job opening, total nonfarm, seasonally adjusted, December 2000–December 2021



Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics, Current Population Survey and Job Openings and Labor Turnover Survey.

View Chart Data

Hires

The total number of annual hires increased to a level of 75.6 million in 2021 (+4.0 percent), compared with 2019, during which the annual hires level increased to 72.6 million (+3.9 percent). The increase in 2021 marked the 12th consecutive year in which the annual hires level increased. (See table 3.)

Table 3. Change in level and percentage of annual hires, by industry and region, not seasonally adjusted, 2019–21 (levels in thousands)

Industry and region	Level by year			Change, 2019–20		Change, 2020–21	
	2019	2020	2021	Level	Percent	Level	Percent
Total	69,911	72,635	75,550	2,724	3.9	2,915	4.0
Industry							
Total private	65,505	68,451	71,164	2,946	4.5	2,713	4.0
Mining and logging	304	199	237	-105	-34.5	38	19.1
Construction	4,994	4,984	4,357	-10	-0.2	-627	-12.6
Manufacturing	4,052	4,810	5,271	758	18.7	461	9.6
Durable goods	2,271	2,750	2,937	479	21.1	187	6.8
Nondurable goods	1,780	2,061	2,335	281	15.8	274	13.3
Trade, transportation, and utilities	13,889	15,436	16,118	1,547	11.1	682	4.4
Wholesale trade	1,776	1,815	2,053	39	2.2	238	13.1
Retail trade	9,011	9,822	10,391	811	9.0	569	5.8
Transportation, warehousing, and utilities	3,099	3,799	3,673	700	22.6	-126	-3.3
Information	1,135	978	1,304	-157	-13.8	326	33.3
Financial activities	2,653	2,660	2,659	7	0.3	-1	0.0
Finance and insurance	1,683	1,667	1,762	-16	-1.0	95	5.7
Real estate and rental and leasing	971	994	897	23	2.4	-97	-9.8
Professional and business services	13,785	13,419	14,771	-366	-2.7	1,352	10.1
Education and health services	8,650	9,365	9,374	715	8.3	9	0.1
Educational services	1,160	1,133	1,241	-27	-2.3	108	9.5
Healthcare and social assistance	7,494	8,232	8,132	738	9.8	-100	-1.2
Leisure and hospitality	13,432	13,565	14,227	133	1.0	662	4.9
Arts, entertainment, and recreation	1,998	1,640	1,960	-358	-17.9	320	19.5
Accommodation and food services	11,434	11,925	12,267	491	4.3	342	2.9
Other services	2,605	3,033	2,849	428	16.4	-184	-6.1
Government	4,403	4,185	4,385	-218	-5.0	200	4.8
Federal	503	887	522	384	76.3	-365	-41.1
State and local	3,904	3,297	3,860	-607	-15.5	563	17.1
Education	2,013	1,647	2,075	-366	-18.2	428	26.0
Excluding education	1,890	1,649	1,787	-241	-12.8	138	8.4
Region							
Northeast	10,853	11,653	11,366	800	7.4	-287	-2.5
South	28,247	28,003	30,619	-244	-0.9	2,616	9.3
Midwest	14,878	15,810	16,479	932	6.3	669	4.2
West	15,930	17,168	17,084	1,238	7.8	-84	-0.5

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Hires by industry

Annual hires increased in 13 of 19 industry supersectors and in total nonfarm in 2021 and decreased in 6 industries. The largest percentage increases in the annual hires levels were in information (+33.3 percent); state and local government education (+26.0 percent); and arts, entertainment, and recreation (+19.5 percent). The largest percentage decreases in hires occurred in federal government (−41.1 percent),[5] construction (−12.6 percent), and real estate and rental and leasing (−9.8 percent). (See table 3.) Seven industries experienced annual series highs for the level of hires in 2021. Hires in professional and business services peaked at 14.8 million, accommodation and food services peaked at 12.3 million, and retail trade peaked at 10.4 million. (See table 4.)

Table 4. Annual series highs, by industry and region, not seasonally adjusted, 2021 (in thousands)

Data element	Industry and region	Level
	Industry	
Hires	Durable goods	2,937
Hires	Nondurable goods	2,335
Hires	Retail trade	10,391
Hires	Professional and business services	14,771
Hires	Educational services	1,241
Hires	Accommodation and food services	12,267
Hires	State and local government education	2,075
Quits	Durable goods	1,885
Quits	Nondurable goods	1,572
Quits	Wholesale trade	1,334
Quits	Retail trade	7,792
Quits	Transportation, warehousing, and utilities	2,077
Quits	Professional and business services	8,597
Quits	Healthcare and social assistance	6,115
Quits	Accommodation and food services	8,574
Quits	State and local government, excluding education	1,101
Other separations	Finance and insurance	346
	Region	
Hires	South	30,619
Hires	Midwest	16,479
Quits	Northeast	6,387
Quits	South	20,192
Quits	Midwest	10,541
Quits	West	10,708
Source: U.S. Bureau of Labor Statistics.		

As the nation's economy continued to recover from the 2020 recession, four industries experienced seasonally adjusted monthly series highs in hires in 2021. The four industries were professional and business services (1.3 million in July), finance and insurance (224,000 in September), state and local government education (211,000 in June), and educational services (125,000 in January). (See table 2.)

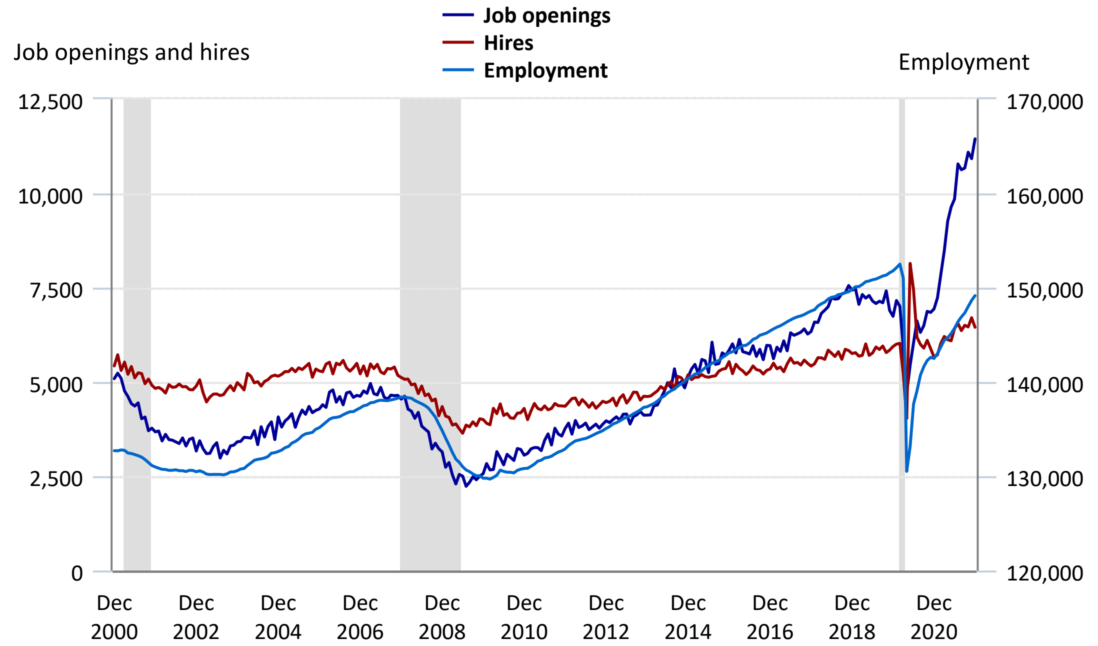
Hires by region

In percentage terms, annual hires increased in 2021 by 9.3 percent in the South and by 4.2 percent in the Midwest, while hires in the Northeast and West declined by 2.5 and 0.5 percent, respectively. This differs from the pattern of regional hires in 2020, when the West had the greatest percentage increase in annual hires of 7.8 percent. This was followed by the Northeast (+7.4 percent) and the Midwest (+6.3 percent). The South (-0.9 percent) declined in 2020. (See table 3.). None of the regions experienced monthly series highs for hires.

Hires and job openings

In January 2021, job openings reached a level of 7.2 million, following increases after the February–April 2020 recession. Job openings continued to increase throughout 2021, reaching a series high in December 2021 of 11.4 million. While hires trended in a similar direction as job openings, the increases were less dramatic. Given the larger increases in job openings compared with hires, the difference between the two data elements reached its largest amount ever in the JOLTS series history, at 5.0 million in December. (See chart 2.)

Chart 2. Job openings, hires, and employment, total nonfarm, seasonally adjusted, December 2000–December 2021 (in thousands)



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

View Chart Data

Total separations

After annual total separations rose to an all-time JOLTS series high in 2020 because of the COVID-19 pandemic, figures in 2021 more closely resembled previous years. Total separations remained consistent as 2021 progressed, with the lowest level recorded in January (5.2 million) and the highest level recorded in November (6.2 million). Compared with 2020, annual total separations in 2021 fell from 80.8 million to 69.0 million, a decrease of 14.5 percent. However, the annual level for 2021 is still 1.4 percent higher than the level of 68.1 million in 2019. (See table 5.)

Table 5. Change in level and percentage of annual total separations, by industry and region, not seasonally adjusted, 2019–21 (levels in thousands)

Industry and region	Level by year			Change, 2019–20		Change, 2020–21	
	2019	2020	2021	Level	Percent	Level	Percent
Total	68,097	80,778	69,045	12,681	18.6	-11,733	-14.5
Industry							
Total private	63,852	75,642	65,055	11,790	18.5	-10,587	-14.0
Mining and logging	352	332	205	-20	-5.7	-127	-38.3
Construction	4,870	4,970	4,216	100	2.1	-754	-15.2
Manufacturing	4,046	5,378	4,923	1,332	32.9	-455	-8.5
Durable goods	2,296	3,158	2,713	862	37.5	-445	-14.1
Nondurable goods	1,748	2,219	2,209	471	26.9	-10	-0.5
Trade, transportation, and utilities	13,722	16,108	15,096	2,386	17.4	-1,012	-6.3
Wholesale trade	1,742	2,105	1,904	363	20.8	-201	-9.5
Retail trade	9,124	10,345	9,945	1,221	13.4	-400	-3.9
Transportation, warehousing, and utilities	2,854	3,654	3,249	800	28.0	-405	-11.1
Information	1,101	1,172	1,101	71	6.4	-71	-6.1
Financial activities	2,491	2,729	2,505	238	9.6	-224	-8.2
Finance and insurance	1,584	1,636	1,716	52	3.3	80	4.9
Real estate and rental and leasing	909	1,091	788	182	20.0	-303	-27.8
Professional and business services	13,512	13,931	13,644	419	3.1	-287	-2.1
Education and health services	8,068	10,364	8,823	2,296	28.5	-1,541	-14.9
Educational services	1,117	1,466	915	349	31.2	-551	-37.6
Healthcare and social assistance	6,951	8,897	7,908	1,946	28.0	-989	-11.1
Leisure and hospitality	13,146	17,071	11,968	3,925	29.9	-5,103	-29.9
Arts, entertainment, and recreation	1,960	2,262	1,510	302	15.4	-752	-33.2
Accommodation and food services	11,187	14,807	10,458	3,620	32.4	-4,349	-29.4
Other services	2,543	3,588	2,573	1,045	41.1	-1,015	-28.3
Government	4,245	5,138	3,991	893	21.0	-1,147	-22.3
Federal	469	825	544	356	75.9	-281	-34.1
State and local	3,774	4,312	3,444	538	14.3	-868	-20.1
Education	1,959	2,434	1,622	475	24.2	-812	-33.4
Excluding education	1,816	1,879	1,822	63	3.5	-57	-3.0
Region							
Northeast	10,405	13,497	10,040	3,092	29.7	-3,457	-25.6
South	27,046	30,200	28,429	3,154	11.7	-1,771	-5.9
Midwest	14,420	17,956	15,115	3,536	24.5	-2,841	-15.8
West	16,223	19,129	15,462	2,906	17.9	-3,667	-19.2

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Total separations include quits, layoffs and discharges, and other separations. Each of these data elements has its own unique trend and cyclical movements. Quits are procyclical, which means that the number of quits typically rises when the economy expands and declines when the economy contracts.

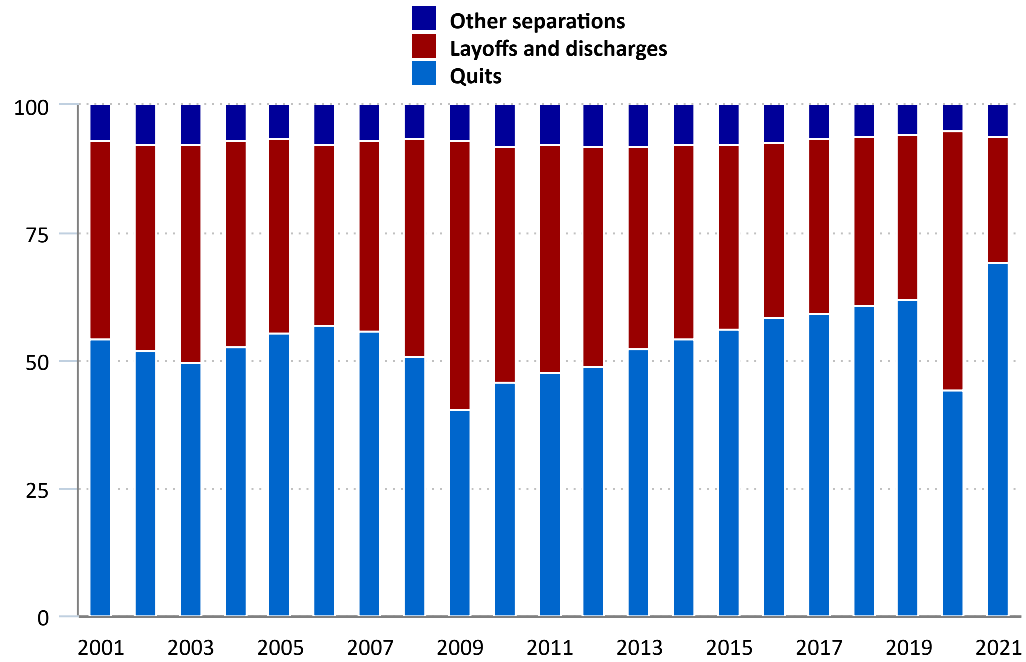
In 2021, quits reached new series highs for both monthly and annual levels. The first new series high was recorded in March 2021 with 3.7 million quits, and that level continued to trend upward, reaching a peak of 4.5 million in November. The annual total of 47.8 million surpassed the annual level for 2020 of 35.9 million by 33 percent and is a new series high. The previous series high of 42.2 million quits was set in 2019.

Layoffs and discharges are countercyclical, which means that the estimates typically rise during economic contractions and fall during economic expansions. Layoffs and discharges levels reached historic lows in 2021. After recording the first new series low of 1.5 million in March, the level continued to trend downward, and reached its bottom in December with 1.3 million. The annual total of 17.0 million is a new series low and contrasts greatly with the series high of 40.8 million recorded in 2020. The previous series low was in 2013 at 21.0 million, and layoffs and discharges levels rose every year from 2016 through 2020.

In 2021, monthly other separations—which include retirements and transfers—increased as the year progressed. The lowest monthly level was recorded in January, at 278,000, matching the series low set in May 2009. The largest monthly level came in June, at 397,000. The annual total of 4.2 million marks the third consecutive year that annual other separations have increased and is the highest annual level since the 4.4 million recorded in 2016.

Chart 3 shows the relationship of the three components of total separations by displaying the percentage of total separations attributed to each type of separation. Quits as a percentage of total separations increased to 69.3 percent in 2021, the highest share ever recorded. Layoffs and discharges as a percentage of total separations decreased to 24.6 percent in 2021, the lowest share ever recorded. Other separations as a percentage of total separations increased to 6.1 percent in 2021 after a series low of 5.1 percent in 2020.

Chart 3. Percentage of components for total separations, total nonfarm, not seasonally adjusted, 2001–21



Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

The number of annual quits rose considerably, from 35.9 million in 2020 to 47.8 million in 2021, for an increase of 33 percent. (See table 6.) The annual quits level has increased in 11 of the past 12 years, with 2020 being the only exception in that span. Annual layoffs and discharges fell notably, from 40.8 million in 2020 to 17.0 million in 2021, for a decrease of 58.3 percent. (See table 7.) The annual level of other separations rose, from 4.1 million in 2020 to 4.2 million in 2021, for an increase of 2.3 percent. (See table 8.)

Table 6. Change in level and percentage of annual quits, by industry and region, not seasonally adjusted, 2019–21 (levels in thousands)

Industry and region	Level by year			Change, 2019–20		Change, 2020–21	
	2019	2020	2021	Level	Percent	Level	Percent
Total	42,193	35,870	47,825	-6,323	-15.0	11,955	33.3
Industry							
Total private	39,951	33,535	45,456	-6,416	-16.1	11,921	35.5
Mining and logging	179	106	117	-73	-40.8	11	10.4
Construction	2,083	1,597	2,198	-486	-23.3	601	37.6
Manufacturing	2,492	2,347	3,457	-145	-5.8	1,110	47.3
Durable goods	1,396	1,274	1,885	-122	-8.7	611	48.0
Nondurable goods	1,092	1,070	1,572	-22	-2.0	502	46.9
Trade, transportation, and utilities	8,916	8,313	11,204	-603	-6.8	2,891	34.8
Wholesale trade	1,029	1,002	1,334	-27	-2.6	332	33.1
Retail trade	6,236	5,650	7,792	-586	-9.4	2,142	37.9
Transportation, warehousing, and utilities	1,650	1,661	2,077	11	0.7	416	25.0
Information	553	444	626	-109	-19.7	182	41.0
Financial activities	1,546	1,314	1,565	-232	-15.0	251	19.1
Finance and insurance	1,004	903	1,045	-101	-10.1	142	15.7
Real estate and rental and leasing	544	410	522	-134	-24.6	112	27.3
Professional and business services	7,768	6,639	8,597	-1,129	-14.5	1,958	29.5
Education and health services	5,537	5,370	6,728	-167	-3.0	1,358	25.3
Educational services	648	486	613	-162	-25.0	127	26.1
Healthcare and social assistance	4,888	4,882	6,115	-6	-0.1	1,233	25.3
Leisure and hospitality	9,242	6,361	9,413	-2,881	-31.2	3,052	48.0
Arts, entertainment, and recreation	941	538	843	-403	-42.8	305	56.7
Accommodation and food services	8,301	5,824	8,574	-2,477	-29.8	2,750	47.2
Other services	1,634	1,046	1,552	-588	-36.0	506	48.4
Government	2,243	2,337	2,372	94	4.2	35	1.5
Federal	209	236	260	27	12.9	24	10.2
State and local	2,033	2,101	2,109	68	3.3	8	0.4
Education	1,108	1,191	1,009	83	7.5	-182	-15.3
Excluding education	927	909	1,101	-18	-1.9	192	21.1
Region							
Northeast	5,706	4,797	6,387	-909	-15.9	1,590	33.1
South	17,273	15,213	20,192	-2,060	-11.9	4,979	32.7
Midwest	9,199	8,005	10,541	-1,194	-13.0	2,536	31.7
West	10,013	7,856	10,708	-2,157	-21.5	2,852	36.3

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Table 7. Change in level and percentage of annual layoffs and discharges by industry and region, not seasonally adjusted, 2019–21 (levels in thousands)

Industry and region	Level			Change, 2019–20		Change, 2020–21	
	2019	2020	2021	Level	Percent	Level	Percent
Total	21,893	40,801	17,019	18,908	86.4	-23782	-58.3
Industry							
Total private	20,639	38,911	16,137	18272	88.5	-22774	-58.5
Mining and logging	154	206	73	52	33.8	-133	-64.6
Construction	2,587	3,221	1,863	634	24.5	-1358	-42.2
Manufacturing	1,311	2,754	1,183	1443	110.1	-1571	-57.0
Durable goods	748	1,721	646	973	130.1	-1075	-62.5
Nondurable goods	563	1,032	536	469	83.3	-496	-48.1
Trade, transportation, and utilities	4,058	7,162	3,238	3104	76.5	-3924	-54.8
Wholesale trade	611	1,029	472	418	68.4	-557	-54.1
Retail trade	2,421	4,368	1,781	1947	80.4	-2587	-59.2
Transportation, warehousing, and utilities	1,027	1,762	987	735	71.6	-775	-44.0
Information	464	662	367	198	42.7	-295	-44.6
Financial activities	640	1,110	537	470	73.4	-573	-51.6
Finance and insurance	319	494	328	175	54.9	-166	-33.6
Real estate and rental and leasing	317	614	211	297	93.7	-403	-65.6
Professional and business services	5,045	6,466	4,170	1421	28.2	-2296	-35.5
Education and health services	2,037	4,473	1,602	2436	119.6	-2871	-64.2
Educational services	404	925	246	521	129.0	-679	-73.4
Healthcare and social assistance	1,635	3,549	1,357	1914	117.1	-2192	-61.8
Leisure and hospitality	3,570	10,412	2,219	6842	191.7	-8193	-78.7
Arts, entertainment, and recreation	982	1,693	628	711	72.4	-1065	-62.9
Accommodation and food services	2,587	8,719	1,590	6132	237.0	-7129	-81.8
Other services	767	2,443	885	1676	218.5	-1558	-63.8
Government	1,257	1,892	882	635	50.5	-1010	-53.4
Federal	121	436	121	315	260.3	-315	-72.2
State and local	1,137	1,455	759	318	28.0	-696	-47.8
Education	556	821	373	265	47.7	-448	-54.6
Excluding education	579	631	385	52	9.0	-246	-39.0
Region							
Northeast	3,977	8,045	2,950	4068	102.3	-5095	-63.3
South	8,264	13,472	6,611	5208	63.0	-6861	-50.9
Midwest	4,426	9,089	3,688	4663	105.4	-5401	-59.4
West	5,230	10,195	3,770	4965	94.9	-6425	-63.0

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Table 8. Change in level and percentage of annual other separations, by industry and region, not seasonally adjusted, 2019–21 (levels in thousands)

Industry and region	Level			Change, 2019–20		Change, 2020–21	
	2019	2020	2021	Level	Percent	Level	Percent
Total	4,006	4,105	4,199	99	2.5	94	2.3
Industry							
Total private	3,263	3,194	3,462	-69	-2.1	268	8.4
Mining and logging	17	19	16	2	11.8	-3	-15.8
Construction	202	153	158	-49	-24.3	5	3.3
Manufacturing	244	278	283	34	13.9	5	1.8
Durable goods	152	165	182	13	8.6	17	10.3
Nondurable goods	89	114	102	25	28.1	-12	-10.5
Trade, transportation, and utilities	748	632	657	-116	-15.5	25	4.0
Wholesale trade	101	76	98	-25	-24.8	22	28.9
Retail trade	467	325	374	-142	-30.4	49	15.1
Transportation, warehousing, and utilities	177	232	184	55	31.1	-48	-20.7
Information	85	66	110	-19	-22.4	44	66.7
Financial activities	303	308	400	5	1.7	92	29.9
Finance and insurance	260	240	346	-20	-7.7	106	44.2
Real estate and rental and leasing	44	68	55	24	54.5	-13	-19.1
Professional and business services	699	827	877	128	18.3	50	6.0
Education and health services	494	522	493	28	5.7	-29	-5.6
Educational services	64	55	59	-9	-14.1	4	7.3
Healthcare and social assistance	427	466	433	39	9.1	-33	-7.1
Leisure and hospitality	333	296	336	-37	-11.1	40	13.5
Arts, entertainment, and recreation	36	28	41	-8	-22.2	13	46.4
Accommodation and food services	295	263	298	-32	-10.8	35	13.3
Other services	143	98	136	-45	-31.5	38	38.8
Government	743	910	735	167	22.5	-175	-19.2
Federal	139	151	163	12	8.6	12	7.9
State and local	603	756	575	153	25.4	-181	-23.9
Education	294	420	241	126	42.9	-179	-42.6
Excluding education	309	337	336	28	9.1	-1	-0.3
Region							
Northeast	723	645	698	-78	-10.8	53	8.2
South	1,507	1,525	1,636	18	1.2	111	7.3
Midwest	796	861	888	65	8.2	27	3.1
West	982	1,073	981	91	9.3	-92	-8.6

Note: Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics.

