BOOK REVIEW

April 2023

Fiscal policies as a response to recessions

Recession Ready: Fiscal Policies to Stabilize the American Economy. Edited by Heather Boushey, Ryan Nunn, and Jay Shambaugh. Washington, DC: The Brookings Institution, Hamilton Project, 2019, 250 pp., download.

The National Bureau of Economic Research has documented 34 business cycles from 1854 to 2020 in the United States. The downturn phases of these business cycles are usually characterized as recessions. During recessionary periods, declines in investment and employment are common. *Recession Ready: Fiscal Policies to Stabilize the American Economy* is a recent addition to the literature on the effectiveness of fiscal policies in minimizing the impacts of economic downturns. Edited by Heather Boushey, Ryan Nunn, and Jay Shambaugh, this book, a collection of papers penned by economists, focuses on two main topics. First, it documents the impacts of recessions and the effectiveness of antirecessionary fiscal policies. Second, it presents several automatic stabilizers that could dampen the effects and length of recessions. Automatic stabilizers are fiscal policies that automatically respond to macroeconomic fluctuations, such as declines in tax revenue during an economic downturn.

In the first chapter of the book, Boushey, Nunn, Jimmy O'Donnell, and Shambaugh review the economic impacts of recessions and the effectiveness of past fiscal responses. The authors empirically show that recessions reduce gross domestic product (GDP), increase unemployment and underemployment, increase the probability of people leaving the labor force, diminish the job prospects of recent college graduates, and reduce private and public investment. The authors estimate the effectiveness of past fiscal responses to economic downturns, concluding that these responses have been slow and too short to counter the impacts of recessions.

In the second chapter, Louise Sheiner and Michael Ng find that federal spending is usually countercyclical, whereas state-level spending is usually procyclical (because many states require their budgets to remain balanced). This finding leads the authors to favor federal-level fiscal spending over state-level spending. Automatic stabilizers are considered an effective response to recessions because they quickly match the timing and duration of spending to recession indicators. Also, automatic stabilizers can target those who are the most adversely affected by economic downturns, such as the unemployed and individuals with low incomes.

In the third chapter, Claudia Sahm proposes an automatic stabilizer involving lump-sum payments to all individuals, regardless of their income. These payments would be triggered by a 0.5-percentage-point increase in the unemployment rate, which is an increase observed only around recessions. Sahm reviews the literature on the effectiveness of lump-sum payments during past recessions, finding that such payments are spent more quickly than payroll deductions or multiple payments. The author also finds that the amount of these payments should total 0.7 percent of GDP, which is approximately half the average spending decrease during past recessions. Such lump-sum payments should be repeated each year in which the unemployment rate is at least 2.0 percentage points above the trigger level.

In the fourth chapter, Matthew Fiedler, Jason Furman, and Wilson Powell argue that federal spending on Medicaid and the Children's Health Insurance Program (CHIP) should automatically increase when a state's unemployment rate reaches a predetermined level. They recommend this funding increase because of the negative social effects of reduced state-level spending during recessions. For example, reduced education spending by states during recessions has hurt student achievement. Besides assessing the direct effects of healthcare spending, the authors estimate that, over the long term, an automatic increase in spending on Medicaid and CHIP would increase GDP by 0.12 percent and reduce the unemployment rate by 0.1 percentage point.

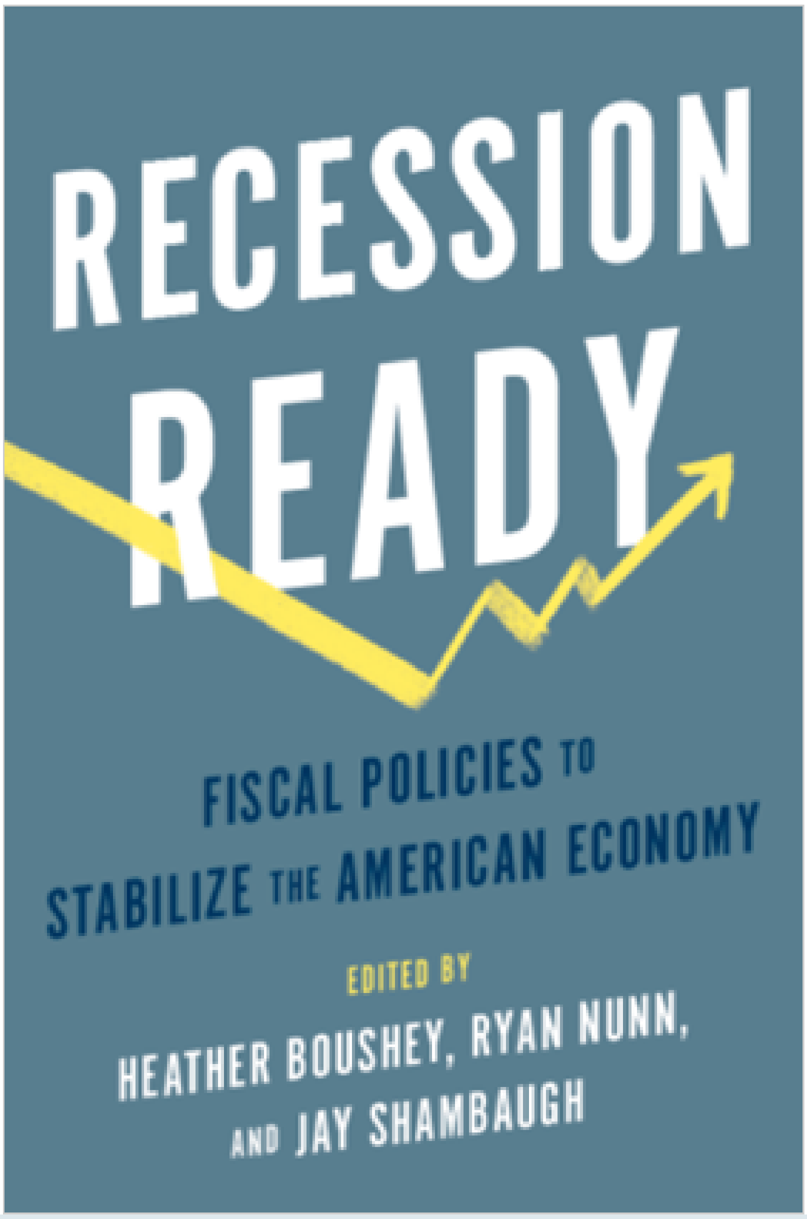
In the fifth chapter, Andrew Haughwout proposes road-repair spending as a countercyclical stabilizer. The author documents this spending as a long-term investment that provides service flows to individuals and businesses. Usually, spending on road repair is seen as a poor countercyclical measure because infrastructure projects involve lengthy planning. According to Haughwout, to make infrastructure spending a timely response to recessions, states should consider developing a catalogue of planned road-repair projects that would be federally financed. This planning would ensure quick project completion, making the spending more effective as a countercyclical policy.

In the sixth chapter, Gabriel Chodorow-Reich and John Coglianese propose an updated and expanded unemployment insurance (UI) program that uses automatic triggers based on unemployment levels. The authors argue that such a program would better serve as a countercyclical antirecessionary policy. Because people who receive UI benefits are usually in need of transfers, unemployed people are likely to spend these transfers relatively quickly, which would provide a countercyclical effect. Chodorow-Reich and Coglianese's recommendations include expanding benefits eligibility, encouraging the filing of more applications, extending benefits automatically during spells of high unemployment, and increasing benefit amounts during recessions (which would increase the use of UI as a macroeconomic stabilizer).

In the seventh chapter, Indivar Dutta-Gupta proposes changes to the Temporary Assistance for Needy Families (TANF) program that would increase the program's effectiveness during recessions. The author argues for increases in both basic assistance and the number of subsidized jobs with supportive services. Under the latter component of the proposal, unemployed individuals would be prepared for and placed in jobs in which their wages are partially or fully subsidized by federal spending. In addition, these individuals would receive services, such as childcare and transportation assistance, that would increase their odds of becoming and staying employed. Dutta-Gupta finds that these changes to TANF would strengthen the program's antipoverty and countercyclical effects.

In the eighth chapter, Hilary Hoynes and Diane Whitmore Schanzenbach argue that the Supplemental Nutrition Assistance Program (SNAP) can be altered to become a more effective automatic stabilizer. The authors show that SNAP has reduced financial hardship and poverty and improved health outcomes, children's educational attainment, and children's economic outcomes during adulthood. SNAP benefits have a fast fiscal effect, as 97 percent of benefits are spent within a month of being received. Hoynes and Schanzenbach argue that increasing SNAP benefit levels and waiving SNAP work requirements during recessions will make the program a better automatic stabilizer.

Recession Ready is an accessible book focusing both on the past effects of recessions and on the policy responses to those effects. Readers new to these topics will find the book to be a good starting place for their research. Professional macroeconomists will benefit from the book's review of current research. Also, the book would be a useful reading in courses on the business cycle or fiscal policy. Despite these strengths, *Recession Ready* does not discuss some policies that could also be used as automatic stabilizers, such as work sharing proposals and public service employment.



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ARTICLE

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Occupational projections overview, 2021–31

The Employment Projections program of the U.S. Bureau of Labor Statistics develops information about the labor market for the nation as a whole for 10 years in the future. This article provides an overview of each occupational group, including projected employment change from 2021 to 2031, information about factors contributing to projected employment change, information on median annual wage, and typical education or on-the-job-training requirements needed for occupational entry.

The Employment Projections (EP) program of the U.S. Bureau of Labor Statistics annually projects employment over a 10-year period for over 800 detailed occupations and nearly 300 industries. Employment in the United States is projected to increase 5.3 percent during the 2021–31 decade, adding about 8.3 million new jobs.[1] These projections form the basis for data and outlook information in the *Occupational Outlook Handbook* (OOH).[2] The EP data and the OOH are used by a wide variety of people, including jobseekers, career counselors, education and training officials, and researchers.

This article is organized by 24 occupational groups,[3] which highlight several of the detailed occupations that are projected to grow the fastest or projected to decline the fastest. Additional information for these occupations may be found within the OOH. This article also illustrates common trends and factors within occupational groups and across groups.

Table 1 displays the projected employment change from 2021 to 2031, sorted by percentage of total new jobs added. This table and all subsequent tables provide information about employment change in two ways: numeric change and percent change. This is important to note because a fast rate of employment growth does not always translate into many new jobs. For example, the math occupational group is projected to grow 28.7 percent from 2021 to 2031, the fastest of any occupational group. However, because of this occupational group’s relatively small size, this percent growth accounts for only about 82,000 new jobs over the projections decade. In contrast, the healthcare occupational group is projected to contribute the most new jobs of any group and projected to grow 12.6 percent. Because of its large size, the healthcare occupational group is projected to add over 2 million new jobs over the decade. That is, the healthcare occupational group is projected to add more new jobs even though its growth rate is lower than that of the math occupational group.

Table 1. Employment of OOH occupational groups, 2021 and projected 2031

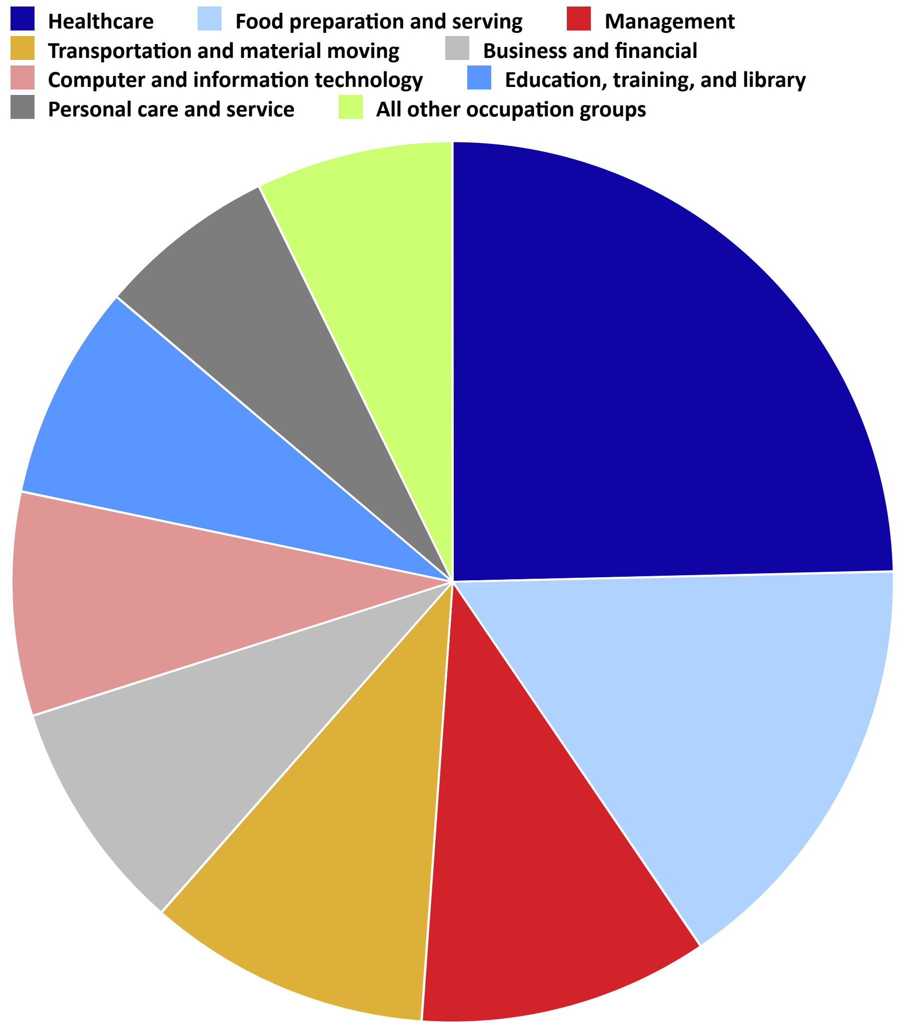
OOH occupational group	Employment		Employment change (2021–31)		Percent of total new jobs projected to be added
	2021	2031	Number	Percent	
Total, all occupations	158,134.7	166,452.1	8,317.4	5.3	[1]
Healthcare	16,254.2	18,303.2	2,049.1	12.6	24.6
Food preparation and serving	11,761.8	13,081.6	1,319.9	11.2	15.9
Management	11,685.3	12,569.2	883.9	7.6	10.6
Transportation and material moving	13,350.7	14,212.6	861.8	6.5	10.4
Business and financial	9,987.4	10,702.5	715.1	7.2	8.6
Computer and information technology	4,665.2	5,348.0	682.8	14.6	8.2
Education, training, and library	9,151.2	9,809.3	658.2	7.2	7.9
Personal care and service	3,868.4	4,413.2	544.8	14.1	6.6
Installation, maintenance, and repair	6,038.7	6,342.6	304.0	5.0	3.7
Community and social service	2,843.2	3,137.8	294.6	10.4	3.5
Building and grounds cleaning	5,415.0	5,705.8	290.8	5.4	3.5
Construction and extraction	7,026.0	7,278.9	252.9	3.6	3.0
Legal	1,368.0	1,499.0	131.0	9.6	1.6
Life, physical, and social science	1,436.0	1,534.7	98.7	6.9	1.2
Entertainment and sports	758.3	853.8	95.5	12.6	1.1
Architecture and engineering	2,562.5	2,653.7	91.3	3.6	1.1
Math	286.3	368.3	82.0	28.7	1.0
Protective service	3,482.2	3,554.8	72.6	2.1	0.9
Media and communication	1,111.9	1,180.5	68.6	6.2	0.8
Arts and design	918.8	939.4	20.5	2.2	0.2
Farming, fishing, and forestry	1,069.6	1,078.0	8.4	0.8	0.1
Production	8,787.1	8,623.5	-163.6	-1.9	-2.0
Sales	14,719.9	14,555.4	-164.5	-1.1	-2.0
Office and administrative support	19,587.0	18,706.2	-880.8	-4.5	-10.6

[1] This entry is not applicable.
Note: Employment numbers are in thousands. Details may not sum to totals because of rounding.
OOH is the Occupational Outlook Handbook.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Overview

Of the 8.3 million new jobs projected to be added by 2031, almost one-quarter will be within the healthcare occupational group. The five occupational groups projected to add the most new jobs from 2021–31 contribute about 70 percent of the 8.3 million new jobs. These five occupational groups include the following: healthcare occupations, food preparation and serving occupations, management occupations, transportation and material moving occupations, and business and financial occupations. (See chart 1.)

Chart 1. Projected number of new jobs to be added from 2021–31, by OOH occupational group



Click legend items to change data display. Hover over chart to view data.
Note: OOH is the Occupational Outlook Handbook.
Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

View Chart Data

The concentrated nature of the employment growth lends itself to some key takeaways. Healthcare occupations are projected to add the most new jobs of any of the occupational groups, contributing over 2.0 million new jobs to the total 8.3 million jobs during the projections period. This projected growth is mainly due to a growing population, whose rising share of older people with chronic conditions is expected to lead to greater demand for healthcare services.

The growth in some industries synergizes with growth in other industries. Business growth and expansion (especially in healthcare, information technology (IT), and e-commerce) will drive demand for services provided by management occupations, transportation and material moving occupations, and business and financial service occupations. These three occupational groups, combined, account for almost 30 percent of all new jobs expected to be added to 2031. The sectors that are projected to grow faster than average, such as healthcare and IT, will consequently result in demand for managers in those areas. Continued growth of e-commerce should increase demand for transportation and warehousing, supporting demand for package delivery services and material movers. The growth in digital marketing and e-commerce will support demand for business and finance occupations that manage activities such as logistics, marketing research, and accounting.

Likewise, demand for the services provided by computer and information technology occupations and math occupations will stem from greater emphasis on collecting and analyzing data, continuing growth in the digital economy, and an increasing need for information security. These two occupational groups, combined, account for a little over 9 percent of all new jobs to be added to 2031, and they are projected to be the two fastest growing groups. Overall, employment in math occupations is projected to grow 28.7 percent, the fastest of any group. Also, employment in computer and information technology occupations is projected to grow 14.6 percent from 2021 to 2031.

In contrast, significant employment gains for some occupational groups are primarily rebounds from the COVID-19 pandemic.[4] Food preparation and serving occupations and personal care and service occupations, combined, are projected to add almost 1.9 million new jobs, contributing about 22 percent of the total 8.3 million jobs projected over the 2021–31 projections cycle. However, a large part of the projected growth for these two groups represents a recovery from the low employment level in 2021 because of the lingering effects of the COVID-19 pandemic.

Not all occupational groups are expected to grow. Production occupations, sales occupations, and office and administrative support occupations are three occupational groups expected to experience a decline in employment over the projections decade. Changes in technology, such as machines or software use that increases productivity or replaces workers altogether, are expected to contribute to a decline in employment and suppress job openings.[5] Nevertheless, the need to replace workers who change occupations or leave the labor force is expected to create some job openings, even in occupations with projected employment declines.

Occupational groups analysis

The occupational groups in this article encompass every civilian job in the United States and can be broken down into individual occupations. Of these, more than 500 detailed occupations in over 300 occupational profiles are covered in the OOH, accounting for about 4 out of 5 jobs in the economy. The OOH includes information on job outlook, job descriptions, entry-level education, training information, and wage data.[6]

Occupations can be grouped by similar duties or purposes; for example, protective service occupations include police and sheriff's patrol officers, security guards, and correctional officers and jailers. Examining the growth of occupational groups reveals the key factors affecting employment over the projections period.

Projected employment information for each of the OOH occupational groups is outlined below, including information about factors that may be contributing to the projected employment change at the group level. In this article, occupational groups are presented in order of the percentage of total new jobs projected to be added over the projections period from the occupational groups projected to add the most new jobs to the occupational groups projected to lose jobs over the projections decade. Detailed occupations are highlighted in each group section with the fastest growing occupations or the fastest declining occupations. The median annual wage and typical education needed for entry into these detailed occupations are provided. Links to the OOH pages are provided for additional information on what they do, work environment, and a list of similar occupations, among other information.

Healthcare occupational group

Overall employment in healthcare occupations is projected to grow 12.6 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 2.0 million new jobs over the decade, the most of any group.[7] Healthcare workers will be needed to assist a growing number of older Americans stay healthy and active and to provide services to those with chronic conditions, such as diabetes. Five of the top 30 fastest growing occupations are detailed occupations within the healthcare occupational group: nurse practitioners, physician assistants, physical therapist assistants, home health and personal care aides, and occupational therapy assistants. (See appendix A-1.)

Table 2. Top five fastest growing occupations within healthcare occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Healthcare	29-0000 and 31-0000	16,254.2	18,303.2	2,049.1	12.6	47,070	[2]
Nurse practitioners	29-1171	246.7	359.4	112.7	45.7	120,680	Master's degree
Physician assistants	29-1071	139.1	177.5	38.4	27.6	121,530	Master's degree
Physical therapist assistants	31-2021	96.5	122.1	25.6	26.5	61,180	Associate's degree
Home health and personal care aides	31-1120	3,636.9	4,560.9	924.0	25.4	29,430	High school diploma or equivalent
Occupational therapy assistants	31-2011	43.4	54.5	11.0	25.4	61,730	Associate's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.

[2] This entry is not applicable.

Note: Employment numbers are in thousands. Details may not sum to totals because of rounding.

Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Nurse practitioners are projected to experience the fastest employment growth of all occupations, with projected growth of 45.7 percent. Healthcare facilities are increasingly using team-based healthcare models, which employ nurse practitioners, physician assistants, and other healthcare practitioners to provide patient care that would otherwise be provided by a doctor. Many of the fastest growing occupations in healthcare work closely with patients to help them maintain or improve their quality of life. Physical therapist assistants assist physical therapists, particularly in long-term care environments; physical therapist assistants have a projected employment growth of 26.5 percent (much faster than the average for all occupations and the fastest growing occupation within the healthcare support occupational group). Occupational therapy assistants will be needed to help occupational therapists in caring for patients with conditions and ailments, such as arthritis and strokes, that may affect their ability to do everyday activities.

Employment of home health and personal care aides is projected to grow by 25.4 percent and add about 924,000 jobs. Both the fast growth of the elderly population and their desire to live in their own homes are expected to underpin demand for more in-home assistance. Demand for assistance and care for individuals in retirement communities, assisted-living facilities, nursing homes, and other facilities is expected to contribute to the overall growth of this occupation.

Healthcare occupations had a median annual wage of $47,070 in May 2021, but wages vary widely; some healthcare occupations are among the highest paying, while others have wages below the median annual wage. Wages are generally correlated with education as occupations with higher levels of typical entry-level education usually pay more. Many of the occupations within this group require on-the-job training, internship, or residency experience.

Food preparation and serving occupational group

Overall employment in food preparation and serving occupations is projected to grow 11.2 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 1.3 million new jobs over the decade.[8] Food preparation and serving occupations are projected to contribute 15.9 percent of the new jobs added over the 2021–31 period. This mostly reflects job recovery from the COVID-19 recession of 2020 because pandemic restrictions had significant effects on employment levels in restaurants. Only one of the top 30 fastest growing occupations projected from 2021 to 2031 is a detailed occupation within the food preparation and serving occupational group, namely, cooks, restaurants. (See appendix A-1.)

Table 3. Top five fastest growing occupations within food preparation and serving occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Food preparation and serving	35-0000	11,761.8	13,081.6	1,319.9	11.2	28,400	[2]
Cooks, restaurant	35-2014	1,255.6	1,715.6	459.9	36.6	30,010	No formal education credentials
Bartenders	35-3011	514.0	606.0	92.0	17.9	26,350	No formal education credentials
Dining room and cafeteria attendants and bartender helpers	35-9011	355.2	415.1	59.9	16.9	27,170	No formal education credentials
Chefs and head cooks	35-1011	152.8	176.3	23.6	15.4	50,160	High school diploma or equivalent
Hosts and hostesses, restaurant, lounge, and coffee shop	35-9031	347.7	400.3	52.6	15.1	24,600	No formal education credentials

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands. Details may not sum to totals because of rounding.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Some employment lost in the food preparation and serving occupations during the pandemic and projected to be recovered over the projections decade has already been recuperated as employment grew rapidly throughout the first half of 2022.[9] Many food service establishments, restaurants, school cafeterias, and food contractors for businesses have already reopened and reemployed workers as consumer food spending patterns returned to their prepandemic trends.

In addition to the immediate recovery discussed above, new restaurant openings and expanded food deliveries will contribute to increases in demand for restaurant food, supporting demand for the services provided by the food preparation and serving occupations. Cooks at restaurants are expected to add the most new jobs within this group as consumers demand more high-quality food from restaurants, contributing about 459,900 new jobs over the projections decade.

The food preparation and serving occupations group is the lowest paid major group, with a median annual wage of $28,400 in May 2021. Most food preparation and serving occupations require on-the-job training, typically lasting up to 30 days; however, typically no education credentials are needed for entry.