Components of separations by industry

Separations are the total number of employees separated from their employer at any time during the reference month. Separations consist of quits, layoffs and discharges, and other separations. This section discusses what happened in 2021 with the components of separations by industry.

Quits

Quits include employees who left their job voluntarily, excluding retirements or transfers to other locations. In 2021, the number of annual quits grew in 18 of 19 industries, while the remaining industry had fewer quits. The largest percentage increases in annual quits levels were in arts, entertainment, and recreation (+56.7 percent), followed by other services (+48.4 percent) and durable goods manufacturing (+48.0 percent). The only decrease in annual quits levels was in state and local government education (−15.3 percent), which had set a series high in 2020. (See table 6.)

Nine of 19 industries reached a series high for the annual level of quits. Among these industries, highs occurred in professional and business services and in accommodation and food services (8.6 million each), and in retail trade (7.8 million). (See table 4.). In addition, 8 of 19 industries reached monthly seasonally adjusted series highs for quits in 2021. (See table 2.).

Layoffs and discharges

Layoffs and discharges includes involuntary separations initiated by the employer, including layoffs with no intent to rehire. In 2021, annual layoffs and discharges decreased in all 19 industries from the COVID-19-induced spikes in 2020. The largest percentage decreases in annual layoffs and discharges were in accommodation and food services (−81.8 percent), educational services (−73.4 percent), and federal government (−72.2 percent). The industries with the lowest percentage decreases in annual layoffs and discharges were in finance and insurance (−33.6 percent), professional and business services (−35.5 percent), and state and local government, excluding education (−39.0 percent). (See table 7.)

During 2021, seven industries reached a series low for monthly layoffs and discharges. These industries include real estate and rental and leasing, at 6,000 in June; wholesale trade, at 20,000 in December; and state and local government education, at 21,000 in January. (See table 9.)

Table 9. Monthly series lows, by industry and region, seasonally adjusted, 2021 (in thousands)

Data element	Industry and region	Month	Level
Industry			
Total separations	State and local government education	January	77
Layoffs and discharges	Construction	September	108
Layoffs and discharges	Durable goods	February	39
Layoffs and discharges	Wholesale	December	20
Layoffs and discharges	Retail trade	December	102
Layoffs and discharges	Real estate and rental and leasing	June	6
Layoffs and discharges	Accommodation and food services	December	104
Layoffs and discharges	State and local government education	January	21
Region			
Layoffs and discharges	Northeast	December	156
Layoffs and discharges	South	April	502
Layoffs and discharges	Midwest	November	244
Layoffs and discharges	West	September	273

Source: U.S. Bureau of Labor Statistics.

Other separations

In 2021, annual other separations increased in 12 of 19 industries, with 7 industries having fewer annual other separations than in the previous year. The largest percentage increases in annual other separations were in information (+66.7 percent); arts, entertainment, and recreation (+46.4 percent); and finance and insurance (+44.2 percent). The industries with the largest percentage declines in annual other separations were in state and local government education (−42.6 percent); transportation, warehousing, and utilities (−20.7 percent); and real estate and rental and leasing (−19.1 percent). (See table 8.) One of the 19 industries reached a series high for the annual level of other separations: finance and insurance at 346,000. (See table 4.) There were two monthly seasonally adjusted series highs in other separations: professional and business services at 118,000 in June, and finance and insurance at 65,000 in September. (See table 2.)

Components of separations by region

This section describes the differences between the components of separations among the four census regions in 2021.

Northeast region

In 2021, the Northeast had an annual level of 10.0 million total separations, a decrease of 25.6 percent compared to 2020, and the largest decrease of all the regions. The Northeast quits level increased to a new series high of 6.4 million (+33.1 percent) but remained the lowest level regionally. For layoffs and discharges, the Northeast notably fell to 3.0 million, the largest percentage (−63.3 percent) decrease of the four regions. The Northeast other separations level rose to 698,000, the largest percentage (+8.2 percent) increase regionally.

South region

In the South, the annual level of total separations fell to 28.4 million, the smallest percentage (−5.9 percent) decrease regionally. Within total separations, the quits level rose to a new series high of 20.2 million for the South, an increase of 32.7 percent. The South layoffs and discharges level fell to 6.6 million, the lowest percentage decrease (−50.9 percent) of the regions, and the other separations level rose to 1.6 million, an increase of 7.3 percent compared to 2020.

Midwest region

In the Midwest, the annual total separations level fell to 15.1 million (−15.8 percent). Within total separations, there were 10.5 million (+31.7 percent) quits in the Midwest, a new series high. There were 3.7 million (−59.4 percent) layoffs and discharges, and other separations rose to 888,000 (+3.1 percent).

West region

In 2021, the West annual total separations level decreased to 15.5 million (−19.2 percent). Within total separations in the West, the quits level rose to 10.7 million, the largest percentage (+36.3 percent) increase among the regions and a new series high. The layoffs and discharges level fell to 3.8 million (−63.0 percent) and the other separations level fell to 981,000. (See tables 5, 6, 7, and 8.)

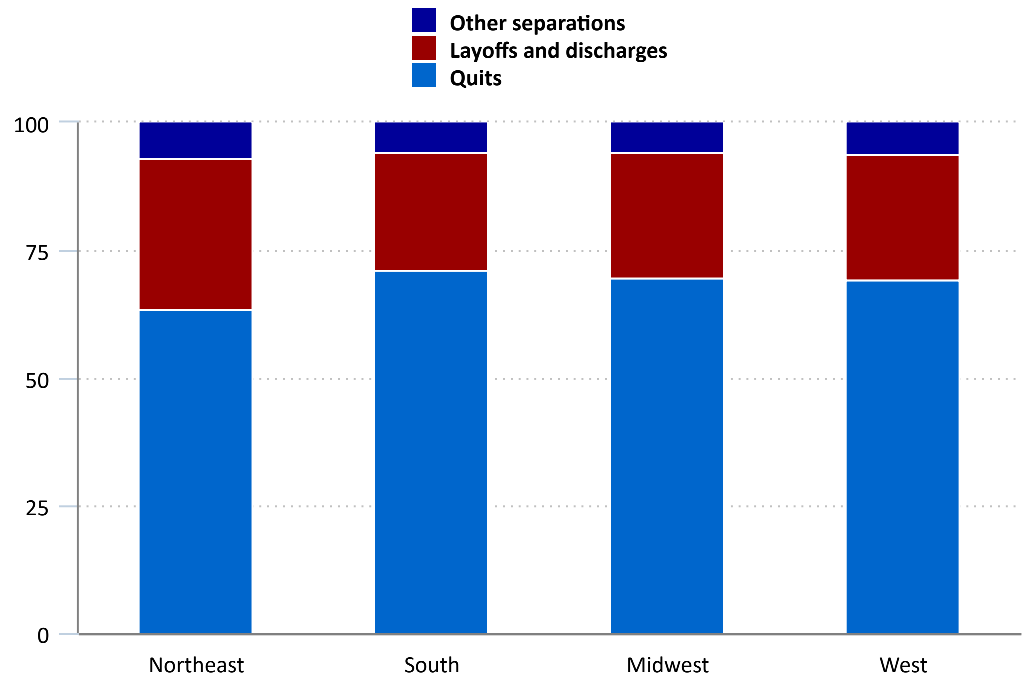
Separations for the regions

All regions reached series highs for annual quits in 2021. (See table 4.) In addition, all regions saw monthly series highs for quits in November 2021. The Northeast quits level reached a monthly series high of 608,000, the South quits level reached a monthly series high of 1.9 million, and the Midwest and West both reached a monthly series high of 1.0 million. None of the four regions reached monthly series highs for total separations, layoffs and discharges, or other separations. (See tables 2 and 4.)

All regions saw new series lows for annual layoffs and discharges. In addition, all regions reached monthly series lows for layoffs and discharges in 2021. The Northeast layoffs and discharges level reached a series low of 156,000 in December, the South reached a series low of 502,000 in April, the Midwest reached a series low of 244,000 in November, and the West reached a series low of 273,000 in both June and September. None of the four regions reached a series low in total separations, quits, or other separations. (See table 9.)

An analysis of each region by quits, layoffs and discharges, and other separations as percentages of total separations illustrates the different characteristics of the JOLTS estimates at the regional level. The Northeast had the smallest percentage of quits within total separations, at 63.6 percent in 2021. The South experienced the highest percentage of quits, at 71.0 percent. In 2021, the Northeast had the largest percentage of layoffs and discharges, at 29.4 percent. The South had the lowest percentage of layoffs and discharges, at 23.3 percent. The Northeast had the highest percentage of other separations, at 7.0 percent, while the South had the lowest percentage, at 5.8 percent. (See chart 4.)

Chart 4. Percentage of components of total separations, by region, 2021



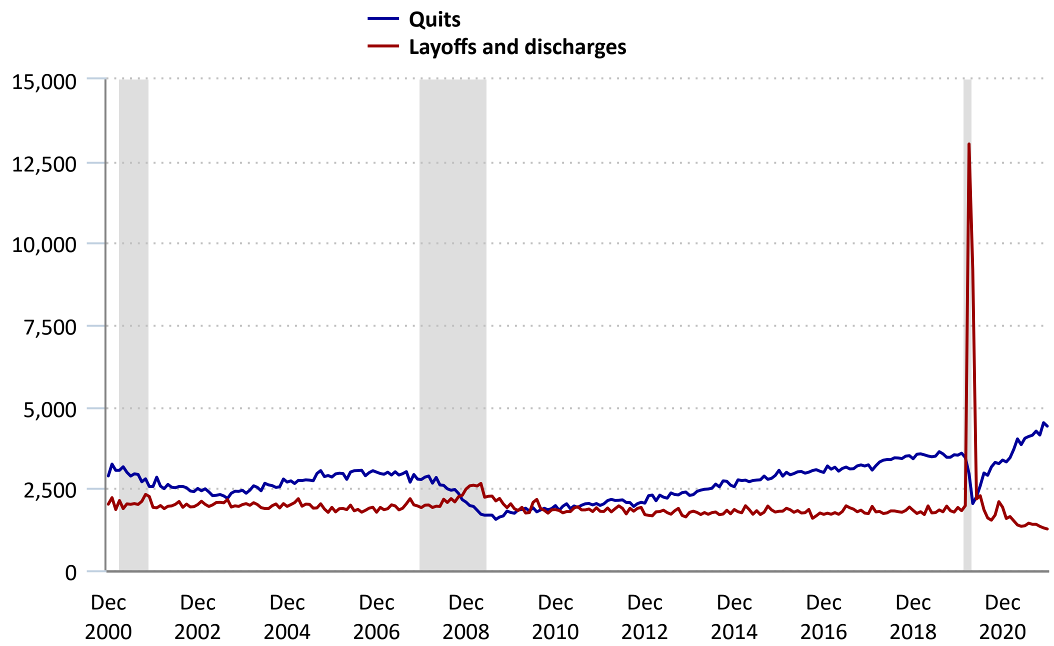
Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Quits compared with layoffs and discharges

As 2021 progressed, the difference between quits and layoffs and discharges continued to grow. In March, quits exceeded layoffs and discharges by 2.2 million. As 2021 continued and quits kept increasing while layoffs and discharges kept decreasing, the gap grew even larger. In November, when quits reached its monthly peak at 4.5 million, the difference between quits and layoffs and discharges also peaked at 3.2 million. The previous series high was 1.8 million in March 2019. (See chart 5.)

Chart 5. Quits and layoffs and discharges, total nonfarm, seasonally adjusted, December 2000–December 2021 (in thousands)



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

View Chart Data

Summary

JOLTS estimates reflected a vastly different labor market in 2021 compared with the 2020 labor market. In 2020, layoffs and discharges spiked at the onset of the COVID-19 pandemic while job openings, hires, and quits fell sharply. Layoffs declined markedly in May 2020 and hires saw a large increase, while the other measures recovered more gradually. Improvement continued in 2021. Job openings increased throughout the year as the demand for labor increased, culminating in a new monthly seasonally adjusted series high of 11.4 million in December. Annual hires increased for the 12th consecutive year, to a new series high of 75.6 million. Quits increased throughout the year, resulting in a monthly series high in November. By contrast, layoffs and discharges fell to a monthly series low in December, as employers sought workers.

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Notes

[1] Job Openings and Labor Turnover Survey publishes rates and levels of job openings, hires, quits, layoffs and discharges, other separations, and total separations (also known as turnover) for the nation as a whole and by state, by ownership (private verses public), region, and supersector and select sectors based on the North American Industry Classification System (NAICS). Annual estimates are not seasonally adjusted, and monthly estimates are both seasonally adjusted and not seasonally adjusted. Over-the-year changes are calculated from December of the previous year through December of the reference year. For more information on the program’s concepts and methodology, see “Job Openings and Labor Turnover Survey," *Handbook of Methods* (Washington, DC: U.S. Bureau of Labor Statistics, July 13, 2020), https://www.bls.gov/opub/hom/jlt/home.htm. See also the JOLTS page on the BLS website, at https://www.bls.gov/jlt/.

[2] According to the finance and investment education website Investopedia, procyclical "refers to a condition of a positive correlation between the value of a good, a service, or an economic indicator and the overall state of the economy. In other words, the value of the good, service, or indicator tends to move in the same direction as the economy, growing when the economy grows and declining when the economy declines." For more information, see Akhilesh Ganti, "Procyclic," Investopedia, updated September 13, 2021, http://www.investopedia.com/terms/p/procyclical.asp.

[3] The National Bureau of Economic Research is the official arbiter of the beginning and ending dates of U.S. business cycle expansions and contractions. For more information, see "U.S. Business Cycle Expansions and Contractions" (Cambridge, MA: National Bureau of Economic Research, September 20, 2010), http://www.nber.org/cycles/.

[4] BLS considers job openings a stock measure and does not produce job openings annual totals.

[5] The large decrease in annual hires for the federal government was largely due to the lack of temporary Census workers in 2021 following the 2020 Decennial Census.

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Noncompete agreements, bargaining, and wages: evidence from the National Longitudinal Survey of Youth 1997

We examine the use of noncompete agreements (NCAs) and their relationship with wage bargaining and wage outcomes using new data from the National Longitudinal Survey of Youth 1997. NCAs cover 18 percent of the workers in our sample, and adoption patterns are broadly consistent with prior research. The NCA–wage correlation is positive and highly sensitive to controls for demographics and job characteristics, suggesting selection into NCAs causes positive bias in the estimates. While it is not obvious what the baseline level of the NCA–wage differential is, some heterogeneous effects are more stable: the NCA–wage differential is lower for workers who do not bargain over wages, have less education, have lower ability, or live in a state that enforces NCAs. Notably, wage bargaining—which is only marginally more likely with NCAs in our most saturated model—does not explain the heterogeneous effects across subgroups. We discuss these findings in light of competing theories of the social value of NCAs.

Amid a decades-long trend of wage stagnation and reduction in job mobility, the last few years have witnessed renewed policy and research interest in the use of noncompete agreements (NCAs). NCAs are employment provisions that prohibit departing workers from joining or starting competing businesses, often within time and geographic limits.[1] Since the 2014 discovery of NCAs in low-wage jobs, more than 69 new state or federal NCA policies have been proposed, including bans on NCAs for all or a subset of the workforce.[2] These proposals join a centuries-long debate over the value of NCAs, which juxtaposes the potential for NCAs to constrain the upward mobility of workers against the potential for NCAs to incentivize firm investment in the development and sharing of valuable information.[3]

A growing stream of academic research has aided this debate by seeking to understand how NCAs, and the policies that regulate them, influence economic activity. Most of this research examines NCA policies alone, that is, without any information on the actual use of NCAs.[4] This omission is critical, given that the limited data we do have on NCAs suggest that they are frequently found in states where they are legally unenforceable. The data also suggest that workers perceive their NCAs to be enforceable when they are not and that NCAs can limit employee mobility regardless of the law.[5] More broadly, existing data on NCAs have four limitations: (1) they are not publicly available, (2) they come from either selected occupations or nonrandom sampling schemes, (3) they are cross-sectional, and (4) they are not repeated cross-sections of the same population or sampling frame. As a result, researchers have not been able to study the evolution of NCA use and how NCAs affect a variety of economic dynamics, like wage stagnation and the historical decline in business dynamism.

To address these concerns, in 2017 the Bureau of Labor Statistics (BLS) added a question on NCAs to the National Longitudinal Survey of Youth 1997 (NLSY97)—a panel dataset consisting of individuals born between 1980 and 1984. The first NLSY97 wave with NCA data was published in December 2019, and data collection efforts are ongoing. These data address the gaps highlighted above by providing a publicly available, longitudinal dataset that will allow researchers to develop new evidence on this important labor market friction.

In this article, we introduce the first wave of these data.[6] We begin with a brief discussion of the theoretical tensions related to NCAs, focusing on bargaining and holdup. Then we describe the NLSY97 and the new NCA question. In our empirical work, we examine the use of NCAs and their correlates, drawing parallels to prior work where possible. We then focus on how NCAs relate to wages, in light of competing predictions made by existing theories. Our estimates here should not be interpreted causally—indeed, one of our key findings is that the sensitivity of the NCA–wage relationship to controls suggests substantial selection into NCA use. In our analysis, we also seek to understand how NCAs relate to wage bargaining and the role of such bargaining in explaining (1) differences in the overall NCA–wage relationship and (2) for differences in effects across gender, education, ability, and NCA enforceability. We conclude with a discussion of research directions as future waves of data become available.

Guiding theory and institutional background

Since the first legal case dating back to 1414, NCAs have been a topic of significant theoretical debate.[7] The essence of the debate is to understand whether, and under what circumstances, it is worth preventing workers from deploying their full set of human capital in a competing firm (typically within some time and geographic boundaries). Courts have generally been concerned that NCAs, like other restraints of trade, can impose significant hardship on workers, since workers who wish to leave the firm without violating their NCA will either have to change industries, leave the geographic area, or sit out of the labor market.[8] Moreover, since NCAs increase the costs of moving to a competitor, they shield the firm from labor market competition, potentially curtailing wage growth for workers.[9]

However, theories rooted in efficient contracting posit that NCAs will only be observed when they are mutually beneficial to firms and workers. The theories tend to have two components. First, workers have the "freedom to contract," such that they would only agree to an NCA if it made them better off.[10] Second, firms would never pay a worker a compensating differential (a higher wage) for an NCA unless they too were benefiting from it. And the reason firms might benefit from NCAs is that they resolve an investment holdup problem.[11] If a firm were to share valuable information with a worker, then without an NCA the worker could holdup the firm by threatening to use that information at a competitor. As a result, the firm may be unwilling to develop such information in the first place or unwilling to share it with the worker, both of which may reduce productivity. Accordingly, under this view NCAs can only be productive for both workers and firms, because they give firms stronger incentives to invest in worker training and to develop valuable information.[12]

Despite a burgeoning literature on NCAs, which of these theories is most accurate is still an open question. These competing theories make different predictions both about where NCAs should be used and (among other things) how NCAs relate to wages. Regarding the use of NCAs, the holdup theory suggests that NCAs will be used mostly in jobs that have access to valuable information (such as trade secrets and client lists) and only in places where they can be enforced (since court enforcement underlies firm confidence that NCAs will resolve the holdup problem).[13] In contrast, theories that firms are using NCAs as value extraction tools posit that they will be used much more broadly—potentially even with low-wage workers who have no access to valuable information and in places where NCAs cannot be enforced.[14]

With regards to wages, three possibilities arise: (1) workers may receive higher pay (whether they had to negotiate for it or if it was included in the offer) for signing an NCA, but then suffer lower wage growth as the NCA prohibits workers from taking jobs with higher paying competitors; (2) wage growth may rise if NCAs indeed spur productivity-enhancing investments and wages are tied to productivity; (3) workers may not receive higher pay (because, for example, they just sign the NCA when asked) and experience lower wage growth.[15]

Prior research finds some evidence in favor of each of these arguments. NCAs are adopted widely, and they tend to be more common in states that enforce them and for workers in technical jobs.[16] Regarding wage outcomes, prior research on NCA enforceability finds negative effects on wage levels and wage growth, while studies of NCA use find positive wage effects and positive wage growth.[17] The discrepancy in wage results could arise from the specific occupations studied, differences between the actual effects of NCA enforceability and NCAs themselves, the period studied, selection into NCA use, the cross-sectional nature of the studies of NCA use, or lack of data on key variables (wage bargaining, job tasks, ability, etc.).[18]

In this regard, new data collected via the National Longitudinal Survey of Youth 1997 offer an important opportunity to push this literature forward, especially as more waves of data are collected over time.

Data

In this section we discuss the details of the NLSY97 and how the NCA question fits into the survey.

Background on the NLSY97 and NCA question design

The National Longitudinal Survey of Youth 1997 (NLSY97) is a nationally representative sample of 8,984 people born in the years 1980 to 1984. Sample members were first interviewed in 1997 when they were ages 12 to 17; the latest data available when we began this article are from the 2017–18 interview, when the sample members were ages 32 to 38. A particular strength of the NLSY97 is the collection of respondents' employment histories from their teenage years until the present. The employment module of the NLSY97 contains a core set of questions that are asked in each survey round about each job held since the date of the last interview, but certain additional modules of interest to research and public policy rotate in and out.

Recent added questions include those on NCAs, job tasks, and wage bargaining. The NCA questions first appeared in the 2017–18 survey and are also in the 2019–20 survey (data released in November 2021). In the 2017–18 survey, the NCA questions were asked of all jobs that were not military or self-employed. In the 2019–20 survey, the NCA questions were restricted to newly reported jobs since the date of the last interview.

In the 2017–18 survey, for each job held since the date of the last interview, the respondent is asked about a series of job characteristics. The NCA question is as follows:

> *"Some employers try to restrict what their employees can do after they leave their job. In this job, did you agree that if you [leave/left] your employer, you [will/would] not start or join a competing business? This is often called a non-compete agreement."*

Because prior research has documented uncertainty in who signs NCAs, a followup question asks, *"*How confident are you in your answer?*"* The wording of the two NLSY97 questions on NCA agreements were based on those asked in prior surveys on the same topic.[19]

Sample construction

To construct our sample, we take the full NLSY97 sample (sample size of 8,984) and keep those who responded to the 2017–18 (round 18) interview (sample size of 6,734). We then restrict the sample to those who reported a job in the interview (sample size of 5,970). We drop the self-employed, government, and military workers, and those who are working for their family without pay (sample size of 4,481). We also drop those whose geographic region is missing (do not reside in the United States at the 2017–18 interview date) (sample size of 4,443). We then restrict our sample to those working at their main job at least 30 hours per week (sample size of 3,589). We use the Consumer Price Index for all Urban Consumers (CPI-U) to inflation-adjust hourly wages to 2017 dollars, and we drop those who earn less than $2 an hour and those who make above $250 an hour or those missing wage information (sample size of 3,490). Finally, we drop those whose NCA variable is missing (sample size of 3,426), those with missing wage bargaining questions (whether they bargained over pay when they were first offered their job) (sample size of 3,092), and a few observations with an unclassifiable occupation (Standard Occupational Classification code of 9990). Our final sample consists of 3,090 people. We use the NLSY97 weights for the 2017–18 interview, which account for the oversamples of Black and Hispanic individuals in the NLSY97 data and the complex survey design.