Management occupational group

Overall employment in management occupations is projected to grow 7.6 percent from 2021 to 2031, faster than the average for all occupations; this increase is expected to result in about 883,900 new jobs over the decade.[10] Only one of the top 30 fastest growing occupations projected from 2021 to 2031 is a detailed occupation within the management occupational group, namely, medical and health services managers. (See appendix A-1.)

Table 4. Top five fastest growing occupations within management occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Management	11-0000	11,685.3	12,569.2	883.9	7.6	102,450	[2]
Medical and health services managers	11-9111	480.7	616.9	136.2	28.3	101,340	Bachelor's degree
Lodging managers	11-9081	51.2	60.4	9.2	18.0	59,430	High school diploma or equivalent
Financial managers	11-3031	730.8	854.0	123.1	16.8	131,710	Bachelor's degree
Entertainment and recreation managers, except gambling	11-9072	21.6	25.2	3.6	16.5	62,000	Bachelor's degree
Computer and information systems managers	11-3021	509.1	591.5	82.4	16.2	159,010	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

The projected employment change for management occupations varies depending on the demand for the services they provide and the need for the supervision of workers. For example, as the demand for healthcare services increases, medical and health services managers will be needed to support this demand, driving employment growth of 28.3 percent from 2021 to 2031. Similarly, the employment of computer and information systems managers is projected to grow 16.2 percent over the projections period as the need for IT services and enhanced security requirements continue to grow.

Both lodging managers and entertainment and recreation managers, except gambling, will also see fast employment growth. However, much of this projected growth will be due to recovery from the COVID-19 recession. The return to prepandemic travel patterns will result in strong demand for lodging managers in hotels and other lodging establishments at the beginning of the projections decade.

The median annual wage for this group was $102,450 in May 2021, which was the highest among the major occupational groups. A bachelor's degree is the required level of education for most jobs within this group. However, requirements vary from a high school diploma to a master's degree across the management occupations. In addition to postsecondary education, most occupations in this group require work experience in a related occupation. For example, financial managers require years of work experience in a related occupation for entry.

Transportation and material moving occupational group

Overall employment in transportation and material moving occupations is projected to grow 6.5 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 861,800 new jobs over the decade.[11] The economy depends on transportation and material moving workers to transport freight and passengers and keep supply chains moving. Expected growth in e-commerce will drive demand for transportation and deliveries. Taxi drivers is the only detailed occupation from the transportation and material moving group among the top 30 fastest growing occupations projected to grow the fastest from 2021 to 2031. (See appendix A-1.)

Table 5. Top five fastest growing occupations within transportation and material moving occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Transportation and material moving	53-0000	13,350.7	14,212.6	861.8	6.5	36,860	[2]
Taxi Drivers	53-3054	128.5	165.1	36.6	28.5	29,310	No formal education credentials
Flight attendants	53-2031	106.3	128.4	22.1	20.8	61,640	High school diploma or equivalent
Shuttle drivers and chauffeurs	53-3053	189.5	215.2	25.8	13.6	30,000	No formal education credentials
Driver/sales workers	53-3031	531.0	594.5	63.5	12.0	29,280	High school diploma or equivalent
Pump operators, except wellhead pumpers	53-7072	11.0	12.3	1.3	11.4	49,580	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Some of the occupations within this group, such as taxi drivers, flight attendants, and shuttle drivers and chauffeurs, were affected by the COVID-19 pandemic; these occupations are expected to experience much faster than average growth over the projections decade. They are expected to recover lost employment from the recession of 2020 as the general population returns to prepandemic travel patterns.

The general demand for delivery options is expected to increase, and the services provided by driver/sales workers are projected to grow as these workers may be needed to deliver items such as food and medical supplies.

The median annual wage for this group was $36,860 in May 2021, which was lower than the median annual wage for all occupations of $45,760. Education requirements for this group range from no education credential to a postsecondary nondegree award, but a high school diploma is generally the level of education needed for entry. Some form of on-the-job training is needed to attain competency in most of the occupations within the transportation and material moving group.

Business and financial occupational group

Overall employment in business and financial occupations is projected to grow 7.2 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 715,100 new jobs over the decade.[12] Continued domestic and international business operations, along with a complex tax and regulatory environment, are expected to create demand for a variety of business and financial services, including accounting, consulting, and investment advisory services. In addition, increasing efforts to understand customers behavior and product demand and to evaluate marketing strategies will lead to growing demand for market research. Only one of the top 30 fastest growing occupations projected from 2021 to 2031 is a detailed occupation within the business and financial occupational group, namely, logisticians. (See appendix A-1.)

Table 6. Top five fastest growing occupations within business and financial occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Business and financial	13-0000	9,987.4	10,702.5	715.1	7.2	76,570	[2]
Logisticians	13-1081	195.0	249.1	54.1	27.7	77,030	Bachelor's degree
Farm labor contractors	13-1074	1.2	1.5	0.3	22.3	47,770	No formal education credentials
Financial examiners	13-2061	62.8	76.0	13.2	21.0	81,410	Bachelor's degree
Market research analysts and marketing specialists	13-1161	792.5	942.8	150.3	19.0	63,920	Bachelor's degree
Meeting, convention, and event planners	13-1121	128.2	151.1	22.9	17.8	49,470	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Logisticians are expected to be in high demand; their employment is projected to grow 27.7 percent from 2021 to 2031, much faster than the average for all occupations. As the growth of e-commerce makes logistics more dynamic and complex, logisticians will be needed to manage multiple supply chains and oversee purchasing, transportation, inventory, and warehousing activities. The increasing use of data and market research across many industries will support the demand for market research analysts and marketing specialists; employment in these occupations is projected to grow 19.0 percent over the projections decade.

Employment of farm labor contractors is projected to grow 22.3 percent from 2021 to 2031, much faster than the average for all occupations, as farms seek the assistance of contractors in recruiting and hiring seasonal and temporary farmworkers. Employment of financial examiners is projected to grow 21.0 percent from 2021 to 2031 as the services they provide are needed to help navigate the regulatory environment and reduce the cost of compliance.

The median annual wage for this group was $76,570 in May 2021, which was higher than the median annual wage for all occupations of $45,760. Most occupations in this group require a bachelor's degree and many require some form of on-the-job training. Farm labor contractors represent the only occupation in this group requiring no education credentials for entry; however, farm labor contractors do require short-term on-the-job training.

Computer and information technology occupational group

Overall employment in computer and information technology occupations is projected to grow 14.6 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 682,800 new jobs over the decade.[13] Before the onset of the COVID-19 pandemic in 2020, many computer and IT jobs were already projected to be in high demand over the next decade, growing much faster than average. The pandemic only served to make IT workers even more important to the future economy.[14] Strong demand for IT security, software development, and new products and services associated with the Internet of Things (IoT) continue to drive demand for the services provided by these computer and IT occupations. Three of the top 30 fastest growing occupations projected from 2021 to 2031 are detailed occupations within the computer and information technology occupational group: information security analysts, web developers, and software developers. (See appendix A-1.)

Table 7. Top five fastest growing occupations within computer and information technology occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Computer and information technology	15-1200	4,665.2	5,348.0	682.8	14.6	97,430	[2]
Information security analysts	15-1212	163.0	219.5	56.5	34.7	102,600	Bachelor's degree
Web developers	15-1254	95.3	124.1	28.9	30.3	77,030	Bachelor's degree
Software developers	15-1252	1,425.9	1,796.5	370.6	26.0	120,730	Bachelor's degree
Computer and information research scientists	15-1221	33.5	40.6	7.1	21.3	131,490	Master's degree
Software quality assurance analysts and testers	15-1253	196.3	237.1	40.8	20.8	98,220	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Employment of information security analysts is projected to grow the fastest among the computer occupations, at 34.7 percent from 2021 to 2031, more than six times the rate of growth that is projected for the total economy. As businesses continue to focus on enhancing cybersecurity, they will need information security analysts to secure new technologies from outside threats or hacks, including IoT-connected devices. As e-commerce continues to expand, organizations will look to utilize the services provided by web developers to create and maintain websites, which will result in projected growth of 30.3 percent from 2021 to 2031.

Software developers and software quality assurance analysts and testers are projected to be among the fastest growing computer occupations (26.0 percent and 20.8 percent, respectively) as the services they provide will be needed to support the increasing number of products that use software. Employment of computer and information research scientists is projected to grow 21.3 percent from 2021 to 2031 as the demand for new and better technology continues to grow.

The median annual wage for computer occupations was $97,430 in May 2021, higher than the median for all occupations in the economy. A bachelor's degree or higher is needed for entry-level positions in most occupations in this group, and some on-the-job training may be needed to attain competency in a few of the occupations.

Education, training, and library occupational group

Overall employment in education, training, and library occupations is projected to grow 7.2 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 658,200 new jobs over the decade.[15] Growth in education, training, and library occupations is influenced by school enrollments and budgets. The number of people attending postsecondary institutions is expected to grow over the projections decade as students continue to seek higher education to gain the knowledge and skills necessary to meet their career goals. Only one of the top 30 occupations projected to grow the fastest from 2021 to 2031 is a detailed occupation within the education, training, and library occupational group: health specialties teachers, postsecondary. (See appendix A-1.)

Table 8. Top five fastest growing occupations within education, training, and library occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Education, training, and library	25-0000	9,151.2	9,809.3	658.2	7.2	57,220	[2]
Health specialties teachers, postsecondary	25-1071	246.7	306.1	59.4	24.1	102,720	Doctoral or professional degree
Nursing instructors and teachers, postsecondary	25-1072	87.0	105.7	18.7	21.5	77,440	Doctoral or professional degree
Self-enrichment teachers	25-3021	347.1	408.3	61.3	17.6	43,580	High school diploma or equivalent
Preschool teachers, except special education	25-2011	483.1	556.0	72.9	15.1	30,210	Associate's degree
Tutors	25-3041	203.4	232.9	29.5	14.5	36,470	Some college, no degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Health specialties teachers and nursing instructors and teachers are projected to be the two fastest growing occupations within this group; they are projected to grow 24.1 and 21.5 percent, respectively, over the projections decade as the increased demand for medical care will support demand for postsecondary teachers to educate workers.

Demand for preschool and child daycare services is expected to be robust as early childhood education is emphasized. As a result, employment of preschool teachers is projected to grow 15.1 percent from 2021 to 2031, much faster than the average for all occupations.

The median annual wage for education, training, and library occupations was $57,220 in May 2021, more than the median for all occupations in the economy. College coursework is required for most jobs within the field, although this varies with the level of instruction. There is no typical on-the-job training needed for the education, training, and library occupations.

Personal care and service occupational group

Overall employment in personal care and service occupations is projected to grow 14.1 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 544,800 new jobs over the decade.[16] Government-imposed closures for entertainment events in some parts of the country and some consumer preferences to avoid these types of events resulted in reduced attendance levels or canceled events throughout 2021. Within the personal care and service occupational group, six of the top 30 occupations projected to grow the fastest from 2021 to 2031 are detailed occupations. This includes the 5 occupations in table 9 and entertainment attendants and related workers, all other. (See appendix A-1.)

Table 9. Top five fastest growing occupations within personal care and service occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Personal care and service	39-0000	3,868.4	4,413.2	544.8	14.1	29,450	[2]
Ushers, lobby attendants, and ticket takers	39-3031	63.2	88.8	25.6	40.5	24,440	No formal education credentials
Motion picture projectionists	39-3021	2.0	2.8	0.8	40.3	29,350	No formal education credentials
Animal caretakers	39-2021	290.7	377.6	86.9	29.9	28,600	High school diploma or equivalent
Animal trainers	39-2011	52.9	67.2	14.3	27.1	31,280	High school diploma or equivalent
Personal care and service workers, all other	39-9099	104.4	130.4	26.0	24.9	29,610	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

The much-faster-than-average growth for ushers, lobby attendants, and ticket takers and motion picture projectionists primarily represents the recovery of jobs from the effects of the COVID-19 pandemic. These occupations are expected to recover early in the projections period as social gatherings and other activities resume.

Increasing pet ownership and spending on pets will continue to contribute to employment growth of animal caretakers and animal trainers.

The median annual wage for personal care and service occupations was $29,450 in May 2021, lower than the median for all occupations in the economy. Most occupations in this group require a high school diploma or equivalent; however, on-the-job training is needed for many of the personal care and service occupations.

Installation, maintenance, and repair occupational group

Overall employment in installation, maintenance, and repair occupations is projected to grow 5.0 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 304,000 new jobs over the decade.[17] Demand for workers in these occupations will stem from the need to install, maintain, and repair a wide variety of equipment, including cars, factory machinery, and equipment used in homes and hospitals. In addition, many buildings will need upkeep and renewal as older homes and buildings typically require more maintenance or repair, especially for pipes, insulation, electrical systems, and air-conditioning and heating systems. Specialized maintenance and repair of these aging systems alongside installation of new systems will support growth for many jobs in this group. One of the detailed occupations within this occupational group, wind turbine service technicians, is among the top 30 occupations projected to grow the fastest from 2021 to 2031. (See appendix A-1.)

Table 10. Top five fastest growing occupations within installation, maintenance, and repair occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Installation, maintenance, and repair	49-0000	6,038.7	6,342.6	304.0	5.0	47,940	[2]
Wind turbine service technicians	49-9081	11.1	16.1	4.9	44.3	56,260	Postsecondary nondegree award
Medical equipment repairers	49-9062	59.1	69.1	10.0	17.0	49,910	Associate's degree
Industrial machinery mechanics	49-9041	384.8	447.9	63.1	16.4	59,840	High school diploma or equivalent
Commercial divers	49-9092	3.0	3.4	0.4	14.7	60,360	Postsecondary nondegree award
Recreational vehicle service technicians	49-3092	16.7	18.7	2.0	12.2	43,560	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Wind turbine service technicians are projected to have the second-fastest employment growth of all occupations. However, there will be relatively few jobs added (about 4,900 over 2021–31) because of the small employment numbers of wind turbine service technicians in 2021. Wind power generation has grown over the past 10 years, and it will require technicians to install, maintain, and repair wind turbines as this generating capacity ages.

The use of medical equipment for diagnosis and treatment will expand as the number of older adults and people with chronic diseases increase. Medical equipment repairers will be needed to maintain and repair medical equipment. Expansion of automation in production activities will support demand for the services provided by industrial machinery mechanics as they are needed to help keep machines in good working order.

The median annual wage for installation, maintenance, and repair occupations was $47,940 in May 2021, which was higher than the median for all occupations in the economy. Most of the occupations within this group require a high school diploma or equivalent and on-the-job training.

Community and social service occupational group

Overall employment in community and social service occupations is projected to grow 10.4 percent from 2021 to 2031, faster than the average for all occupations; this increase is expected to result in about 294,600 new jobs over the decade.[18] As demand remains strong for mental health, addiction, and school and career-counseling services, employment of community and social service occupations is projected to experience fast growth over the projections period.

Table 11. Top five fastest growing occupations within community and social service occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Community and social service	21-0000	2,843.2	3,137.8	294.6	10.4	48,410	[2]
Substance abuse, behavioral disorder, and mental health counselors	21-1018	351.0	428.5	77.5	22.1	48,520	Bachelor's degree
Community health workers	21-1094	67.0	77.7	10.6	15.9	46,590	High school diploma or equivalent
Marriage and family therapists	21-1013	65.3	74.3	9.1	13.9	49,880	Master's degree
Social and human service assistants	21-1093	420.6	472.9	52.4	12.5	37,610	High school diploma or equivalent
Healthcare social workers	21-1022	179.5	199.3	19.9	11.1	60,840	Master's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Much-faster-than-average employment growth is expected for substance abuse, behavioral disorder, and mental health counselors as people continue to seek addiction and mental health counseling services. An emphasis on promoting healthy behaviors, particularly those based on experiences from the COVID-19 pandemic, is expected to increase demand for the services provided by community health workers over the projections decade.

Much-faster-than-average employment growth is expected for marriage and family therapists. Growth is expected because of the increasing use of integrated care, which is the treatment of multiple problems at the same time by a group of specialists. In providing integrated care, marriage and family therapists are working with counselors, such as substance abuse, behavioral disorder, or mental health counselors, to address patients' issues as a team.

The median annual wage for community and social service occupations was $48,410 in May 2021, which was higher than the median for all occupations in the economy. Education requirements vary from high school diploma to a master’s degree, tending to be higher for more complex social needs. Several occupations within this group also require on-the-job training, internship, or residency experience.

Building and grounds cleaning occupational group

Overall employment in building and grounds cleaning occupations is projected to grow 5.4 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 290,800 new jobs over the decade.[19] None of the detailed occupations within this occupational group are projected to be among the top 30 fastest growing occupations from 2021 to 2031. Building and grounds cleaning workers will be needed to keep up with continued demand for lawn care, landscaping, and cleaning services from both commercial and residential spaces.

Table 12. Top five fastest growing occupations within building and grounds cleaning occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Building and grounds cleaning	37-0000	5,415.0	5,705.8	290.8	5.4	30,240	[2]
Maids and housekeeping cleaners	37-2012	1,237.4	1,353.8	116.4	9.4	28,780	No formal education credentials
Pest control workers	37-2021	90.6	96.7	6.1	6.8	37,540	High school diploma or equivalent
Pesticide handlers, sprayers, and applicators, vegetation	37-3012	27.6	29.2	1.6	5.8	38,270	High school diploma or equivalent
First-line supervisors of housekeeping and janitorial workers	37-1011	253.0	266.7	13.7	5.4	39,630	High school diploma or equivalent
Landscaping and groundskeeping workers	37-3011	1,191.6	1,248.5	56.9	4.8	34,430	No formal education credentials

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Maids and housekeeping cleaners are expected to see strong employment growth mostly because of recovery from the COVID-19 recession of 2020. The return to prepandemic travel patterns will translate to strong demand for maids and housekeeping cleaners in hotels and other traveler accommodations at the start of the projections decade. The job recovery also is expected in other establishments that were affected by the COVID-19 pandemic, including private households, hospitals, and nursing care centers.

Landscaping and groundskeeping workers will see employment growth associated with increasing demand for lawn care and landscaping services from homeowners and from large institutions, such as universities and corporate campuses.

The median annual wage for building and grounds cleaning was $30,240 in May 2021, which was lower than the median for all occupations in the economy. Many of the occupations within this group do not require an education credential, but a high school diploma or equivalent is needed for entry into higher paying building and grounds cleaning occupations. On-the-job training is needed for most of the building and grounds cleaning occupations.

Construction and extraction occupational group

Overall employment in construction and extraction occupations is projected to grow 3.6 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 252,900 new jobs over the decade.[20] Overall growth in the economy will increase demand for new buildings, roads, and other structures, which will create jobs in construction and extraction occupations. Alternative-energy-related activities will contribute to the growth of construction occupations, including the installation of electric vehicle (EV) charging stations, photovoltaic (PV) panels, and wind turbines.[21] Two of the top 30 occupations projected to grow the fastest from 2021 to 2031 are detailed occupations within the construction and extraction occupational group: solar photovoltaic installers and roustabouts, oil and gas. (See appendix A-1.)

Table 13. Top five fastest growing occupations within construction and extraction occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Construction and extraction	47-0000	7,026.0	7,278.9	252.9	3.6	48,210	[2]
Solar photovoltaic installers	47-2231	17.1	21.7	4.6	27.2	47,670	High school diploma or equivalent
Roustabouts, oil and gas	47-5071	37.3	45.9	8.6	23.0	38,920	No formal education credentials
Rotary drill operators, oil and gas	47-5012	12.1	14.3	2.1	17.6	56,380	No formal education credentials
Service unit operators, oil and gas	47-5013	35.7	42.0	6.3	17.5	48,410	No formal education credentials
Derrick operators, oil and gas	47-5011	8.6	10.0	1.4	16.9	47,230	No formal education credentials

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

With the continued expansion and adoption of solar photovoltaic (PV) systems, the employment of solar PV installers is projected to grow 27.2 percent from 2021 to 2031. This is much faster than the average for all occupations.

The exploration and extraction of oil and gas will support demand for the services provided by roustabouts, rotary drill operators, service unit operators, and derrick operators.

The median annual wage for this group was $48,210 in May 2021, which was higher than the median annual wage for all occupations. Many of these occupations typically do not require education for entry, however most construction trades occupations do require a high school diploma or equivalent. Nearly all construction and extraction occupations require on-the-job training, and many construction trades occupations require an apprenticeship.

Legal occupational group

Overall employment in legal occupations is projected to grow 9.6 percent from 2021 to 2031, faster than the average for all occupations; this increase is expected to result in about 131,000 new jobs over the decade.[22] Legal services are expected to be in demand and contribute to employment growth in this occupational group.

Table 14. Top four fastest growing occupations within legal occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Legal	23-0000	1,368.0	1,499.0	131.0	9.6	82,430	[2]
Paralegals and legal assistants	23-2011	352.8	402.7	49.9	14.1	56,230	Associate's degree
Lawyers	23-1011	833.1	913.3	80.2	9.6	127,990	Doctoral or professional degree
Arbitrators, mediators, and conciliators	23-1022	8.9	9.5	0.6	6.2	49,410	Bachelor's degree
Title examiners, abstractors, and searchers	23-2093	61.2	62.4	1.2	1.9	47,310	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Demand for specialized and expert legal services will contribute to the overall employment growth of lawyers and legal-related occupations.

Despite this need for legal services, continuing price competition over the projections decade may lead law firms to rethink project staffing to reduce costs to clients. For example, paralegals and legal assistants are less costly than lawyers in performing a variety of tasks previously assigned to entry-level lawyers.

The median annual wage for this group was $82,430 in May 2021, which was higher than the median annual wage for all occupations of $45,760. Most occupations within this group require at least a bachelor's degree, and several of the occupations within this group may also require on-the-job training.

Life, physical, and social science occupational group

Overall employment in life, physical, and social science occupations is projected to grow 6.9 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 98,700 new jobs over the decade.[23] Increasing demand for expertise in the sciences, particularly in occupations involved in biomedical research, psychology, and environmental protection, is projected to result in employment growth in this group. One of the detailed occupations within the life, physical, and social science occupational group, epidemiologists, is among the top 30 occupations projected to grow the fastest from 2021 to 2031. (See appendix A-1.)

Table 15. Top five fastest growing occupations within life, physical, and social science occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Life, physical, and social science	19-0000	1,436.0	1,534.7	98.7	6.9	72,740	[2]
Epidemiologists	19-1041	8.6	10.9	2.2	25.8	78,830	Master's degree
Medical scientists, except epidemiologists	19-1042	119.2	140.0	20.8	17.4	95,310	Doctoral or professional degree
Biochemists and biophysicists	19-1021	37.5	43.2	5.7	15.3	102,270	Doctoral or professional degree
Animal scientists	19-1011	3.7	4.2	0.4	11.8	65,090	Bachelor's degree
Forensic science technicians	19-4092	17.6	19.6	2.0	11.4	61,930	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Employment of epidemiologists is projected to grow 25.8 percent from 2021 to 2031 because of the increased need to identify and mitigate the impact of diseases. However, because the occupation is small, the fast growth of epidemiologists will result in only about 2,200 new jobs over the projections decade. An increase in the number of people in older age groups will drive the demand to develop new medicines and treatments to prevent, cure, or manage disease. The increased demand, in turn, is expected to contribute to the much-faster-than-average projected employment growth of medical scientists and biochemists and biophysicists.

Animal scientists are expected to be needed to research more sustainable farming methods, especially in livestock production. However, because the occupation is small, the fast growth of animal scientists will result in only about 400 new jobs over the projections decade.

As scientific and technological advances are expected to increase the availability, reliability, and usefulness of objective forensic information used as evidence in trials, more forensic science technicians will be needed. Because this is a small occupation, its fast growth is expected to result in only about 2,000 new jobs over the projections decade.

The median annual wage for life, physical, and social science occupations was $72,740 in May 2021, which was higher than the median annual wage for all occupations of $45,760. Some form of postsecondary education is needed for entry-level positions in nearly all occupations in this group. Some occupations within this group require on-the-job training, internship, or residency experience.

Entertainment and sports occupational group

Overall employment in entertainment and sports occupations is projected to grow 12.6 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 95,500 new jobs over the decade.[24] Strong demand from the public for entertainment options, including movies and television shows, and the continued popularity of sports will contribute to job growth for the entertainment and sports occupations. However, some of the projected employment growth in these occupations is due to recovery from the COVID-19 recession of 2020; this growth is likely to occur early in the projections decade as participation and attendance in recreational activities, including organized sports and performances, resume. Four of the top 30 occupations projected to grow the fastest from 2021 to 2031 are detailed occupations within the entertainment and sports occupational group: athletes and sports competitors; umpires, referees, and other sports officials; dancers; and choreographers. (See appendix A-1.)