The incidence of NCAs

We begin by examining the incidence of NCAs. Table 1 provides summary statistics on NCA incidence from the NLSY97 in columns 1 and 2, and, for comparison purposes, data from the 2014 Noncompete Survey Project in column 3 and data from the 2019 Cornell National Social Survey (CNSS), collected by Stewart Schwab and Evan Starr, in column 4.[20] Overall, 18.1 percent of the NLSY97 sample is bound by an NCA, identical to the overall multiple imputation estimates reported by Starr, Prescott, and Bishara in 2021, but slightly larger than the lower-bound estimates for this age group.[21] The estimates are also nearly identical to the CNSS estimates. With regards to uncertainty regarding whether they have an NCA, 90.4 percent are very confident in their answer, whereas 9.0 percent are somewhat confident and 0.7 percent are not confident.[22]

Table 1. Incidence of NCAs across worker and firm characteristics in the NLSY97, 2014 NSP, and 2019 CNSS

Characteristic	NLSY97		2014 NSP, lower bound NCA incidence (in percent)	2019 CNSS, NCA incidence (in percent)
	NCA incidence (in percent)	Observations		
Overall	18.07	3,090	16.09	19.23
Male	20.08	1,665	16.56	18.95
Female	15.37	1,425	15.50	19.86
Non-Black, non-Hispanic	19.21	1,625	15.01	10.00
Black, non-Hispanic	15.69	777	16.26	11.90
Hispanic	14.84	665	[1]	14.29
Less than a bachelor's degree	14.77	2,125	11.06	13.85
Bachelor's degree or higher	24.27	953	25.15	22.22
State enforces NCAs	18.45	2,683	15.62	19.94
State does not enforce NCAs	15.19	407	19.02	11.11
Hourly wage less then $20	14.36	1687	10.81	[1]
Hourly wage greater or equal to $20	21.74	1,403	20.34	[1]
Tenure less than 3 years	16.76	1,431	10.96	[1]
Tenure greater or equal to 3 years	19.51	1,619	18.75	[1]
Private sector	19.64	2,653	17.05	[1]
Nonprofit sector	7.41	325	4.78	[1]
Union	16.57	254	20.33	[1]
No union	18.59	2,499	15.70	[1]
Employer size				
Less than 20 employees	17.22	747	12.95	[1]
20 to 99 employees	17.84	725	18.89	[1]
100 or more employees	19.58	1,168	16.50	[1]

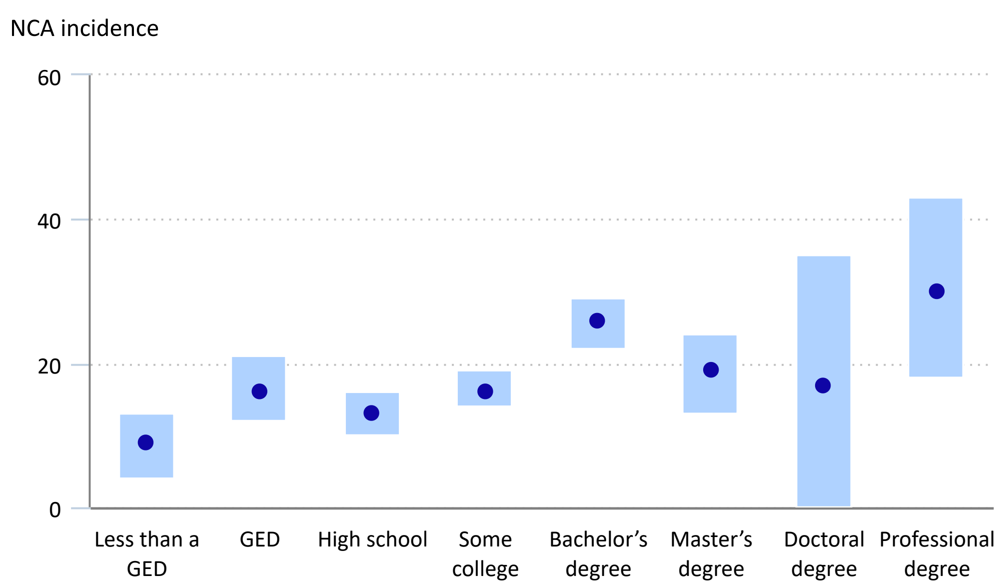
Notes: NCA = noncompete agreement. *n* = sample size. 2014 NSP = 2014 Noncompete Survey Project (data are limited to workers ages 32–38 in 2014. *n* = 1649); incidence estimates from the NSP are lower bound estimates. 2019 CNSS = 2019 Cornell National Social Survey, collected by Stewart Schwab and Evan Starr in 2019 via random digit dial survey (data are limited to ages 25–50 in 2019: *n* = 338). NLSY97 = National Longitudinal Survey of Youth 1997.

[1] Not applicable.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview); 2014 NSP; 2019 CNSS. Authors' calculation.

We briefly describe some of the NLSY97 NCA incidence results from table 1. In the NLSY97, men are about 5 percentage points more likely than women to report signing an NCA at their job (20 percent versus 15 percent), while non-Black, non-Hispanic workers are 4 percentage points more likely to be bound by an NCA than either Black or Hispanic workers. Chart 1 shows that NCA incidence rises with education, with 15 percent of those without a bachelor's degree signing one, compared with 24 percent with at least a bachelor's degree.

Chart 1. Incidence (in percent) of NCAs in the NLSY97 by highest level of educational degree

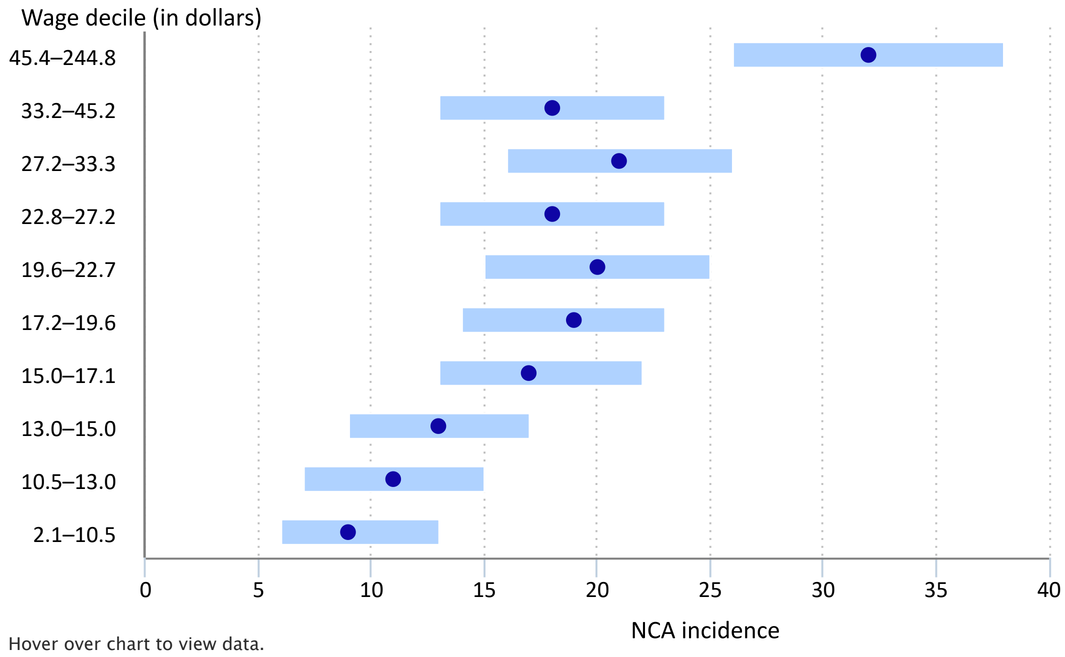


Hover over chart to view data.
Notes: GED = general equivalency diploma. NCA = noncompete agreement.
NLSY97 = National Longitudinal Survey of Youth 1997.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

In terms of worker and firm characteristics, table 1 shows that NCAs rise with tenure and that NCAs are 12 percentage points more common for those working in the for-profit sector than the nonprofit sector (19.6 percent versus 7.4 percent). Unionized workers are only somewhat less likely to sign NCAs (16.6 percent versus 18.6 percent). With regards to wages, chart 2 shows that the incidence of NCAs is 9 to 11 percent for those in the bottom two wage deciles and rises with wages such that those with wages in the top decile (at least $45 per hour) have a 32 percent chance of having an NCA. Overall, NCAs are still found at the low end of the wage distribution, with 14.4 percent of workers earning less than median hourly wages signing one.

Chart 2. Incidence (in percent) of NCAs in the NLSY97 by hourly wage decile

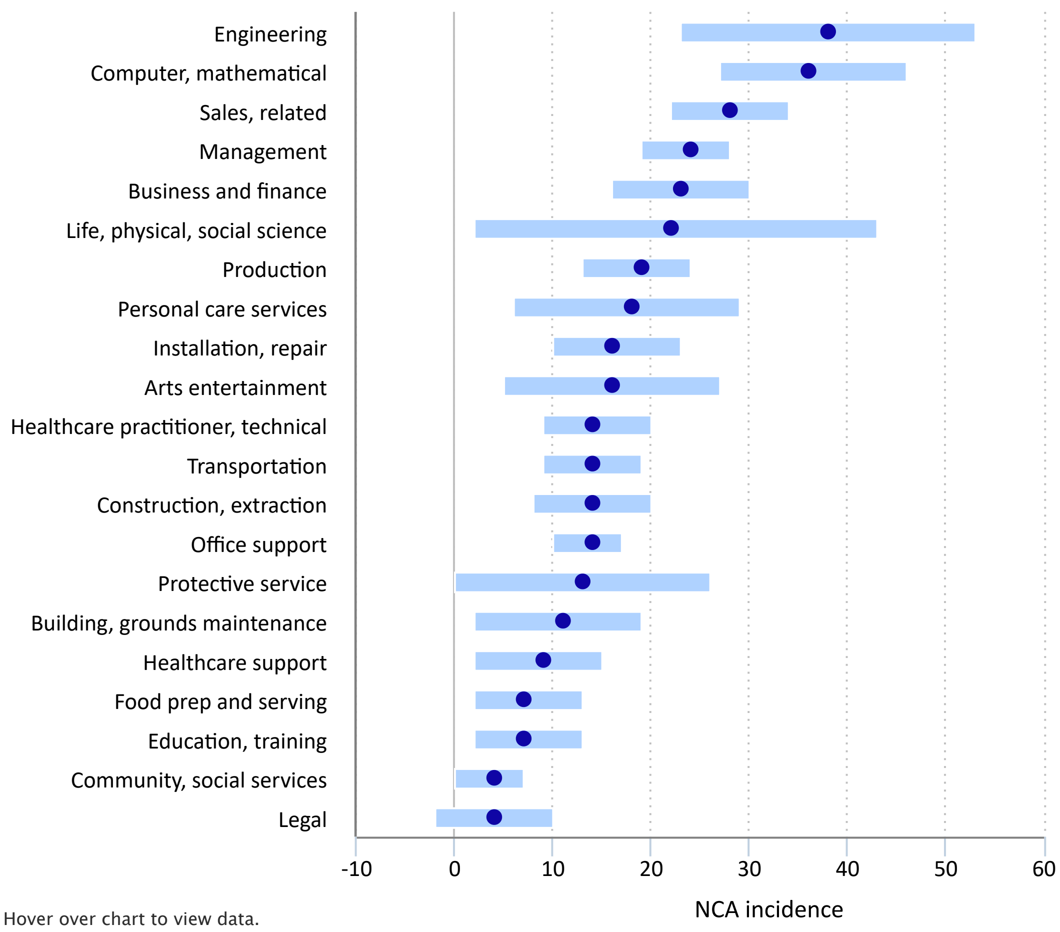


Hover over chart to view data.
Notes: NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

Charts 3 and 4 show the distribution of NCAs by two-digit occupational and industrial codes (conditional on having at least 20 observations in the occupation or industry).

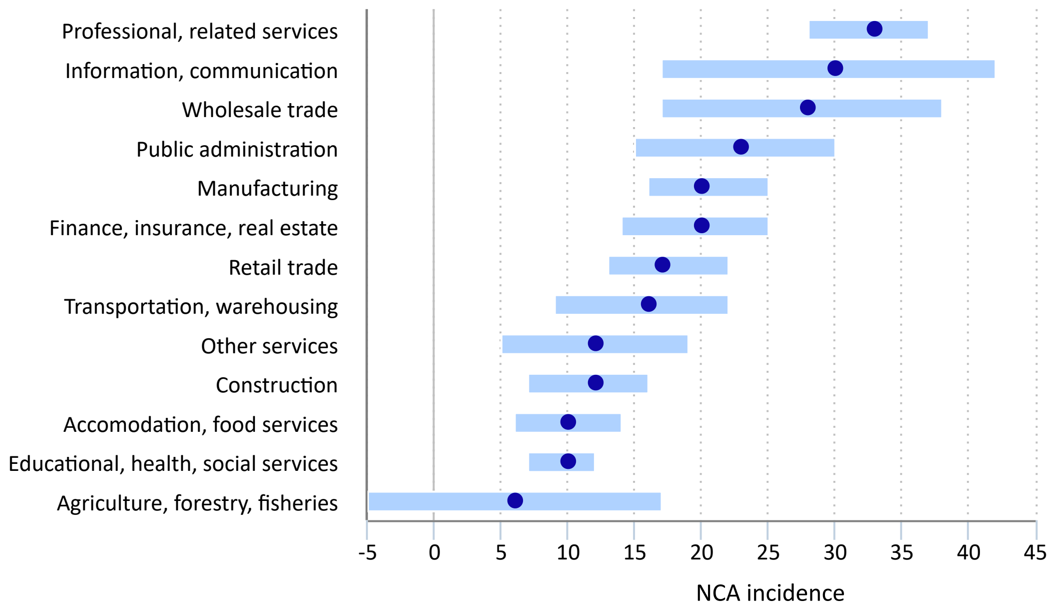
Chart 3. Incidence (in percent) of NCAs in the NLSY97 by occupation



Hover over chart to view data.
Notes: NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997.
Estimates can be negative because of the linear probability model.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

Chart 4. Incidence (in percent) of NCAs in the NLSY97 by industry



Hover over chart to view data.
Notes: NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997.
Estimates can be negative because of the linear probability model.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

Consistent with holdup theories, occupations in which NCAs are found most frequently are in more technical areas such as engineering (38 percent), computer science (36 percent), sales (28 percent), and management (24 percent). Occupations such as food preparation (7 percent) and social services (4 percent) have very low reported NCA incidences.[23] Similarly, chart 4 shows that workers in industries such as professional services and information have high rates of NCAs (33 percent and 30 percent, respectively) in contrast to workers in social services, food services (10 percent), or agriculture (6 percent).

We also consider whether NCAs are deployed even in states that would not enforce them. Only three states—California, North Dakota, and Oklahoma—will void all NCAs agreed to in the employment context, and these policies have been in place since the 1800s.[24] Table 1 shows that 15.0 percent of workers who live in these states are bound by NCAs, compared with 18.5 percent elsewhere.

Overall, while there are some discrepancies between the magnitude or direction of the NLSY97 results relative to both the 2014 NSP and the 2019 CNSS, the general patterns and magnitudes are roughly in line.

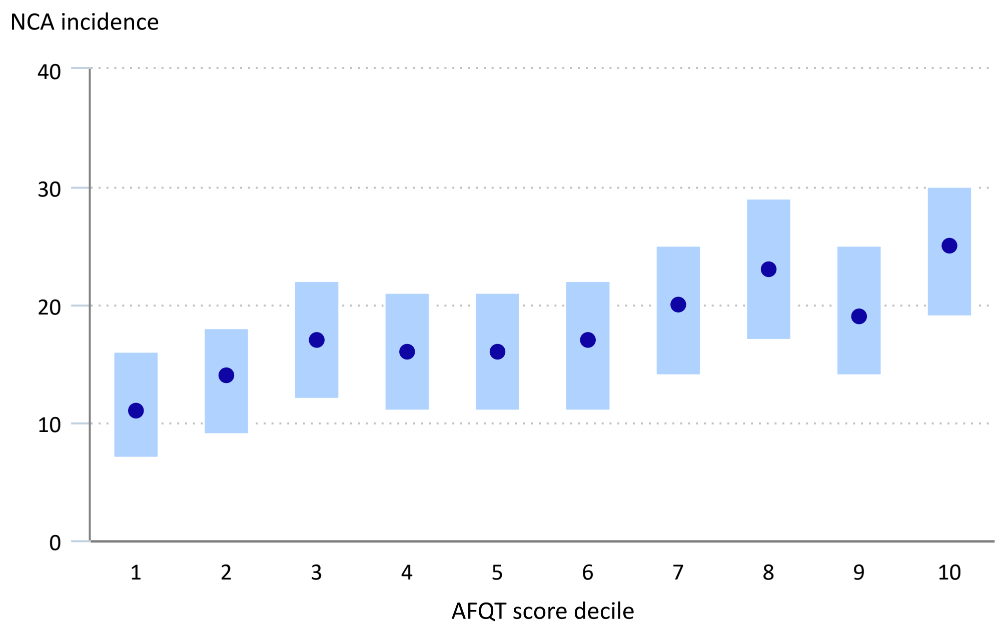
In table 2 we examine variables unique to the NLSY97. First, although investing in worker training is an oft-referenced rationale for using NCAs, workers whose employers have provided at least some training in the past are only marginally more likely to have NCAs (19.8 percent to 17.7 percent).[25] Second, the NLSY97 includes a unique measure of ability—the Armed Forces Qualification Test (AFQT) (math and verbal aptitude percentile score).[26] Chart 5 breaks down AFQT scores by decile, showing that the incidence of NCAs is 11 percent for those with the lowest AFQT scores but rises consistently such that those with the highest AFQT score have a 25-percent likelihood of agreeing to an NCA.

Table 2. Incidence of NCAs across variables specific to the NLSY97

Characteristic	NCA incidence (in percent)	Observations
Some employer-provided training	19.76	523
No employer-provided training	17.68	2,567
AFQT score below 50th percentile	15.08	1,346
AFQT score equal or above 50th percentile	20.91	1,177
Job tasks		
Repetitive tasks for more than half the workday	14.86	1,511
Repetitive tasks for less than half the workday	21.39	1,434
Physical tasks for more than half the workday	14.18	1,490
Physical tasks less than half the workday	22.20	1,463
Supervise or manage more than half the workday	20.53	1,037
Supervise or manage less than half the workday	17.12	1,913
Problem solve every day	23.99	1,255
Problem solve less than every day	13.60	1,697
Read long documents	23.80	635
Does not read long documents	16.51	2,315
A lot of face-to-face contact with noncoworkers	17.85	1,467
Not a lot of face-to-face contact with noncoworkers	18.73	1,487

Notes: AFQT = Armed Forces Qualification Test. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997.
Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

Chart 5. Incidence (in percent) of NCAs in the NLSY97 by AFQT decile



Hover over chart to view data.
Notes: AFQT = Armed Forces Qualification Test. NCA = noncompete agreement.
NLSY97 = National Longitudinal Survey of Youth 1997.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

Lastly, job tasks show considerable variation with NCA use:[27] Individuals in jobs that require more physical and repetitive tasks are about 7 percentage points less likely to report signing an NCA, whereas individuals in jobs with more problem solving, reading long documents, and supervising are much more likely to sign one.

Since many of the characteristics described above are likely to be correlated with each other, in table 3 we incorporate these variables into a linear probability model to assess which characteristics are correlated with NCA use, conditional on the other variables. We cluster the standard errors by state. Several patterns emerge: Across all models, having a bachelor's degree is associated with a greater chance of signing an NCA, even though AFQT scores are uncorrelated with NCA use.[28] Nonprofit jobs are also far less likely to have NCAs relative to for-profit jobs (9.1 percentage points in the model with the most controls). Although the use of NCAs appears to be lower in states that cannot legally enforce NCAs, this difference becomes statistically insignificant with more controls. We also see that, even conditional on occupation and industry, several job tasks are still correlated with NCA use, including face-to-face contact with others (+4.4 percentage points), reading longer documents (+4.5 percentage points), solving problems daily (+6.3 percentage points), or frequent physical tasks (-3.3 percentage points).

Table 3. Multivariate model of NCA incidence in the NLSY97

Variable	Model specification 1	Model specification 2	Model specification 3	Model specification 4
At least a bachelor's degree	0.093[1]	0.085[1]	0.063[1]	0.064[1]
	(0.017)	(0.021)	(0.021)	(0.022)
Hispanic	-0.015	-0.015	-0.018	-0.018
	(0.019)	(0.019)	(0.018)	(0.018)
Black, non-Hispanic	-0.011	-0.001	0.002	0.001
	(0.017)	(0.016)	(0.016)	(0.017)
Mixed race	-0.054	-0.045	-0.027	-0.057
	(0.057)	(0.053)	(0.052)	(0.057)
Female	-0.057[1]	-0.033[2]	-0.035[2]	-0.013
	(0.014)	(0.016)	(0.017)	(0.017)
AFQT percentile score				
25 percent to 50 percent	0.011	0.006	-0.005	-0.004
	(0.018)	(0.020)	(0.020)	(0.021)
50 percent to 75 percent	0.024	0.013	0.000	-0.002
	(0.018)	(0.017)	(0.018)	(0.019)
75 percent or higher	0.019	0.006	-0.012	-0.018
	(0.025)	(0.025)	(0.025)	(0.024)
State does not enforce NCAs	-0.031[3]	-0.035[3]	-0.031	-0.026
	(0.018)	(0.020)	(0.020)	(0.018)
Nonprofit	[4]	-0.144[1]	-0.156[1]	-0.091[1]
	[4]	(0.019)	(0.021)	(0.025)
Hourly wage				
2nd quartile	[4]	0.051[2]	0.042[2]	0.043[2]
	[4]	(0.020)	(0.021)	(0.020)
3rd quartile	[4]	0.040[2]	0.018	0.011
	[4]	(0.018)	(0.017)	(0.018)
4th quartile	[4]	0.073[1]	0.032[3]	0.016
	[4]	(0.018)	(0.018)	(0.021)
Employer size				
21 to 100 employees	[4]	0.003	0.001	0.014
	[4]	(0.022)	(0.023)	(0.022)
Greater than 100 employees	[4]	0.002	0.001	0.003
	[4]	(0.019)	(0.020)	(0.021)
Employer ever trained worker	[4]	-0.003	-0.013	-0.017
	[4]	(0.021)	(0.022)	(0.022)
Unionized	[4]	-0.005	0.012	0.026
	[4]	(0.032)	(0.032)	(0.034)
Tenure, 3 years or more	[4]	0.007	0.010	0.010
	[4]	(0.012)	(0.012)	(0.011)
Frequency with which contact with others is "a lot"	[4]	[4]	0.023	0.044[2]
	[4]	[4]	(0.019)	(0.020)
Longest document read at work is at least 11 pages	[4]	[4]	0.024	0.045[2]
	[4]	[4]	(0.019)	(0.019)
Use math to solve problems at least once a day	[4]	[4]	-0.009	-0.015
	[4]	[4]	(0.024)	(0.022)
Solve problems at least once a day	[4]	[4]	0.073[1]	0.063[1]

Notes: Observations = 3,090. AFQT = Armed Forces Qualification Test. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997. Standard errors, clustered by state of residence, are in parentheses. Regressions are weighted with round 18 survey weights. If the variable of interest is missing for some values, an indicator is included (but not reported) which equals 1 if the variable is missing. Results are available from the authors.

[1] $p < 0.01$.

[2] $p < 0.05$.

[3] $p < 0.10$.

[4] Variable is not used in this model specification.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

Variable	Model specification 1	Model specification 2	Model specification 3	Model specification 4
	[4]	[4]	(0.017)	(0.017)
Supervise or manage others more than half the time	[4]	[4]	0.014	0.014
	[4]	[4]	(0.019)	(0.019)
More than half of tasks are physical	[4]	[4]	-0.045[1]	-0.033[3]
	[4]	[4]	(0.017)	(0.019)
Short and repetitive tasks more than half the time	[4]	[4]	-0.012	-0.010
	[4]	[4]	(0.016)	(0.017)
Occupation and industry fixed effects	No	No	No	Yes
R^2	0.022	0.040	0.054	0.099

Notes: Observations = 3,090. AFQT = Armed Forces Qualification Test. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997. Standard errors, clustered by state of residence, are in parentheses. Regressions are weighted with round 18 survey weights. If the variable of interest is missing for some values, an indicator is included (but not reported) which equals 1 if the variable is missing. Results are available from the authors.

[1] $p < 0.01$.

[2] $p < 0.05$.

[3] $p < 0.10$.

[4] Variable is not used in this model specification.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

NCAs, bargaining, and wages

In this section we use NLSY97 wage and wage bargaining data to examine how NCAs relate to wage bargaining and wage outcomes.