Table 16. Top five fastest growing occupations within entertainment and sports occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Entertainment and sports	27-2000	758.3	853.8	95.5	12.6	49,470	[2]
Athletes and sports competitors	27-2021	15.8	21.5	5.7	35.7	77,300	No formal education credentials
Umpires, referees, and other sports officials	27-2023	13.2	17.4	4.2	31.7	35,860	High school diploma or equivalent
Choreographers	27-2032	6.3	8.1	1.9	29.7	42,700	High school diploma or equivalent
Dancers	27-2031	6.2	7.7	1.5	24.5	[3]	No formal education credentials
Coaches and scouts	27-2022	244.3	293.1	48.8	20.0	38,970	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
[3] Wages for some occupations that do not generally work year-round, full time, are reported either as hourly wages or annual salaries depending on how they are typically paid. The median hourly wage for dancers was $18.78 in May 2021.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

In addition to the recovery from the COVID-19 recession of 2020, an increased public interest in professional sports will support demand for athletes and sports competitors; umpires, referees, and other sports officials; and coaches and scouts.

Dancers and choreographers also were affected by the COVID-19 recession and are projected to experience strong growth as they recover early in the decade. However, because these are small occupations, their fast growth is expected to result in only about 1,500 new jobs for dancers and 1,900 new jobs for choreographers.

The median annual wage for entertainment and sports occupations was $49,470 in May 2021, slightly higher than the median for all occupations in the economy. While typical entry-level education requirements vary within this occupational group, most occupations in the entertainment and sports occupations group require on-the-job training.

Architecture and engineering occupational group

Overall employment in architecture and engineering occupations is projected to grow 3.6 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 91,300 new jobs over the decade.[25] None of the detailed occupations within this occupational group are among the top 30 occupations projected to grow the fastest from 2021 to 2031. Most of the projected job growth in this group is for engineers; their services will be in demand in areas such as manufacturing, construction, and renewable energy.

Table 17. Top five fastest growing occupations within architecture and engineering occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Architecture and engineering	17-0000	2,562.5	2,653.7	91.3	3.6	79,840	[2]
Chemical engineers	17-2041	26.9	30.7	3.7	13.9	105,550	Bachelor's degree
Industrial engineers	17-2112	301.0	331.6	30.6	10.2	95,300	Bachelor's degree
Bioengineers and biomedical engineers	17-2031	17.9	19.7	1.7	9.8	97,410	Bachelor's degree
Petroleum engineers	17-2171	22.8	24.6	1.9	8.3	130,850	Bachelor's degree
Civil engineers	17-2051	318.3	340.4	22.1	6.9	88,050	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

The employment of chemical engineers is projected to grow much faster than average, at 13.9 percent from 2021 to 2031, as chemical engineering services are needed across various manufacturing industries. However, because the occupation of chemical engineers is small, its fast growth will result in only about 3,700 new jobs over the projections decade.

Increased adoption of industrial robotics and integration of automation will continue to create demand for industrial engineers to design efficient manufacturing processes, resulting in projected employment growth of 10.2 percent over the projections decade. Employment of bioengineers and biomedical engineers is projected to grow 9.8 percent from 2021 to 2031 as demand for biomedical devices and procedures, such as hip and knee replacements, continues to increase.

The median annual wage for architecture and engineering occupations was $79,840 in May 2021, which was higher than the median for all occupations in the economy. Some form of postsecondary education is needed for entry-level positions in nearly all occupations in this group. A few occupations within this group require on-the-job training, internship, or residency experience.

Math occupational group

Overall employment in math occupations is projected to grow 28.7 percent from 2021 to 2031, much faster than the average for all occupations; this increase is expected to result in about 82,000 new jobs over the decade.[26] Expected robust growth in data and the associated demand for data to be collected and analyzed are major factors behind the strong projected employment growth for math occupations. Growth is anticipated as larger amounts of digital and electronic data are collected with the expanding digital economy. Workers in math occupations will be needed to collect, organize, and analyze data to help optimize and improve business processes. Three of the top 30 occupations projected to grow the fastest from 2021 to 2031 are detailed occupations within the math occupational group: data scientists, statisticians, and operations research analysts. (See appendix A-1.)

Table 18. Top five fastest growing occupations within math occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Math	15-2000	286.3	368.3	82.0	28.7	98,680	[2]
Data scientists	15-2051	113.3	153.9	40.5	35.8	100,910	Bachelor's degree
Statisticians	15-2041	34.2	45.3	11.2	32.7	95,570	Master's degree
Operations research analysts	15-2031	104.2	128.3	24.2	23.2	82,360	Bachelor's degree
Actuaries	15-2011	28.3	34.2	5.9	20.8	105,900	Bachelor's degree
Mathematical science occupations, all other	15-2099	4.4	4.6	0.3	6.6	62,460	Bachelor's degree

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Because organizations rely on data scientists and statisticians to mine and analyze the large amounts of information and data collected, employment in these occupations is projected to growth by 35.8 percent and 32.7 percent, respectively, over the projections decade. Data scientists and statisticians are among the top 10 fastest growing occupations overall. (See appendix A-1.) As technology advances and companies and government agencies seek efficiency and cost savings, demand for operations research analysts should continue to grow.

Actuaries also are expected to experience much-faster-than-average employment growth as their services will be needed to develop, price, and evaluate a variety of insurance products and calculate the costs of new risks. Employment of actuaries is projected to grow 20.8 percent from 2021 to 2031.

The median annual wage for math occupations was $98,680 in May 2021, higher than the median for all occupations in the economy. Postsecondary education is needed for entry-level positions in math occupations. All occupations within this group do not require on-the-job training except for actuaries; they typically require long-term, usually more than a year, on-the-job training.

Protective service occupational group

Overall employment in protective service occupations is projected to grow 2.1 percent from 2021 to 2031, slower than the average for all occupations; the increase is expected to result in about 72,600 new jobs over the decade.[27] Demand for various types of protective services is expected to persist over the projections decade and support employment growth for many occupations in this group. These services include protection from fires, crimes, and injuries in sporting and recreational activities.

Table 19. Top five fastest growing occupations within protective service occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Protective service	33-0000	3,482.2	3,554.8	72.6	2.1	46,590	[2]
Forest fire inspectors and prevention specialists	33-2022	2.9	3.4	0.6	19.4	42,600	High school diploma or equivalent
Lifeguards, ski patrol, and other recreational protective service workers	33-9092	120.8	140.7	19.9	16.4	25,630	No formal education credentials
Crossing guards and flaggers	33-9091	85.1	92.9	7.8	9.2	31,450	No formal education credentials
Gambling surveillance officers and gambling investigators	33-9031	9.5	10.3	0.8	8.5	35,450	High school diploma or equivalent
School bus monitors	33-9094	53.5	57.1	3.6	6.7	29,100	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Forest fire inspectors and prevention specialists will continue to be needed to help control fires and investigate the cause of fires. These inspectors' and specialists' services will continue to be in demand as they will be needed to enforce outdoor fire regulations and other means of forest fire prevention. The severity of wildfires in several states has increased in recent years, resulting in a greater need for these workers.[28]

Crossing guards and flaggers and school bus monitors will be needed to protect school children crossing the street, getting on and off the bus, and traveling by bus.

The median annual wage for protective service occupations was $46,590 in May 2021, slightly higher than the median for all occupations in the economy. Typical entry-level education for most protective service occupations is a high school diploma or equivalent, and candidates typically receive on-the-job training.

Media and communication occupational group

Overall employment in media and communication occupations is projected to grow 6.2 percent from 2021 to 2031, about as fast as the average for all occupations; this increase is expected to result in about 68,600 new jobs over the decade.[29] Demand for media and communication occupations is expected because of the continued need to create, edit, translate, and disseminate information through a variety of different platforms.

Table 20. Top five fastest growing occupations within media and communication occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Media and communication	27-3000 and 27-4000	1,111.9	1,180.5	68.6	6.2	61,140	[2]
Interpreters and translators	27-3091	69.4	83.4	14.0	20.2	49,110	Bachelor's degree
Audio and video technicians	27-4011	68.6	79.3	10.7	15.7	48,820	Postsecondary nondegree award
Lighting technicians	27-4015	5.7	6.5	0.8	14.7	51,470	Postsecondary nondegree award
Film and video editors	27-4032	48.1	54.7	6.6	13.8	62,680	Bachelor's degree
Photographers	27-4021	125.6	136.8	11.2	8.9	38,950	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Employment of interpreters and translators is projected to grow 20.2 percent from 2021 to 2031 as demand for translation services continues to grow with increasing globalization and a more diverse U.S. population.

Media and communication equipment workers will be in demand to support the increased need for audio and visual support, including audio and video technicians, lighting technicians, film and video editors, and photographers. This is in addition to an increase in demand for new content produced for streaming services.

The median annual wage for media and communication workers, including media and communication equipment workers, was $61,140 in May 2021, which was higher than the median annual wage for all occupations of $45,760. Most occupations within this group require some form of postsecondary education and on-the-job training.

Arts and design occupational group

Overall employment in arts and design occupations is projected to grow 2.2 percent from 2021 to 2031, slower than the average for all occupations; the increase is expected to result in about 20,500 new jobs over the decade.[30] Some of the projected employment growth in arts and design occupations is due to recovery from the COVID-19 recession of 2020 and is likely to occur early in the projections decade as recreational activities resume.

Table 21. Top five fastest growing occupations within arts and design occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Arts and design	27-1000	918.8	939.4	20.5	2.2	48,220	[2]
Fine artists, including painters, sculptors, and illustrators	27-1013	27.1	28.8	1.7	6.4	60,820	Bachelor's degree
Special effects artists and animators	27-1014	58.9	62.1	3.2	5.4	78,790	Bachelor's degree
Set and exhibit designers	27-1027	27.0	28.5	1.4	5.2	54,860	Bachelor's degree
Craft artists	27-1012	10.7	11.2	0.5	5.1	35,930	No formal education credentials
Merchandise displayers and window trimmers	27-1026	161.6	169.1	7.5	4.6	32,060	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Employment of fine artists, including painters, sculptors, and illustrators is projected to grow 6.4 percent from 2021 to 2031, and employment of craft artists is projected to grow 5.1 percent over the projections decade as recreational activities resume.

Special effects artists and animators will be needed to meet the demand for animation and visual effects in video games, movies, television, and smartphone applications, seeing a projected employment growth of 5.4 percent from 2021 to 2031. The employment of set and exhibit designers and merchandise displayers and window trimmers is projected to grow about as fast as the average for all occupations (5.2 percent and 4.6 percent, respectively) from 2021 to 2031.

The median annual wage for arts and design occupations was $48,220 in May 2021, slightly higher than the median for all occupations in the economy. Most occupations within this group typically require a bachelor’s degree for entry, and some of these occupations require on-the-job training.

Farming, fishing, and forestry occupational group

Overall employment in farming, fishing, and forestry occupations is projected to show little or no change from 2021 to 2031; this limited growth is expected to result in about 8,400 new jobs over the decade.[31] The need for domestic agricultural products should support demand for these workers to produce and supply food. Continued mechanization of farming and forestry may limit employment in some occupations and benefit employment of other occupations in this group.

Table 22. Top five fastest growing occupations within farming, fishing, and forestry occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Farming, fishing, and forestry	45-0000	1,069.6	1,078.0	8.4	0.8	29,860	[2]
Agricultural equipment operators	45-2091	66.6	74.7	8.0	12.1	36,360	No formal education credentials
First-line supervisors of farming, fishing, and forestry workers	45-1011	53.3	56.7	3.4	6.4	48,640	High school diploma or equivalent
Agricultural workers, all other	45-2099	11.6	12.1	0.6	4.9	32,550	No formal education credentials
Animal breeders	45-2021	7.3	7.6	0.3	4.3	40,090	High school diploma or equivalent
Log graders and scalers	45-4023	4.5	4.6	0.2	3.5	37,820	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

An expected increase in the use of agricultural equipment will require more agricultural equipment operators relative to farmworkers and laborers. Small farms that sell their products directly to consumers through venues such as farmers’ markets might create opportunities for some agricultural workers, including animal breeders and other agricultural workers.

The median annual wage for farming, fishing, and forestry occupations was $29,860 in May 2021, lower than the median for all occupations in the economy. Most of these occupations do not require any formal education, but a high school diploma and on-the-job training are usually necessary in more specialized jobs in this occupational group.

Production occupational group

Overall employment in production occupations is projected to decline 1.9 percent from 2021 to 2031, a decrease of about 163,600 jobs over the decade.[32] The increasing automation of production processes is expected to continue to require fewer manufacturing jobs, which account for a large share of production occupations. Thirteen of the top 30 occupations projected to decline the fastest from 2021 to 2031 are detailed occupations within the production occupational group, including the 5 occupations shown in table 23. (See appendix A-2.)

Table 23. Top five fastest declining occupations within production occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Production	51-0000	8,787.1	8,623.5	-163.6	-1.9	37,710	[2]
Cutters and trimmers, hand	51-9031	8.2	5.9	-2.3	-28.4	30,230	No formal education credentials
Nuclear power reactor operators	51-8011	4.8	3.5	-1.3	-26.8	104,260	High school diploma or equivalent
Print binding and finishing workers	51-5113	42.2	31.8	-10.5	-24.8	36,590	High school diploma or equivalent
Prepress technicians and workers	51-5111	26.0	20.1	-5.9	-22.7	42,610	Postsecondary nondegree award
Aircraft structure, surfaces, rigging, and systems assemblers	51-2011	34.3	27.7	-6.6	-19.4	49,480	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Improved precision technologies enable machines to cut various materials, resulting in reduced demand for cutters and trimmers. Increased use of robotics will enable assemblers and fabricators to work alongside robots (a development also known as collaborative robotics). These robots can perform more complex tasks such as drilling holes, cutting materials, or painting equipment, which reduces demand for some assemblers and fabricators.

Employment declines in some production occupations also will result from shifts in product preferences. As nuclear energy power production faces steep competition from renewable energy sources, decommissioning plans for several reactors are reducing demand for nuclear power reactor operators. Similarly, increased customer demand for digital products compared with printed materials will reduce the demand for the services provided by print binding and finishing workers and prepress technicians.

The median annual wage for production occupations was $37,710 in May 2021, lower than the median for all occupations in the economy. Education requirements range from no formal education to a postsecondary nondegree award, but a high school diploma and some on-the-job training are typically needed.

Sales occupational group

Overall employment in sales occupations is projected to show little or no change from 2021 to 2031, seeing a decrease of about 164,500 jobs over the decade.[33] The increasing use of digital marketing and advertising is contributing to the projected decline in employment of many sales occupations. Alternative methods of direct marketing (including web advertisements, emails, and text messages) have emerged as substitutes for telemarketing and door-to-door sales marketing. Telemarketers are the only detailed occupation from the sales occupational group among the top 30 occupations projected to decline the fastest from 2021 to 2031. (See appendix A-2.)

Table 24. Top five fastest declining occupations within sales occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Sales	41-0000	14,719.9	14,555.4	-164.5	-1.1	30,600	[2]
Telemarketers	41-9041	115.7	94.7	-21.0	-18.2	28,910	No formal education credentials
Door-to-door sales workers, news and street vendors, and related workers	41-9091	54.7	49.0	-5.7	-10.4	29,390	No formal education credentials
Cashiers	41-2011	3,371.6	3,036.0	-335.7	-10.0	27,260	No formal education credentials
Advertising sales agents	41-3011	100.7	92.7	-8.0	-7.9	52,340	High school diploma or equivalent
First-line supervisors of retail sales workers	41-1011	1,505.7	1,427.5	-78.2	-5.2	39,230	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
[2] This entry is not applicable.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Telemarketers; door-to-door sales workers, news and street vendors, and related workers; and advertising sales agents are all projected to experience a decline in employment from 2021 to 2031. The growth of digital advertising also will reduce demand for paper advertisements and increase demand for virtual promotional products.

Cashiers are projected to have the largest decline of any occupation over the projections period. Employment of cashiers is expected to decline because of advances in technology, such as the increased use of online sales, digital payment, and self-checkout systems.

The median annual wage for sales occupations was $30,600 in May 2021, lower than the median for all occupations in the economy. Most occupations in this group typically require no education credentials, but some of the occupations may require a high school diploma. Also, some form of on-the-job training may be needed.

Office and administrative support occupational group

Overall employment in office and administrative support occupations is projected to decline 4.5 percent from 2021 to 2031, a decrease of about 880,800 jobs over the decade.[34] Office and administrative support occupations constitute the largest of all groups, composing about 12.4 percent of all jobs in 2021; however, this group is also expected to lose the most jobs of any occupational group by 2031. Technological changes are expected to continue to negatively affect the future employment of office and administrative support occupations. Computer and application software tools, digital data collection, and automated scheduling systems continue to be improved and used in many office and administrative support tasks. Seven of the top 30 occupations projected to decline the fastest from 2021 to 2031 are detailed occupations within the office and administrative support occupational group, including the 5 occupations in table 25, legal secretaries and administrative assistants, and order clerks. (See appendix A-2.)

Table 25. Top five fastest declining occupations within office and administrative support occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]	Typical education needed for entry
		2021	2031	Number	Percent		
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760	[2]
Office and administrative support	43-0000	19,587.0	18,706.2	-880.8	-4.5	38,050	[2]
Word processors and typists	43-9022	46.1	28.5	-17.6	-38.2	44,030	High school diploma or equivalent
Data entry keyers	43-9021	155.9	117.4	-38.5	-24.7	35,630	High school diploma or equivalent
Telephone operators	43-2021	4.0	3.0	-1.0	-24.5	37,630	High school diploma or equivalent
Switchboard operators, including answering service	43-2011	49.0	37.2	-11.8	-24.0	30,150	High school diploma or equivalent
Executive secretaries and executive administrative assistants	43-6011	508.0	405.4	-102.6	-20.2	62,060	High school diploma or equivalent

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.

[2] This entry is not applicable.

Note: Employment numbers are in thousands.

Source: U.S. Bureau of Labor Statistics, Employment Projections program.

Many office tasks (for example, data entry, telephone, and answering services) continue to be automated. As a result, employment in office and administrative support occupations is projected to decline. For example, technological improvements will require fewer secretaries and administrative assistants as many secretarial tasks can now be completed by other workers. Word processors and typists is the occupation with the fastest projected employment decline of all occupations as computer use continues to enable many occupations to acquire typing skills. Employment in this occupation is projected to decline by 38.2 percent from 2021 to 2031.

Despite projected employment declines, openings in office and administrative support occupations are expected to result from the need to replace workers who transfer to other occupations or exit the labor force, such as retirees.

The median annual wage for office and administrative support occupations was $38,050 in May 2021, lower than the median for all occupations in the economy. A high school diploma or equivalent is the most common entry-level education requirement for occupations in this group, and some form of on-the-job training may be needed.

Discussion and analysis

While specific factors drive employment change for each detailed occupation, there are broader macroeconomic factors that can affect occupations within an occupational group or even across occupational groups. About 8.3 million new jobs are projected to be added over the 2021–31 projections decade. Nearly one in four new jobs will be in the healthcare occupational group. Computer and information technology occupations and math occupations are projected to experience much-faster-than-average employment growth because of the strong demand for informational technology (IT) services and an expected robust growth in data analysis. The food preparation and serving occupations and personal care and service occupations are projected to experience fast growth over the projections period. However, a part of this projected growth represents recovery from a low employment level in 2021. Production occupations, sales occupations, and office and administrative occupations are the occupational groups projected to decline over the projections decade because of changes in technology, business practices, and outsourcing activities.

Appendix A-1: Top 30 fastest growing occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]
		2021	2031	Number	Percent	
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760
Nurse practitioners	29-1171	246.7	359.4	112.7	45.7	120,680
Wind turbine service technicians	49-9081	11.1	16.1	4.9	44.3	56,260
Ushers, lobby attendants, and ticket takers	39-3031	63.2	88.8	25.6	40.5	24,440
Motion picture projectionists	39-3021	2.0	2.8	0.8	40.3	29,350
Cooks, restaurant	35-2014	1,255.6	1,715.6	459.9	36.6	30,010
Data scientists	15-2051	113.3	153.9	40.5	35.8	100,910
Athletes and sports competitors	27-2021	15.8	21.5	5.7	35.7	77,300
Information security analysts	15-1212	163.0	219.5	56.5	34.7	102,600
Statisticians	15-2041	34.2	45.3	11.2	32.7	95,570
Umpires, referees, and other sports officials	27-2023	13.2	17.4	4.2	31.7	35,860
Web developers	15-1254	95.3	124.1	28.9	30.3	77,030
Animal caretakers	39-2021	290.7	377.6	86.9	29.9	28,600
Choreographers	27-2032	6.3	8.1	1.9	29.7	42,700
Taxi drivers	53-3054	128.5	165.1	36.6	28.5	29,310
Medical and health services managers	11-9111	480.7	616.9	136.2	28.3	101,340
Logisticians	13-1081	195.0	249.1	54.1	27.7	77,030
Physician assistants	29-1071	139.1	177.5	38.4	27.6	121,530
Solar photovoltaic installers	47-2231	17.1	21.7	4.6	27.2	47,670
Animal trainers	39-2011	52.9	67.2	14.3	27.1	31,280
Physical therapist assistants	31-2021	96.5	122.1	25.6	26.5	61,180
Software developers	15-1252	1,425.9	1,796.5	370.6	26.0	120,730
Epidemiologists	19-1041	8.6	10.9	2.2	25.8	78,830
Occupational therapy assistants	31-2011	43.4	54.5	11.0	25.4	61,730
Home health and personal care aides	31-1120	3,636.9	4,560.9	924.0	25.4	29,430
Personal care and service workers, all other	39-9099	104.4	130.4	26.0	24.9	29,610
Dancers	27-2031	6.2	7.7	1.5	24.5	[2]
Health specialties teachers, postsecondary	25-1071	246.7	306.1	59.4	24.1	102,720
Entertainment attendants and related workers, all other	39-3099	4.7	5.8	1.1	23.2	24,170
Operations research analysts	15-2031	104.2	128.3	24.2	23.2	82,360
Roustabouts, oil and gas	47-5071	37.3	45.9	8.6	23.0	38,920

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.

[2] Wages for some occupations that do not generally work year-round, full time, are reported either as hourly wages or annual salaries depending on how they are typically paid. The median hourly wage for dancers was $18.78 in May 2021.

Note: Employment numbers are in thousands.

Source: U.S. Bureau of Labor Statistics, Consumer Expenditure Surveys Public-Use Microdata.

Appendix A-2: Top 30 fastest declining occupations, 2021 and projected 2031

Occupation		Employment		Change (2021–31)		Median annual wage, 2021 [1]
		2021	2031	Number	Percent	
Total, all occupations	00-0000	158,134.7	166,452.1	8,317.4	5.3	$45,760
Word processors and typists	43-9022	46.1	28.5	-17.6	-38.2	44,030
Parking enforcement workers	33-3041	8.6	5.4	-3.2	-37.1	46,590
Cutters and trimmers, hand	51-9031	8.2	5.9	-2.3	-28.4	30,230
Nuclear power reactor operators	51-8011	4.8	3.5	-1.3	-26.8	104,260
Print binding and finishing workers	51-5113	42.2	31.8	-10.5	-24.8	36,590
Watch and clock repairers	49-9064	2.2	1.7	-0.5	-24.7	44,250
Data entry keyers	43-9021	155.9	117.4	-38.5	-24.7	35,630
Telephone operators	43-2021	4.0	3.0	-1.0	-24.5	37,630
Switchboard operators, including answering service	43-2011	49.0	37.2	-11.8	-24.0	30,150
Electronic equipment installers and repairers, motor vehicles	49-2096	9.2	7.1	-2.2	-23.4	40,670
Prepress technicians and workers	51-5111	26.0	20.1	-5.9	-22.7	42,610
Roof bolters, mining	47-5043	1.9	1.5	-0.4	-21.5	59,770
Floral designers	27-1023	44.4	35.1	-9.3	-21.0	29,880
Manufactured building and mobile home installers	49-9095	3.9	3.1	-0.8	-20.3	36,360
Refractory materials repairers, except brickmasons	49-9045	0.7	0.5	-0.1	-20.2	54,250
Executive secretaries and executive administrative assistants	43-6011	508.0	405.4	-102.6	-20.2	62,060
Aircraft structure, surfaces, rigging, and systems assemblers	51-2011	34.3	27.7	-6.6	-19.4	49,480
Legal secretaries and administrative assistants	43-6012	157.8	127.5	-30.4	-19.2	47,710
Grinding and polishing workers, hand	51-9022	16.1	13.1	-3.0	-18.7	35,670
Drilling and boring machine tool setters, operators, and tenders, metal and plastic	51-4032	6.9	5.6	-1.3	-18.6	38,580
Forging machine setters, operators, and tenders, metal and plastic	51-4022	11.8	9.6	-2.2	-18.3	44,520
Timing device assemblers and adjusters	51-2061	0.6	0.5	-0.1	-18.3	37,780
Telemarketers	41-9041	115.7	94.7	-21.0	-18.2	28,910
Coil winders, tapers, and finishers	51-2021	11.4	9.3	-2.0	-17.9	38,360
Loading and moving machine operators, underground mining	47-5044	4.5	3.7	-0.8	-17.8	57,900
Milling and planing machine setters, operators, and tenders, metal and plastic	51-4035	15.2	12.5	-2.7	-17.7	46,850
Order clerks	43-4151	143.9	119.7	-24.2	-16.8	37,920
Nuclear technicians	19-4051	5.4	4.5	-0.9	-16.6	99,340
Structural metal fabricators and fitters	51-2041	63.6	53.6	-10.1	-15.8	45,480
Power plant operators	51-8013	29.2	24.7	-4.5	-15.5	80,850

[1] Data are from the Occupational Employment and Wage Statistics program, U.S. Bureau of Labor Statistics. Wage data cover nonfarm wage and salary workers and do not cover the self-employed, owners and partners in unincorporated firms, or household workers.
Note: Employment numbers are in thousands.
Source: U.S. Bureau of Labor Statistics, Employment Projections program.