Empirical approach

We begin with a discussion of the ideal empirical designs to estimate the effect of NCAs, what our approach is, and why, ultimately, our results should be thought of as correlational and not causal. The ideal empirical design to estimate the causal effect of NCAs on bargaining and wages is to randomly ask some sample of workers to sign NCAs. Then one could consider who turns down the offer outright, who negotiates over the NCA or the terms of the offer, and wage outcomes. If NCAs were randomly assigned, then no other firm or worker characteristics (observed or unobserved) would differ between who received an NCA and who did not—at least before the NCA was deployed—allowing us to isolate the effect of NCAs. To our knowledge, such an experiment has yet to be run in the real world.

An alternative approach to estimating the causal effect of NCAs is to find an instrument—something that would randomly cause some firms to use NCAs but would not be correlated with wages or bargaining through any other pathway. The most natural instrument, it might seem, would be the enforceability of NCAs, which might exogenously increase the firm's willingness to use them. However, the fact that firms still use NCAs relatively frequently in states that do not enforce NCAs poses some challenges for this approach. The exclusion restriction is also likely to be violated if the instrument is just cross-sectional state NCA enforceability, since other state characteristics might be correlated with the policy and outcomes of interest. Variation over time in state NCA enforceability, combined with variation over time in NCA use, is likely to be a more plausible identification strategy. Another approach that future data collection makes possible could use Bartik-style instruments that interact industry shares with national growth rates.[29]

To date, no research has been able to use these research designs, mostly because of the cross-sectional nature of data on NCAs. Instead, prior work documents conditional correlations. With just one cross-section of data, we face the same challenges (even though the NLSY97 contains some rich measures of job attributes) and so we also estimate conditional correlations.

We estimate models of the form $y_i = b_0 + b_1\text{NCA} + \alpha X_i + e_i$ using ordinary least squares, where y_i is a dependent variable, X_i is a vector of covariates, and e_i is an error term. In order for b_1 to estimate the true causal effect of an NCA, we need a conditional independence assumption to hold—that $\text{cov}(\text{NCA}, e) = 0$, conditional on X_i.[30] This assumption is highly unlikely to hold. Based on where we see NCAs being deployed, our estimates of the NCA–wage differential will likely be seriously biased upward. For example, since NCAs are more common in technical jobs or for workers with more education, a worker bound by an NCA is highly likely to earn more than a worker not bound by an NCA—but this difference is perhaps mostly or entirely due to differences in their human capital, the type of job they are in, and the tasks they are asked to perform. We can control for some of these variables at a broad level, which should mitigate these concerns. However, because we cannot hold constant all the variables that determine both NCA use and wages, the positive bias will likely persist.

Nevertheless, inclusion of different covariates can be informative of the extent of selection into NCAs and thus the extent to which the NCA–wage differential is biased upward. Accordingly, we estimate two sets of models, one with "basic" controls, which are exogenous demographic characteristics. These are education, gender, race, AFQT score at or above 50th percentile, and whether the state enforces NCAs. We also estimate models that seek to compare workers who are in the same type of job and doing the same set of tasks. To do this, we add "advanced" controls in addition to the basic controls. These are the for-profit status of the firm, job tasks (as shown in table 2), and two-digit occupation and industry fixed effects. We note that some of the advanced controls may be bad controls in that they may be endogenous to agreeing to an NCA (that is, the tasks a worker does may depend on whether that worker agrees to an NCA).[31] Due caution is required when interpreting the NCA coefficient with these controls.

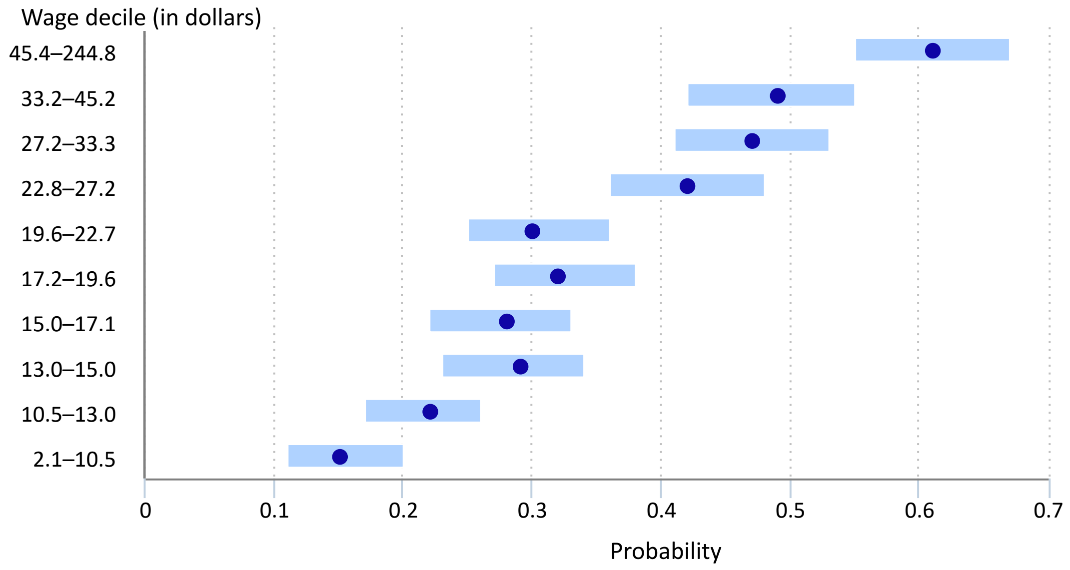
Wage bargaining and wage outcomes

We focus first on bargaining as an outcome of NCA use and later as a mediator and moderator of the NCA–wage relationship. Bargaining is relevant because NCAs give firms power only *after* an NCA is signed. As a result, NCAs put some pressure on the initial negotiations for workers to receive compensation for their postemployment concessions. Before we turn to the results, it is worth considering why bargaining may or may not arise in response to NCAs.

Different models of the labor market differ in how they consider bargaining. For example, wage-posting models assume employers simply post a take-it-or-leave-it offer, precluding the possibility of bargaining.[32] In these models, as long as the NCA is sufficiently observable and perceived as costly to the worker, a compensating differential may be built into the posted wages, rendering bargaining unnecessary. Other wage bargaining models assume that workers bargain for some proportion of the surplus from the job, but these models are agnostic to the precise mechanics of how the bargaining occurs.[33] Such a process may look as follows in the case of NCAs: the firm may initially offer an NCA paired with a wage offer that is at or slightly above the wages offered by firms that do not use NCAs. In this situation, the worker may either accept the contract as presented, turn it down, or ask for higher pay. In the third case, we might observe a positive relationship between bargaining and NCAs.

To set a baseline, prior research suggests that only approximately one-third of workers bargain over their wages at all and the only evidence on negotiation over NCAs suggests that only 10 percent of NCA signers report negotiating over the terms of their NCA or for other benefits in exchange for signing.[34] In the NLSY97, 36 percent of workers report that their wage was bargained over, while the rest indicate that it was a take it or leave it offer. Chart 6 shows that the likelihood of wage bargaining rises effectively monotonically across the wage distribution, with 15 percent of the lowest earners bargaining over their wages, compared with 61 percent of the highest.

Chart 6. Probability of a worker in the NLSY97 bargaining over wages by hourly wage decile



Hover over chart to view data.
Notes: NLSY97 = National Longitudinal Survey of Youth 1997.
Source: Authors' calculations based on data from the 2017–18 interview of the NLSY97 cohort.

View Chart Data

In light of this discussion, we begin by assessing whether NCAs are associated with a greater chance of wage bargaining. Table 4 panel A shows that while NCAs are associated with a 9.5-percentage-point increase in the likelihood of wage bargaining, controlling for basic controls and advanced controls reduces the differential to 2.1 percentage points and becomes statistically insignificant. Thus, the positive relationship between NCAs and wage bargaining seems largely driven by certain individual- or job-specific characteristics.

Table 4. Interaction of NCAs, bargaining, and wages in NLSY97

Variable	Incidence of bargaining over wages			Logarithm of hourly wages		
	Model specification 1	Model specification 2	Model specification 3	Model specification 1	Model specification 2	Model specification 3
Panel A: Baseline bargaining and wages						
NCA	0.095[1]	0.069[2]	0.021	0.221[1]	0.120[1]	0.049[2]
	(0.027)	(0.027)	(0.026)	(0.024)	(0.020)	(0.018)
Controls	None	Basic	Advanced	None	Basic	Advanced
Percent increase in wages associated with NCA	[5]	[5]	[5]	24.7	12.7	5.0
Panel B: Wages as a function of bargaining						
Variable	Logarithm of hourly wages					
	Model specification 1	Model specification 2	Model specification 3	Model specification 4	Model specification 5	Model specification 6
NCA	0.192[1]	0.111[1]	0.047[1]	0.155[1]	0.074[2]	0.018
	(0.018)	(0.015)	(0.017)	(0.028)	(0.030)	(0.022)
Bargaining over wages	0.287[1]	0.175[1]	0.101[1]	0.271[1]	0.171[1]	0.087[1]
	(0.024)	(0.017)	(0.019)	(0.026)	(0.020)	(0.018)
NCA interaction with bargaining over wages	[4]	[4]	[4]	0.091[3]	0.079[3]	0.070[3]
	[4]	[4]	[4]	(0.052)	(0.047)	(0.036)
Controls	None	Basic	Advanced	None	Basic	Advanced
Percent increase in wages associated with NCA	21.2	11.7	4.8	16.8	7.7	1.8
Percent increase in wages associated with bargaining	33.2	19.1	10.6	31.1	18.6	9.1
Percentage of NCA-wage differential explained by bargaining	13.1	7.5	4.1	[5]	[5]	[5]

Notes: Observations = 3,090. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997. Basic controls include three education categories (less than a college degree, a college degree, and more than a college degree), indicators for race and ethnicity, Armed Forces Qualification Test (AFQT) score at 50th percentile or more, gender, and an indicator for whether the state of residence does not enforce NCAs. Advanced controls add an indicator for for-profit or nonprofit status, occupation and industry fixed effects (two digit Standard Occupational Classification and North American Industry Classification System codes), and indicators for job tasks including indicators for repetitive work, frequency of contact with others, the length of the longest document read on the job, solving problems, using math to solve problems, supervising others, and the extent of physical tasks. If the variable of interest is missing for some values, an indicator is included (but not reported) that equals 1 if the variable is missing. Results are available from the authors. Standard errors, in parentheses, are clustered by state of residence. Regressions are weighted with round 18 survey weights. The “Percentage of NCA-wage differential explained by bargaining” row takes the NCA coefficients from model specifications 1 to 6 from from panel B and divides them by the corresponding NCA coefficient in the top panel's "Logarithm of hourly wages," model specifications 1 to 3.

[1] $p < 0.01$.

[2] $p < 0.05$.

[3] $p < 0.10$.

[4] Variable is not used in this model specification.

[5] Not applicable.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

Columns 4 to 6 of table 4 panel A examine the baseline wage results. Unconditionally, those bound by NCAs earn about 25 percent more.[35] However, as in the case of bargaining, the inclusion of basic controls reduces this coefficient to 12.7 percent, and the inclusion of advanced controls reduces it to just 5.0 percent. Given the precipitous drop in the coefficient on NCAs as controls are added, the correlation between NCAs and wages is highly susceptible to unobserved variables. That is, there are many other variables that we cannot observe (for instance, access to valuable trade secrets and clients) that might drive both NCA use and wage outcomes. Such omitted variables will positively bias the NCA–wage correlation, even with the granular controls we observe in the NLSY97.

There are two unanswered questions that follow with regards to NCAs, wages, and bargaining. First, how much of the NCA–wage differential can be explained by baseline differences in bargaining behavior? Second, do workers with NCAs who bargain actually end up with higher wages, perhaps because they asked for a greater compensating differential?

Columns 1 to 3 of panel B of table 4 address the first question. Column 1 shows that, without basic or advance controls, controlling for bargaining causes the NCA coefficient to fall by 13.1 percent (from 0.221 to 0.192). However, when we include controls, the NCA–wage differential explained by bargaining falls to 7.5 percent and 4.1 percent (columns 2 and 3), and the extent to which bargaining itself positively relates to wages falls. Thus, bargaining only modestly drives the NCA–wage relationship.

Columns 4 to 6 of panel B considers question two and allow for bargaining to have a different relationship to wages depending on if a worker signed an NCA or not. Column 4 shows that, without controls, the NCA–wage differential for workers who do not bargain over wages is 16.8 percent—a 29.9-percent decrease from the baseline—while the NCA–wage differential is 9.5 percent higher among those who do bargain. Moreover, while the controls reduce the NCA–wage differential for those who do not bargain—reducing it by 63.3 percent in the most saturated model relative to the main effect in panel A (0.018 vs. 0.049)—the NCA–wage differential for those who bargain remains 7 percent higher.

Taken together, this suite of results suggests that NCAs are positively associated with wages but that there is strong selection into NCA use. Our analysis does not show that NCAs cause higher wages; in fact, it may be that NCAs reduce wages but that we cannot account for all the variables that confound the NCA–wage relationship. Our results also show that wage bargaining can explain a substantial amount of the NCA–wage relationship; not because workers with NCAs are necessarily more likely to bargain over wages, but because those with NCAs who do bargain drive much of the positive baseline relationship.

Heterogeneous wage effects

In this section we examine several potential heterogeneous effects discussed in the prior literature as well as novel heterogeneous effects made possible by the rich data in the NLSY97. The prior literature has emphasized the potential for historically disadvantaged populations to be especially harmed by NCAs. For example, Lipsitz and Starr found in 2021 that women particularly benefit when NCAs are banned, while Johnson, Lavetti, and Lipsitz found in 2020 that both women and Black workers are better off when NCA enforceability is weakened.[36] Lastly, Starr found in 2019 evidence that those with less education are more likely to be harmed when NCAs are more likely to be enforced.[37] Several rationales for these findings have been proposed, including that disadvantaged populations may be more likely to voluntarily abide by an NCA, that firms may selectively target such groups for enforcement, and that such workers are less likely to bargain over the NCA.

However, all of these studies examine state NCA policies, and none of the studies of NCA use have examined similar predictions. Accordingly, in table 5 we present analyses examining how, in the cross-section, the relationship of NCAs to wages is different for various groups. As before, we estimate models that include the same basic and advanced controls, clustering the standard errors by state.

Table 5. Heterogeneous wage effects of NCAs in the NLSY97

Variable	Logarithm of hourly wages			
	Model specification 1	Model specification 2	Model specification 3	Model specification 4
Panel A: Education				
NCA	0.088[1]	0.024	0.076[1]	0.022
	(0.022)	(0.019)	(0.023)	(0.019)
Bachelor's degree	0.446[1]	0.278[1]	0.414[1]	0.252[1]
	(0.029)	(0.028)	(0.036)	(0.031)
Education higher than a bachelor's degree	0.703[1]	0.474[1]	0.706[1]	0.482[1]
	(0.041)	(0.036)	(0.053)	(0.053)
Interaction of NCA and bachelor's degree	0.008	0.011	0.010	0.012
	(0.051)	(0.048)	(0.050)	(0.049)
Interaction of NCA and education higher than bachelor's degree	0.227[2]	0.175[2]	0.224[3]	0.176[2]
	(0.085)	(0.078)	(0.085)	(0.078)
R^2	0.349	0.527	0.372	0.534
Panel B: Race and ethnicity				
NCA	0.134[1]	0.053[2]	0.116[1]	0.049[3]
	(0.027)	(0.025)	(0.026)	(0.024)
Black or Hispanic	-0.091[1]	-0.063[1]	-0.078[1]	-0.052[2]
	(0.020)	(0.021)	(0.025)	(0.025)
Interaction of NCA and Black or Hispanic	-0.058	-0.017	-0.043	-0.012
	(0.040)	(0.037)	(0.042)	(0.038)
R^2	0.344	0.525	0.368	0.532
Controls	Basic	Advanced	Basic	Advanced
Bargaining indicator	No	No	Yes	Yes
Interaction of bargaining indicator and group indicators	No	No	Yes	Yes
Panel C: Gender				
NCA	0.158[1]	0.067[1]	0.144[1]	0.066[1]
	(0.026)	(0.025)	(0.028)	(0.025)
Female	-0.159[1]	-0.116[1]	-0.150[1]	-0.117[1]
	(0.025)	(0.028)	(0.033)	(0.030)
Interaction of NCA and Female	-0.102[2]	-0.049	-0.099[2]	-0.051
	(0.047)	(0.044)	(0.049)	(0.046)
R^2	0.347	0.526	0.371	0.532
Panel D: AFQT				
NCA	0.082[1]	-0.007	0.076[1]	-0.007
	(0.020)	(0.019)	(0.020)	(0.019)
AFQT score 50 percent or higher	0.139[1]	0.036	0.122[1]	0.029
	(0.023)	(0.024)	(0.024)	(0.029)
Interaction of NCA and AFQT Score 50 percent or higher	0.092[2]	0.113[1]	0.079[3]	0.108[1]
	(0.040)	(0.037)	(0.041)	(0.038)
R^2	0.359	0.527	0.380	0.533
Panel E: State NCA enforceability				
NCA	0.117[1]	0.042[2]	0.106[1]	0.040[2]
	(0.019)	(0.020)	(0.016)	(0.018)
State does not enforce NCAs	0.134[2]	0.131	0.130[2]	0.130[3]
	(0.066)	(0.081)	(0.055)	(0.070)
Interaction of NCA and whether a state does not enforce NCAs	0.040	0.065[2]	0.043[2]	0.065[2]

Notes: Observations = 3,090. AFQT = Armed Forces Qualification Test. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997. The dependent variable is log hourly wage. Basic controls include three education categories (less than a college degree, a college degree, and more than a college degree), indicators for race and ethnicity, AFQT score at 50th percentile or more, gender, and an indicator for whether the state of residence does not enforce NCAs. Advanced controls add an indicator for for-profit or nonprofit status, occupation and industry fixed effects (two digit Standard Occupational Classification and North American Industry Classification System codes), and indicators for job tasks including indicators for repetitive work, frequency of contact with others, the length of the longest document read on the job, solving problems, using math to solve problems, supervising others, and the extent of physical tasks. If the variable of interest is missing for some values, an indicator is included (but not reported) that equals 1 if the variable is missing. Results are available from the authors. Standard errors, clustered by state of residence, are in parentheses. Regressions are weighted with round 18 survey weights.

[1] $p < 0.01$.

[2] $p < 0.05$.

[3] $p < 0.10$.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

Variable	Logarithm of hourly wages			
	Model specification 1	Model specification 2	Model specification 3	Model specification 4
	(0.024)	(0.031)	(0.020)	(0.030)
R^2	0.358	0.526	0.380	0.532
Controls	Basic	Advanced	Basic	Advanced
Bargaining indicator	No	No	Yes	Yes
Interaction of bargaining indicator and group indicators	No	No	Yes	Yes

Notes: Observations = 3,090. AFQT = Armed Forces Qualification Test. NCA = noncompete agreement. NLSY97 = National Longitudinal Survey of Youth 1997. The dependent variable is log hourly wage. Basic controls include three education categories (less than a college degree, a college degree, and more than a college degree), indicators for race and ethnicity, AFQT score at 50th percentile or more, gender, and an indicator for whether the state of residence does not enforce NCAs. Advanced controls add an indicator for for-profit or nonprofit status, occupation and industry fixed effects (two digit Standard Occupational Classification and North American Industry Classification System codes), and indicators for job tasks including indicators for repetitive work, frequency of contact with others, the length of the longest document read on the job, solving problems, using math to solve problems, supervising others, and the extent of physical tasks. If the variable of interest is missing for some values, an indicator is included (but not reported) that equals 1 if the variable is missing. Results are available from the authors. Standard errors, clustered by state of residence, are in parentheses. Regressions are weighted with round 18 survey weights.

[1] $p < 0.01$.

[2] $p < 0.05$.

[3] $p < 0.10$.

Source: U.S. Bureau of Labor Statistics, NLSY97 (2017–18 interview). Authors' calculation.

The results largely accord with what we saw in the case of wage bargaining: The main effects are highly sensitive to the inclusion of controls, while in most cases, the heterogeneous effects of NCAs are more stable (and often line up with the prior literature). For example, panel A shows that relative to the NCA–wage differential for those with less than a bachelor's degree, the NCA–wage differential for those with a bachelor's degree is practically no different, while for those with more than a bachelor's degree it is 19 percent to 25 percent higher.

The heterogeneous effects of NCAs are more sensitive when it comes to race and gender. Panel B shows that the NCA–wage differential for minority (Black or Hispanic) workers is lower than the NCA–wage differential for non-Black non-Hispanic workers, but the estimates are noisy and fall close to zero in the most saturated model. Similarly, panel C shows that, at baseline, men bound by NCAs earn between 7 percent and 16 percent more than men without NCAs. The same differential for women, however, ranges from 5 to 10 percent lower than that of men, with the difference being statistically significant only in the model with basic controls.

Given the literature's focus on disadvantaged workers, in panel D we consider whether higher ability workers, as measured by having an AFQT score at or above the 50th percentile, have higher NCA–wage differentials than lower ability workers. Indeed, the wage difference between those who signed NCAs and those who did not was larger for workers who had a high AFQT score than for those who had a low score.

Finally, we consider heterogeneous NCA–wage effects based on the extent of enforceability of the NCA. Under the efficient contracting theories, it is the actual law (i.e., whether a contract will be held up in court) that determines whether the firm can ultimately be protected from a holdup problem. Accordingly, under this theory, workers should be better off where NCAs are more enforceable—either because of being more likely to bargain or because access to valuable information makes them more productive. In contrast, if NCAs are value extraction tools for firms, then NCAs might more effectively extract value when firms can legitimately threaten a worker with a lawsuit for violating an NCA. Panel E shows that relative to states that enforce NCAs, the wage differential associated with NCAs when they are not enforceable is 4 to 7 percent higher.

Taken together, because the base rates are so sensitive to controls, our results suggest that it is not obvious whether the baseline positive NCA–wage relationship is driven by selection or treatment. However, the more consistent heterogeneous effects suggest that, whatever the baseline effect is, the wage differential associated with NCAs is lower for women, for those with less education, for those with low AFQT scores, and in states more able to enforce NCAs.

In columns 3 and 4 of table 5, we consider the plausible theory that the observed NCA–wage differentials are driven by group differences in bargaining. If, for example, women are less likely to bargain over wages or when they do bargain ask for smaller compensating differentials, then these baseline bargaining differences may explain why NCAs are more harmful to women than men. Accordingly, we rerun our heterogeneous effects models controlling for whether the individual bargained for their wages, and we allow for different groups (as defined for each panel) to have differential effects from bargaining. In each case, we observe that subgroup bargaining patterns do not explain the differences in pay, since the estimated NCA–wage differentials move little when including these controls.

Discussion

This study is motivated by the recent and historical debates over the value of NCAs and by the relative lack of data on NCAs themselves, amidst a growing literature studying state NCA policies. Using new data collected on NCAs as part of the NLSY97, we examine who signs NCAs, how NCAs are related to wages and wage differentials between groups, and the role of bargaining in explaining these differentials. Our results both support the prior literature on NCAs and extend it in new, important ways.

Overall, we find that 18.1 percent of workers ages 32–38 in 2017 were bound by NCAs, very similar to prior estimates.[38] We also document similar patterns to the prior literature—that the use of NCAs is more common for workers with more education and that NCAs are more common in technical occupations and industries. However, as the prior literature also suggests, NCAs are still used for a wide swath of workers at the low end of the wage distribution or even workers in states that would never enforce such an agreement.[39] We extend these findings by showing that NCAs are also more common for workers with high ability and that even within a job-type, variation in job tasks (such as problem solving) are strongly associated with NCA use. Interestingly, our results suggest little selection into NCA use by ability after conditioning on broad demographics.

Examining wage outcomes, we find that NCAs are positively associated with wages but that this association is highly sensitive to demographic and job characteristics, as in prior work.[40] As a result, we recommend interpreting the main correlations with due caution. Heterogeneous effects in the NCA–wage differential are more stable, however. For example, the wage increase associated with NCAs is lower for those with less education (relative to more education), lower for those with lower ability (relative to higher ability), and lower for women (relative to men) in some models. Although we also find that the NCA–wage differential is lower for those who do not bargain over wages (relative to the NCA–wage differential for those who do bargain), bargaining differentials across groups do not explain the NCA–wage differentials across groups. Finally, our results suggest that the enforceability of NCAs reduces NCA–wage differentials, as found by Starr, Prescott, and Bishara in 2021.[41]

Taken together, our results are consistent with elements of the efficient contracting perspective, for example that NCAs are more common in high-skilled jobs and that NCAs are associated with higher wages on average. But our results also challenge that narrative because (1) the use of NCAs is widespread, (2) the NCA–wage effect is highly sensitive to demographic and job controls, and (3) the fact that the positive wage associations with NCAs dissipate where NCAs are more enforceable suggest that the baseline positive wage estimates may be highly selected. Our results also suggest that since bargaining power differentials are unlikely to underlie the NCA–wage differentials for the groups we study, alternative theories may be considered, such as differential to access to legal services or acquiescence to legal threats.

Limitations and future directions

While these analyses advance our understanding of NCA adoption, wage setting, and wage bargaining, they have several important shortcomings. Notably, the data are from a single cross-section, making it difficult to extract anything but correlational relationships and precluding a study of longitudinal earnings or job mobility dynamics. However, as more data are collected, there are several clear opportunities to exploit the richness of the NLSY97. In this section, we lay out a broader research agenda that these data will allow researchers to fill.

First, one of the major challenges in this literature is finding exogenous variation in the use of NCAs, given the existence of only cross-sectional data. However, as more states change their policies on NCAs, and as more data on NCAs are collected in the NLSY97, it seems natural that such policy variation could be used to instrument for NCA use. For example, between 2017 and 2021 several states banned NCAs for low-wage workers. These policy changes will likely exogenously reduce the use of NCAs among the low-wage population, especially those policies that impose penalties for using NCAs deemed illegal. As long as these policies leave unaffected the enforcement for those above the wage threshold (which some seem to do), then the exclusion restriction may plausibly hold (i.e., that these policies affect various outcomes only through their effect on NCA use). With this and perhaps Bartik-style approaches, we can hopefully begin to tease out the selection and treatment effects of NCAs.

Second, as longitudinal data are collected, the scope of variables one can analyze grows substantially, enabling analyses of within-individual wage profiles, job mobility choices, entrepreneurial behavior, and variation in nonwage benefits. NLSY97 data on moves and their timing also allow one to explore the relationship between NCAs and migration. Data on spouse and partner labor supply could be used to study the role job restrictions like NCAs play in dual labor market decisions. The NLSY97 also has unique data on several other dimensions that could be used to examine unique heterogeneous effects (such as job tasks, bargaining, AFQT, and more), which would not be possible with other data. Moreover, those interested in understanding the causal drivers of NCA use will be better positioned to use time-variant identification strategies. For example, one can examine how changes in minimum wages over time affect NCA use or how changes in subsidies or tax incentives for investment might drive firms into using NCAs.

Third, as longitudinal data on the use of NCAs becomes available, one can calculate estimates of the growth of NCAs and relate them to various outcomes relevant to multiple disciplines. For example, one important question is what are the downstream effects of NCAs? How does the rise of NCAs affect prices, product quality, research and development expenditures and innovation, and consumer welfare more broadly?[42] Another set of questions relates to the patterns of wage stagnation and economic dynamism and what role NCAs played in those dynamics. Note that care should be given to these estimates because estimates of the growth of NCAs will track the use of NCAs among a given age cohort and so may just reflect how NCA adoption changes as a cohort ages. Thus, it may be helpful to benchmark the results to other nationally representative cross-sections to separate out the trends from cohort-specific effects.[43]

As the NLSY97 data continue to accumulate, so too will the opportunities to learn more about how these contractual restrictions on employee mobility affect many important economic dynamics.

DISCLAIMER: The views expressed are those of the authors and do not reflect the policies of the BLS or the views of other BLS staff members.

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Notes

[1] See "Non-compete contracts: economic effects and policy implications," U.S. Department of Treasury Office of Economic Policy, March 2016; and *Non-Compete Agreements: Analysis of the Usage, Potential Issues, and State Responses*, (Washington: DC: The White House, May 5, 2016).

[2] See Steven Greenhouse, "Noncompete clauses increasingly pop up in array of jobs," *New York Times*, June 8, 2014, https://www.nytimes.com/2014/06/09/business/noncompete-clauses-increasingly-pop-up-in-array-of-jobs.html; Dave Jamieson, "Jimmy John's makes low-wage workers sign 'oppressive' noncompete agreements," *Huffington Post*, October 13, 2014, https://www.huffpost.com/entry/jimmy-johns-non-compete_n_5978180; Evan Starr, J.J. Prescott, and Norman Bishara, "Noncompete agreements in the US labor force," *The Journal of Law and Economics,* vol. 64, no. 1, 2021, pp.53–84; and Matthew S. Johnson and Michael Lipsitz. "Why are low-wage workers signing noncompete agreements?" *Journal of Human Resources,* vol. 57, May 12, 2020, pp. 0619-10274R2. For an example of potential state and federal actions, in 2021 the Uniform Law Commission promulgated the Uniform Restrictive Employment Agreement Act for adoption by state legislatures. The proposed act bans noncompete agreements (NCAs) and related restrictive agreements for low-wage workers and mandates notice and other requirements for other workers (see "Restrictive employment agreement act," *Uniform Law Commission* (2022), https://www.uniformlaws.org/committees/community-home?communitykey=f870a839-27cd-4150-ad5f-51d8214f1cd2&tab=groupdetails). For other state and federal policies, see generally Russell Beck, "The Changing landscape of trade secrets laws and noncompete laws around the country," *Fair Competition Law*, May 2021, https://faircompetitionlaw.com/changing-landscape-of-trade-secrets-laws-and-noncompete-laws/. In addition, state Attorneys General have investigated more than a dozen NCA cases (see Lisa Madigan, and Jane Flanagan, "Protecting competition on behalf of the people: the role of state Attorneys General in challenging noncompetes and other restraints on employee mobility," In Sharon Block and Benjamin H. Harris, editors, *Inequality and the Labor Market: The Case for Greater Competition* (Washington, DC: Brookings Institution Press, 2021), pp. 107–26, http://www.jstor.org/stable/10.7864/j.ctv13vdhvm.12.). The Federal Trade Commission has considered making a rule related to regulating NCAs, and several federal agencies have written reports on the topic (see "Non-compete contracts: economic effects and policy implications," U.S. Department of Treasury Office of Economic Policy, March 2016; and *Non-Compete Agreements*, the White House.

[3] Paul H. Rubin and Peter Shedd, "Human capital and covenants not to compete," *Journal of Legal Studies,* vol. 10, no. 1, January 1981, pp. 93–110, http://www.jstor.org/stable/724227.

[4] See Norman Bishara and Evan Starr, "The incomplete noncompete picture," *Lewis and Clark Law Review,* vol. 20, 2016, pp. 497–546. For a review of NCA use literature, see Evan Starr, "Consider this: training, wages, and the enforceability of covenants not to compete," *ILR Review,* vol. 72, no. 4, August 2019, pp. 783–817, https://doi.org/10.1177/0019793919826060. Indeed, only a handful of studies possess data on the use of NCAs (see Alan B. Krueger and Eric A. Posner, "A proposal for protecting low-income workers from monopsony and collusion," *The Hamilton Project*, February 2018). Of these studies, most examine a specific occupational context, such as executives (see Stewart J. Schwab and Randall S. Thomas, "An empirical analysis of CEO employment contracts: What do top executives bargain for?" *Washington and Lee Law Review,* vol. 63, no. 1, Winter 2006, p. 231, https://scholarlycommons.law.wlu.edu/wlulr/vol63/iss1/6; and Norman D. Bishara, Kenneth J. Martin and Randall S. Thomas, "An empirical analysis of noncompetition clauses and other restrictive postemployment covenants," *Vanderbilt Law Review,* vol. 68, no. 1, January 2015, pp.1–51), engineers (see Matt Marx, "The firm strikes back: non-compete agreements and the mobility of technical professionals." *American Sociological Review,* vol. 76, no. 5, August 24, 2011, pp. 695–712), physicians (see Kurt Lavetti, Carol Simon, and William D. White, "The impacts of restricting mobility of skilled service workers evidence from physicians," *Journal of Human Resources,* vol. 55, no. 3, Summer 2020, pp. 1025–67), and hair stylists (see Johnson and Lipsitz, "Why are low-wage workers signing noncompete agreements?").

[5] For NCAs found in states where they are unenforceable, see Sarath Sanga, "Incomplete contracts: An empirical approach," *Journal of Law, Economics, and Organization,* vol. 34, no. 4, November 2018, pp. 650–79, https://doi.org/10.1093/jleo/ewy012; Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force,"; and Alexander J.S. Colvin and Heidi Shierholz, "Noncompete agreements: ubiquitous, harmful to wages and to competition, and part of a growing trend of employers requiring workers to sign away their rights," *Economic Policy Institute,* December 10, 2019. For workers' perception of NCA enforceability, see J.J. Prescott and Evan Starr, "Subjective beliefs about contract enforceability," *University of Michigan Law and Economics* Research Paper, 2022. For how NCAs limit mobility regardless actual law, see Evan Starr, J.J. Prescott, and Norman Bishara, "The behavioral effects of (unenforceable) contracts," *Journal of Law, Economics, and Organization,* vol. 36, no. 3, November 2020, pp. 633–87.

[6] For a concurrent work that also examine the incidence of NCAs using the National Longitudinal Survey of Youth 1997 (NLSY97) data, see Tyler Boesch, Katherine Lim, and Ryan Nunn, "Non-compete contracts sideline low-wage workers." *Federal Reserve Bank of Minneapolis,* 2021, https://www.minneapolisfed.org/article/2021/non-compete-contracts-sideline-low-wage-workers.

[7] Harlan M. Blake, "Employee agreements not to compete," *Harvard Law Review,* 1960, pp. 625–91.

[8] See Marx, "The firm strikes back: non-compete agreements and the mobility of technical professionals."; Matt Marx, Jasjit Singh, and Lee Fleming, "Regional disadvantage? Employee non-compete agreements and brain drain," *Research Policy,* vol. 44, no. 2, November 11, 2014, pp. 394–404; and Natarajan Balasubramanian, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr, "Locked in? The enforceability of covenants not to compete and the careers of high-tech workers," *Journal of Human Resources,* May 2020, pp. 1218–9931R1.

[9] See Starr, "Consider this: training, wages, and the enforceability of covenants not to compete,"; Michael Lipsitz and Evan Penniman Starr, "Low-wage workers and the enforceability of non-compete agreements," *Management Science,* vol. 68, no.1, January 2022, https://doi.org/10.1287/mnsc.2020.3918; and Matthew S. Johnson, Kurt Lavetti, and Michael Lipsitz. "The labor market effects of legal restrictions on worker mobility," *SSRN Electronic Journal,* June 6, 2020, https://dx.doi.org/10.2139/ssrn.3455381.

[10] See David Friedman, "Non-competition agreements: some alternative explanations," unpublished preliminary draft, April 2, 1991, http://daviddfriedman.com/Academic/non-comp/Non-Competition.html; and Maureen B. Callahan, "Post-employment restraint agreements: A reassessment," *The University of Chicago Law Review,* vol. 52, no.3, Summer 1985, pp. 703–28.

[11] Rubin and Shedd, "Human capital and covenants not to compete."

[12] Jonathan M. Barnett, and Ted Sichelman. "The case for noncompetes," *University of Chicago Law Review,* 87, 2020, pp. 953–1049.

[13] In practice, unenforceable NCAs may resolve holdup problems to some degree if, (1) workers are unaware of the law (as in Prescott and Starr, "Subjective beliefs about contract enforceability"), or (2) workers cannot access legal counsel or otherwise face costs of breaking an unenforceable contract (as in Starr, Prescott, and Bishara, "The behavioural effects of (unenforceable) contracts,"). Classic efficient contracting theories do not consider these possibilities.

[14] David J. Balan, "Labor non-compete agreements: tool for economic efficiency, or means to extract value from workers?" *The Antitrust Bulletin,* vol. 66, no. 4, December 2021, pp. 593–608, https://doi.org/10.1177/0003603X211045443.

[15] Arnow-Richman, Rachel S, "Cubewrap contracts and worker mobility: the dilution of employee bargaining power via standard form noncompetes," *Michigan State Law Review,* vol. 2006, No. 963, December 2006.

[16] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force;" and Natarajan Balasubramanian, Evan Starr, and Shotaro Yamaguchi, "Bundling employment restrictions and value capture from employees." *SSRN Electronic Journal,* April 2021.

[17] For a summary, see Evan Starr, "Are noncompetes holding down wages?" In Sharon Block and Benjamin H. Harris, editors, *Inequality and the Labor Market: The Case for Greater Competition* (Washington, DC: Brookings Institution Press, 2021), http://www.jstor.org/stable/10.7864/j.ctv13vdhvm.13. For studies on the negative effects of NCAs, see Natarajan Balasubramanian, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr, "Locked in? The enforceability of covenants not to compete and the careers of high-tech workers," *Journal of Human Resources,* May 2020, pp. 1218–9931R1; Lipsitz and Starr, "Low-wage workers and the enforceability of non-compete agreements,"; Johnson and Lipsitz, "Why are low-wage workers signing noncompete agreements?"; and Starr, "Consider this: training, wages, and the enforceability of covenants not to compete." For studies finding positive effects, see Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force"; Lavetti, Simon, and White, "The impacts of restricting mobility of skilled service workers evidence from physicians"; Omesh Kini, Ryan Williams, and David Yin, "CEO noncompete agreements, job risk, and compensation," *Review of Financial Studies,* vol. 34, no. 10, October 2021, pp. 4701–44, https://doi.org/10.1093/rfs/hhaa103; Liyan Shi, "The macro impact of noncompete contracts," *EIEF Working Papers Series,* 2103, revised 2021.

[18] Balasubramanian, Starr, and Yamaguchi in 2021 used data on NCAs and three other restrictions and show that selection effects likely underlie the positive average NCA–wage differential, while the true effect is negative. See Balasubramanian, Starr, and Yamaguchi, "Bundling employment restrictions and value appropriation from employees."

[19] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force" and Balasubramanian, Starr, and Yamaguchi, "Bundling Employment Restrictions and Value Appropriation from Employees."

[20] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force." Data from the 2014 Noncompete Survey Project is described in greater detail in J.J. Prescott, Norman Bishara, and Evan Starr, "Understanding noncompetition agreements: The 2014 Noncompete Survey Project," *Michigan State Law Review,* vol. 2016, no.2, 2016, pp. 369–464. The project covers in total 11,505 respondents. It derives from an online survey that the authors created and deployed via Qualtrics in 2014. Note that data from the 2014 Noncompete Survey Project include both imputed and lower bound estimates, which differ in how they treat individuals who are unaware whether they have signed a noncompete; here we emphasize the lower-bound estimates. See also Stewart Schwab and Evan Starr, "Cornell National Social Survey," unpublished data, 2019. Data from the Cornell National Social Survey (CNSS) derives from a random digit dial survey of 1,000 respondents. The noncompete question from the CNSS data is very similar to the one in the NLSY97. Note that, relative to the NLSY97, which is cohort-specific, these surveys cover all age categories. Accordingly, in the Noncompete Survey Project Data we limit to the same age range as the NLSY97, and in the CNSS, we limit to 25–50, in order to keep a large enough sample to say anything meaningful.

[21] Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force."

[22] Values do not sum to 100 because of rounding. We also examined confidence levels by gender, education, wages, and NCA status. Across all these stratifications, at least 81.0 percent of workers are very confident in their NCA answer and at most 1.6 percent are not confident.

[23] Legal jobs have the lowest use of NCAs (4 percent), which likely arises because they are the only occupation in which NCAs are unenforceable in all 50 states. See Russell C. Buffkin, "Non-competition clauses in law firm partnership agreements: how far can partnership agreements control future conduct of lawyers," *Journal of the Legal Profession,* vol. 23, 1999, p. 325; and Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force."

[24] See Rachel Arnow-Richman, "The new enforcement regime: revisiting the law of employee mobility (and the scholarship of Charles Sullivan) with 2020 vision," *Seton Hall Law Review,* vol. 50, 2020, pp. 1223–59. Other states have NCA bans for some sets of workers, though most of these bans started in 2017 or later, see Russell Beck, "The changing landscape of trade secrets laws and noncompete laws around the country," *Fair Competition Law*, May 2021, https://faircompetitionlaw.com/changing-landscape-of-trade-secrets-laws-and-noncompete-laws/.

[25] Rubin and Shedd, "Human capital and covenants not to compete."

[26] The Armed Forces Qualification Test (AFQT) covers four sections of the Armed Services Vocational Aptitude Battery (ASVAB) and measures math and verbal aptitude. This test was given to NLSY97 respondents in 1997–98.

[27] For information on job tasks, see David H. Autor and Michael J. Handel, "Putting tasks to the test: human capital, job tasks, and wages," *Journal of Labor Economics,* vol. 31, no. 2, June 2009, pp. S59-S96.

[28] Theoretically, one may worry that workers sort into NCAs on the basis of unobserved ability; and since unobserved ability also drives wages, such sorting will cause upward bias in the NCA–wage effect. The results in table 3 suggest that workers are not sorting in NCAs by ability, conditional on demographic characteristics.

[29] Paul Goldsmith-Pinkham, Isaac Sorkin, and Henry Swift. "Bartik instruments: what, when, why, and how," *American Economic Review,* vol. 110, no. 8, August 2020, pp. 2586–624.

[30] Practically, this condition means that anything else that affects wages must not also be related to NCAs. This condition will be violated if there are omitted variables that affect NCAs and wages, if there is reverse causality, etc.

[31] Carlos Cinelli, Andrew Forney, and Judea Pearl. "A crash course in good and bad controls," *SSRN Electronic Journal,* September 9, 2020, https://dx.doi.org/10.2139/ssrn.3689437.

[32] Kenneth Burdett and Dale T. Mortensen. "Wage differentials, employer size, and unemployment," *International Economic Review,* vol. 39, no.2, May 1998, pp. 257–73.

[33] Dale T. Mortensen and Christopher A. Pissarides, "Job creation and job destruction in the theory of unemployment," *The Review of Economic Studies* vol. 61, no. 3, July 1, 1994, pp. 397–415, https://doi.org/10.2307/2297896.

[34] See Robert E. Hall, and Alan B. Krueger, "Evidence on the incidence of wage posting, wage bargaining, and on-the-job search," *American Economic Journal: Macroeconomics,* vol. 4, no. 4, October 2012, pp. 56–67; and Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force."

[35] Percent changes are calculated by raising the constant *e* to the power of the coefficient in the table and then subtracting 1. In this case, $e^{0.22} - 1 = 0.246$, a 25-percent increase.

[36] See Lipsitz and Starr, "Low-wage workers and the enforceability of non-compete agreements"; and Matthew S. Johnson, Kurt Lavetti, and Michael Lipsitz. "The labor market effects of legal restrictions on worker mobility," *SSRN Electronic Journal,* June 6, 2020, https://dx.doi.org/10.2139/ssrn.3455381.

[37] See Starr, "Consider this: training, wages, and the enforceability of covenants not to compete."

[38] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force"; and Schwab and Starr, "Cornell National Social Survey."

[39] See Johnson and Lipsitz. "Why are low-wage workers signing noncompete agreements?"

[40] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force;" and Balasubramanian, Starr, and Yamaguchi, "Bundling Employment Restrictions and Value Appropriation from Employees."

[41] See Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force."

[42] See Michael Lipsitz and Mark Tremblay, "Noncompete agreements and the welfare of consumers," *SSRN Electronic Journal,* January 25, 2022, https://dx.doi.org/10.2139/ssrn.3975864; and Naomi Hausman, and Kurt Lavetti. "Physician practice organization and negotiated prices: evidence from state law changes." *American Economic Journal: Applied Economics,* vol. 13, no. 2, April 2021, pp. 258–96.

[43] See Natarajan Balasubramanian, Evan Starr, and Shotaro Yamaguchi, "Bundling employment restrictions and value capture from employees," *SSRN Electronic Journal,* April 2021; and Starr, Prescott, and Bishara, "Noncompete agreements in the US labor force."

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ARTICLE

JUNE 2022

Were wages converging during the 2010s expansion?

This article uses multiple surveys and data sourced from administrative records to examine trends in wage inequality from 2003 to 2019. Survey evidence shows that wages were growing more unequal from 2003 to 2013 as wages grew faster among high-wage workers than among low-wage workers. However, from 2013 to 2019, the same surveys show substantial wage gains for workers in the second and third deciles of the wage distribution, particularly among material moving workers and health aides. Administrative tax data also show substantial gains in annual wage and salary earnings income for earners in the lower portion of the earnings distribution in the same years. Wage growth among lower wage workers was large enough to reduce overall wage inequality from 2013 to 2019 in Occupational Employment and Wages Survey data. In tax data, wage growth among lower earning workers was large enough to reduce overall earnings inequality from 2010 to 2018. In data from the Current Population Survey, a plateau was found in overall wage inequality—rather than the clear decline found in the other two data sources—in the later years of the economic expansion.

Growing inequality of incomes is one of the most important economic issues of our time. When wages are not rising over time for a large fraction of American workers, these workers do not fully share in economic growth. Moreover, inequality of incomes becomes inequality in household resources. As household resources become more important in equipping new workers for jobs in which they can earn higher incomes (for example, funding from parents and other relatives to pay for postsecondary education), inequality today has the potential to further increase inequality in succeeding generations. Such ever-widening inequality will mean growing gaps in opportunities between Americans of different household income levels.

For more than four decades, inequality of incomes has been growing nearly continuously and has been the subject of a tremendous amount of empirical research. Lawrence F. Katz and David Autor provide a thorough survey of this literature as it stood 20 years ago.[1] Since then, the works of David S. Lee and of David Card and John E. DiNardo have been particularly influential in emphasizing the potential role of declining real minimum wages and of unionization in explaining the growth of wage inequality.[2] The work of David H. Autor, Lawrence F. Katz, and Melissa S. Kearney has also been particularly influential in emphasizing the importance of technological change in explaining wage inequality growth, because automation reduced demand for what had been routine work done by middle-income employees.[3] A related literature using tax data to study income inequality has followed the work of Thomas Piketty and Emmanuel Saez,[4] who used these tax data to show dramatic increases in incomes for people at the top of the income distribution.

All these studies focus on understanding details in the patterns of income inequality growth to better understand the underlying causes of inequality growth. However, recent research articles based on data from the Current Population Survey (CPS) show some evidence of a change from the trend of ever-increasing income and wage inequality in the years immediately preceding the 2020 recession. In their recent survey of the wage inequality literature, Florian Hoffmann, David S. Lee, and Thomas Lemieux include figures showing small declines in labor income inequality for men beginning around 2015.[5] Jay C. Shambaugh and Michael R. Strain also present figures showing that wages at the lower percentiles of the wage distribution had greater growth than median wages from 2017 to 2019.[6]

In this article, we examine recent trends in wage inequality using the confidential microdata collected from the Occupational Employment and Wage Statistics (OEWS) survey, which relies on a large representative sample of employers in the United States. We also examine the wage questions in the confidential version of the CPS data, collected from a large representative sample of households in the United States. The OEWS and CPS data are completely independent surveys that include wage information. James R. Spletzer and Elizabeth Weber Handwerker show very similar patterns of wage variances between the CPS and the OEWS survey from 1998 to 2010, overall, by sector, industry, and occupation, and in the fraction of wage variance explained by these factors.[7] Here, we examine what happened to wage inequality in these two surveys from late 2002 or 2003 through 2019. We further corroborate our findings from these two surveys with annual wage and salary earnings data from income tax filings.