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Notes

1 "Employment projections: 2021–2031 summary," USDL-22-1805 (U.S. Bureau of Labor Statistics, September 8, 2022), https://www.bls.gov/news.release/ecopro.nr0.htm.

2 *Occupational Outlook Handbook* (U.S. Bureau of Labor Statistics, last modified on September 8, 2022), https://www.bls.gov/ooh.

3 The *Occupational Outlook Handbook* (OOH) groups occupations into 25 occupational groups, but BLS employment projections cover the civilian workforce only. Therefore, the military occupational group was excluded from this article. The OOH uses the 2018 Standard Occupational Classification (SOC) system structure. However, the OOH groups occupations differently in some scenarios to show similar groups together or to show a more detailed level of information. Healthcare practitioners and technical occupations (29-0000) and healthcare support occupations (31-0000) are combined under healthcare occupations; computer and mathematical occupations (15-0000) are shown in the OOH at the three-digit SOC level for computer and information technology occupations (15-1200) and mathematical science occupations (15-2000); and arts, design, entertainment, sports, and media occupations are shown at the three-digit SOC level for arts and design workers (27-1000), entertainers and performers, sports and related workers (27-2000), and media and communication workers (27-3000 and 27-4000). All other groups are a direct match between the data shown in the OOH and the two-digit SOC structure.

4 The COVID-19 pandemic affected occupational groups in different ways. Some employment lost during the pandemic and projected to be recovered over the projections decade has already been recovered as employment grew rapidly throughout the first half of 2022. As a result, some occupational groups have fast projected growth that reflects short-term recovery rather than long-term expected gains. The pandemic also has been a catalyst for some structural changes in demand for certain goods and services, which are expected to affect long-term demand for employment in a select group of industries and occupations. For more information on the effects of the COVID-19 pandemic on the 2021–31 projections, see "Employment projections: 2021-2031 summary."

5 Although declining employment dampens hiring as job separations outnumber openings, turnover generates more openings than occupation growth; even in declining occupations, demand for replacement of outgoing workers continues to support available opportunities. For more information on occupational separations, see https://www.bls.gov/emp/documentation/separations.htm; for replacements, see https://www.bls.gov/emp/documentation/replacements.htm.

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ARTICLE

ERRATA Automotive dealerships 2019–22: dealer markup increases drive new-vehicle consumer inflation

April 2023

Automotive dealerships 2019–22: dealer markup increases drive new-vehicle consumer inflation

Using U.S. Bureau of Labor Statistics data and novel analytical methods, this article shows how automotive dealerships contributed to new-vehicle consumer inflation through markup increases during the economic recovery from the COVID-19 pandemic. Dealerships have a major role in managing the inventory of unsold vehicles and typically have a significant amount of unsold inventory rotating through their lots and garages. Being an inventory intermediary in the vehicle supply chain, and already having subdued margins due to previous profit-margin compressions, dealerships were well positioned to expand profit margins from new-vehicle sales in the recent economic expansion. These increases contributed substantially to new-vehicle consumer inflation over the last 3 years.

The automotive industry is an important part of the U.S. economy. During the recent economic expansion associated with the recovery from the COVID-19 pandemic, price increases for new cars and trucks contributed moderately to overall consumer inflation. In the previous expansion, which followed the global financial crisis of 2008 and lasted from 2009 to 2019, new-vehicle prices were largely subdued because of profit-margin compression at vehicle dealerships. However, the competitive dynamics and trends that developed during this earlier expansion set the stage for dealerships to subsequently increase profits from the sale of new vehicles, contributing largely to new-vehicle consumer inflation in the COVID-19 economic expansion.[1] This latest development, analyzed in this article, reflects dealerships' major role as an inventory intermediary in the vehicle supply chain.[2]

Industry and theoretical background

The U.S. Bureau of Labor Statistics (BLS) publishes several price indexes that track price changes for different goods and services in the automotive supply chain. The Consumer Price Index (CPI) for new cars and trucks (hereafter referred to as "CPI for new vehicles") tracks prices paid by consumers for new vehicles. The Producer Price Index (PPI) for motor vehicles (hereafter referred to as "PPI for new vehicles") tracks prices paid by wholesalers, dealerships, intermediaries, and other businesses to manufacturers of new motor vehicles. The Import Price Index (MPI) for automobile and light duty motor vehicle manufacturing (hereafter referred to as "MPI for new vehicles") tracks prices for imported cars and trucks. Finally, the PPI for vehicle sales (hereafter referred to as "PPI for dealership markups") tracks margins or markups,[3] which are the retail selling prices received by dealerships for cars and trucks (regardless of whether the vehicles were manufactured in the United States or imported) less their acquisition prices.

A central theme of this analysis is that changes in retail markups drive the statistical and conceptual differences between changes in producer vehicle prices and changes in consumer vehicle prices.[4] Table 1 shows the trends in the CPI for new vehicles, the PPI for new vehicles, and the PPI for dealership markups for the last three business cycles: December 2000 to September 2007 (peak to peak), September 2007 to December 2019 (peak to peak), and December 2019 to December 2022 (peak to December 2022). When the CPI for new vehicles and the PPI for new vehicles move similarly in magnitude and direction, the PPI for dealership markups is relatively stable; when they diverge, the PPI for dealership markups changes substantially.

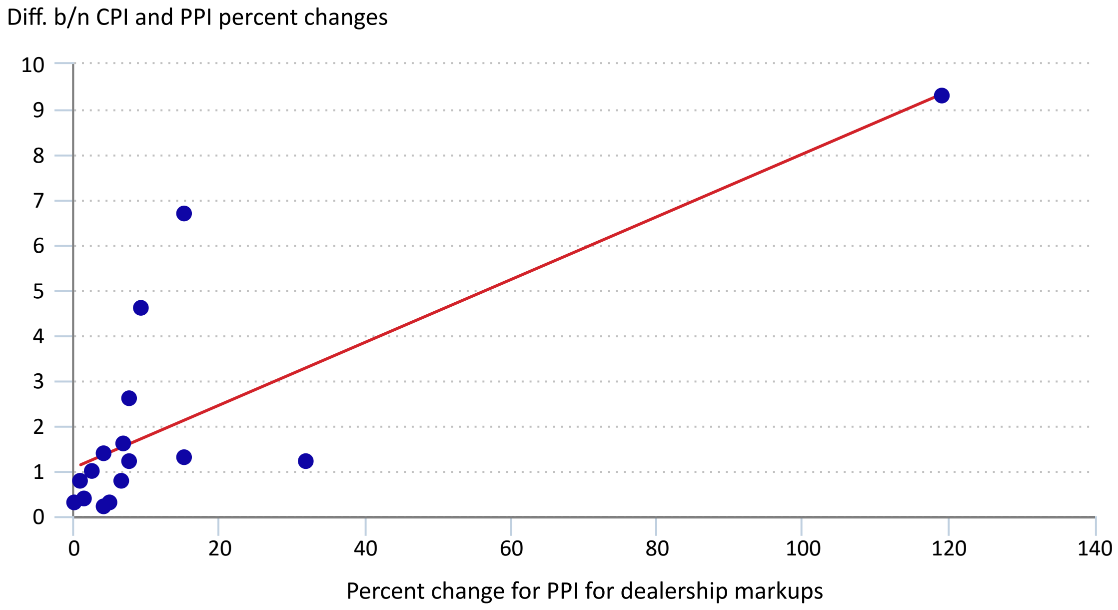
Table 1. Trends in CPI for new vehicles, PPI for new vehicles, and PPI for dealership markups, December 2000–December 2022

Business cycle	Percent change for CPI for new vehicles	Percent change for PPI for new vehicles	Percent change for PPI for dealership markups	Difference between percent changes for CPI and PPI for new vehicles	Absolute difference between percent changes for CPI and PPI for new vehicles	Absolute value of percent change for PPI for dealership markups
December 2000 to September 2007 (peak to peak)	-6.0	-8.8	2.6	2.8	2.8	2.6
September 2007 to December 2019 (peak to peak)	8.4	22.4	-32.9	-14.0	14.0	32.9
December 2019 to December 2022 (peak to December 2022)	20.7	7.9	144.7	12.8	12.8	144.7

Note: CPI = Consumer Price Index; PPI = Producer Price Index.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

Covering the period from 2007 through 2022, charts 1 and 2 display scatterplots showing the absolute value of the year-ending annual percent change for the PPI for dealership markups (horizontal axis) and the absolute value of the difference between the year-ending annual percent changes for the CPI for new vehicles and the PPI for new vehicles (vertical axis). (Chart 1 includes the pandemic years, whereas chart 2 excludes them.) The PPI for dealership markups changes the most when the CPI for new vehicles and the PPI for new vehicles move in opposite directions, but it also fluctuates when the movements of those indexes differ substantially in magnitude. The comparatively larger magnitude of change in the PPI for dealership markups is due to the fact that, by definition, a markup is a marginal differential output of inputs that exist on much larger scales than the markup. These trends, which show how dealerships function as an intermediary materially affecting price transmission, are also corroborated by financial reporting data from the U.S. Securities and Exchange Commission (SEC).[5]

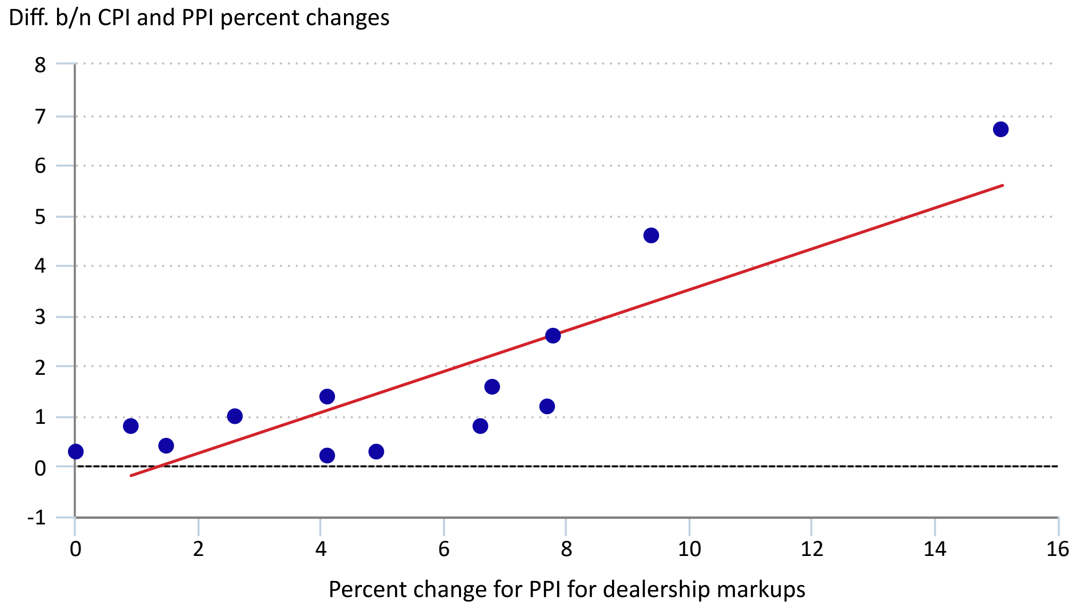
Chart 1. Absolute year-ending annual percent change for PPI for dealership markups and absolute difference between year-ending annual percent changes for CPI and PPI for new vehicles, pandemic included, 2007–22



Hover over chart to view data.
Note: R-squared = 0.5998. CPI = Consumer Price Index; PPI = Producer Price Index.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

View Chart Data

Chart 2. Absolute year-ending annual percent change for PPI for dealership markups and absolute difference between year-ending annual percent changes for CPI and PPI for new vehicles, pandemic excluded, 2007–19



Hover over chart to view data.
Note: R-squared = 0.743. CPI = Consumer Price Index; PPI = Producer Price Index.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

View Chart Data

The competitive dynamics that evolved in the decades preceding the COVID-19 pandemic uniquely positioned dealerships to expand profits from new-vehicle sales during the recent economic expansion. During the 2007–19 business cycle, dealerships experienced substantial profit-margin compression on new-vehicle sales because they faced higher prices from manufacturers and did not fully push those higher prices onto consumers. Instead, dealerships weathered the margins squeeze by expanding their value proposition by selling more finance and insurance products that subsidized the sale of low-to-no-margin vehicles. Dealerships were caught in the margins squeeze for two reasons. First, the interdependencies and market-power dynamics between dealerships and manufacturers resulted in manufacturers pushing large amounts of inventory onto dealerships, with the latter being unable to negotiate on price. Second, after the Great Recession of 2007–09, consumers were very sensitive to high prices.[6]

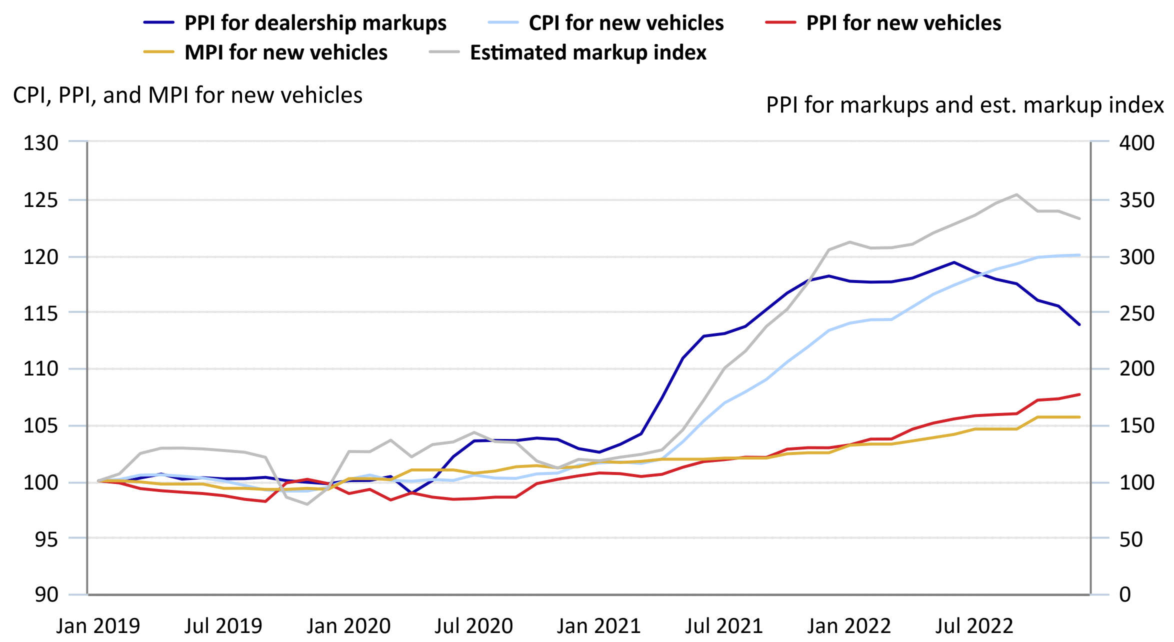
The pandemic, along with the economic stimulus provided in response to it, created the perfect combination of exogenous shocks to invert the competitive dynamics of the preceding expansion. First, manufacturers encountered significant supply shortages and supply-chain bottlenecks, both due to the pandemic-related shutdowns adopted across the globe.[7] Although this shock acutely affected manufacturers' production, dealerships, which tend to have between 60 and 90 days of inventory on hand, initially had inventory volumes that did not require the purchase of additional vehicles from manufacturers.[8] Moreover, during the initial phases of the pandemic, economic actors across the supply chain believed the recession would follow a typical path of sustained decreases in demand, so they cut output and scrambled to push inventories downstream to dealerships.[9] Second, U.S. fiscal and monetary policy provided unprecedented stimulus in response to the pandemic, and this stimulus resulted in a large increase in personal savings.[10] Third, the perceived economic cost of consuming services increased dramatically because of the consumer concern that services came with the increased cost of potentially contracting COVID-19. Consequently, consumers' total budgets, boosted by stimulus, pivoted substantially toward physical goods, with the net result being a sharp increase in the consumption of those goods.[11]

The consumer spending changes and economic stimuluses associated with the pandemic merit special consideration because of their unprecedented scale and apparent impact on new-vehicle demand. The confluence of the three aforementioned factors allowed dealerships to substantially increase markups during the 2020–22 economic expansion, boosting their profits and sizably contributing to new-vehicle consumer inflation.

Data analysis

Graphical and statistical analyses of BLS price-index data for vehicles and dealership services indicate that, because of profit-margin increases at dealerships over the last 3 years, consumer prices for new vehicles outpaced manufacturer and import prices for new vehicles. Chart 3 shows that, from December 2019 to December 2022, the CPI for new vehicles grew by 20.7 percent, the PPI for new vehicles grew by 7.9 percent, the MPI for new vehicles increased by 6.4 percent, and the PPI for dealership markups increased by 144.7 percent. It should be noted that, during 2019, consumer, producer, and import prices for new vehicles remained largely unchanged, so the PPI for dealership markups was also relatively stable over the year. During 2020, consumer prices only slightly outpaced producer and import prices, so the PPI for dealership markups increased by only 31.9 percent in that year. However, the difference in trends for consumer, producer, and import prices accelerated sharply in 2021, resulting in the margins index increasing by 119.0 percent in 2021 alone. That year saw the largest ever absolute difference between the year-ending annual percent changes for the CPI for new vehicles and the PPI for new vehicles, as well as the largest ever year-ending annual increase (119.0 percent) for the PPI for dealership markups.

Chart 3. CPI, PPI, and MPI for new vehicles, PPI for dealership markups, and estimated markup index, January 2019–December 2022



Click legend items to change data display. Hover over chart to view data.
Note: CPI = Consumer Price Index; PPI = Producer Price Index; MPI = Import Price Index.
Source: U.S. Bureau of Labor Statistics (BLS) and author's calculations based on BLS data.

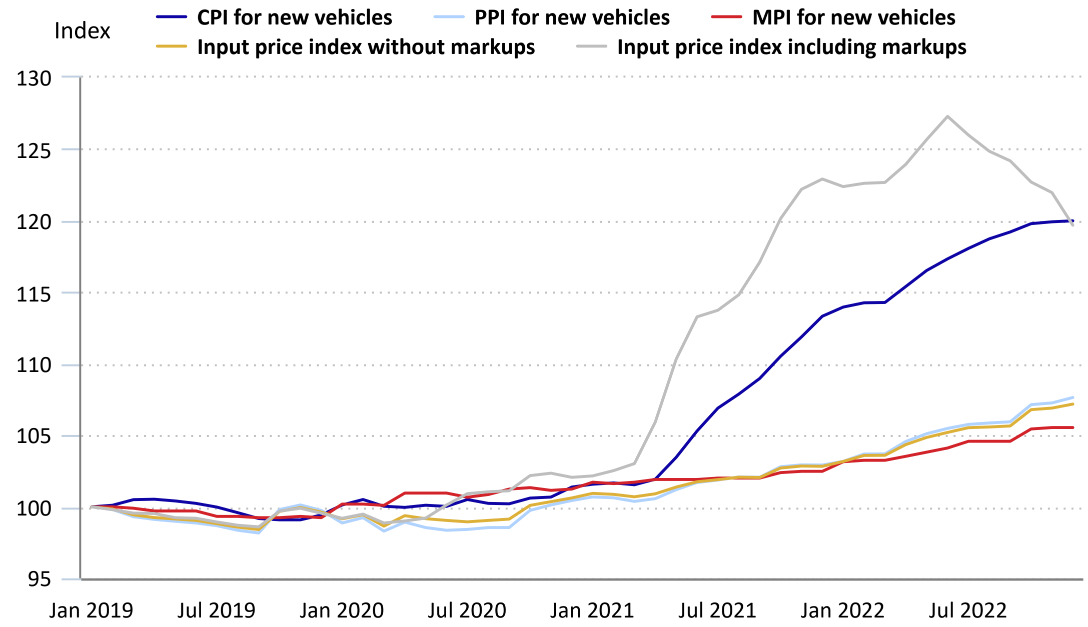
View Chart Data

Besides showing the official PPI for dealership markups, chart 3 also presents an estimated markup index derived from a linear residual of the short-term price relatives (STRs) of the PPI for new vehicles and the CPI for new vehicles (long-term price relatives (LTRs) are constructed from STRs defined in equation set 1 in the appendix).[12] Similarly to the PPI for dealership markups, the estimated markup index grew sharply from December 2019 to December 2022, rising by 255.1 percent. And similarly to the official price measures, the estimated markup index did not begin rapidly increasing until 2021. Under the assumption of an average markup of 5.0 percent in January 2019, the PPI for dealership markups would suggest that the markup would have peaked at 14.7 percent in June 2022, and under the same assumption, the estimated markup index would suggest that the markup would have peaked at 17.7 percent in September 2022. By December 2022, these estimated markups would have fallen to 11.9 and 16.6 percent, respectively. Both of these estimates are largely corroborated by SEC financial data, which show that average new-vehicle markups increased by 146.0 percent from the first quarter of 2019 to the third quarter of 2022, reaching 13.1 percent before falling to 10.9 percent in the fourth quarter of 2022.[13]

Combining the methodologies presented in two other *Monthly Labor Review* articles,[14] one can use the PPI for new vehicles, the PPI for dealership markups, and the MPI for new vehicles to recreate the CPI for new vehicles. This can be accomplished through a weighted input price index (input price index including markups) that includes the services provided at a dealership, with margin percentages serving as weights.[15] Conceptually, the equation for calculating this index (see equation set 2 in appendix) treats the PPI for new vehicles and the MPI for new vehicles as vehicle prices and the PPI for dealership markups as a markup, using actual (known) margin percentages as initial weights and estimated margin percentages as weights beyond the initial period.[16]

Chart 4 and table 2 show the correlations between the input price index including markups and the official CPI for new vehicles. The statistical and graphical correlations between the two series are strong, further demonstrating that profit-margin changes at dealerships explain the difference between the CPI for new vehicles and the PPI for new vehicles. The test statistics and graphical results exceed thresholds established in BLS-domain-hosted literature characterizing methods to recreate official BLS price measures.[17] From December 2019 to December 2020, the CPI for new vehicles increased by 2.0 percent and the estimated input price index including markups increased by 2.5 percent, whereas the PPI for new vehicles increased by only 0.7 percent. Additionally, from December 2020 to December 2022, a period in which dealership markups increased dramatically, the CPI for new vehicles increased by 18.4 percent and the estimated input price index including markups increased by 17.3 percent, whereas the PPI for new vehicles increased by only 7.2 percent. The statistically univariate regression model between the STRs of the CPI for new vehicles and the STRs of the input price index including markups is the only model showing a statistically significant correlation at the 1-percent level of significance (p-value of 0.00) and a meaningfully high correlation coefficient of 0.57. All other models—those using only the PPI for new vehicles, only the MPI for new vehicles, only the PPI for dealership markups, or only the input price index without markups—have p-values greater than 0.01 and low correlation coefficients.

Chart 4. CPI, PPI, and MPI for new vehicles and input price indexes with and without markups, January 2019–December 2022



Click legend items to change data display. Hover over chart to view data.
Note: CPI = Consumer Price Index; PPI = Producer Price Index; MPI = Import Price Index.
Source: U.S. Bureau of Labor Statistics (BLS) and author's calculations based on BLS data.