We find that wages were growing more unequal from 2003 to 2013 in both the CPS and OEWS data, because wages increased more among high-wage workers than among low-wage workers. However, from 2013 to 2019, both surveys show substantial wage gains for workers in the second and third deciles of the wage distribution. In the OEWS data, wage growth among lower wage workers was great enough to reduce overall wage inequality from 2013 to 2019, while in the CPS data, wage inequality plateaued. In tax data, we find substantial increases in annual earnings among workers with lower annual earnings, which were great enough to reduce overall earnings inequality from 2010 through 2018 (the most recent year available). Occupational information in the CPS and OEWS data allows us to identify the occupations most important for wage growth among lower wage workers, because of their wage gains and employment levels. These occupations included health aides and material moving workers. We also examine which characteristics of workers and their employers were particularly important for wage inequality in the CPS and OEWS data and highlight the importance of occupations in wage inequality.

Data

We begin by describing the wage or wage and salary data available from each of our sources and the differences between the data available from each one.

Wage data from the Occupational Employment and Wage Statistics program

In either May or November each year, the OEWS survey asks employers about their occupational and wage patterns, with approximately 200,000 establishments surveyed at each date. Administrative data on the occupations and wages of employees are also collected from state and federal governments. The OEWS data do not include much of the agricultural sector, the unincorporated self-employed, or private household employers. Employers are asked to report hourly wage rates for part-time or hourly workers and annual rates for salaried workers and for workers in occupations that are generally paid an annual salary but work less than full-time hours over the course of a year, such as pilots, flight attendants, and teachers. Wages in this survey include base pay, guaranteed pay, incentive pay, commissions, bonuses, and tips. They do not include overtime pay, severance pay, or employer costs for employee benefits. Before 2020, the OEWS survey collected wage information in 12 wage intervals, defined in terms of either hourly wages or annual wages equivalent to hourly wages multiplied by 2,080 hours.

The OEWS survey has a complex sample design. A full sample is selected over a 3-year period, with establishments generally not selected more than once every 3 years. All OEWS estimates rely on 3 years of data, as well as data from other U.S. Bureau of Labor Statistics (BLS) programs. Within each wage band, a mean hourly wage is estimated by using wage data collected by the BLS National Compensation Survey.[8] To adjust wage estimates collected at different dates, the OEWS program uses the BLS Employment Cost Index for each occupational division. Employers that do not respond to the survey have occupational employment and wage values imputed on the basis of responses from employers that are similar in location, industry, and size (in Quarterly Census of Employment and Wages [QCEW] data). All OEWS estimates are benchmarked to employment totals from the BLS QCEW, by location, industry, and size, in the final year of data collection. More information about the OEWS survey can be found in the BLS *Handbook of Methods*.[9]

We use the OEWS microdata beginning in November 2002, when that survey began sampling 200,000 establishments every November and May and had completed training all staff in using the Standard Occupational Classification (SOC) system. We convert the resulting nominal wage estimates into constant 2016 dollars using the CPI for All Urban Consumers (CPI-U). Because OEWS estimates are based on 3 years of data, OEWS estimates cannot be compared from one year to the next. We have calculated estimates for every 3-year aggregation of data (November 2002 to May 2005, November 2003 to May 2006, etc.) but present only estimates for the 3-year aggregations ending in May 2005, May 2010, May 2013, May 2016, and May 2019. The choice of years we have chosen for presentation does not substantially change our findings, although the overall log wage variance measured in the OEWS is highest for November 2011 to May 2014 (this period has a standard deviation of 0.618, compared with the standard deviation of 0.616 for November 2010 to May 2013 shown in the charts discussed later in this article).

Wage data from the Current Population Survey

The CPS data are generally used in studies of wage and income inequality, because microdata from this survey have been publicly available to researchers for several decades. This survey uses a rotational sample design, in which each household in the sample is interviewed for 4 consecutive months and then, 8 months later, interviewed for another 4 consecutive months. For the best comparison to the OEWS, we focus on the CPS wage questions, which are asked in the fourth and eighth interviews. Since these are the months when respondents are rotating out of the sample, they are referred to as Outgoing Rotational Groups (ORGs). We use CPS data from the ORG beginning in 2003, when the CPS began using the same SOC system used in the OEWS as the basis for its occupational codes, allowing us to compare wage trends by occupation between the CPS and the OEWS. Authors who focus more on overall income inequality (rather than wages) use questions about income from the previous year, which the CPS asks only in the Annual Social and Economic Supplement.

The wage questions in the CPS are only asked of respondents about their main jobs and are not asked of self-employed people. We add overtime pay, tips, and commissions to hourly wages for those who report these types of income. We use hourly wages for jobs reported as such and otherwise convert annual, monthly, or weekly earnings to hourly wages using usual hours reports, following research by Anne E. Polivka and by John Schmitt.[10] About 58 percent of respondents report hourly wages. Depending on the year, 2.5 percent to 3.8 percent of respondents report annual, monthly, or weekly earnings but not an hourly wage and report that their usual hours vary, making it difficult to calculate their hourly wages. For these people, we use a regression-based imputation method to model weekly hours separately for men and women working full- or part-time, based on age, race, education, marital status, and immigration status. All wage data in the CPS are reported in nominal terms and converted into constant 2016 dollars using the CPI-U. To avoid the top coding of incomes applied to the public-use version of the CPS data to protect the confidentiality of respondents, we use the confidential CPS microdata not available to researchers outside BLS or the U.S. Census Bureau. However, in the appendix (to this article), we show that the public-use version of these data yield very similar trends in wage inequality over time.

The greatest hourly wage reportable in the CPS data is $99.99, but this affects only 0.05 percent of hourly wage reports; most high earners report their earnings annually, monthly, or weekly, not hourly, and the CPS allows respondents to report weekly earnings up to $99,999.99 per week. Following Card and DiNardo, Thomas Lemiuex, and Sarah A. Donovan and David H. Bradley,[11] we remove observations with an hourly wage of less than $1 or more than $100 in 1979 dollars—less than $3.50 or more than $350 in 2016 dollars. This censoring of particularly high- and low-wage values means dropping 0.8 percent to 0.9 percent of observations in the confidential data, varying very slightly by year.

The most important differences in wage data collection between the OEWS and the CPS are that wage information is collected from employers in the OEWS and from workers in the CPS and that wage questions in the CPS ask respondents only about their main job.

Earnings data from Form W-2 tax records

We additionally examine annual person-level wage and salary income reported on Form W-2 Wage and Tax Statement to the Internal Revenue Service (IRS) by employers for each wage earner in each job in each year. The U.S. Census Bureau has received an extract of these data from tax years 2005 through 2018 and is authorized to use these data to improve measurements of income and produce new income statistics. Form W-2 data are annual, but they reflect earnings on each job, and so many W-2 observations have low values representing short duration jobs. We aggregate wage income across all W-2 forms for each person to capture total annual wage earnings in these data.

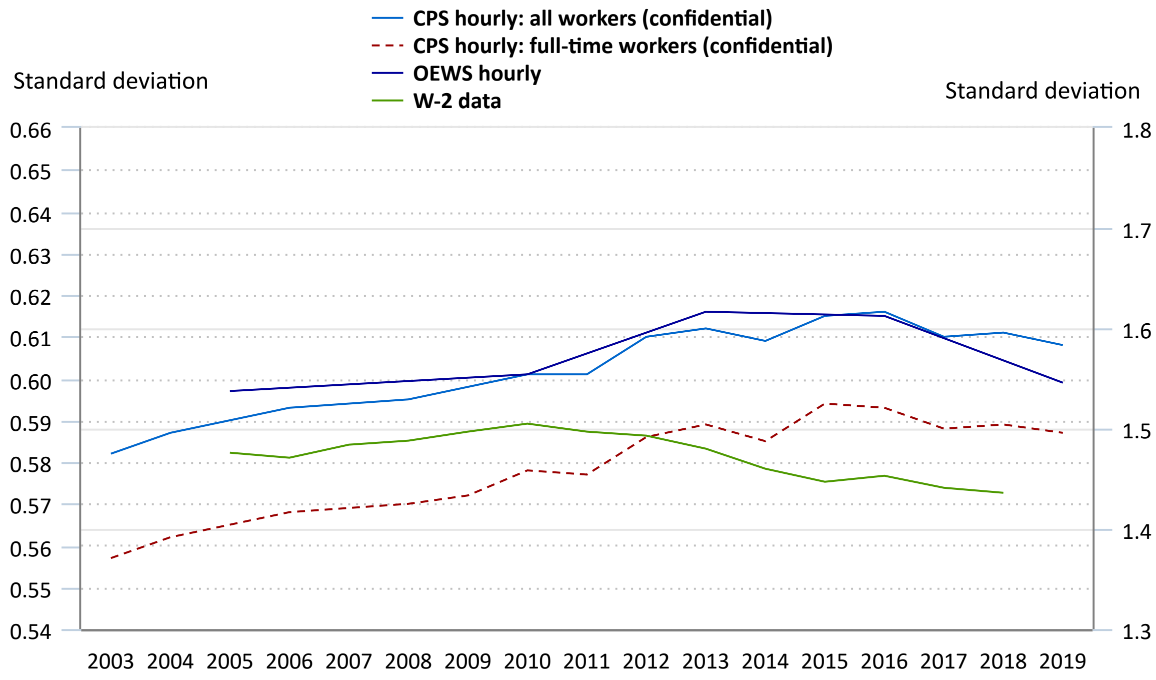
There are several ways this annual wage and salary earnings measure differs from the CPS and OEWS wage measures. The W-2 data include wage and salary income across all jobs over a calendar year, rather than the current "main jobs" for which we measure wages in the CPS. They do not include any measure of hours or weeks worked, rather than the hourly wage report in the CPS or the hourly wage or equivalent annual salary reported in the OEWS. This wage and salary earnings measure will be affected not only by wages but also by hours worked per week and by weeks worked per year. The W-2 data can also include overtime pay (like the CPS but unlike the OEWS), severance pay (unlike either the CPS or the OEWS), and potentially other forms of compensation, such as stock options and bonuses. Nonetheless, we include these annual earnings here to show how trends in the wage inequality measured with the OEWS and the CPS compare with trends in inequality in overall wage and salary incomes measured with income tax data.

Overall wage variation results

We begin by showing trends in the standard deviation of log wage income in the CPS-ORG, OEWS data, and W-2 data. We examine trends in the CPS-ORG data in two ways. First, to compare our results with authors in the economic literature, we examine trends in the CPS for full-time workers and weight these workers by the number of hours they work. (We cannot further restrict the data to full-year work, because these questions are only asked in the CPS-ORG data for workers who report wages on an annual basis.) Second, to better compare wage variation in the CPS with the OEWS and the W-2 data, we examine trends in the CPS for all workers, without weighting workers by the number of hours worked, since the OEWS and W-2 data include part-time and seasonal workers and cannot be weighted by the number of hours worked.

Chart 1 thus compares trends in the standard deviation of log hourly wage income in the OEWS with two versions of overall trends of the standard deviation of log hourly wage income in the CPS-ORG and with trends in the standard deviation of log annual wage and salary income in the W-2 data. Note that the standard deviation of log annual wage and salary income in the W-2 data is much greater than the standard deviation of hourly wages in the OEWS and CPS data, and so it is plotted on a different scale.

Chart 1. Standard deviation of log hourly wages in OEWS and CPS outgoing rotations and log annual wage and salary income in W-2 data, 2003–19



Click legend items to change data display. Hover over chart to view data.
Note: Data are for only those years shown because every OEWS estimate is based on 3 years of data collection. W-2 data are available only for the years shown. W-2 wages are from the Form W-2 Wage and Tax Statement, reported to the Internal Revenue Service. CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics survey. CPS estimates are based on the confidential version of the CPS microdata available to BLS employees, not the public-use version of the microdata.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

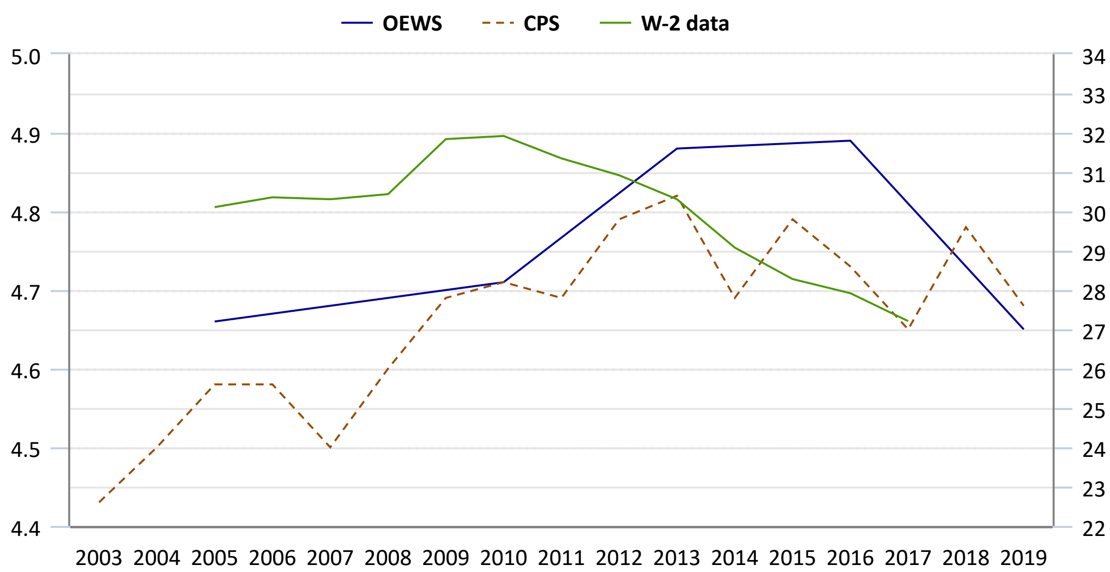
Comparing worker restrictions and weightings within versions of the CPS data, we find greater dispersion of wages among all workers than among full-time workers only. However, weighting full-time workers by the number of hours they work increases the dispersion in their wages, since higher earning full-time workers work more hours. Combining both worker restrictions and hours weighting, we find a greater dispersion of wages overall among all workers who are not weighted by hours worked (estimates more comparable to the OEWS) than among full-time workers only who are weighted by hours worked (estimates more comparable to the wage variation literature). However, the two versions of the CPS wage inequality series show similar time trends in wage inequality. In both CPS series, wage inequality was clearly rising from 2003 to 2013 and then stopped rising, with perhaps some modest decline from 2016 through 2019. Versions of these series estimated using public-use CPS data are shown in the appendix.

Comparing the CPS data to the OEWS and W-2 data, we see that all three data sources show growing inequality from the beginning of the series through 2010. OEWS data show increased inequality of wages through 2013 and declining inequality of wages thereafter, particularly from 2016 to 2019. CPS data show a similar increase in wage inequality to the OEWS through 2016, but they do not show as much decline in inequality thereafter. The CPS series for all workers not weighted by hours is much more similar to the OEWS data in its measured level of wage inequality than the CPS series for full-time workers weighted by hours worked. The two CPS series, however, show similar time trends in wage inequality. The W-2 data show earnings inequality that peaked in 2010 and has been declining thereafter.

The rest of this article examines the distribution of wages further by using only the OEWS and the confidential version of the CPS from 2003 through 2019 that is more comparable to the OEWS (all workers, not weighted by hours) as well as the distribution of annual wage and salary income in the W-2 data.

Another common measure of overall wage inequality is the ratio of wages at the 90th percentile of the wage distribution to wages at the 10th percentile of the wage distribution. We show this measure for all three data sources in chart 2 and find broadly similar patterns to those shown in chart 1. In the OEWS data, this measure is increasing from 2005 to 2013, flat from 2013 to 2016, and decreasing from 2016 to 2019. In the CPS data, this measure is increasing from 2003 to 2013 and flat or declining from 2013 to 2019. In the W-2 data, this measure is increasing from 2005 to 2010 and declining afterward. We note that the OEWS is the last series to show a decline, perhaps because each OEWS estimate is based on 3 years of data; an OEWS estimate for May 2016 uses data collected in November 2013 through May 2016.

Chart 2. Ratio of 90th percentile to 10th percentile hourly wages in CPS outgoing rotations and OEWS and of annual wage and salary income in W-2 data, 2003–19

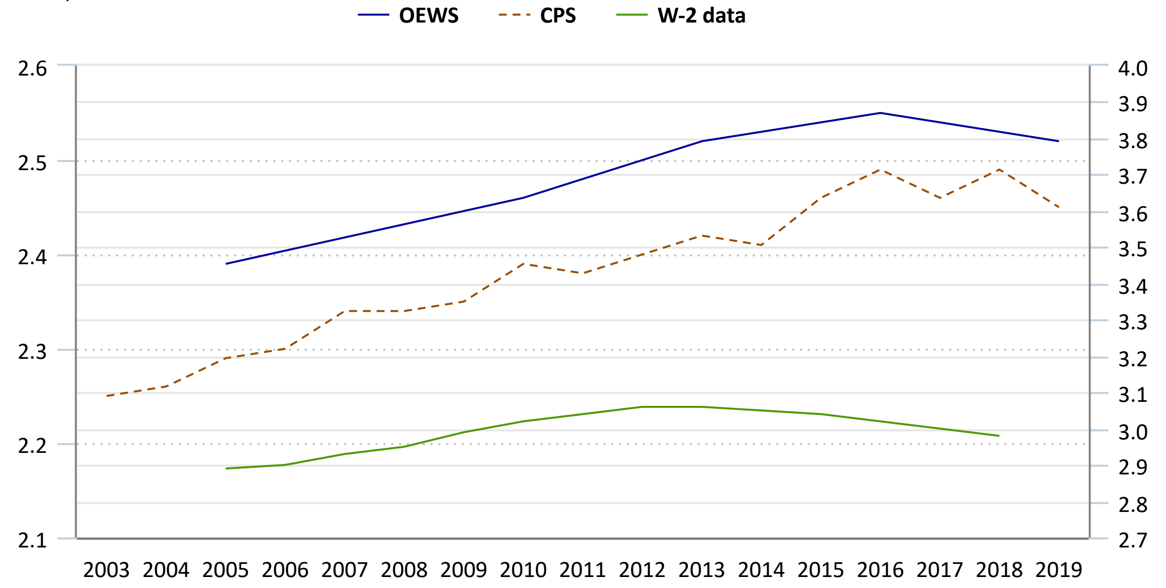


Click legend items to change data display. Hover over chart to view data.
Note: Data are for only those years shown because every OEWS estimate is based on 3 years of data collection. W-2 data are available only for the years shown. W-2 wages are from the Form W-2 Wage and Tax Statement, reported to the Internal Revenue Service. CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics survey. CPS estimates are based on the confidential version of the CPS microdata available to BLS employees, not the public-use version of the microdata.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

The overall pattern of declining wage/earnings inequality after 2013 in all three data sources could be driven either by slower wage growth for high earners or by particularly strong wage growth for lower earners. Thus, chart 3 shows a common measure of wage/earnings inequality for the top half of the wage distribution, the ratio of wages at the 90th percentile of the wage distribution to wages at the 50th percentile. In the OEWS data, this measure is increasing from 2005 to 2016 and decreasing from 2016 to 2019. In the CPS data, this measure is generally increasing from 2003 to 2016, with unclear trends from 2016 to 2019. In the W-2 data, this measure is increasing from 2005 to 2012, flat from 2012 to 2013, and declining afterward.

Chart 3. Ratio of 90th percentile to 50th percentile of hourly wages in CPS outgoing rotations and OEWS and of annual wage and salary income in W-2 data, 2003–19

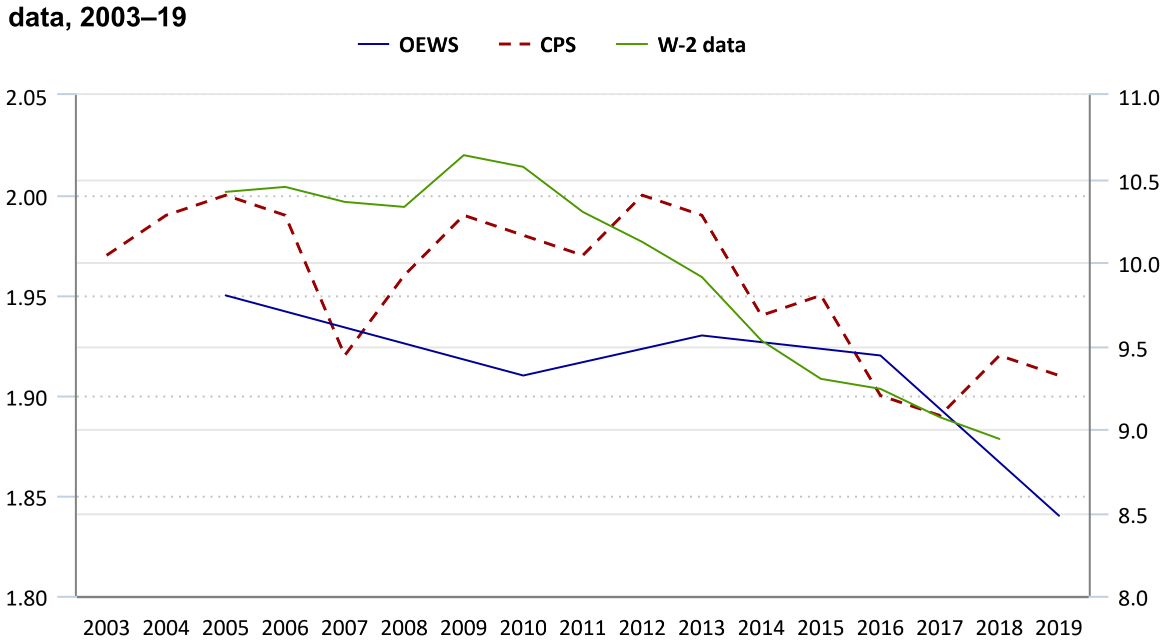


Click legend items to change data display. Hover over chart to view data.
Note: OEWS data are for only those years shown because every OEWS estimate is based on 3 years of data collection. W-2 data are available only for the years shown. W-2 wages are from the Form W-2 Wage and Tax Statement, reported to the Internal Revenue Service. CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics survey. CPS estimates are based on the confidential version of the CPS microdata available to BLS employees, not the public-use version of the microdata
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Chart 4 shows a similar measure of wage inequality for the bottom half of the wage distribution, the ratio of wages at the 50th percentile to wages at the 10th percentile of the wage distribution. In the OEWS data, this measure is flat or declining over the whole period (except for a small increase from 2010 to 2013), with a particularly strong decline from 2016 to 2019. In the CPS data, this measure is flat or declining over the full period, with a clear decline from 2012 to 2017. In the W-2 data, this measure is flat or slightly increasing from 2005 to 2009 and declining strongly thereafter. Again, the declining wage inequality in OEWS data is similar to a pattern of declining earnings inequality in the W-2 data but with a lag.

Chart 4. Ratio of 50th percentile to 10th percentile of hourly wages in CPS outgoing rotations and OEWS and of annual wage and salary income in W-2 data, 2003–19



Click legend items to change data display. Hover over chart to view data.
Note: OEWS data are for only those years shown because every OEWS estimate is based on 3 years of data collection. W-2 data are available only for the years shown. W-2 wages are from the Form W-2 Wage and Tax Statement, reported to the Internal Revenue Service. CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics survey.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

For a more complete understanding of how overall wage inequality has been declining in recent years in the OEWS and W-2 data (but not as clearly in the CPS data), we show the percentage changes in wages or annual earnings from 2013 to 2019 for selected percentiles of the wage/earnings distribution in all three data sources in table 1. This table shows an overall greater growth in hourly wages in the CPS than in the OEWS survey, particularly for wage earners at the 75th, 90th, and 95th percentiles of the wage distribution. The W-2 data have greater growth in annual earnings than either the OEWS or the CPS at the 10th, 25th, and 50th percentiles of the wage distribution. The earnings growth levels in the W-2 data are between those of the OEWS and the CPS at the 75th, 90th, and 95th percentiles of the wage/earnings distribution (estimates of earnings growth in the W-2 data for the 5th percentile are omitted for disclosure avoidance purposes).

Table 1. Real log wage growth, at specified percentiles, since 2013

Percentile	OEWS survey		CPS						W-2				
	2016	2019	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018
5th	2.7	2.9	0.4	1.2	3.8	5.6	6.7	7.2	[1]	[1]	[1]	[1]	[1]
10th	3.4	**8.7**	2.1	3.9	7.9	11.1	9.4	**11.9**	5.3	11.3	12.9	17.1	**20.1**
25th	3.7	**9.5**	0.2	3.8	5.6	7.3	9.3	**15.3**	2.7	7.8	9.4	12.7	**15.2**
Median	2.7	3.7	–0.4	1.6	3.1	5.3	5.5	7.2	1.2	4.5	5.2	7.3	8.4
75th	2.5	2.6	0.0	3.0	4.4	5.7	5.9	7.9	0.8	3.5	3.6	5.0	5.5
90th	3.5	3.5	–0.8	3.2	5.8	7.1	8.4	**8.5**	1.0	3.9	3.9	5.2	5.7
95th	4.1	3.4	–1.1	4.0	6.1	5.3	9.2	**10.0**	1.3	4.2	4.6	5.8	6.4

[1] Estimates of earnings growth in the W-2 data for the 5th percentile are omitted for disclosure avoidance purposes.
Note: W-2 wages are from the Form W-2 Wage and Tax Statement, reported to the Internal Revenue Service. CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics. Numbers in bold highlight percentiles of the wage distribution with particularly high real log wage growth from 2013 to 2019 in each of the three data sources. CPS estimates are based on the confidential version of the CPS microdata available to U.S. Bureau of Labor Statistics employees, not the public-use version of the microdata.
Source: U.S. Bureau of Labor Statistics and U.S. Census Bureau.

This greater wage growth for high-wage workers in the CPS than in the OEWS explains why overall wage inequality declined in the OEWS but plateaued in the CPS from 2013 to 2019. Both surveys show particularly strong wage growth during this period for wages at the 10th and 25th percentiles of the wage distribution.

The even stronger wage growth for low-wage and salary workers in the W-2 data drives the difference in overall wage inequality growth patterns between the W-2 and the OEWS. Perhaps the particularly strong annual earnings growth for low earners in the W-2 data reflects increases in their hours worked per week or weeks worked per year.

Results by occupation

The analysis just discussed shows that wage growth at the 10th and 25th percentiles of the log wage distribution was particularly strong during the 2013–19 period in both the OEWS survey and CPS data and in the W-2 data. We can say more about the occupations of the worker who saw this wage growth in the OEWS survey and CPS data, because both these surveys ask workers and employers about occupations. In each survey, these responses are then assigned detailed occupational codes by statistical agency staff or their state partner agencies. A similar analysis of the occupations experiencing strong earnings growth is not currently possible in the W-2 data, because although U.S. individual tax returns ask each tax filer to report an occupation, the U.S. Census Bureau does not currently receive occupational responses from tax filers.

We start by examining workers into 10 equally sized deciles of the wage distribution in each time in each dataset. For each decile d at time t, overall wages w are the sum of wages earned by people working in each occupation j, w_{jt}^{d}, multiplied by the share s of people in that decile who work in each occupation j, s_{jt}^{d}. Thus, the overall wage level for each decile in each time is $w_t^d = \sum_j w_{jt}^d \times s_{jt}^d$. The change in the average wage in decile d between time t_0 and time t_1 is the change in wages for each occupation within that decile, $\left(w_{jt_1}^d - w_{jt_0}^d\right)$, multiplied by the share of decile employment for each occupation at time t_1, plus the change in the share of employment in the decile accounted for by each occupation, $\left(s_{jt_1}^d - s_{jt_0}^d\right)$, multiplied by the initial wage level for each occupation:

$$\Delta w^d = \sum_j \left[s_{jt_1}^d \times \left(w_{jt_1}^d - w_{jt_0}^d\right) + w_{jt_0}^d \times \left(s_{jt_1}^d - s_{jt_0}^d\right)\right].$$

We conduct this analysis at the minor occupational category (three-digit SOC code) level, slightly adjusting the SOC codes to make them consistent over time and consistent between the CPS and the OEWS. After codes are adjusted, there are 92 occupational categories.

During the 2005–19 period overall, both the CPS and the OEWS data show that the largest increases in wages were for the top three deciles of the wage distribution. Within each decile, changes in wages were overwhelmingly due to occupation-specific wage changes, rather than to changes in the distribution of occupations within the decile. However, the CPS shows larger increases in wages in the top three deciles of the wage distribution than the OEWS shows, and the CPS shows even less of this change was due to changes in the distribution of occupations within each decile than the OEWS.

From 2005 to 2013, wage inequality was increasing in both the CPS and OEWS data. In both surveys, increasing wage inequality was due to large increases in wages for the top decile of wage earners, accompanied by wage declines for most of the seven lowest deciles of wages. Again, in both surveys (but even more in the CPS than in the OEWS), these patterns were driven more by wage changes within occupations than by shifts in the occupational composition.

By contrast, from 2013 to 2019, wage inequality was declining in the OEWS and flat in the CPS data. Both surveys showed rising wages in every decile, with particularly substantial increases in wages for the second and third deciles of the wage distribution, in both the CPS and the OEWS. The decile-level decomposition of these wage changes, summed across all occupations, is shown in table 2. This table shows that in both the OEWS and the CPS, these wage increases were due almost entirely to within-occupation wage increases rather than to changes in the shares of each occupation. It also shows that the difference in overall wage inequality trends in the CPS and the OEWS from 2013 to 2019 comes from greater increases in wages for the top deciles of the wage distribution in the CPS than in the OEWS. These greater increases in wages at the top in the CPS meant that overall wage inequality in the CPS held steady, while smaller increases in wages at the top in the OEWS meant that overall wage inequality in the OEWS declined during this period.

Table 2. Wage growth (in dollars) in each wage decile from 2013 to 2019 and its decomposition into occupation shares and occupation wages for all occupations in the OEWS survey and the CPS

Decile	OEWS survey					CPS				
	2013 real hourly wage	2019 real hourly wage	Difference	Change due to occupation-specific wages	Change due to occupation shares	2013 real hourly wage	2019 real hourly wage	Difference	Change due to occupation-specific wages	Change due to occupation shares
1	$8.34	$8.67	$0.33	$0.33	$0.00	$7.75	$8.36	$0.61	$0.64	–$0.03
2	9.31	10.59	1.29	1.23	0.06	9.67	10.95	1.28	1.27	0.00
3	10.98	12.41	1.43	1.43	0.00	11.36	12.98	1.63	1.62	0.00
4	13.57	14.23	0.66	0.66	0.00	13.56	14.91	1.35	1.35	0.00
5	16.05	16.26	0.21	0.14	0.06	16.03	17.42	1.39	1.39	0.00
6	18.72	19.87	1.15	1.08	0.07	19.00	20.36	1.36	1.35	0.01
7	22.59	23.70	1.12	1.13	–0.01	22.67	24.42	1.74	1.74	0.01
8	27.94	28.97	1.03	1.01	0.02	27.79	30.01	2.22	2.21	0.02
9	36.62	37.61	0.99	0.94	0.05	36.05	39.19	3.14	3.11	0.03
10	66.01	68.79	2.78	3.05	–0.26	64.41	70.94	6.53	6.64	–0.10

Note: CPS = Current Population Survey, and OEWS = Occupational Employment and Wage Statistics. CPS estimates are based on the confidential version of the CPS microdata available to U.S. Bureau of Labor Statistics employees, not the public-use version of the microdata.
Source: U.S. Bureau of Labor Statistics.

We delve into the individual occupations aggregated in table 2 to answer two questions about the 2013–19 period:

1. Both the OEWS and the CPS show remarkable wage growth in the second and third deciles of the wage distribution during this period. Which occupations benefited from this wage growth?
2. The CPS showed much greater wage increases than the OEWS in the top deciles of the wage distribution during this period. Which occupations drove this difference in measured wage growth?

Occupations driving wage growth in the second and third deciles of the wage distribution

What occupations accrued these wage increases in the second and third deciles of the wage distribution during this period? The answers differ somewhat between the OEWS and the CPS; the correlation of occupation-specific contributions to these wage increases between the two surveys is 0.28 in the second decile and 0.22 in the third decile.

Table 3 presents the 10 minor occupational groups that contributed most to wage growth in OEWS data in the second and third deciles of the wage distribution. In the OEWS data, health aides (SOC code 31-1) were the most important minor occupational category in explaining wage growth within the second decile from 2013 to 2019, with large increases in both employment and wages in this decile of the wage distribution. This occupational group includes such occupations as home health and personal care aides (SOC code 31-1120) and nursing assistants (SOC code 31-1131). Much of the employment growth in this occupational category was the result of including about half a million additional workers in the OEWS beginning in 2017 who were providing nonmedical home care for the elderly or people with disabilities. These additional workers were added to the OEWS as the result of an effort in some states to more consistently classify such work as part of North American Industry Classification System (NAICS) code 624120, services for the elderly and disabled (covered by the OEWS) instead of NAICS code 814110, private households (not covered by the OEWS).[12] The same occupational group had a smaller contribution to wage growth in the third decile of the OEWS, because it had wage growth but did not increase its share of employment in this decile of the wage distribution.

Table 3. Occupational groups contributing most to wage growth from 2013 to 2019 in the second and third deciles of the wage distribution in OEWS survey data

Decile	SOC		Share of employment		Average wage		Contribution to wage growth
	Code	Title	2013	2019	2013	2019	
2	31-1000	Health aides	0.040	0.087	$9.92	$10.64	$0.53
	37-2000	Building cleaning and pest control workers	0.044	0.054	9.46	10.58	0.15
	43-4000	Information and record clerks	0.032	0.042	9.41	10.54	0.15
	43-5000	Material recording, scheduling, dispatching, and distributing workers	0.036	0.042	9.21	10.57	0.11
	35-2000	Cooks and food preparation workers	0.051	0.055	9.45	10.61	0.09
	39-9000	Other personal care and service workers	0.018	0.021	9.44	10.61	0.06
	33-9000	Other protective service workers	0.016	0.020	9.60	10.59	0.05
	35-1000	Supervisors of food preparation and serving workers	0.005	0.010	10.08	10.55	0.05
	51-9000	Other production occupations	0.018	0.019	9.38	10.54	0.03
	51-2000	Assemblers and fabricators	0.013	0.014	9.35	10.52	0.03
3	35-3000	Food and beverage serving workers	0.057	0.073	10.90	12.16	0.26
	53-7000	Material moving workers	0.048	0.059	11.04	12.39	0.21
	29-2000	Health technologists and technicians	0.014	0.022	11.03	12.58	0.12
	47-2000	Construction trades workers	0.015	0.022	10.98	12.56	0.11
	49-9000	Other installation, maintenance, and repair occupations	0.015	0.022	11.01	12.57	0.11
	31-1000	Health aides	0.073	0.073	10.91	12.31	0.10
	25-9000	Other educational instruction and library occupations	0.021	0.024	10.99	12.52	0.07
	13-1000	Business operations specialists	0.004	0.009	11.14	12.60	0.07
	21-1000	Counselors, social workers, and other community and social service specialists	0.009	0.014	11.01	12.56	0.07
	43-5000	Material recording, scheduling, dispatching, and distributing workers	0.043	0.043	11.02	12.45	0.06

Note: OEWS = Occupational Employment and Wage Statistics, and SOC = Standard Occupational Classification.
Source: U.S. Bureau of Labor Statistics.

In the third decile of the OEWS wage distribution, food and beverage serving workers contributed most to wage growth, with a rising share of employment and rising wages. This occupational group consists of workers in occupations such as bartenders (SOC code 35-3011), fast food and counter workers (SOC code 35-3023), and waiters and waitresses (SOC code 35-3031). However, this occupational group did not contribute to wage growth in the second decile of the wage distribution because its employment fell sharply in this wage group. Overall, this occupational group saw little change in total employment across all wage deciles from 2013 to 2019, but strong wage growth meant that its employment shifted from the first two deciles to higher deciles of the overall wage distribution.

Similarly, material moving workers were the second most important occupational group contributing to wage growth in the third decile of the OEWS wage distribution, with rising employment and rising wages, but this occupational group also had a negative impact on wage growth in the second decile of the wage distribution because its employment fell in this decile of the wage distribution. Although the material moving occupational group grew overall from 2013 to 2019, wage growth for this occupational group meant that it made up an increasing share of employment in the third, fourth, and fifth deciles of the overall wage distribution and a decreasing share of employment in the first and second deciles.

Table 4 presents the 10 minor occupational groups that contributed most to wage growth in CPS data in the second and third deciles of the wage distribution. In both deciles, the minor occupational group that contributed most is material moving workers, which grew in employment in both deciles and had large increases in average wages. This group includes such occupations as crane and tower operators (SOC code 53-7021), industrial truck and tractor operators (SOC code 53-7050), and stockers and order fillers (SOC code 53-7065),[13] an occupation that would include many e-commerce order fulfillment workers. The second most important contributing occupational group in the second decile of the wage distribution is retail sales workers, who had declining employment but sharply rising wages during 2013 to 2019. Another important contributing occupational group in both the second and third deciles of the wage distribution is health technologists and technicians, such as lab technicians (SOC code 29-2010), paramedics (SOC code 29-2040), and licensed practical nurses (SOC code 29-2061), who had growing employment and rising wages. Yet another such group is information and record clerks, such as customer service representatives (SOC code 43-4050), file clerks (SOC code 43-4071), and order clerks (SOC code 43-4150), who also had growing employment and rising wages.[14]

Table 4. Occupational groups contributing most to wage growth from 2013 to 2019 in the second and third deciles of the wage distribution in CPS data

Decile	SOC		Share of employment		Average wage		Contribution to wage growth
	Code	Title	2013	2019	2013	2019	
2	53-7000	Material moving workers	0.048	0.050	$9.63	$10.99	$0.09
	41-2000	Retail sales workers	0.113	0.108	9.55	10.84	0.09
	29-2000	Health technologists and technicians	0.009	0.015	9.78	11.00	0.08
	43-4000	Information and record clerks	0.053	0.053	9.69	10.97	0.08
	35-2000	Cooks and food preparation workers	0.055	0.056	9.61	10.91	0.07
	31-1000	Health aides	0.059	0.059	9.70	10.87	0.07
	51-9000	Other production occupations	0.024	0.027	9.53	10.99	0.07
	43-5000	Material recording, scheduling, dispatching, and distributing workers	0.040	0.041	9.59	10.86	0.06
	11-9000	Other management occupations	0.017	0.020	9.74	11.05	0.06
	43-9000	Other office and administrative support workers	0.019	0.022	9.75	10.97	0.06
3	53-7000	Material moving workers	0.044	0.049	11.36	13.02	0.13
	43-4000	Information and record clerks	0.055	0.056	11.34	12.93	0.10
	51-9000	Other production occupations	0.029	0.034	11.42	12.93	0.10
	29-2000	Health technologists and technicians	0.015	0.021	11.42	12.98	0.09
	43-9000	Other office and administrative support workers	0.026	0.029	11.38	13.07	0.09
	35-2000	Cooks and food preparation workers	0.040	0.041	11.24	12.88	0.08
	47-2000	Construction trades workers	0.040	0.041	11.41	13.08	0.08
	31-9000	Other healthcare support occupations	0.015	0.020	11.35	12.98	0.08
	11-9000	Other management occupations	0.023	0.026	11.35	13.11	0.08
	41-2000	Retail sales workers	0.066	0.064	11.22	12.84	0.07

Note: CPS = Current Population Survey, and SOC = Standard Occupational Classification.
Source: U.S. Bureau of Labor Statistics.

One possible reason we might find different occupational groups contributing the most to this wage growth in the OEWS and the CPS could be that the CPS measures wages only in workers' main jobs, whereas the OEWS survey measures wages in all jobs. However, this reason does not appear to explain the difference in which occupations have particularly strong wage growth. Although the CPS does not record wages for workers' second jobs, it does record the occupations worked in these jobs. The most common second jobs in the CPS are in construction trades and teaching, and these are not the jobs with particularly strong wage growth in the OEWS survey.

Occupations driving higher wage growth in the CPS than the OEWS for top deciles of the wage distribution

While both the CPS and OEWS data show strong wage growth in the second and third deciles of the wage distribution from 2013 to 2019, the CPS data show much greater wage growth in the top deciles than the OEWS data during this same period. Using the same methodology as just previously described, we can identify the occupational groups that contribute most to this difference in wage growth between the surveys. We find that the pattern of which occupations contributed most to decile-level wage increases is remarkably similar between the two surveys. The correlation of occupation-specific contributions to wage increases between surveys is 0.51 in the eighth decile, 0.71 in the ninth decile, and 0.51 in the tenth decile.

Table 5 lists the occupation-wage-decile combinations for which the difference in contributions to wage growth in the OEWS and the CPS during this period is greater than or equal to 50 cents. "Other management occupations" appears in this table in all three of the uppermost wage deciles. This occupational group includes such occupations as farm managers, construction managers, education administrators, engineering managers, food service managers, medical managers, postmasters, funeral home managers, and others. Both surveys show an increasing share of employment in the top deciles between 2013 and 2019, as well as increasing wages in both surveys but somewhat greater share growth and substantially greater wage growth in the CPS than in the OEWS. "Computer occupations" appears in this table in the top two wage deciles. This occupational category includes such occupations as computer systems analysts, computer and information research scientists, computer network support specialists, network administrators, computer programmers, and others. Again, both surveys show an increasing share of employment for this occupational category in the top deciles between 2013 and 2019, as well as increasing wages in both surveys, but somewhat greater share growth and substantially greater wage growth in the CPS than in the OEWS. The last two occupational groups in table 5 are "Health diagnosing or treating practitioners" and "Sales representatives, wholesale and manufacturing," which appear only in the top decile. The occupational group of health diagnosing or treating practitioners includes such occupations as dentists, dieticians, optometrists, pharmacists, physician assistants, nurses, physicians, surgeons, and others. This group made up a growing share of employment in the top decile in the CPS but a falling share of employment in the OEWS during this period, and it showed greater wage growth in the CPS than in the OEWS (overall and within the top decile). Sales representatives, wholesale and manufacturing, made up a falling share of employment in the top decile in both surveys and saw an increase in wages of more than $13.00 an hour in the CPS but a decrease in wages in the OEWS of $0.23 during this period.

Table 5. Occupation-wage-decile combinations contributing 50 cents or more to the divergence between OEWS survey and CPS wage growth from 2013 to 2019

Decile	SOC Code	SOC Title	Contribution to the change in wages in OEWS survey data	Contribution to the change in wages in CPS data	Difference in contributions
8	11-9000	Other management occupations	$0.08	$0.58	$0.50
9	15-1000	Computer occupations	0.26	0.94	0.67
	11-9000	Other management occupations	0.37	0.90	0.52
10	11-9000	Other management occupations	0.48	1.69	1.22
	15-1000	Computer occupations	0.79	1.88	1.09
	29-1000	Healthcare diagnosing or treating practitioners	–0.00	1.05	1.06
	41-4000	Sales representative, wholesale and manufacturing	–0.36	0.17	0.53

Note: CPS = Current Population Survey, OEWS = Occupational Employment and Wage Statistics, and SOC = Standard Occupational Classification. CPS estimates are based on the confidential version of the CPS microdata available to U.S. Bureau of Labor Statistics employees, not the public-use version of the microdata.
Source: U.S. Bureau of Labor Statistics.

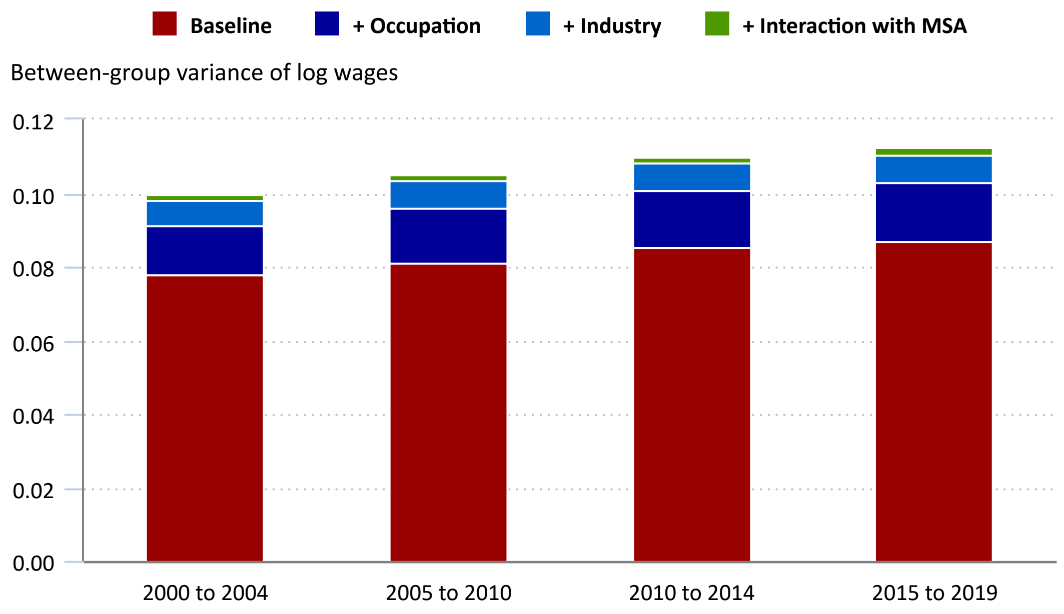
Further decomposition results

The richness of the survey data from the OEWS and the CPS allow us to show how much wage inequality can be explained by various characteristics of workers and their employers and how this explanatory power has been changing over time. In the previous section, we emphasized the role of occupations in identifying which workers have seen notable changes in wages, because occupations are collected in both the OEWS and the CPS. In contrast, Hoffman and coauthors emphasize the important role of education in driving wage inequality growth in the United States in recent decades by showing that after accounting for education, occupations explain very little more of wage variation among workers.[15] However, education and occupation are closely related; one mechanism for the strong relationship between education and wage inequality is the way that education determines occupations of workers. For example, Daron Acemoglu and Pascual Restrepo find that much of the divergence in wage growth from 1980 to 2016 for people of different education levels can be explained by the different exposure of people with different education levels to automation technologies.[16]

In this section, we closely follow Hoffman and coauthors, regressing wages on categorical dummy variables and showing how much variation in wages can be explained by each variable individually or how much additional variation can be explained in regressions that include multiple variables.[17] These figures plot R^2 values (and increases in R^2 values from wage regressions including additional variables), multiplied by the wage variance in each period. The categorical variables used here are broad age, education, occupation, industry, and metropolitan statistical area (MSA) groups. Categories are eight 5-year age groups, five broad education categories, ten broad occupational groups using the current CPS broad occupational recoding,[18] thirteen broad industry groups using the current CPS broad industry recoding, and three geographic area groups (the largest 15 metropolitan areas, all other metropolitan areas, and the balance of the United States).

In chart 5, we reproduce results from Hoffman, Lee, and Lemieux (their figure 4) using the confidential CPS-ORG data, combining data on men and women.[19] Chart 5 replicates the result in Hoffman and coauthors that most of the impact of growing wage inequality comes through their "baseline," which includes the impact only of the interaction between age/experience and schooling levels, with smaller additional amounts explained by occupation, industry, and interactions with geographic areas. However, when we reverse the order of this decomposition to show the impact of the interaction between age/experience and occupation first and then add education later, in chart 6, this pattern is reversed, showing an increasing amount of wage variation explained by occupation (with a smaller additional amount explained by education).