View Chart Data

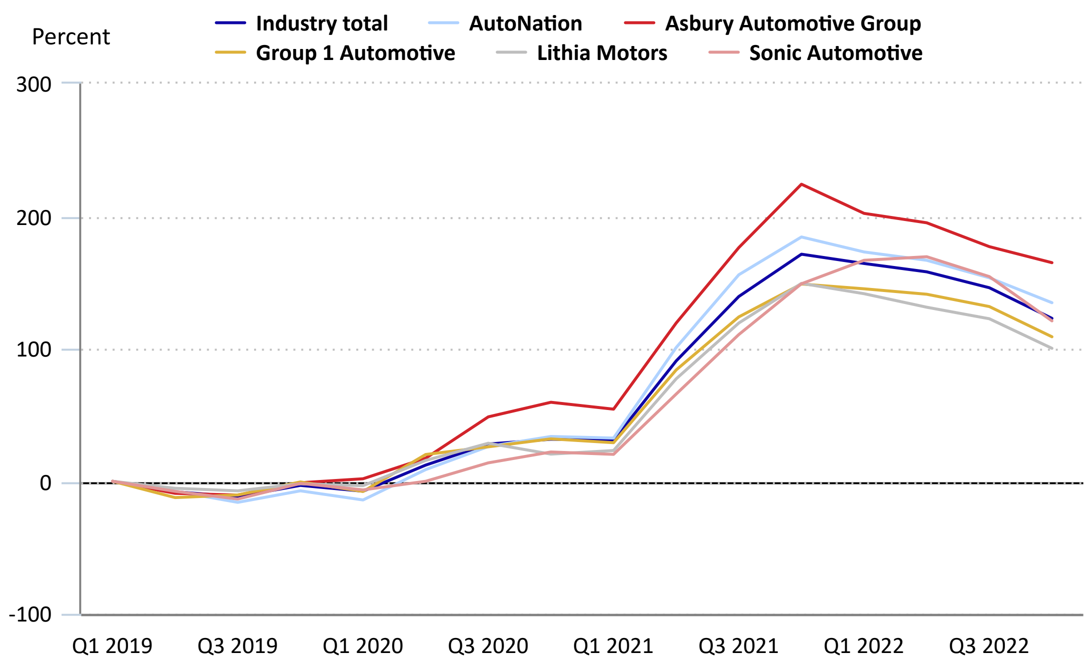
Table 2. Correlations between CPI for new vehicles and PPI and MPI for new vehicles, PPI for dealership markups, and input price indexes with and without markups, 1-month percent changes, January 2019–December 2022

Independent variable	Correlation coefficient	*p*-value
PPI for new vehicles (STR)	0.30	0.04
MPI for new vehicles (STR)	0.17	0.24
PPI for dealership markups (STR)	0.25	0.08
Input price index without markups (STR)	0.31	0.04
Input price index including markups (STR)	0.57	0.00

Note: CPI = Consumer Price Index; PPI = Producer Price Index; MPI = Import Price Index; STR = short-term price relative.
Source: Author's calculations based on data from the U.S. Bureau of Labor Statistics.

The strong graphical correlations between the official PPI for dealership markups and the estimated markup index, as well as between the CPI for new vehicles and the input price index including markups, further demonstrate that markup increases at dealerships drove the gaps among the CPI for new vehicles, the PPI for new vehicles, and the MPI for new vehicles. These gaps are crucial to understanding the drivers of new-vehicle consumer inflation during the COVID-19 pandemic, because they help isolate where in the supply chain inflation occurred—in this case, at dealerships. To further corroborate the trends apparent in BLS data, chart 5 and table 3 illustrate profit-margin changes at publicly traded dealerships from 2019 through 2022. Like BLS-derived estimates, SEC financial data for publicly traded dealerships show that markups grew from an average of 5.0 percent in 2019 to an average of 13.1 percent in 2022. This observation further demonstrates the impact of profit-margin growth on consumer vehicle prices and confirms the validity of the BLS-derived estimates presented earlier. Measuring profits as a percentage of the average vehicle price shows that the proportion of the consumer price represented by dealership markups grew from 4.8 percent in 2019 to 11.5 percent in 2022.[18]

Chart 5. Cumulative percent change in markups for publicly traded dealerships, first quarter 2019 to fourth quarter 2022



Click legend items to change data display. Hover over chart to view data.
Source: Author's calculations based on U.S. Securities and Exchange Commission data.

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Table 3. Percent change in markups for publicly traded dealerships, first quarter 2019 to fourth quarter 2022

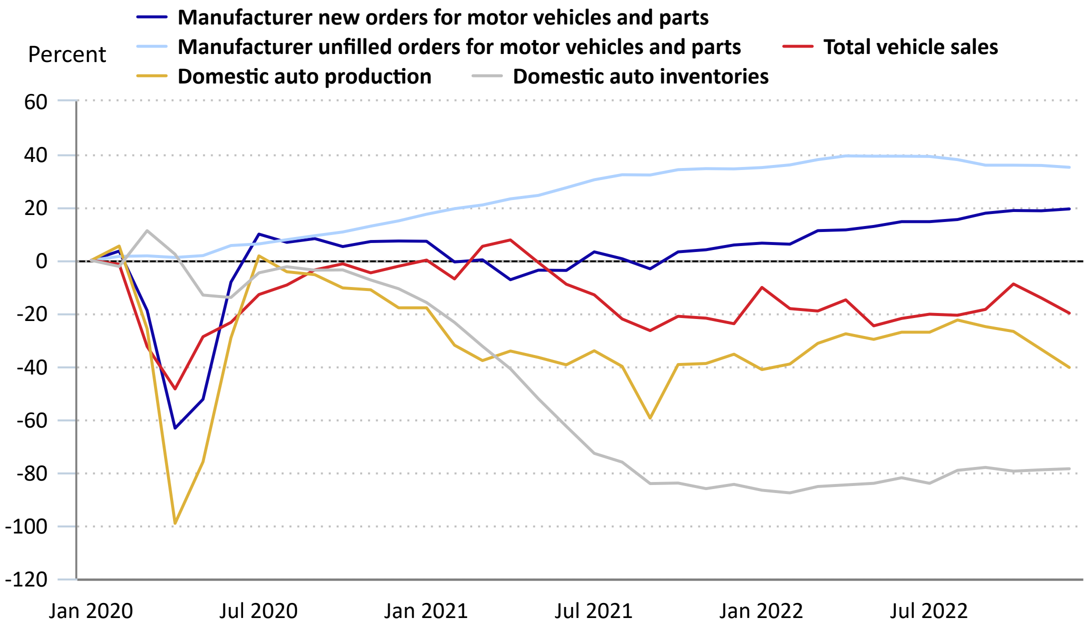
Quarter	Industry total	AutoNation	Asbury Automotive Group	Group 1 Automotive	Lithia Motors	Sonic Automotive
Q1 2019	5.3	5.1	4.5	5.3	6.2	5.3
Q2 2019	4.9	4.7	4.1	4.7	5.9	4.9
Q3 2019	4.7	4.3	4.1	4.8	5.8	4.6
Q4 2019	5.2	4.8	4.5	5.3	6.1	5.2
Q1 2020	4.9	4.4	4.6	4.9	6.0	5.0
Q2 2020	6.0	5.6	5.3	6.4	7.2	5.3
Q3 2020	6.8	6.5	6.8	6.7	8.0	6.1
Q4 2020	7.0	6.9	7.3	7.0	7.5	6.5
Q1 2021	7.0	6.8	7.0	6.9	7.7	6.4
Q2 2021	10.2	10.3	10.0	9.8	11.1	8.8
Q3 2021	12.8	13.1	12.6	11.9	13.7	11.2
Q4 2021	14.5	14.6	14.7	13.2	15.6	13.2
Q1 2022	14.1	14.0	13.7	13.0	15.1	14.2
Q2 2022	13.8	13.7	13.4	12.8	14.4	14.3
Q3 2022	13.1	13.0	12.6	12.3	13.9	13.5
Q4 2022	11.9	12.0	12.0	11.1	12.5	11.7

Source: Author's calculations based on U.S. Securities and Exchange Commission data.

Although pandemic-related supply-chain bottlenecks and semiconductor shortages significantly affected the quantity of vehicles produced by manufacturers—and also had an impact on producer prices for new vehicles—chart 3 shows that these disruptions had a stronger effect on consumer prices than on producer prices.[19] From December 2019 through December of 2022, the compound annual rate of change for the PPI for new vehicles was 2.6 percent, which is only 0.9 percentage point higher than the average rate of 1.7 percent during the 2007–19 business cycle. Over the same 2019–22 period, the compound annual rate of change for the MPI for new vehicles was 2.1 percent, which is only 1.9 percentage points higher than the average rate of 0.2 percent during the 2007–19 business cycle. The increases in the PPI and MPI rates of change are overshadowed by the change in trend for the CPI for new vehicles. From December 2019 through December 2022, the CPI for new vehicles grew at a compound annual rate of 6.0 percent, which is 5.3 percentage points higher than the average rate of 0.7 percent during the 2007–19 business cycle. These stark differences further demonstrate that increases in dealership profit margins were a stronger driver of consumer price changes than were manufacturer price increases.

Trends in vehicle production, total sales, and vehicle inventories help explain the subdued price transmission from manufacturers to consumers, and from consumers to producers, in the automotive supply chain during the 2020–22 business cycle. Chart 6 shows that dealership inventories shrank substantially during the recent economic expansion. Shortly after stimulus checks were issued in two rounds in late 2020 and early 2021 (the first stimulus round occurred in April 2020), dealership sales surged in March and April of 2021, and monthly sales continued to remain above their pandemic lows during the remainder of 2021. However, chart 6 shows that dealerships did not substantially increase their orders of new vehicles from manufacturers, which led to shrinking inventories and subdued production. The drop in inventories and the increase in sales that occurred shortly after the second and third stimulus payments coincide with the rapid increase in consumer prices shown in charts 3 and 4.

Chart 6. Cumulative percent change in manufacturer new and unfilled orders for motor vehicles and parts, total vehicle sales, and domestic auto production and inventories, January 2020–December 2022



Click legend items to change data display. Hover over chart to view data.
Note: Manufacturer new and unfilled orders for motor vehicles and parts are in millions of dollars, monthly, seasonally adjusted. Total vehicle sales are in millions of units, monthly, seasonally adjusted (annual rate). Domestic auto production and inventories are in thousands of units, monthly, seasonally adjusted.
Source: U.S. Census Bureau, U.S. Bureau of Economic Analysis, and author's calculations.

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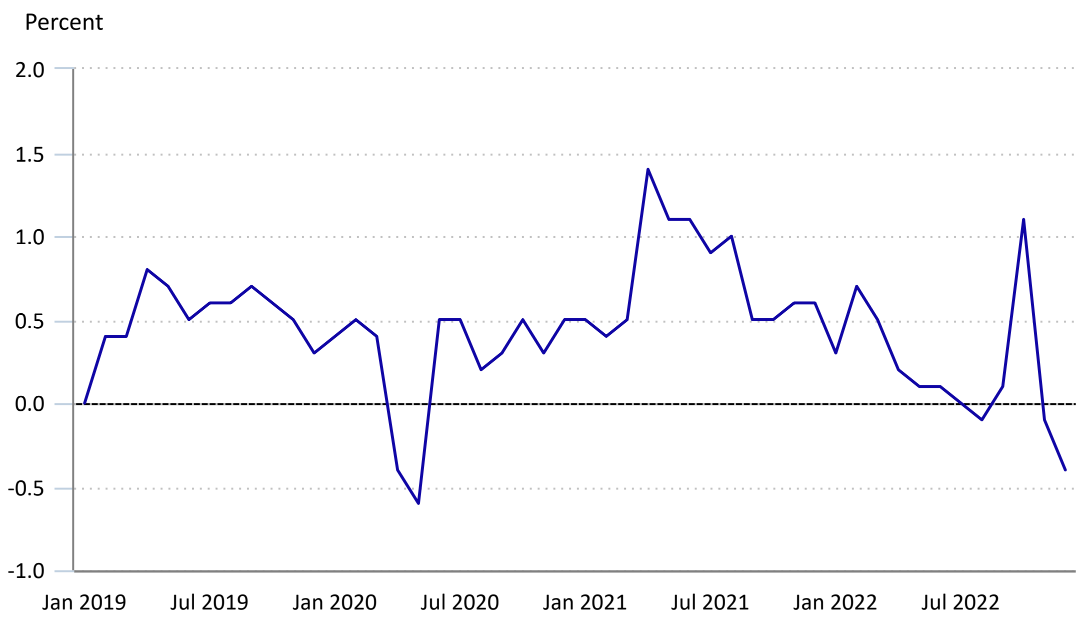
Normally, dealerships maintain large vehicle inventories that are costly to manage and that can force dealers to offer competitive price cuts to consumers. However, given supply-chain disruptions and persistently high demand, dealership inventories shrank to all-time lows in 2021 and 2022, applying upward pressure on consumer prices.[20] In January 2020, average inventories stood at 526,000 units, but by February 2022, that number had dropped to a record low of 65,000 units, a decline of 87.6 percent. In 2021, some dealerships averaged less than 2 weeks' worth of inventory, down from a more typical 2 to 3 months of inventory before the pandemic. AutoNation, for example, averaged only 9 days' worth of inventory in 2021, compared with an average of 52 days in 2019 and 60 days in 2018.[21] Shrinking retail inventories are crucial to understanding the divergence between consumer and producer vehicle prices. Instead of relying on manufacturer supplies to meet consumer demand, dealerships drew down their existing inventories. As a result, backward demand transmission from consumer-demand increases was insufficient to generate demand increases for manufactures, and dealerships absorbed the existing demand through markup increases and inventory drawdowns.

During the pandemic downturn and the subsequent economic expansion, new-vehicle orders, unfilled orders, and factory output were highly volatile, contributing to the inventory drought at dealerships. Chart 6 shows that, from February 2020 through May 2020, new-vehicle orders to manufacturers collapsed as economic actors across the supply chain anticipated a large decrease in demand. Although new-vehicle orders quickly rose to prepandemic levels in June 2020, they failed to consistently remain above those levels after some initial spikes in the summer of 2020, despite surges in consumer demand. Additionally, because new-vehicle orders are a flow that cumulates into a stock of total orders, the 5 below-trend months from February to May 2020 had a cumulative impact on the stock of overall orders that the industry never overcame. Factories also shut down entirely in March 2020, with output falling 99.8 percent in a single month. Finally, when new-vehicle orders recovered, manufacturers failed to fill them because of global supply-chain disruptions. In 2020 and 2021, unfilled orders grew and manufacturing remained flat, causing further declines in dealer inventories.

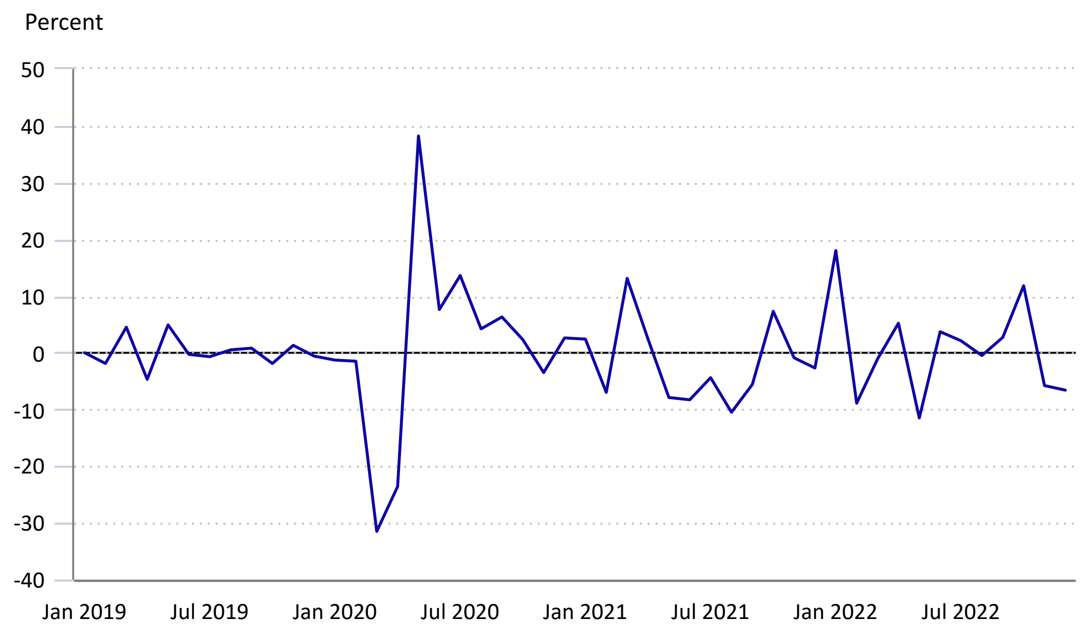
Charts 7 and 8 show that automotive sales and automotive loans increased substantially during and immediately after the three rounds of stimulus payments in 2020 and 2021. The 1-month percent change for automotive sales jumped to an all-time high of 38.2 percent in April 2020, and this jump coincided with the initial COVID-19 stimulus. Additionally, the 1-month percent change for automotive loans reached an all-time high of 1.4 percent in April 2021, immediately after the stimulus of March 2021. The data strongly suggest that many consumers used their stimulus payments to support the purchase of vehicles. Personal savings and government expenditures all increased substantially during the months of the stimulus payments. These increases also coincided with increases in vehicle prices, decreases in vehicle inventories, and increases in vehicle sales (see charts 3 and 6).

Chart 7. One-month percent change in automotive loans, all commercial banks, billions of dollars, seasonally adjusted, January 2019–December 2022



Hover over chart to view data.
Note: The periods of stimulus payments are April 2020, December 2020–January 2021, and March 2021.
Source: Author's calculations based on data from the Board of Governors of the Federal Reserve System.
View Chart Data

Chart 8. One-month percent change in total vehicle sales, millions of units, monthly, seasonally adjusted annual rate, January 2019–December 2022



Hover over chart to view data.
Note: The periods of stimulus payments are April 2020, December 2020–January 2021, and March 2021.
Source: Author's calculations based on data from the U.S. Bureau of Economic Analysis.
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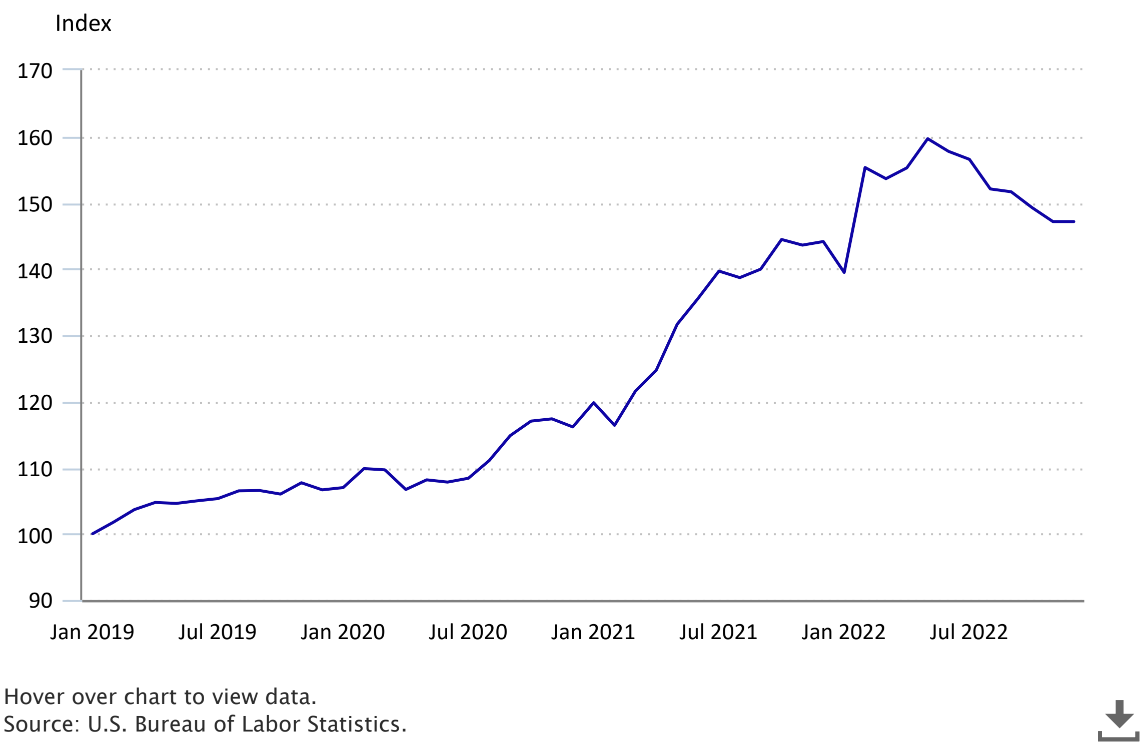
Taken together, the trends in consumer prices, producer prices, dealership markups, automotive inventories, automotive production, and stimulus expenditures suggest that dealership profit-margin increases in response to stimulus-driven demand contributed substantially to new-vehicle consumer inflation in 2020 and 2021. Given the considerable evidence that profit-margin increases caused a divergence between the PPI for new vehicles and the CPI for new vehicles, the inflationary impact of those increases can be estimated simply as the difference between the two indexes. If the CPI for new vehicles had moved in lockstep with the PPI for new vehicles from 2019 to 2022 (meaning dealer margins were stable), it would have increased by 7.9 percent, which is 12.8 percentage points lower than the actual 20.7-percent increase (or 38.3 percent of the total change). SEC financial data show that the share of markups in a vehicle's retail price increased by 140.9 percent during the pandemic, rising from an average of 4.9 percent in 2019 to an average of 11.5 percent in 2022. In total, profit-margin increases were responsible for 34.7 percent of dealerships' total increase in revenues from new-vehicle sales. Using the implicit counterfactuals from BLS and SEC data, one can estimate that dealership markups, working through price transmission, contributed between 34.7 and 61.7 percent of total new-vehicle consumer inflation from 2019 through 2022. Given that new vehicles account for 4.3 percent of the overall

CPI, the transmission of dealership markups to consumer prices contributed roughly 0.3 to 0.5 percentage point to the overall 15.6-percent increase in the CPI from December 2019 through December 2022.

In addition to raising new-vehicle prices, dealerships also substantially increased prices for other services. Chart 9 shows that these price increases coincided with the stimulus payments issued in late 2020 and early 2021. The dealership service index for "other receipts," which mostly tracks the sale of financial, insurance, and extended warranty products, began increasing rapidly in March and April of 2021. Because products captured by the "other receipts" index are not affected by the supply chain, their price increases are entirely due to increased demand for dealership services. In February 2022, the "other receipts" index recorded a 12-month increase of 33.5 percent, an all-time high. The fact that prices for other dealership services and dealer markups increased at the same time further demonstrates that dealerships experienced an influx of customers in early 2021.

Chart 9. Producer Price Index for dealership services—other receipts, January 2019–December 2022



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

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Conclusion

During the COVID-19 pandemic, dealership profit-margin increases drove new-vehicle consumer inflation and contributed modestly to overall consumer inflation. The implicit relationships between BLS consumer and producer price data illustrate these inflationary dynamics. By relying on their existing inventories to supply consumers with vehicles, dealerships shrank those inventories and gained more pricing power. The PPI for dealership markups is a moderator variable that bridges the gaps in the implicit relationships among the CPI, PPI, and MPI for physical goods. These relationships may work in other industries and could offer a predictive path to estimating lagged quarterly profits with the more timely BLS monthly price data.

Appendix: Equation sets

This appendix presents two equation sets for calculating the STR of the estimated markup index (equation set 1) and the input price index including markups (equation set 2).

Equation set 1

The STR of the estimated markup index is calculated as follows:

$$\text{Estimated Markup Index STR}_t = \frac{(\text{AVTP}_{t-1} \times \text{CPI STR NV}_t) - (\text{AVWP}_{t-1} \times \text{PPI STR NV}_t)}{(\text{AVTP}_{t-2} \times \text{CPI STR NV}_{t-1}) - (\text{AVWP}_{t-2} \times \text{PPI STR NV}_{t-1})},$$

where AVTP_{t-1} and AVTP_{t-2} are the average vehicle transaction prices in, respectively, periods $t-1$ and $t-2$; AVWP_{t-1} and AVWP_{t-2} are the average vehicle wholesale prices in, respectively, periods $t-1$ and $t-2$; and PPI STR NV_t and PPI STR NV_{t-1} are the PPI STRs for new vehicles in, respectively, periods t and $t-1$.

The values of AVTP_{t-i} and AVWP_{t-i} are calculated as follows:[22]

$$\text{AVTP}_{t-i} = \text{AVTP}_{t-i-1} \times \text{CPI STR NV}_{t-i}$$

$$\text{AVWP}_{t-i} = \text{AVWP}_{t-i-1} \times \text{PPI STR NV}_{t-i}$$

The initial average vehicle wholesale price in the base period of January 2019 is calculated as

$$\text{AVWP}_{\text{January 2019}} = \frac{\text{AVTP}_{\text{January 2019}}}{1 + \text{Markup}_{\text{January 2019}}},$$

where $\text{Markup}_{\text{January 2019}}$ is 4.9 percent, and $\text{AVTP}_{\text{January 2019}}$ is 1.

Equation set 2

The input price index including markups is calculated as follows:

$$\text{IPI With Markups}_T = \frac{(\text{PPI DM}_T) \times (\text{Wm}_T) + (\text{IPI Without Markups}_T) \times (1 - \text{Wm}_T)}{(\text{PPI DM}_{T-t}) \times (\text{Wm}_{T-t}) + (\text{IPI Without Markups}_{T-t}) \times (1 - \text{Wm}_{T-t})},$$

where PPI DM_T and PPI DM_{T-t} are the PPIs for dealership markups in, respectively, periods T and $T-t$; $\text{IPI Without Markups}_T$ and $\text{IPI Without Markups}_{T-t}$ are the input price indexes without markups in, respectively, periods T and $T-t$; and Wm_T and Wm_{T-t} are the weights in, respectively, periods T and $T-t$.

The input price index excluding markups is calculated as follows:

$$\text{IPI Without Markups}_T = \frac{(\text{PPI NV}_T) \times (\text{Wp}_T) + (\text{MPI NV}_T) \times (1 - \text{Wp}_T)}{(\text{PPI NV}_{T-t}) \times (\text{Wp}_{T-t}) + (\text{MPI NV}_{T-t}) \times (1 - \text{Wp}_{T-t})},$$

where PPI NV_T and PPI NV_{T-t} are the PPIs for new vehicles in, respectively, periods T and $T-t$; MPI NV_T and MPI NV_{T-t} are the MPIs for new vehicles in, respectively, periods T and $T-t$; and Wp_T and Wp_{T-t} are the weights in, respectively, periods T and $T-t$.

The values of Wm_T, $\text{Wm}_{\text{January 2019}}$, and Wp_T are calculated as follows:

$$\text{Wm}_T = \text{Wm}_{T-t} \times \frac{\text{PPI DM}_T}{\text{PPI DM}_{T-t}}$$

$$\text{Wm}_{\text{January 2019}} = \frac{\text{Average Markup}_{\text{January 2019}}}{\text{Average Transaction Price}}$$

$$\text{Wp}_T = \frac{\text{DPV US}_T}{\text{DPV US}_T + \text{IV US}_T}$$

In the last equation, DPV US_T is the total dollar amount of domestically produced vehicles sold in the United States in period T, and IV US_T is the total dollar amount of imported vehicles sold in the United States in period T.

SUGGESTED CITATION:

Michael Havlin, "Automotive dealerships 2019–22: dealer markup increases drive new-vehicle consumer inflation," *Monthly Labor Review,* U.S. Bureau of Labor Statistics, April 2023, https://doi.org/10.21916/mlr.2023.7

Notes

1 Kevin M. Camp, Michael Havlin, and Sara Stanley, "Automotive dealerships 2007–19: profit-margin compression and product innovation," *Monthly Labor Review*, October 2022, https://doi.org/10.21916/mlr.2022.26.

2 This article focuses on new-vehicle prices because supply-chain disruptions most proximally affected the manufacturing of new vehicles, rather than immediately causing shortages in the used-vehicle market. Used vehicles played an important role in the used-car shortage through their substitutability with new vehicles and merit attention in a separate analysis; however, the dynamics of the used-car market are quite distinct from those of the new-car market, and the used-car shortage is subordinate to the initial supply-chain shocks.

3 The U.S. Bureau of Labor Statistics (BLS) Producer Price Index (PPI) program publishes several margins indexes for dealer services, including an index for total vehicle sales, new-vehicle sales, and used-vehicle sales. This analysis uses the BLS index for total vehicle sales because corroborating evidence from corporate financial data (see chart 5) shows that this index was a much better estimator of new-vehicle margins during the pandemic.

4 This relationship is demonstrated in Camp, Havlin, and Stanley, "Automotive dealerships 2007–19."

5 See ibid. Company-specific information is from the 10-K forms filed with the U.S. Securities and Exchange Commission (SEC), which are stored in the SEC EDGAR database (https://www.sec.gov/edgar/search/).

6 Camp, Havlin, and Stanley, "Automotive dealerships 2007–19."

7 David Coffin, Dixie Downing, Jeff Horowitz, and Greg LaRocca, "The roadblocks of the COVID-19 pandemic in the U.S. automotive industry," Working Paper ID-091 (U.S. International Trade Commission, June 2022), https://www.usitc.gov/publications/332/working_papers/final_the_roadblocks_of_the_covid-19_pandemic_in_the_automotive_industry.pdf.

8 Christian Zimmermann, "Clocking the sales of cars and homes," *The FRED Blog* (Federal Reserve Bank of St. Louis, July 23, 2018), https://fredblog.stlouisfed.org/2018/07/clocking-the-sales-of-cars-and-homes/?utm_source=series_page&utm_medium=related_content&utm_term=related_resources&utm_campaign=fredblog.

9 Automotive manufacturers commonly seek to move excess inventories to dealerships because these inventories are costly to maintain.

10 "Personal saving" (FRED, Federal Reserve Bank of St. Louis, February 23, 2023), https://fred.stlouisfed.org/series/PSAVE.

11 Kristen Tauber and Willem Van Zandweghe, "Why has durable goods spending been so strong during the COVID-19 pandemic?" (Federal Reserve Bank of Cleveland, July 7, 2021), https://www.clevelandfed.org/publications/economic-commentary/2021/ec-202116-durable-goods-spending-during-covid19-pandemic.

12 The estimated markup index was generated by inflating the average consumer and producer vehicle prices in 2019 by the CPI for new vehicles and the PPI for new vehicles, subtracting those products from each other, and calculating a cumulative percent change from the derived margin. The dollar amounts in 2019 are algebraically and mathematically irrelevant to the results, so they simply serve to make the linear combination more intuitive for the reader. The determinative assumption in this recreation is the base-period margin, which is assumed to be 5.0 percent, pursuant to SEC data. Although the calculation of a proper input index should also include the import index, the latter was excluded because (1) the import prices of vehicles trended with producer prices, (2) vehicle imports had a small weight, and (3) the inclusion of the import index would have introduced complexity without changing the results.

13 These data are from the 10-K forms filed with the SEC, which are stored in the SEC EDGAR database (https://www.sec.gov/edgar/search/).

14 Michael Havlin, "From wholesalers to gas tanks: with gasoline, two plus two really does equal four," *Monthly Labor Review* (forthcoming); and Jayson Pollock and Jonathan C. Weinhagen, "A new BLS satellite series of net inputs to industry price indexes: methodology and uses," *Monthly Labor Review*, September 2020, https://doi.org/10.21916/mlr.2020.22.

15 Pollock and Weinhagen, "A new BLS satellite series of net inputs to industry price indexes."

16 Here, margin percentages, rather than markups, should be used as weights because the weights reflect how a markup relates to its proportion of the final price.

17 Don A. Fast and Susan E. Fleck, "Unit values for import and export price indexes: a proof of concept," in Katharine G. Abraham, Ron S. Jarmin, Brian C. Moyer, and Matthew D. Shapiro, eds., *Big data for twenty-first-century economic statistics* (Chicago, IL: University of Chicago Press, 2022), pp. 275–295, https://www.bls.gov/mxp/data/unit-values-import-export-price-

indexes.pdf; and Don Fast, Susan E. Fleck, and Dominic A. Smith, “Unit value indexes for exports—new developments using administrative trade data,” *Journal of Official Statistics*, Sciendo, vol. 38, no. 1, March 2022, pp. 83–106, https://doi.org/10.2478/jos-2022-0005.

[18] Company-specific information is from the 10-K forms filed with the SEC, which are stored in the SEC EDGAR database (https://www.sec.gov/edgar/search/).

[19] Coffin, Downing, Horowitz, and LaRocca, “The roadblocks of the COVID-19 pandemic in the U.S. automotive industry.”

[20] See Hannah Lutz, “Auto dealers find inventory loans more costly,” *Automotive News*, April 8, 2019, https://www.autonews.com/nada/auto-dealers-find-inventory-loans-more-costly; and Ayelet Israeli, Fiona Scott-Morton, Jorge Silva-Risso, and Florian Zettelmeyer, “How market power affects dynamic pricing: evidence from inventory fluctuations at car dealerships,” *Management Science*, vol. 68, no. 2, February 2022, pp. 895–916, https://www.hbs.edu/faculty/Pages/item.aspx?num=59497.

[21] AutoNation 2019 10-K form (annual report) retrieved from SEC EDGAR database (https://www.sec.gov/ix?doc=/Archives/edgar/data/0000350698/000035069820000042/an10k2019.htm).

[22] The starting average vehicle transaction price and the starting average vehicle wholesale price are entirely irrelevant for the equation’s result. The determinative assumption is the initial percent difference between the average vehicle transaction price and the average vehicle wholesale price, and this difference is assumed to be 4.9 percent in the initial period (January 2019).

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- Consumer price index
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ARTICLE CITATIONS

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Errata

04/24/2023 - Automotive dealerships 2019–22: dealer markup increases drive new-vehicle consumer inflation

Several numbers have been corrected in the paragraph that follows chart 8. There were also small changes to numbers in chart 5 and table 3 for the fourth quarter of 2022, which did not affect the overall trend of the data.
Corrections made on 05/23/2023.

* For errata data prior to 2020, please see our Archived Errata Table.

For all errata information, please see our Errata Home Page.

BEYOND BLS

Beyond BLS briefly summarizes articles, reports, working papers, and other works published outside BLS on broad topics of interest to MLR readers.

April 2023

Remote work to blame for rise in housing prices

Summary written by: Eleni X. Karageorge

Remote work is mainly responsible for soaring home prices and rentals, according to a recent study. In "Remote work and housing demand" (*Economic Letter*, Federal Reserve Bank of San Francisco, September 26, 2022), authors Augustus Kmetz, John Mondragon, and Johannes Wieland show that housing prices rose 24 percent between November 2019 and November 2021, with remote work contributing to more than 60 percent of that increase. In addition, this surge in home prices is similar for rent prices. As of August 2022, approximately 30 percent of work in the United States is still remote work. Between November 2019 and November 2021, remote work increased to 16 percentage points.

The shift to remote work during the pandemic led workers to search for cheaper housing and more desirable amenities. Consequently, as workers left relatively expensive areas looking for cheaper housing in less expensive cities, the overall price of homes increased. Workers' desire for homes in warmer climates with more space also affected advancing home prices.

For their analysis, Kmetz and coauthors researched the relationship between the share of remote jobs in 2020 compared with the share of prepandemic remote work. They looked at core-based statistical areas (CBSAs)—geographic areas that consist of one or more counties associated with at least one urbanized area of at least 10,000 people connected by commuting.

To show that they had an accurate measure of migration across CBSAs, the researchers isolated the effect of remote work on housing demand, separate from the effect of prepandemic migration. Even after adjusting for this migration, the authors estimated that an additional percentage-point increase of remote work caused a 1.5-percent rise in home prices. By tracking migration and its effect on housing demand, the researchers found that from November 2019 to November 2021, the surge in remote work alone increased home prices by approximately 15 percent.

Their analysis also revealed that the types of jobs available in a city matter because many jobs are not conducive to remote work. A work-from-home environment may increase demand for housing because jobs done previously in an office environment will likely use additional space and time at home. Cities considered more desirable for remote work saw the biggest increase in home prices because the limited supply of homes could not keep up with the influx of demand. Areas with higher shares of remote work experienced substantially higher housing prices than those areas with less remote work.

Kmetz and coauthors conclude that the fundamentals of housing demand have changed since the pandemic and that housing prices and inflation are likely to rise in the future as the shift to remote work becomes permanent.

ARTICLE

April 2023

Developing a consumption measure, with examples of use for poverty and inequality analysis: a new research product from BLS

This study provides an update on the work being done by the U.S. Bureau of Labor Statistics (BLS) to produce a research-based consumption measure and explores its potential use in poverty and inequality analysis. For this study, and for most U.S.-based studies in the literature, the Consumer Expenditure Surveys serve as the base to develop the measure. The consumption measure presented in this study accounts for the flow of services from homeownership and owned vehicles, in-kind transfers from government and private entities, and for the full value of health insurance; very few researchers have accounted for all of these. The main contribution is to provide the literature with an update on BLS activities, which include a plan to include home production in the consumption measure and information regarding an upcoming BLS research series. Using the measures produced in this study, we find that consumption without health insurance is 16 percent lower, on average, than total expenditures. Using a consumption measure, with or without health insurance, results in lower poverty rates than when using measures based on total expenditures or pretax income, and consumption for all the measures is more equal than the distributions of total expenditures or income. Using an absolute poverty measure, we find a noticeable decrease in the poverty rate from 2019 to 2021, when measured by consumption without health insurance.

Much of the economic well-being research focused on understanding the effects of behavior and policies on utility relies on the relationship between utility and household consumption or utility and household income. That research primarily uses income data from surveys. In the United States and other countries with more advanced economies, income data are more readily available from surveys and thus are more commonly used as a proxy for well-being than consumption.[1] Additionally, researchers might prefer income as a measure of well-being because it reflects access to resources that could be used for consumption, whereas well-being measured by consumption could be artificially low because of preferences. However, income is more sensitive to short-run fluctuations, whereas consumption better reflects long-term resources and is more likely to capture disparities that result from differences across households in access to credit or the accumulation of assets.[2] There is also evidence that components of consumption that are particularly important for poor people are well captured in household surveys, while many components of income important to poor people may not be as well captured in such surveys.[3] Furthermore, some researchers have suggested that consumption is more strongly correlated with other indicators of economic well-being than is income.[4] However, rather than promoting one measure over another, other research efforts support multidimensional measures of economic well-being, thereby noting that unidimensional measures are not sufficient.[5]

Although consumption may be a better measure of economic well-being than income, determining the actual consumption level for an individual or a group of individuals—a person or family that forms a consumer unit (CU), for example—is difficult because it depends on the individual's or group's particular circumstances, choices, use of purchases, and time usage.[6] In addition, data limitations make the problem of valuing consumption even more difficult. For example, combining expenditures data with time-use data has been particularly challenging.[7] As a result, many researchers have used expenditures as a proxy for consumption.[8] The U.S. Bureau of Labor Statistics (BLS) Consumer Expenditure Surveys (CE) have been the primary source of expenditures data at the CU level for researchers and government agencies since the late 19th century. And, as such, the CE is the oldest BLS product that collects household or consumer expenditures as a measure of living conditions for the United States.[9]

BLS has long been interested in the creation of a measure of consumption with CE data as the base,[10] as have other researchers.[11] For example, Fisher, Johnson, and Smeeding (2015)[12] produced a measure of consumption to study inequality, and Meyer and Sullivan (2012, 2013)[13] produced a consumption measure to study poverty and inequality. However, recent experiences with the COVID-19 pandemic have highlighted the need for a more comprehensive consumption measure than has previously been produced. Throughout the pandemic, family and household members have played an increasingly important role in the well-being of other members of their households through the provision of services such as childcare, eldercare, more home-cooked meals, and education, all of which are nonmarket transactions and not captured with expenditures alone. For these transactions, a comprehensive consumption measure needs to account for the time household members spend in home production for their own consumption. These shortcomings of expenditures as an economic measure of well-being have motivated researchers at BLS to develop a more comprehensive consumption measure that accounts for a broader set of in-kind benefits than accounted for in previous measures and for the value of home production for own consumption.

Our first attempt at BLS to produce a consumption measure was published in the May 2022 edition of *AEA Papers and Proceedings* as "Building a consumption poverty measure: initial results following recommendations of a federal interagency working group."[14] In this article, we build upon our earlier work by expanding what is included in consumption and refining our methods to produce the measure. The primary difference between the earlier consumption measure and the one presented in this article is that we introduce a value of health insurance; this makes our most recent consumption measure more like the ones produced by Meyer and Sullivan (2012, 2013). This enables us to produce three consumption measures: one that excludes health insurance, one that includes health insurance capped as a percentage of consumption, and one that includes health insurance not capped. The measure based on capping health insurance expenditures for poverty measurement is based on a recommendation made by the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty (ITWG).[15] As illustrations of how the measures can be used, we produce simple means for the consumption measures and components and inequality statistics for 2019, 2020, and 2021. The consumption-based poverty and inequality statistics are compared with statistics based on pretax income and CE-defined total expenditures.[16]

In our analysis, we find that the value of CU consumption without health insurance averaged about 16 percent less than CE total expenditures over the 3-year period, and that the values of CU consumption with health insurance (capped and uncapped) was about 14 percent more than CE total expenditures in 2019 and 2020, and about 12 percent more in 2021. For all consumption measures, compared with total expenditures and pretax income, poverty rates are lower when based on a relative concept. The absolute concept that we used for this study sets all poverty rates the same in 2019; such an approach allows us to see how poverty rates changed over the period while holding the base poverty rate the same. Our results show a noticeable decrease in the poverty rate from 2019 to 2021 when it is measured by consumption without health insurance. For all 3 years, consumption distributions are more equal than distributions of total expenditures and pretax income. Relative to 2019, we find that consumption poverty fell in 2020, with the onset of the pandemic, and that distributions of consumption became more equal. Compared with 2020, for all the consumption measures, poverty rose in 2021 when we used a relative measure, and inequality rose but not to the same levels as in 2019.

The consumption measures presented in this article represent work in progress. Next steps in the development of the BLS research consumption measure include the addition of the value of time for home production. During the 2021–23 period, BLS sponsored research to impute values of select home-production activities using the BLS American Time Use Survey and other data in combination with the CE. Once the value of home production is included, the goal of BLS to produce a more comprehensive measure of consumption can be realized. In addition, BLS plans to publish a consumption-measure research series based on internal CE data and imputation; this series will be available to the public through published tables of means. The series will not be an official BLS production series, but it can be referred to as an official research series. Depending upon available resources, BLS plans to release an auxiliary public-use data file that includes research-based consumption values.

Background and related literature

In standard economic models, individual utility is a function of consumption. In the life-cycle model, individuals choose the level of consumption in each period to maximize utility subject to lifetime income. The consumption level in a given period can be more or less than the income level in that period because individuals can use savings and borrowing to smooth consumption over their life cycle. The implication of the life-cycle model is that income, consumption, and savings will follow a predictable pattern over an individual’s life. Income is expected to exceed consumption during the prime working years and be less than consumption early in life and in retirement. Individuals can also use savings and borrowing to smooth consumption in response to unexpected fluctuations in income. This view of consumption was developed by Modigliani and Brumberg (1954) and extended by Friedman (1957).[17] As noted by Jappelli and Pistaferri (2017), models of consumption developed in the 1970s through the 2000s further account for intertemporal choice under uncertainty, as well as the tradeoff between leisure and home production.[18]

Given its direct relationship with utility, consumption is often considered a better unidimensional measure of well-being compared with income or expenditures. In a framework focused on households, it is assumed that the members of the household collectively choose a level of consumption that maximizes utility for a given budget constraint defined by available resources. Consumption can be viewed as an outcome variable reflecting what *has been achieved*, with income acting as one of many inputs. This contrasts with economic well-being outcome measures that focus on what *could be achieved*, such as income, for example.

Many researchers have attempted to construct measures that reflect consumption. Early examples include Cutler and Katz (1991) and Slesnick (1991), who use a flow-of-services approach to value durables consumption.[19] Later studies that examined household consumption as distinct from expenditures include Johnson, Smeeding, and Torrey (2005); Krueger and Perri (2006); Attanasio, Battistin, and Ichimura (2007); Heathcote, Perri, and Violante (2010); Aguiar and Bils (2011); Coibion, et al (2012), and Attanasio, Hurst, and Pistaferri (2012).[20] The studies from the economics literature most related to our attempt to construct a consumption measure at the household level are those by Meyer and Sullivan (2013, 2023) and Fisher, Johnson, and Smeeding (2015).[21] (The next section provides a more detailed discussion of the similarities and differences between the Meyer-Sullivan and Fisher-Johnson-Smeeding measures and those presented in this article.)

There is a large body of literature produced by international and national organizations that provides guidance on the development of a consumption measure. At the international level, guidance has been provided by the International Labour Organization (ILO), the Organisation for Economic Co-operation and Development (OECD), the United Nations Economic Commission for Europe, and the World Bank.[22] At the U.S. national level, the ITWG included in its 2021 report a comprehensive review of the literature on the development of consumption measures and their use in poverty measurement.[23] Then, in 2022, BLS published a report by Curtin et al. called “A conceptual framework for the U.S. Consumer Expenditure Surveys,” which includes a measure of consumption.[24]

Data

In this section, we discuss the data and methods used to construct our consumption measures. We describe the methods used to produce the earlier consumption measure and those reflecting the addition of health insurance and improvements to our methodology. We also provide a discussion of the scope of our measures and then compare our measures with those produced by other researchers.

Consumer Expenditure Surveys and variables

The CE Interview Survey is the primary data source for the consumption measures presented in this article. The CE uses two survey instruments to collect expenditures at the CU level: the Diary Survey and the Interview Survey. Respondents are selected to participate in only one of the two surveys. The Diary Survey focuses on collecting expenditures for certain frequently purchased goods and services, such as food at home and food away from home, apparel, and other products and services purchased on a regular basis. In contrast, the Interview Survey collects expenditures more comprehensively, capturing approximately 95 percent of total expenditures, which is why we use it for our consumption measure.[25] The Interview Survey is conducted throughout the year on a rolling basis and has a 3-month reference period. CUs complete the Interview Survey up to four times at 3-month intervals.

For our analysis, we compare consumption with CE-defined total expenditures and a measure of income. To define income, we start with the CE definition of pretax income available in the microdata files and subtract the value of Supplemental Nutrition Assistance Program (SNAP) benefits.[26] This income measure matches the U.S. Census Bureau measure of money income used to produce the official U.S. poverty statistics.[27] Note that unemployment benefits are included in this definition, so the impact of changes to benefit generosity are captured in the absolute magnitude of benefits collected in the CE from year to year. However, benefits related to the COVID-19 pandemic, such as the Economic Impact Payments, the expanded Child Tax Credit, and other tax credits are not included in the income measure because they are income-tax adjustments; however, the use of these credits are likely to be reflected in our consumption measures.

Consumption measure

In defining the scope of the consumption measure, we generally follow the ILO and OECD guidelines and the consensus recommendations of the ITWG.[28] We deviate from the ILO and OECD guidelines, which include education and health insurance in final consumption, and instead follow the ITWG recommendations by excluding education but including values for health insurance. We also considered the research of others in the development of the consumption measures presented in this article.

In many countries, including the United States, household surveys are used to collect expenditure data that can be used, in part, to create a consumption measure. For most categories, consumption will equal expenditures in a given period. However, not all components of consumption satisfy this equality. For durable goods, the value of consumption is defined as a flow of services over the life of the product, rather than as the expenditures needed to acquire the good. International guidelines recommend that the flow of services from housing and vehicles be represented by, for example, rental equivalence or user cost. For our measures—the earlier measure and those presented in this article—we use rental equivalence for owner-occupied shelter as collected in the CE, and we impute elements of user costs for cars and trucks not collected in the CE (i.e., depreciation and the opportunity costs of capital).[29]

International guidelines and the ITWG also recommend that the value of in-kind benefits be counted in consumption; however, the value of these benefits is often not collected in national household surveys. In the CE, the value of most in-kind benefits—those from the government (e.g., subsidized school meals and energy assistance) and from employers (e.g., health insurance)—are not collected. One exception is that SNAP benefits are collected in the CE. Because SNAP benefits are administered in the form of electronic benefit transfer (EBT), we assume that they are used like money income and are implicitly included in reported food expenditures. For other government and employer in-kind benefits, imputed values are included in our measure of consumption. Government in-kind benefits for food, energy, and rental assistance were included in the earlier BLS consumption measure; two of the consumption measures presented in this study include government and employer in-kind benefits in the form of health insurance. Although we do not include home production in the current version of the consumption measure, we plan to include it in future versions.

Expenditures in categories such as education and health can be better thought of as investments rather than as providing for current consumption. Following the recommendation of the ITWG,[30] in this and in our earlier consumption measure, we exclude education expenditures. We also exclude out-of-pocket spending on medical goods and services because the ITWG did not reach a consensus recommendation for the treatment of those expenditures. But health insurance provides current utility in the form of risk protection, unlike expenditures for medical goods and services, which provide utility indirectly by their effect on health. The inclusion of health insurance in a consumption measure for poverty analysis is controversial. Following the ITWG recommendation, and as presented in this article, we produce consumption measures with and without health insurance. But one concern with including health insurance in the measure for poverty analysis is that the value of government-provided health insurance can make up an outsized share of total consumption and almost singlehandedly push people out of poverty. To prevent overstating the effect of government-provided health insurance, we produce a consumption measure that restricts health insurance to be no more than half of total consumption with health insurance (uncapped) and use this measure in our poverty analysis. For consistency, we also use consumption with health insurance capped for our inequality analysis.