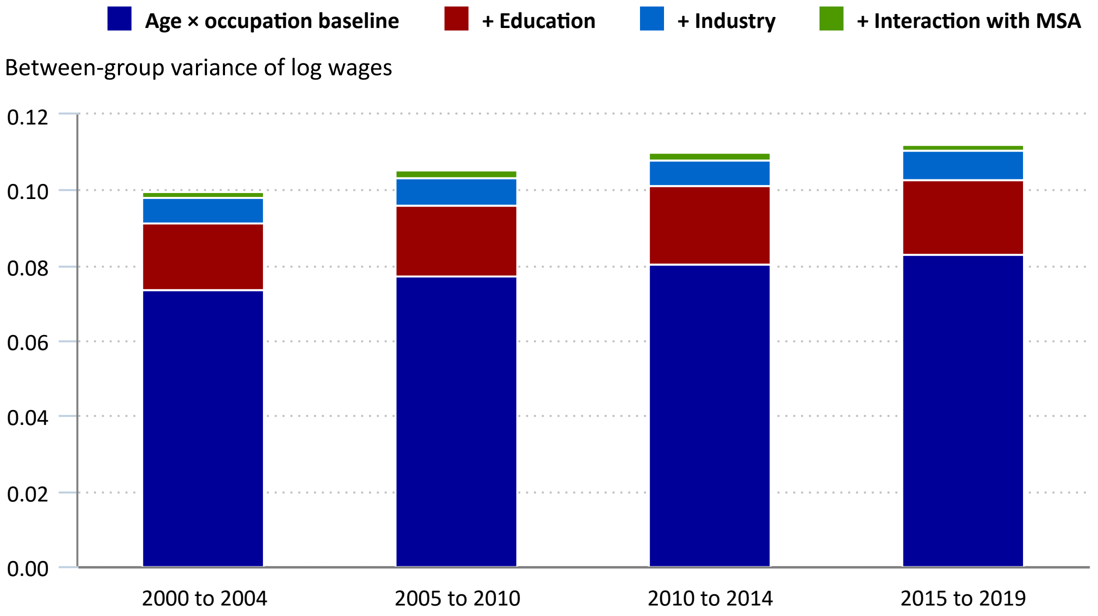
Chart 5. Effect of additional covariates on the between-group variance of Current Population Survey hourly wages, with age × education as the baseline, 2000–19



Click legend items to change data display. Hover over chart to view data.
Note: MSA = metropolitan statistical area.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Chart 6. Effect of additional covariates on the between-group variance of Current Population Survey hourly wage, with age × occupation as baseline, 2000–19

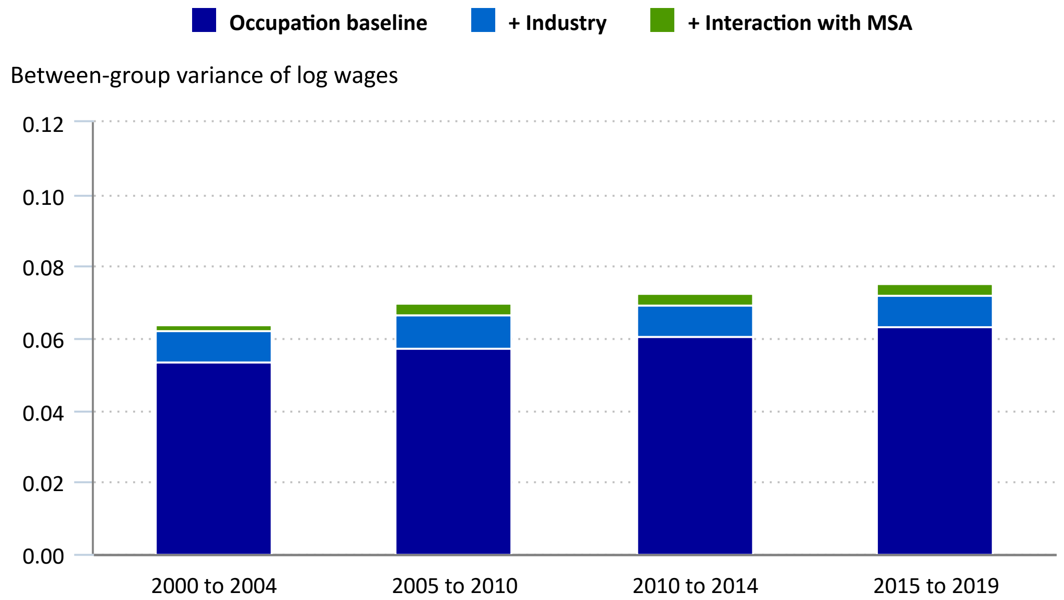


Click legend items to change data display. Hover over chart to view data.
Note: MSA = metropolitan statistical area.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

We cannot observe either the education or age of workers in the OEWS data, but we can observe their occupations and the industries and locations of their employers. Chart 7 shows the amount of growing wage inequality in the confidential CPS wage data that can be explained by only these three variable categories, while chart 8 shows the same results in the OEWS data.

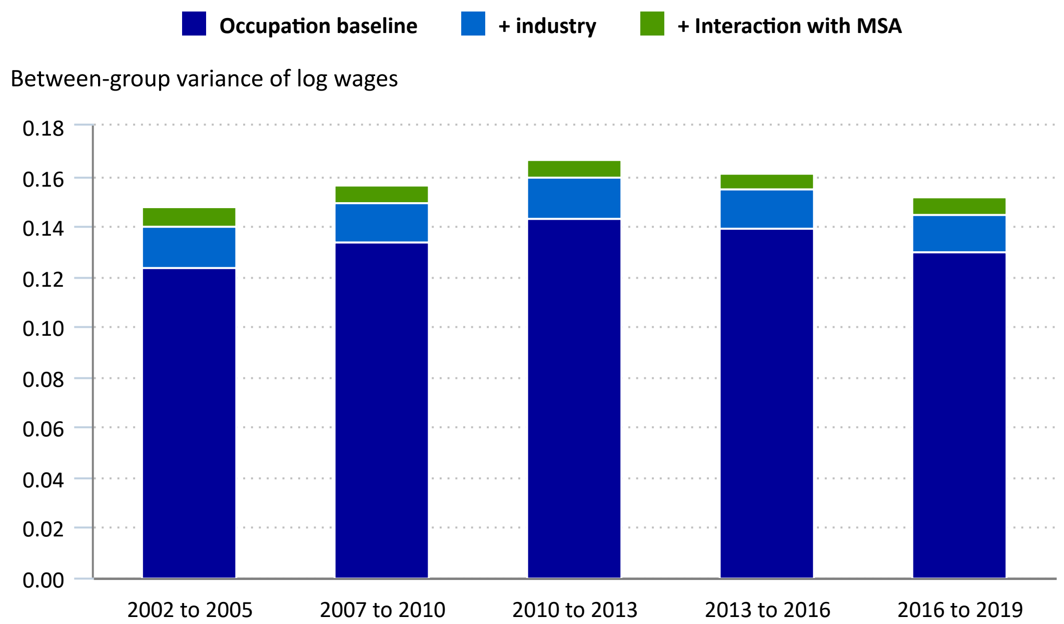
Chart 7. Effect of additional covariates on the between-group variance of Current Population Survey hourly wages, using only covariates available in the Occupational Employment and Wage Statistics survey, 2000–19



Click legend items to change data display. Hover over chart to view data.
MSA = metropolitan statistical area.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Chart 8. Effect of additional covariates on the between-group variance of Occupational Employment and Wage Statistics survey hourly wages, 2002–19



Click legend items to change data display. Hover over chart to view data.
Note: MSA = metropolitan statistical area.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Three notable differences are apparent between charts 7 and 8. First, as shown earlier in this article, the total amount of wage variation in the OEWS data (but not in the CPS data) is declining from the 2010–13 period to the 2016–19 period. Second, the amount of wage variation because of occupation—even the extremely broad occupational groups used in Hoffman and colleagues—is much greater in the OEWS than in the CPS. Third, the amount of wage variance that can be explained by broad occupational groups continues to increase in the CPS throughout this period, but the amount of wage variance that can be explained by occupation in the OEWS declines from the 2010–13 period to the 2016–19 period.

This article is not the first to show that more wage variation can be explained by occupation in the OEWS data than in the CPS data. Spletzer and Handwerker found a very similar result for major occupational groups in the 1998–2010 period.[20] Katharine G. Abraham and James R. Spletzer found a similar result for detailed occupations in the 2003 and 2004 data and attributed it to more accurate occupational reporting by employers in the OEWS than by employees in the CPS.[21]

The declining amount of wage variation that can be explained by occupation in the OEWS (but not in the CPS) is consistent with the evidence shown earlier in this article. As table 4 shows, in the OEWS, several lower wage occupations had substantial wage gains from 2013 to 2019, while table 5 gives examples of high-wage occupations with much more substantial wage growth in the CPS than in the OEWS. This combination of increasing wages for lower wage occupations and relatively less wage growth for higher wage occupations in the OEWS generates this pattern of a declining amount of wage variation explained by occupation.

The explanatory power of industry or MSA groups on wage inequality in the OEWS is much less than the impact of occupational groups, even when we do not first condition on occupation. While occupational groups alone explain more than one-third of log wage variation in each OEWS period, industry groups alone can explain less than one-seventh, and MSA status alone can explain only one-fortieth.

Discussion and conclusion

This article documents the expansion and compression of wage and earnings inequality using three data sources: wage data collected in the OEWS employer survey, wage data collected in the CPS household survey, and W-2 earnings reports to the IRS. All three show expanded inequality of wages or earnings from 2005 to 2010. However, in the CPS, we find that wage inequality has been flat since 2013 (for all workers) or 2015 (for full-time workers), and in the OEWS, we find that wage inequality was basically flat from 2013 to 2016 and decreased from 2016 to 2019. This finding—that wage inequality did not continue rising through the 2010s—is consistent with evidence that workers' annual wage and salary earnings in the W-2 tax data are compressing from 2010 to 2018.

All three of these very different data sources show that wages/earnings were becoming more equal among workers in the bottom half of the wage/earnings distribution from about 2013 to 2018 or 2019, because of particularly strong wage/earnings growth for workers near the 10th and 25th percentiles of the wage distribution. In the CPS and OEWS data, we show particularly strong wage growth in the second and third deciles among workers who worked in occupational groups such as material moving workers, health technologists and technicians, and information and record clerks (in the CPS) and health aides, food and beverage serving workers, and material moving workers (in the OEWS).

These results are consistent with those of Jay C. Shambaugh and Michael R. Strain, who show particularly strong wage growth at the lower percentiles of the wage distribution from 2017 to 2019.[22] They are also consistent with other research suggesting a change in the trend of ever-increasing income and wage inequality in recent years. Using data from millions of households with checking accounts, Fiona Greig, Chris Wheat, George Eckerd, Melissa O'Brien, and Shantanu Banerjee examine income growth over 2-year periods, grouping households into quartiles by average incomes in their ZIP Code of residence.[23] They find income growth rates for households in the lowest income quartile that exceeded the income growth rates for households in the highest income quartile beginning with the 2-year period from 2016 to 2018. Ellora Derenoncourt, Clemens Noelke, and David Weil use online job postings to study wage spillovers for low-wage workers in the same labor markets as the workers of Walmart, Target, Costco, and Amazon/Whole Foods.[24] These large employers announced company policies of paying all U.S. workers wages of no less than $9–$15 per hour between 2014 and 2019. Derenoncourt and coauthors find that the wage policies of these employers not only affected wages for their own workers but also raised wage offers for lower wage workers hired by other employers in the same geographic areas.

Our examination of which occupations have played substantial roles in wage convergence during this period is accompanied by evidence that occupations play a large and growing role in wage inequality in CPS data—and even more so in wage inequality in OEWS data. However, the role of occupations in wage inequality in OEWS data was lessened from 2013 to 2019, while low-wage occupations saw large wage gains and high-wage occupations saw small wage gains in these data. Other authors, such as Hoffman, Lee, and Lemieux, have emphasized the role of education in wage inequality.[25] We suggest that readers looking to reconcile these findings consider that occupation is often a mechanism by which education affects wages.

We also caution our readers that wage inequality—despite its importance—is only one piece of overall inequality in labor markets. The Organisation for Economic Cooperation and Development suggests indicators of job quality that include not only earnings but also working time arrangements (such as the share of workers with "unsocial" hours of work), job security, workplace relationships, work-related access to programs for health insurance, pensions, unemployment insurance, and family-related paid leave, as well as workplace safety.[26] As an example of how workplace safety may affect the overall "quality" of an occupation, we note that despite the increasing wages we have found in multiple datasets for material moving workers, the BLS Injuries, Illnesses, and Fatalities program found that workers in the broader category of transportation and material moving occupations have among the highest rates of workplace injuries and illnesses of any broad occupational group in 2018.[27]

Nonetheless, wage inequality is a very important part of overall inequality in labor markets. Thus, it is important that wage inequality either plateaued or began to reverse because of high wage growth for lower wage workers in the later years of the last economic expansion.

ACKNOWLEDGMENT: Any opinions and conclusions expressed herein are those of the authors and not the U.S. Census Bureau or the U.S. Bureau of Labor Statistics. The U.S. Census Bureau reviewed the results derived from Title 13 protected data for unauthorized disclosure of confidential information and approved the disclosure avoidance practices applied to this release (approval ID: CBDRB-FY21-CES014-040). The U.S. Bureau of Labor Statistics reviewed results derived from OEWS and CPS data for unauthorized disclosure.

Appendix: Wage inequality trends in public-use versions of the CPS data

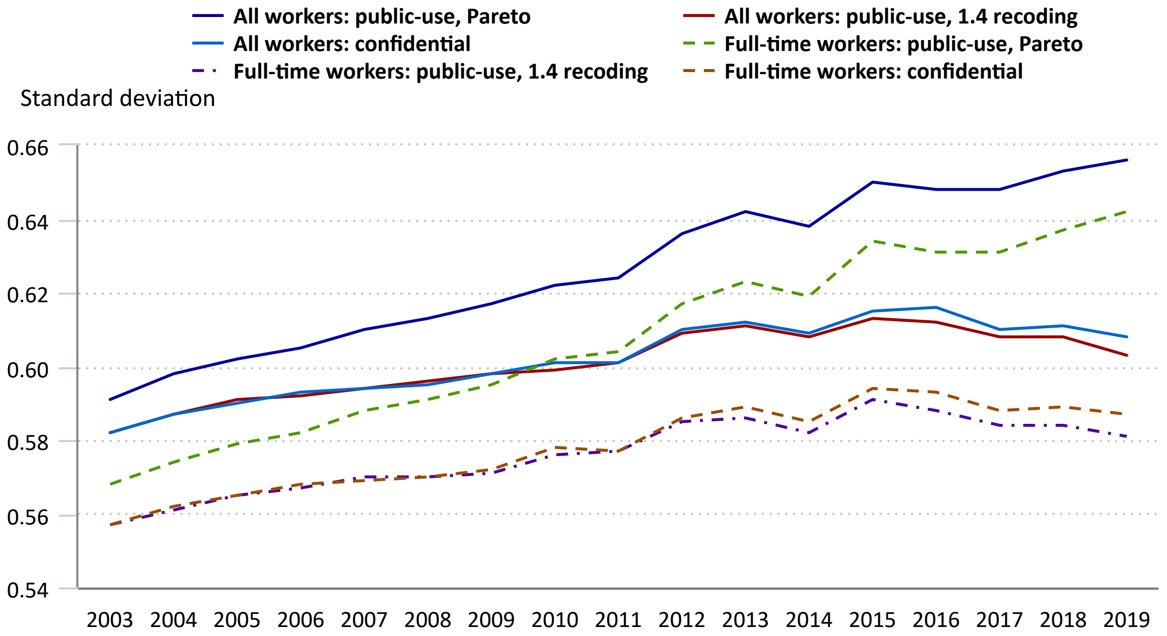
In our main results, we use the confidential CPS microdata not available to researchers outside BLS or the U.S. Census Bureau. The difference between the public-use and confidential versions of the CPS data is whether actual wages are reported for people earning more than $2,884.61 a week. The CPS public-use data are top coded at $2,884.61 a week to protect the confidentiality of the respondents.[28] This top coding affects a growing share of respondents. In 2003, it affected 0.9 percent of respondents; in 2019, it affected 4.1 percent of respondents. Researchers working with public-use data have approached the problem of modeling earnings above this top-coding threshold in two different ways: assuming a Pareto distribution and assuming wages of 1.4 multiplied by $2,884.61 ($4,038.45). We follow two approaches to these top-coded public-use data in the published literature. Following Thomas Lemieux, we apply a uniform factor of 1.4 multiplied by the top-coded value to all these observations.[29] Following Sandra A. West, Anne E. Polivka, and Barry T. Hirsch and David A. Macpherson,[30] we fit a Pareto distribution to the non-top-coded observations to impute values for the top-coded observations by using 300 bins below the top-coded wage value. We note that the Pareto distribution parameters we estimate using the confidential microdata are quite similar to those published by MacPherson and Hirsch.[31] Neither the 1.4 uniform factor nor the Pareto distribution approach to top-coded data is necessary in the confidential CPS microdata, because this version of the data is not top coded the same way.

Following Card and DiNardo, Lemiuex, and Donovan and Bradley,[32] we remove observations with an hourly wage of less than $1 or more than $100 in 1979 dollars—less than $3.50 or more than $350 in 2016 dollars. This means dropping 0.8 percent to 0.9 percent of observations in the confidential data, varying very slightly by year, and 0.6 percent to 0.8 percent of observations in the public-use CPS data.

In appendix chart 1, we compare six variations of overall trends of the standard deviation of log hourly wage income in the CPS-ORG. Trends in

1. the confidential CPS data for all workers (the main specification shown in the article);
2. the confidential CPS data for full-time workers only, weighted by their weekly hours;
3. the public-use data for all workers, assuming a Pareto distribution of wages for those who earn more than $2,884.61 a week;
4. the public-use CPS data for full-time workers only, weighted by their weekly hours, and assuming a Pareto distribution of wages for those who earn more than $2,884.61 a week,
5. the public-use CPS data for all workers, assuming weekly earnings of $4,038.45 for those who earn more than $2,884.61 a week; and
6. the public-use CPS data for full-time workers only, weighted by their weekly hours, and assuming weekly earnings of $4,038.45 for those who earn more than $2,884.61 a week.

Appendix chart 1. Standard deviation of log hourly wages for all workers and full-time workers in CPS outgoing rotations, public-use (with two different corrections for the censoring of high-wage observations) and confidential internal versions, 2003–19



Click legend items to change data display. Hover over chart to view data.
Note: CPS = Current Population Survey. Public-use microdata are adjusted for the censoring of high wages in two different ways (using a Pareto distribution and multiplying the maximum reported value by 1.4). This adjustment is not done in the confidential internal version of these data.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Comparing worker restrictions and weightings within each version of the CPS data (comparing 1 with 2, 3 with 4, and 5 with 6), we find that without weighting by the number of hours worked, a greater dispersion of wages is found among all workers than among full-time workers. Weighting full-time workers by the number of hours they work increases the dispersion in their wages, since higher earning full-time workers work more hours. In all versions of the CPS data, a greater dispersion of wages is found overall among all workers, not weighted by hours worked (estimate more comparable to the OEWS) than among full-time workers only, weighted by hours worked (estimates more comparable to the wage variation literature).

Comparing the various versions of the CPS data (comparing 1 with 3 and 5 and 2 with 4 and 6), we find much greater variation in overall wages when wages above $2,884.61 a week are modeled using a Pareto distribution fit to the shape of the earning distribution below $2,884.61 a week than if all wages above $2,885.00 are assumed to be $4,038.45 ($2,884.61 multiplied by 1.4). We also find that the assumption that all these top-coded earners earn $4,038.45 a week better fits the trend in the confidential version of these data than modeling the top-coded data using a Pareto distribution each period. The use of the Pareto distribution to model wages above the top code introduces more variation in wages in recent years than exists in the confidential data. Both the public-use version of the CPS wage data—using the assumption that top-coded wages are $4,038.45 a week—and the confidential version of the CPS data show that wage inequality plateaued after 2012.

SUGGESTED CITATION:

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[14] The within-decile employment and wage trends hold for these occupations as a whole in the CPS data, not just within the second and third deciles of the wage distribution. During this period, material moving workers, grew in employment and had large increases in average wages overall; retail sales workers, had declining employment but rising wages overall, and health technologists and technicians as well as information and record clerks had growing employment and wages overall.

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BOOK REVIEW

JUNE 2022

The legalities of the uniquely American employee benefits system

Understanding Employee Benefits Law, 2nd ed. By Kathryn L. Moore. Durham, NC: Carolina Academic Press, 2020, 531 pp., $51.00 paperback.

In a nation where welfare and pension benefits largely come from employers, the rules and laws governing how employers distribute those benefits hold outsized importance. According to a recent survey from Principal Financial Group, less than half of Americans are confident they will have enough saved to ensure a secure retirement. And a recent study from the Pew Research Center suggests that most Americans are unhappy with the employer-based healthcare system they currently have, with a clear majority (63 percent) favoring a single, national government program to provide healthcare coverage. With ever-evolving rules on pensions and various legal challenges to the most significant healthcare legislation, the Affordable Care Act (ACA), keeping up with where the law stands at any given time could be troublesome. A recent text on the subject could make it a lot simpler.

In *Understanding Employee Benefits Law* (2nd edition), author Kathryn L. Moore provides a comprehensive overview of what is a broad and complex area of law. She addresses employer pension and healthcare plans, detailing the unique features of the U.S. employer-based benefits system. The book provides indepth discussion of the impact of the ACA on employer-provided healthcare plans, as well as the effect of the Employee Retirement Income Security Act (ERISA) on employer-provided pension plans. What Moore offers is an end product that would satisfy students, practitioners, and the intellectually curious alike.

The book begins with an overview of pension plans, distinguishing between defined benefit (DB) and defined contribution (DC) plans. DB plans are what many would consider traditional pension plans, with beneficiaries receiving a fixed amount during retirement. DC plans, which are more prevalent today, are individual retirement accounts into which money is contributed, with benefits resulting from accumulated savings. The author offers detailed examples of how specific plan terms and varying benefit formulas would affect a participant's total benefit for different types of DB and DC plans.

Next is an introduction to employment-based healthcare plans. The author puts forth a brief history of the U.S. employment-based healthcare system, reporting that this system is unique among advanced nations and attributing its rise to wage and price controls dating back to World War II, when employee benefits became an increasingly important recruitment tool. The book reveals several problems with the system—including its inability to insure people, its high cost, and its poorly functioning individual and small-group markets—and then moves on to discuss the ACA, the 2010 legislation designed to address these problems.

Moore's discussion of the ACA is centered around the act's three key components: market reforms, individual and employer mandates, and health insurance exchanges. Among the market reforms discussed are prohibiting health insurance companies from denying coverage on the basis of preexisting conditions, allowing young adults to retain their parents' coverage until age 26, and prohibiting lifetime and annual caps on benefits. The author devotes considerable time to discussing the evolution of the individual mandate, which originally carried a monetary penalty for individuals who failed to purchase health insurance coverage. After the penalty was eliminated by Congress in 2017, the mandate survived legal challenges to its constitutionality and remains in effect today. With respect to the health insurance marketplaces established by the ACA, the book describes the individual and small business marketplaces, including covered benefits, cost-sharing limits, and actuarial-value requirements. The author is careful to point out what the legislation does not do—create a single coherent system; eliminate the employer-based system; or change the large-group, small-group, and individual-market segmentation of the current system.

The book next turns to the ERISA regulatory requirements that govern the day-to-day operation of employee benefit plans, including items such as the written plan documents describing the operation and provisions of those plans, reporting and disclosure requirements, and procedures for amending plans. In addition, Moore offers a detailed review of the four ERISA section 510 prohibitions (exercise clause, interference clause, whistleblower provision, and multiemployer plan provision) protecting employees from adverse employment action for exercising their rights in relation to the plan, and she also provides several practical examples of violations of those protections.

Later chapters discuss the intricacies of regulating pension plans, ERISA fiduciary standards, civil enforcement, ERISA preemption, nondiscrimination rules for qualified plans, the tax rules governing pension plans, and plan termination. In the hands of a less capable writer, this weighty material might have been presented in a way that is muddled and tedious to read. But here, the substantive information is well arranged and easy to comprehend.

A major strength of the book is its presentation style. Moore offers practical examples showing how the technical concepts she discusses might operate in the real world. The examples found in the chapter on tax rules, for instance, are particularly helpful in showing the tax implications that different Internal Revenue Service regulations would have on DB and DC plan participants of various incomes. The author also provides flow charts that illustrate how some of the more complex processes would work in practical terms. For example, the chapter on nondiscrimination rules for qualified plans, which contains some of the thorniest material in the text, effectively uses flow charts to break the information down and make it easy to follow.

Understanding Employee Benefits Law is a legal text that is broadly accessible and not restricted to the legal community. It uses clear examples and strong visual aids to make complicated material digestible. I would recommend this book as a reference for legal practitioners or an introduction for people looking to expand their knowledge of the legal aspects of employee benefit programs.

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