Several previous studies have created measures of consumption. Table 1 provides a comparison between the research consumption measures presented in this article and a selection of other measures. The measures most closely aligned with our measure are those created by Meyer and Sullivan (2012, 2013) and Fisher, Johnson, and Smeeding (2015).[31] Although these measures are similar to ours, there are some important distinctions.[32] With respect to the components of consumption, both Meyer and Sullivan and Fisher, Johnson, and Smeeding used rental equivalence for owner shelter but not for vacation homes.[33] We include rental equivalence for owner shelter and vacation homes in our earlier consumption measure and in the current consumption measure. Our measures and those of Meyer and Sullivan replace reported rent with imputed market rents for renters who report receiving government subsidies and for those who reside in public housing. Meyer and Sullivan assigned the value of rent as the maximum of the reported rent versus the imputed rent.[34] In contrast, we assign the imputed rent regardless of its size relative to the reported value. In addition, we impute rents for CUs living in rent-controlled units, those living rent free, and those living in college dormitories. Fisher, Johnson, and Smeeding imputed government rental and public-housing subsidies and added them to reported rents. For vehicles, Meyer and Sullivan estimated varying depreciation rates, but they did not account for opportunity cost.[35] Fisher, Johnson, and Smeeding accounted for opportunity costs but used a fixed rate (5 percent); in addition, they used a fixed rate of depreciation (10 percent).[36] Finally, Meyer and Sullivan did not include out-of-pocket health expenditures or education in their consumption measure. However, they included an imputed value of health insurance, which is capped at 30 percent of total consumption in their poverty analysis.[37] We take a similar approach in this article, but we cap health insurance at 50 percent of consumption.[38] In contrast, Fisher, Johnson, and Smeeding included out-of-pocket health and education expenditures in their consumption measure.[39]

Table 1. Comparison of various consumption measures with those of the present study

Spending category	Consumption or expenditures						Nondurables						Unknown
	Present study[1]	Fisher, Johnson, and Smeeding (2015)	Meyer and Sullivan (2013)	Johnson, Smeeding, and Torrey (2005)	Slesnick (2001)	Cutler and Katz (1991)	Attanasio, Hurst, and Pistaferri (2012)	Coibion, Gorodnichenko, Kueng, and Silvia (2012)	Aguiar and Bils (2011)	Heathcote, Perri, and Violante (2010)	Attanasio, Battistin, and Ichimura (2007)	Krueger and Perri (2006)	Hassett and Mathur (2012)
Food at home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Food away from home	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Alcoholic beverages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Housing													
Rental equivalence for owned home	Yes	Yes	Yes	Yes	Yes	Yes	X	X	Yes	X	X	Yes	Unknown
Mortgage interest and principal	X	X	X	X	X	X	X	X	X	X	X	X	Unknown
Rent for renters	Yes	Yes	Yes	Yes	Yes	Yes	X	X	Yes	X	X	Yes	Unknown
Maintenance, repair, and insurance	Partial	Yes	Yes	Yes	Yes	Yes	Partial	X	X	X	Yes	Yes	Unknown
Other lodging	Partial	Yes	Yes	Yes	Yes	Yes	Yes	Yes	X	X	X	Yes	Unknown
Rental equivalence for vacation home	Yes	X	X	X	X	X	X	X	X	X	X	X	Unknown
Utilities (e.g., electricity, water, etc.)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	X	Yes	Yes	Unknown
Household operations (e.g., cleaning)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Home furnishings and equipment	Yes	Yes	Yes	Yes	Yes	Yes	Partial	Yes	Yes	X	X	Yes	Unknown
Apparel	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Transportation													
Service flow from owned vehicles	Yes	Yes	Yes	X	Yes	Yes	X	X	X	X	X	Yes	Unknown
Net outlays for vehicles	X	X	X	Yes	X	X	X	X	Yes	X	X	X	Unknown
Gasoline and motor oil	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Maintenance and repair	Yes	Yes	Yes	Yes	Yes	Yes	Unknown	X	Yes	X	Yes	Yes	Unknown
Insurance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	X	Yes	X	X	Yes	Unknown
Vehicle rental	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	X	Yes	Yes	Unknown
Public transportation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Out-of-pocket health expenditures	X	Yes	X	Yes	Yes	Yes	X	X	Yes	Yes	X	Yes	Unknown
Imputed value of health insurance	Yes	X	Yes	X	X	X	X	X	X	X	X	X	Unknown
Entertainment													
Fees and admissions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Durable equipment	Partial	Yes	Yes	Yes	Yes	Yes	X	X	Yes	Yes	X	Yes	Unknown

[1] The measure presented in this study is similar to the one presented in Armstrong, et al., with the exceptions that the previous measure included expenditures for individuals outside the consumer unit (e.g., gifts) and did not include a value of health insurance or a flow-of-services housing services for consumers living rent free or in college or university dormitories. See Grayson Armstrong, Caleb Cho, Thesia I. Garner, Brett Matsumoto, Juan Munoz, and Jake Schild, "Building a consumption poverty measure: initial results following recommendations of a federal interagency working group," *AEA Papers and Proceedings*, vol. 112, May 2022, pp. 335–39, https://doi.org/10.1257/pandp.20221041.

Key: "Yes" means item is included, "X" means item is excluded, and "Partial" means that only part of the category is included in the measure. CE = Consumer Expenditure Surveys; CPS = Current Population Survey; PSID = Panel Study of Income Dynamics.

Note: The information in this table, with the exception of the column for the present study, is taken from Jonathan Fisher, David S. Johnson, and Timothy M. Smeeding, "Inequality of income and consumption in the U.S.: measuring the trends in inequality from 1984 to 2011 for the same individuals," *Review of Income and Wealth*, vol. 61, no. 4, December 2015, pp. 630–50, https://doi.org/10.1111/roiw.12129; see the appendix (supporting information available only in the online version), especially table A3, "Comparison of consumption definitions by terminology used to describe the measure"; see the references in Fisher, Johnson, and Smeeding for citation information for the various studies listed in this table.

Spending category	Consumption or expenditures						Nondurables						Unknown
	Present study[1]	Fisher, Johnson, and Smeeding (2015)	Meyer and Sullivan (2013)	Johnson, Smeeding, and Torrey (2005)	Slesnick (2001)	Cutler and Katz (1991)	Attanasio, Hurst, and Pistaferri (2012)	Coibion, Gorodnichenko, Kueng, and Silvia (2012)	Aguiar and Bils (2011)	Heathcote, Perri, and Violante (2010)	Attanasio, Battistin, and Ichimura (2007)	Krueger and Perri (2006)	Hassett and Mathur (2012)
Personal care items	Yes	Yes	Yes	Yes	Yes	Yes	Partial	Yes	Yes	Yes	Yes	Yes	Unknown
Reading materials (e.g., books)	Yes	Yes	Yes	Yes	Yes	Yes	Partial	X	Yes	Yes	Partial	Yes	Unknown
Education	X	Yes	X	Yes	Yes	Yes	X	X	Yes	Yes	X	Yes	Unknown
Tobacco	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Unknown
Miscellaneous	Yes	Yes	Yes	Yes	Yes	Yes	Yes	X	Yes	X	X	Yes	Unknown
Life insurance	X	X	X	X	X	X	Yes	X	X	X	X	X	Unknown
Sample information													
Urban or rural	Both	Both	Both	Both	Both	Unknown	Urban	Unknown	Urban	Urban	Urban	Urban	Unknown
Includes incomplete income reporters	Yes	Yes	Yes	X	Unknown	X	X	Unknown	X	X	Yes	X	Unknown
4-quarter consumer units	X	Yes	X	Yes	X	X	X	X	Yes	Yes	X	Yes	Unknown
Age restriction	X	X	X	X	Unknown	X	25-65	Unknown	25-64	25-60	25-60	Nonelderly	X
Single females	Yes	Yes	Yes	Yes	X	X	Yes	Yes	Yes	Yes	X	Yes	Yes
Income data source	CE	CE	CPS	CE	X	CPS	PSID	CE	CE	CPS	X	CE	CPS

[1] The measure presented in this study is similar to the one presented in Armstrong, et al., with the exceptions that the previous measure included expenditures for individuals outside the consumer unit (e.g., gifts) and did not include a value of health insurance or a flow-of-services housing services for consumers living rent free or in college or university dormitories. See Grayson Armstrong, Caleb Cho, Thesia I. Garner, Brett Matsumoto, Juan Munoz, and Jake Schild, "Building a consumption poverty measure: initial results following recommendations of a federal interagency working group," *AEA Papers and Proceedings*, vol. 112, May 2022, pp. 335–39, https://doi.org/10.1257/pandp.20221041.

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Imputations for consumption

In cases in which in-kind benefits are not collected as part of the CE, a value of in-kind benefits must be imputed. For some types of in-kind benefits, such as government rental assistance and health insurance (both employer provided and government), participation is captured in the CE; for these programs, we only need to assign a value to the benefits. For other in-kind benefits, such as the National School Lunch Program (NSLP), the Women Infants and Children (WIC) program, and the Low Income Home Energy Assistance Program (LIHEAP), the CE does not ask about participation. For these programs, participation and benefits must be imputed. Finally, in terms of the flow of services from housing and durable goods, as noted previously, the CE asks about rental equivalence for owner-occupied housing; however, rental equivalence is not asked for vehicles. Instead, we apply a user-cost approach to impute values of the service flows arising from vehicle (i.e., car and truck) ownership. For the consumption value of consumer units who are not homeowners but are identified as renters, select imputations are also produced. In this section, we provide a summary of the imputation methods. (See the appendix for a more detailed description of imputation methods.)

As previously noted, the CE does not collect program-participation or benefit values for NSLP, WIC, or LIHEAP. To impute benefit values to the CE, we start by modelling participation for these programs and LIHEAP benefits as reported in the Current Population Survey Annual Social and Economic Supplement (CPS ASEC). Once participation in these programs is imputed to CUs in the CE, a value of the in-kind benefits is assigned. This value comes from administrative sources for NSLP and WIC. For LIHEAP, the reported benefit amounts from the CPS ASEC are used to impute a value of the benefits. Imputations for NSLP and LIHEAP for the measures presented in this article are the same as those included in the earlier measure; however, improvements in methodology to produce WIC imputations are introduced.

In addition to owner-occupied housing, in certain instances it is expected that reported rents do not reflect the full consumption value of rented shelter. Regarding renters living in units for which we consider their reported rents are less than market values, imputations for the value of shelter consumption are needed. We consider renters who are paying additional rental-related expenses—for example, those for maintenance and repairs—as not reporting rents that represent their consumption. In addition, the CE includes questions about whether the renter receives government assistance in paying rent, lives in public housing, lives in rent-controlled units, or lives rent free. However, not asked is the value of the difference in what renters pay for shelter and the market value of similar units. We use regression models for those who pay full market value to calculate the implied market value for those who pay less than the full value. The imputed market values represent the consumption value of rental shelter for these renters. Improvements in the rent imputations are introduced with the current measure, and imputed rents for renters living rent-free were added.

The CE asks about different types of health insurance coverage and collects data on out-of-pocket insurance premiums associated with each type of insurance. The CE also collects out-of-pocket expenditures on medical goods and services. As noted previously, for one of the measures presented in this article, the consumption value of health insurance is included. To derive this value, we first impute the full value of health insurance on the basis of insurance type. For private health insurance, the full value is based on the market price. This includes the out-of-pocket premiums that are captured by the CE and the employer contribution for employer-provided plans, or the value of any subsidy received for individual plans. For public insurance programs, the full value is based on the cost to the government (including administrative costs).

Finally, for vehicles, we begin with the CE definition for all transportation expenditures, which includes the expenditures for the purchase of all new and used vehicles, vehicle finance charges, gasoline and motor oil, maintenance and repairs, vehicle insurance, public transportation, and vehicle rental licenses and other charges. We remove expenditures for the purchase of all vehicles and vehicle finance charges that were made during the 3-month reference period. These expenditures are replaced with a flow-of-services value for cars and trucks that is imputed using a user-cost approach. The user cost is defined as the depreciation plus the opportunity cost of capital (current estimated value of the car multiplied by an interest rate) plus maintenance and repair costs. To derive a flow of services from the ownership of vehicles, which we limit to cars and trucks, we include imputed values of vehicle depreciation and opportunity costs of capital. Other components of user costs are already accounted for in the transportation expenditures that we keep. We estimate vehicle depreciation using vehicle purchase information in the CE by comparing similar vehicles purchased at different ages. A consumption flow-of-service value is imputed to CUs for the stock of cars and trucks owned for nonbusiness use. Although the flow of services from cars and trucks was included in the earlier BLS consumption measure, improvements in the methodology have been introduced and are reflected in the current measure. Note that our user costs will undervalue the flow of services from the stock of vehicles that are not cars or trucks; these other vehicles include, for example, planes, boats with motors, and motorized campers.

Going from expenditures to consumption

To help readers understand the relationship between consumption and total expenditures as defined by BLS and presented in its published tables, we present a step-by-step description. Because we are interested in the CU's consumption level, and not the consumption among people who do not live in that CU, we first remove expenditures for goods and services purchased to be given to someone outside the CU; these are identified as "gifts." Next, we remove expenditures related to home ownership and the purchase of vehicles because these values will be captured instead by the flow-of-services value for shelter and vehicles, respectively. And, as noted previously, we also remove education and noninsurance medical expenditures because we view these as being more investment than consumption. For the measure of consumption with health insurance (uncapped and capped), we add the imputed value of health insurance. Finally, we do not include certain expenditures that are included in CE total expenditures that can be better thought of as financing future consumption (e.g., retirement contributions, life insurance purchases, etc.).

Methods for analysis

In this section, we present the methods used to examine the impact of moving to a consumption measure from CE total expenditures. Then, we describe the methods used to examine the impact of using consumption as opposed to total expenditures or income for poverty and inequality analysis.

Means

We analyze five measures of expenditures and consumption: total expenditures as defined by the CE, total expenditures as defined by the CE excluding gift expenditures, consumption without health insurance, consumption with the value of health insurance capped, and consumption with health insurance uncapped. To calculate the averages, we pool four quarters of data starting with the second quarter of the current calendar year through the first quarter of the following year. Quarters refer to the calendar period when the CE data were collected; for example, quarter one includes expenditures collected during interviews that took place from January to March; the reference period for January interviews is October through December of the previous year, while March interviews reference expenditures made in December of the previous year through February of the current year. Thus, when we refer to "quarterly" expenditures, these are actually 3-month values. For example, to calculate the quarterly averages for 2019, we use data from the second quarter of 2019 through the first quarter of 2020. We present CU-level quarterly averages that are weighted using one-fourth of the CU weight included in the CE data file; CE data are weighted quarterly and thus scaling by one-fourth accounts for the fact that four quarters of data are pooled together. Annual means can be produced by taking the quarterly mean and multiplying by four, but these values will differ from the means reported in the published CE tables.[40]

Poverty and inequality analysis

We present results for three consumption measures: one that does not include health insurance, a second that includes health insurance capped, and a third that includes health insurance uncapped. For comparison, we also present results for CE total expenditures and pretax income. The income measure that we use differs from the income measure that appears in BLS published tables with CE expenditures data.[41] Unlike the pretax income measure in the published CE tables, the one in this study does not include SNAP benefits or food and rent as pay. For each measure, we create equivalized values using a three-parameter equivalence scale.[42] Poverty and inequality statistics are based on equivalized values.

For studying poverty, we produce two sets of poverty rates. The first set is based on purely relative thresholds. These thresholds are defined to be 60 percent of the median equivalized value for each measure for each year. The second set of poverty rates is based on the implicit thresholds that result when all poverty rates are anchored to the same rate for a single measure; this is a type of absolute measure. We anchored the poverty rates for all the measures in 2019 to be the same as the 2019 relative poverty rate for consumption with health insurance capped. For 2020 and 2021, the implicit 2019 thresholds (based on equivalized-measure values) resulting from this anchoring are updated to account for inflation. To approximate inflation, we create an annual index as the average of the monthly Chained Consumer Price Index for All Urban Consumers for all items and all urban areas.[43] When the respective measure for the CU is below the threshold, the CU is considered poor, and all members of that CU are considered poor. For example, if the CU's equivalized consumption without health insurance is below the poverty threshold for consumption without health insurance, then the CU and everyone in it are considered poor. The poverty rates that we show refer to the percentage of people in the United States below the thresholds.

For studying inequality, we produce Gini indexes and Lorenz curves for each measure for each year. CUs are ranked on the basis of their equivalized value of each measure, and population weights are used to produce the distributions. For each measure, the Lorenz curve is a plot of the cumulative share of the population plotted against cumulative share of each measure. For example, 60 percent of the population accounts for 40 percent of overall consumption without health insurance.

Results

The results are calculated for 2019, 2020, and 2021 and are broken into three parts. The first section presents a discussion of the means. The second and third sections present the results of the poverty and inequality analysis, respectively. Results for 2021 are labeled as "preliminary" because some of the underlying non-BLS data used to produce the consumption measures are not finalized. Specifically, select 2021 health insurance values are subject to revision. In addition, WIC data are not finalized until up to a year after initial release by the U.S. Department of Agriculture (USDA). When updates to these non-BLS data are released, we will produce revised estimates for 2021.

Means

Quarterly CU averages are presented in tables 2 and 3. Table 2 includes results for 2019, 2020, and 2021 for the three consumption measures and two expenditures measures. Table 3 includes means for the consumption and expenditure subcomponents for 2020. (Detailed results for all 3 years are presented in table A-1 of the appendix for comparison at the subcomponent level.)

As shown in table 2, the trend from 2019 to 2021 is similar across all five measures, although the levels are slightly different. Means are lowest for 2020 relative to 2019 and 2021; this pattern is expected because of changes in consumption and expenditure patterns during the first year of the COVID-19 pandemic.[44] Quarterly means are lowest for consumption without health insurance (from $12,158 to $13,562). The next highest means are for total expenditures that do not include those for gifts, followed by total expenditures that include those for gifts. Quarterly means for both expenditure measures are about $2,000 higher than those for consumption without health insurance. The quarterly means for consumption with health insurance capped and uncapped are more than $4,000 higher than the means for all years for consumption without health insurance.

Table 2. Nominal quarterly means for measures of expenditures and consumption, 2019 to 2021

Measure	2019	2020	2021[1]
CE-defined total expenditures	$14,717	$14,555	$16,196
CE-defined total expenditures (not including gifts)	14,509	14,386	15,955
Consumption without health insurance	12,395	12,158	13,562
Consumption with health insurance	16,792	16,767	18,062
Consumption with health insurance capped	16,716	16,675	18,004

[1] Data for 2021 are preliminary.
Note: CE = Consumer Expenditure Surveys.
Source: U.S. Bureau of Labor Statistics.

Focusing on 2020, table 3 presents a complete breakdown, by subcomponent, of the quarterly means for total expenditures with and without gifts, consumption without health insurance, and consumption with health insurance uncapped. The quarterly mean for total expenditures is $14,555. The quarterly mean drops, as expected, to $14,386, when we remove expenditures for goods and services purchased to be given to people who live outside the CU (i.e., identified as gifts by BLS). When we move to consumption without health insurance, the quarterly mean drops further, to $12,158. As revealed by the subcomponent means, the lower mean for total consumption without health insurance relative to the means for both measures of total expenditures is largely due to the removal of health insurance and the deduction of out-of-pocket expenditures, as well as switching from the net purchase price of vehicles to a flow of services. However, the decline was mitigated by increases in the consumption values of owned dwelling, rented dwelling, and other lodging; these reflect the movement from expenditures to rental equivalence for owned housing and imputed rents for renter shelter. Including health insurance increases the consumption measure to $16,767. Capping health insurance to 50-percent of consumption only slightly reduces the mean, to $16,675.

Table 3. Nominal quarterly means of expenditures and consumption, by subcomponent, 2020

Category	Total expenditures	Total expenditures, excluding gifts	Consumption without health insurance	Consumption with health insurance uncapped	Consumption with health insurance capped
Average quarterly expenditures or consumption	$14,555	$14,386	$12,158	$16,767	$16,675
Percent of consumption that is imputed	[1]	[1]	11.31%	31.87%	29.86%
Food[2]	$2,139	$2,136	$2,142	$2,142	$2,142
Alcoholic beverages	112	112	112	112	112
Housing	5,037	4,995	[1]	[1]	[1]
Shelter	3,133	3,114	[1]	[1]	[1]
Owned dwellings[3]	1,849	1,849	3,518	3,518	3,518
Rented dwellings[4]	1,100	1,089	1,188	1,188	1,188
Other lodging[5]	184	176	308	308	308
Utilities, fuels, and public services[6]	1,049	1,044	1,047	1,047	1,047
Household operations	362	357	[1]	[1]	[1]
Child daycare expenses[7]	48	48	[1]	[1]	[1]
Out-of-pocket expenses, excluding child daycare	313	309	309	309	309
Household furnishings and equipment	493	480	[1]	[1]	[1]
Purchase of major kitchen appliances[8]	72	72	[1]	[1]	[1]
Out-of-pocket expenses, excluding household furnishings and equipment	422	408	408	408	408
Apparel and services	251	237	237	237	237
Transportation	2,430	2,404	[1]	[1]	[1]
Vehicle purchases (net outlay)[9]	1,208	1,188	[1]	[1]	[1]
Depreciation and opportunity costs of owning vehicles	[1]	[1]	829	829	829
Gasoline, other fuels, and motor oil	386	384	384	384	384
Other vehicle expenses	782	782	782	782	782
Public and other transportation	54	51	51	51	51
Health	1,227	1,225	[1]	[1]	[1]
Health insurance[10]	918	917	[1]	4609	4517
Medical services	217	215	[1]	[1]	[1]
Prescription drugs	65	65	[1]	[1]	[1]
Medical supplies	29	28	[1]	[1]	[1]
Entertainment	626	615	[1]	[1]	[1]
Motorized recreational vehicles (net outlay)	55	55	[1]	[1]	[1]
Out-of-pocket expenses, excluding motorized recreational vehicles	571	560	560	560	560
Personal care products and services	68	67	67	67	67
Reading	16	15	15	15	15
Education[9]	284	223	[1]	[1]	[1]
Tobacco products and smoking supplies	76	76	76	76	76
Miscellaneous	135	124	124	124	124

[1] Not applicable.
[2] For consumption, includes National School Lunch Program and Women, Infants, and Children program. Also includes an adjustment for board for students who report living in a dorm.
[3] For consumption, includes rental equivalence for primary residence.
[4] For consumption, includes market value of rental units. Consumer units residing in a college dorm were assigned the national average value for dorms using data from the U.S. Department of Education.
[5] For consumption, includes rental equivalence for vacation homes. Consumption also includes an adjustment for expenditures on dorms for students who report living in a dormitory.
[6] For consumption, includes energy assistance using Low-Income Home Energy Assistance Program..
[7] Not included in consumption because considered part of education.
[8] Not included in consumption because considered part of rental equivalence and rent.
[9] Item not included in consumption.
[10] For consumption, only the imputation for the full value of health insurance is included. For 2021, the value of health insurance is based on 2020 imputations adjusted for inflation.
[11] Definition excludes food and rent as pay. This definition differs from the definition of income used in the published Consumer Expenditure Surveys tables, which includes food and rent as pay.
[12] Does not include the value of Supplemental Nutrition Assistance Program or food and rent as pay.
Note: CE = Consumer Expenditure Surveys.
Source: U.S. Bureau of Labor Statistics.

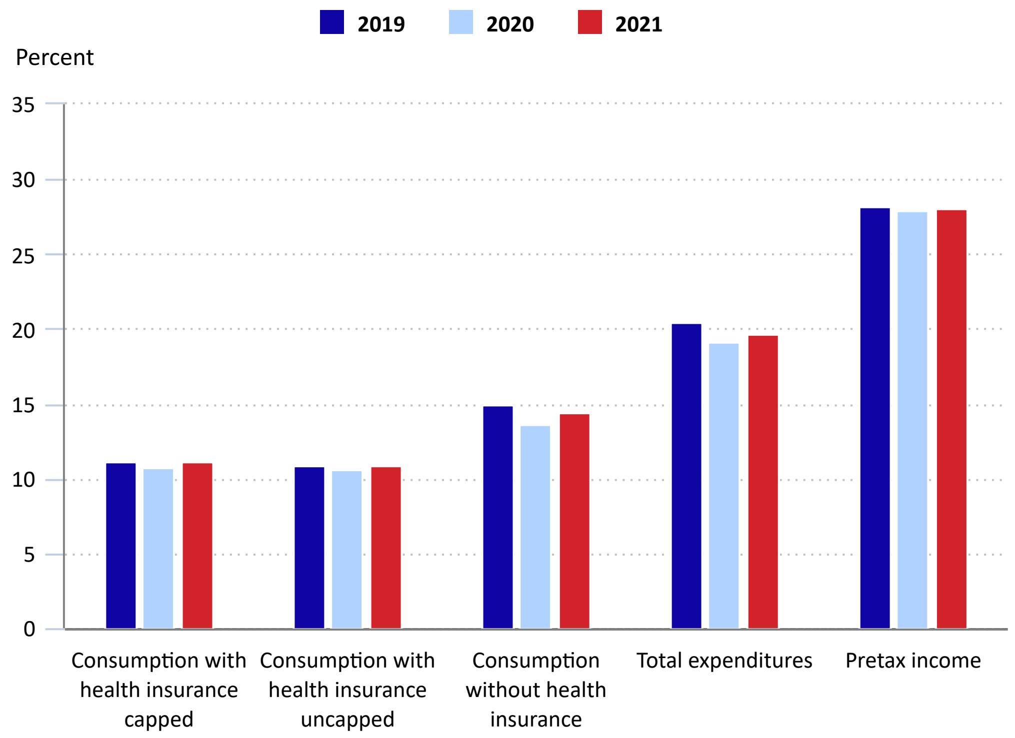
Category	Total expenditures	Total expenditures, excluding gifts	Consumption without health insurance	Consumption with health insurance uncapped	Consumption with health insurance capped
Personal insurance and pensions[9]	1,592	1,592	[1]	[1]	[1]
Life and other personal insurance[9]	121	121	[1]	[1]	[1]
Pensions and Social Security[9]	1,471	1,471	[1]	[1]	[1]
Cash contributions[9]	564	564	[1]	[1]	[1]
Income:					
CE-defined quarterly pretax income[11]	$21,156	$21,156	$21,156	$21,156	$21,156
Census Bureau-defined quarterly pretax income[12]	$21,094	$21,094	$21,094	$21,094	$21,094
Number of consumer units (in thousands)	131,542	131,542	131,542	131,542	131,542
Number of sample interviews	20,158	20,158	20,158	20,158	20,158
Consumer unit characteristics:					
Age of reference person	52.14	52.14	52.14	52.14	52.14
Average number in consumer unit:					
People	2.47	2.47	2.47	2.47	2.47
Children under 18	0.58	0.58	0.58	0.58	0.58
Adults 65 and older	0.42	0.42	0.42	0.42	0.42
Earners	1.29	1.29	1.29	1.29	1.29
Vehicles:					
Vehicles (owned)	1.8	1.8	1.8	1.8	1.8
Vehicles (leased)	0.08	0.08	0.08	0.08	0.08
Percent distribution:					
Reference person:					
Men	47	47	47	47	47
Women	53	53	53	53	53
Housing tenure:					
Homeowner	66	66	66	66	66
With mortgage	39	39	39	39	39
Without mortgage	27	27	27	27	27
Renter	33	33	33	33	33

[1] Not applicable.
[2] For consumption, includes National School Lunch Program and Women, Infants, and Children program. Also includes an adjustment for board for students who report living in a dorm.
[3] For consumption, includes rental equivalence for primary residence.
[4] For consumption, includes market value of rental units. Consumer units residing in a college dorm were assigned the national average value for dorms using data from the U.S. Department of Education.
[5] For consumption, includes rental equivalence for vacation homes. Consumption also includes an adjustment for expenditures on dorms for students who report living in a dormitory.
[6] For consumption, includes energy assistance using Low-Income Home Energy Assistance Program..
[7] Not included in consumption because considered part of education.
[8] Not included in consumption because considered part of rental equivalence and rent.
[9] Item not included in consumption.
[10] For consumption, only the imputation for the full value of health insurance is included. For 2021, the value of health insurance is based on 2020 imputations adjusted for inflation.
[11] Definition excludes food and rent as pay. This definition differs from the definition of income used in the published Consumer Expenditure Surveys tables, which includes food and rent as pay.
[12] Does not include the value of Supplemental Nutrition Assistance Program or food and rent as pay.
Note: CE = Consumer Expenditure Surveys.
Source: U.S. Bureau of Labor Statistics.

Poverty

Chart 1 presents the poverty rates defined using relative thresholds (set at 60 percent of each equivalized measure value). For exposition purposes, we focus on consumption with health insurance capped, consumption without health insurance, total expenditures, and pretax income. Relative consumption poverty rates with or without health insurance (about 11 and 14 percent, respectively) or health insurance capped (about 11 percent) are lower than relative poverty rates based on total expenditures (averaging 20 percent) and those based on pretax income (averaging 28 percent).[45] Relative poverty rates for all measures fell in 2020 and increased slightly in 2021. Focusing on 2019 relative to 2021, we see that there was little to no change in relative consumption poverty.[46] For consumption without health insurance, total expenditures (that include gifts) and pretax income, there were declines in relative poverty.

Chart 1. Poverty rates for total population based on relative poverty thresholds, 2019 to 2021

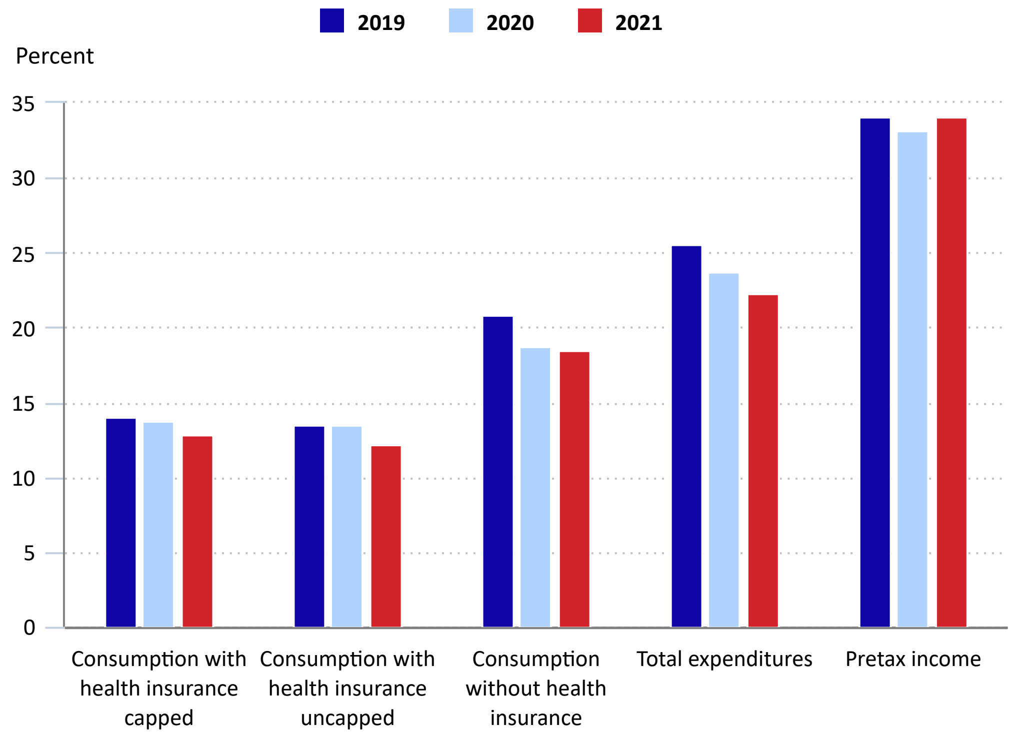


Click legend items to change data display. Hover over chart to view data.
Note: Data for 2021 are preliminary.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Using the same relative thresholds as for the total population, chart 2 shows the poverty rates for the population who are less than 18 years of age. The rates for this younger population relative to the rates for the total population are higher for all measures. Unlike for the total population, for which poverty increased from 2020 to 2021, for people less than 18 years of age, there was a continued decline in consumption poverty and in total expenditures poverty in 2021.[47] Income poverty increased in 2021, returning to its 2019 level. Note that the income measure we use does not include the expanded Child Tax Credit or the Economic Impact Payments issued during the pandemic. However, receipt of these subsidies could be reflected in the consumption estimates.[48]

Chart 2. Poverty rates for people under age 18, using relative thresholds for total population, 2019 to 2021

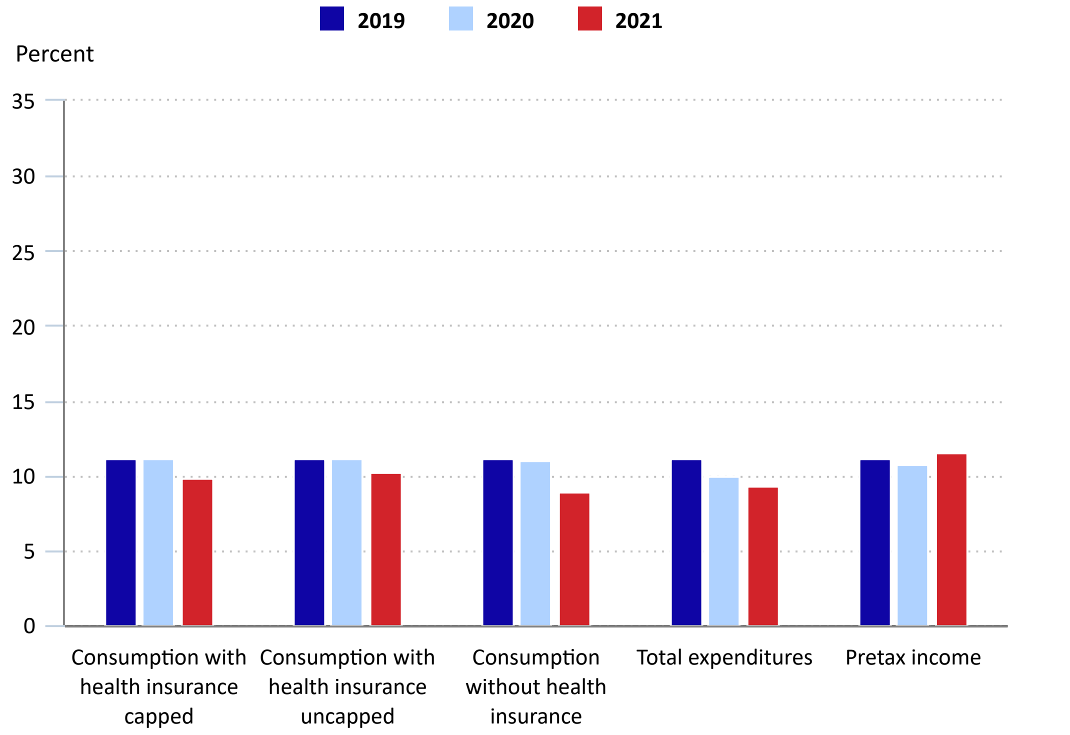


Click legend items to change data display. Hover over chart to view data.
Note: Data for 2021 are preliminary.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Chart 3 presents the poverty rates based on an absolute concept of poverty, rather than a relative concept. Thresholds are absolute in that they are "fixed" in 2019 and updated only for inflation. The thresholds for each measure are derived in such a way that the 2019 poverty rates for all the measures equal the 2019 relative poverty rate based on consumption with health insurance capped. Thus, the starting poverty rates for all measures are set to equal 11.2 percent. Using this measure, we find that poverty fell from 2019 to 2021 for each of the consumption measures, with the largest drop occurring for consumption without health insurance. Poverty rates for total expenditures also dropped, while pretax income poverty rose from 2020 to 2021.

Chart 3. Poverty rates for total population based on relative thresholds that result in same total population 2019 consumption poverty rates, 2019 to 2021

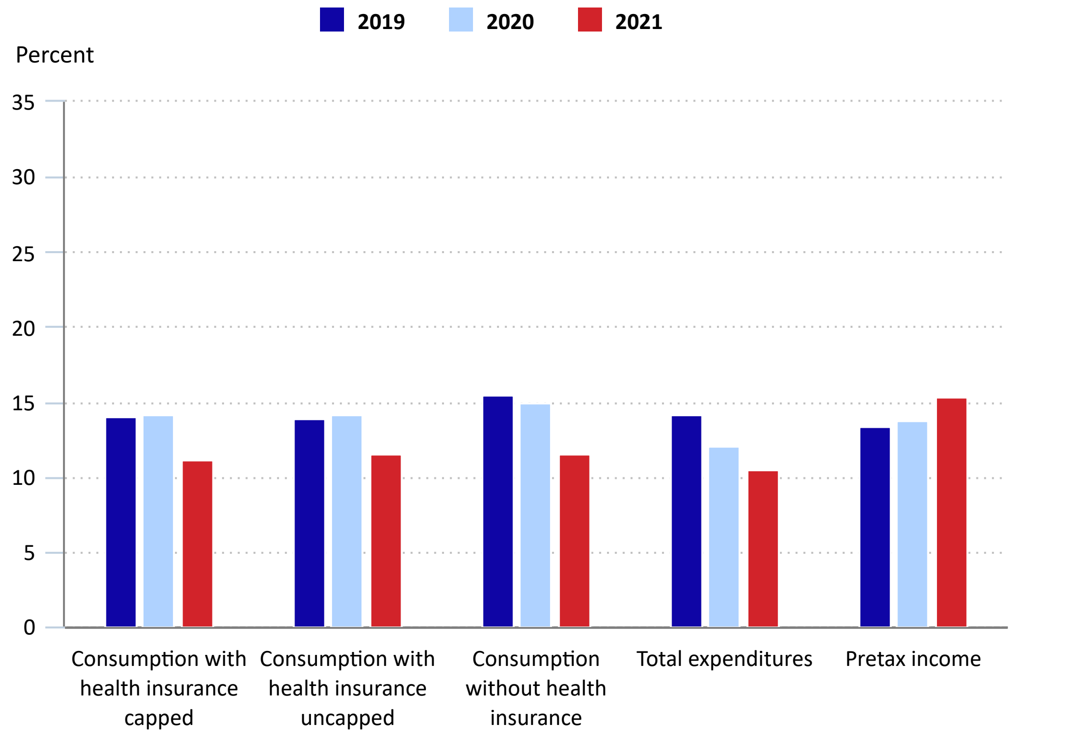


Click legend items to change data display. Hover over chart to view data.
Note: Data for 2021 are preliminary.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Chart 4 presents the poverty rates for children (under age 18) that are based on the same absolute thresholds as those used for the total population (with the poverty rate set at 11.2 percent). Child poverty rates are not anchored. As with the relative thresholds, poverty rates for children are higher than those for the total population. However, by 2021, consumption-based child poverty rates had fallen more (from 2.4 to 4.0 percentage points) than did the poverty rates for the total population (from 1.0 to 2.3 percentage points). In contrast, the pretax-income child poverty rate for 2020 to 2021 increased by more (2.0 percentage points) than did the total population income poverty rate (0.9 percentage point).

Chart 4. Poverty rates for people under age 18, using relative thresholds that result in same total population 2019 consumption poverty rates, 2019 to 2021



Click legend items to change data display. Hover over chart to view data.
Note: Data for 2021 are preliminary.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Inequality

Table 4 presents the Gini indexes for the different measures. Gini indexes are a summary measure of inequality. They range from 0 to 1, with higher values corresponding to less equal distributions. Consumption is distributed more equally than total expenditures, which are distributed more equally than pretax income. Adding health insurance to the consumption measure makes the distribution more equal. The greatest inequality across the 3 years occurred in 2019 for all measures except total expenditures. The distributions of all the measures became more equal in 2020; but inequality increased in 2021.

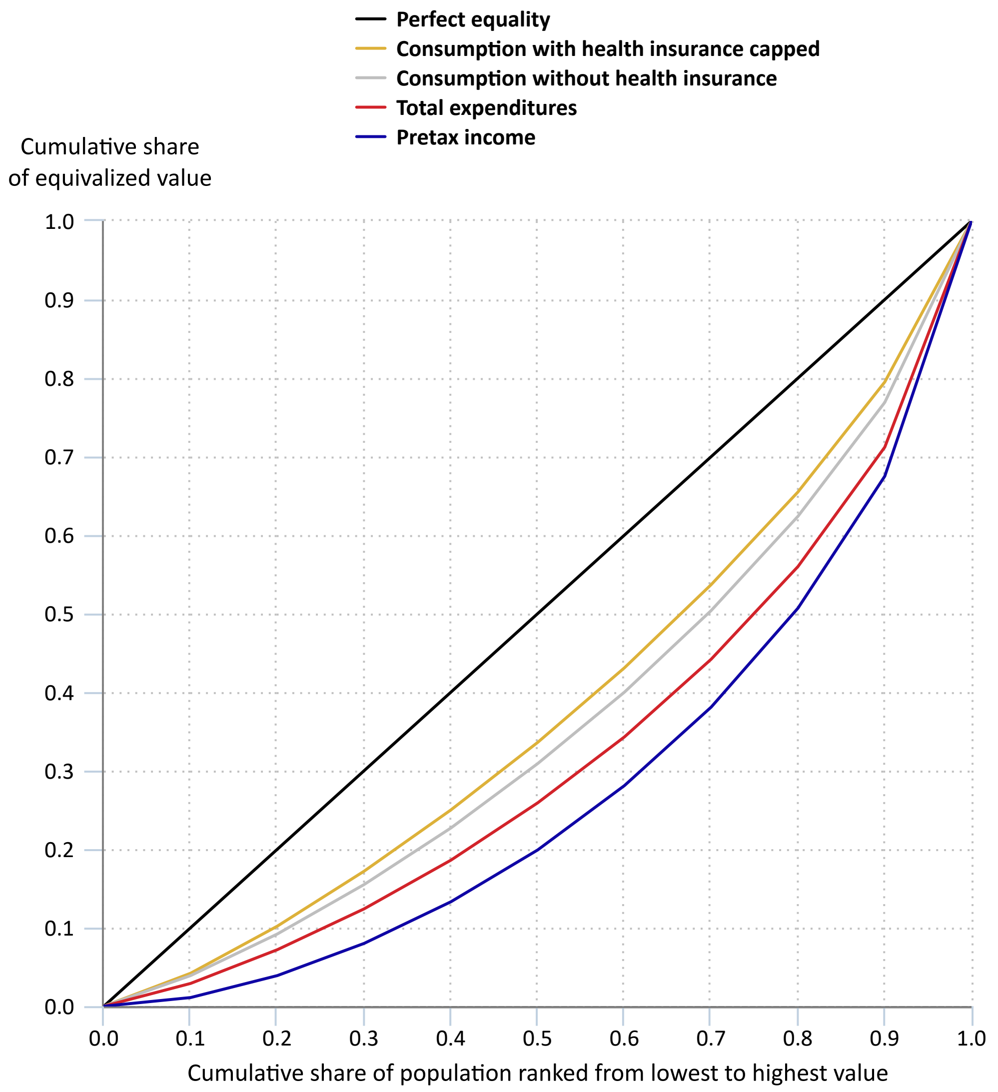
Table 4. Gini indexes for consumption with health insurance (capped and uncapped), consumption without health insurance, total expenditures, and pretax income, 2019 to 2021

Measure	2019	2020	2021[1]
Consumption with health insurance capped	0.250	0.241	0.247
Consumption with health insurance uncapped	0.247	0.239	0.245
Consumption without health insurance	0.295	0.282	0.289
Total expenditures	0.372	0.364	0.376
Pretax income	0.464	0.449	0.455

[1] Data for 2021 are preliminary.
Source: U.S. Bureau of Labor Statistics.

Chart 5 presents the Lorenz curves for 2020. Lorenz curves are a visual representation of inequality and show the cumulative share of the population (ranked by the value of each measure from lowest to highest value) on the *x*-axis at or below the cumulative share of the measure as represented on the *y*-axis. Perfect equality is represented by the 45-degree line; the closer the Lorenz curve is to the line for perfect equality, the more equal the distribution. If a measure is equally distributed across the population, an equal share of the population would account for an equal share of the measure—for example, 50 percent of the population would account for 50 percent of consumption. An example of an unequal distribution is shown in chart 5 by the measure for consumption without health insurance: 50 percent of the population accounts for 30 percent of consumption. As with the Gini index results, pretax income is the least equally distributed of the measures, and consumption with health insurance capped is the most equally distributed. The Lorenz curves for consumption with health insurance and with health insurance capped are indistinguishable, and thus only one of the curves is presented. Lorenz curves for 2019 and 2021 (based on preliminary data) exhibit similar patterns.

Chart 5. Lorenz curves for consumption with and without health insurance, total expenditures, and pretax income, by own-rank deciles, 2020



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

View Chart Data

Conclusion

In this article, we construct an initial version of a comprehensive consumption measure for the United States and use it to study poverty and inequality from 2019 to 2021. Our results show that the average value of consumption without including health insurance is lower than the average value of total expenditures. However, when we include health insurance, capped or uncapped, average consumption exceeds average total expenditures. We also find that consumption poverty rates defined using relative thresholds are lower than expenditure- or income-based poverty rates, regardless of whether health insurance is included. Consumption is also more equally distributed than expenditures or income. Poverty rates across all our measures fell in 2020 relative to 2019, and the distributions of the measures became more equal. This general finding is likely an effect of the COVID-19 pandemic, but verifying that claim is beyond the scope of this article.

BLS will continue to develop a comprehensive consumption measure for the United States with the CE providing the core data. The next main area of improvement is to incorporate the value of home production. Because home production is not a market transaction and relies instead on household members spending time performing tasks that add value to the household, we must impute time use to CUs participating in the CE. Home production includes the provision of childcare and eldercare. When purchased, both services can represent heavy financial burdens for families, some of whom will be priced out of the market. In such cases, children and elders in these families often receive care from other family members or friends through nonmarket transactions. We expect that the inclusion of home production in the CE will help us better understand consumption dynamics during the COVID-19 pandemic, when many childcare centers were closed.

The consumption measures presented in this article represent research in progress. However, BLS plans to release to the public a research series of consumption values in tables similar to the currently published data tables for CE total expenditures. These tables will include average consumption values. In addition, and dependent upon available resources, BLS is considering making available an auxiliary public-use microlevel data file that researchers could use to reproduce these consumption measures or create new ones of their own.[49] Finally, BLS expects its ongoing development work to result in methodological improvements that will be reflected in the CE data and in the consumption measure particularly.

Appendix: Imputation methods

In this appendix, we present the details of the imputation methods for NSLP, WIC, and LIHEAP benefits, market rents for which reported rents are expected to undervalue consumption, health insurance, and vehicle flow of services that are used in the construction of our consumption measures.

NSLP, WIC, and LIHEAP

The basic approach for imputing these in-kind government benefits is based on that of Garner and Gudrais (2018) in their research on producing Supplemental Poverty Measure (SPM) thresholds that account for in-kind benefits.[50] For the BLS consumption measure, we draw upon more recent methods developed by BLS (described below) and those developed by the Census Bureau to assign NSLP benefits to CPS-ASEC households for the SPM resource measure during the COVID-19 pandemic period.[51]

To produce the new consumption measure, the first step is to restrict, when necessary, the CPS-ASEC sample to households that are potentially eligible for in-kind programs. The full sample is asked the LIHEAP questions, and thus there are no sample restrictions for the imputation of LIHEAP benefits. However, only subsets of CPS-ASEC households are asked NSLP and WIC questions. The CPS ASEC only asks the NSLP-participation question of survey respondents in households with school-aged children (ages 5 to 18) who usually ate a hot lunch at school. During CPS-ASEC data collection, if a Census Bureau field representative was asked what is meant by “usually,” the response would be more than 50 percent of the time when the reference period was 2019; for the 2020 and 2021 reference periods, the response to what is meant by “usually” would have been when students were in school prior to the pandemic or when schools remained open during the pandemic.[52] The WIC question is only asked of households with women ages 15 to 45 with no children (to include women who could potentially be pregnant) and women ages 15 and older with children under 5 years of age. These same sample restrictions for the NSLP and WIC benefit program are applied to the CE, with one exception. In the CPS ASEC, the NSLP questions are only asked of households with children who usually ate a hot meal at school; this information is not collected in the CE, which means we cannot restrict the CE sample along this dimension. The CE and CPS-ASEC data are then pooled. In the pooled data, NSLP and WIC participation and LIHEAP benefits are not missing in the CPS ASEC, but they are missing in the CE by design. A logistic regression model is used to impute participation when participation values are missing (in this case, the CE). For LIHEAP, a logistic regression model is used to first impute participation and then for those with imputed receipt, an ordinary least squares regression model is used to impute LIHEAP-benefit values from the CPS ASEC to the CE. For the statistical models, the explanatory variables are demographic variables that are defined the same for the CPS ASEC and the CE. For the imputed participation in these programs, the estimated model coefficients are used to generate participation probabilities for CE respondents, and then, using these predicted probabilities, participation (yes or no) is assigned randomly.[53]

From the CPS-ASEC data, there are three possible outcomes for NSLP: (1) receive free or reduced school lunch, (2) pay full price for school meals, and (3) does not consume school meals. All school lunches provided to children are subsidized. Thus, children in the second group are NSLP participants, but we refer to them as “paid” in that they paid fully for their school lunches. For “free” and “reduced,” the CPS-ASEC question for NSLP participation does not distinguish between these two levels of meal support; thus, we assign children to “free” and “reduced” by using a method similar to that used by the Census Bureau for assigning benefits to participating households when calculating SPM resources. NSLP-program benefit values for the three categories—free, reduced, and paid—are based on data from the USDA.[54]

Two different methods were used to assign free and reduced benefits, one for 2019 and a different one for 2020 and 2021. The method used for 2019 is based on CU pretax income (not including SNAP benefits) and a random assignment. If this pretax income measure is less than 150 percent of the official poverty threshold, children in the CU are all assumed to receive free meals. CUs with an NSLP-participation assignment of free or reduced and income equal to or above this threshold are randomly assigned to either being free or reduced NSLP participants.[55] For 2019, the number of school days for which these benefits are assigned is based on the state average number of school days in an academic year.[56] In contrast, for SPM resources, the Census Bureau assigns NSLP benefits using a national average of 179 school days.

The method to assign NSLP benefits for 2020 and 2021 for the BLS consumption measure is an adaption of the method developed by Census Bureau staff when accounting for NSLP benefits in SPM resources.[57] The method accounts for both school closures and receipt of EBTs to assign school lunch values. It is based on a combination of school operating status, SNAP receipt, and an additional question that was added to the CPS ASEC for 2020 and 2021: “Did your children continue receiving free/reduced price meals through your school or school district if schools were closed during the pandemic?” For 2020 and 2021, free lunch NSLP benefits are assigned to consumers reporting SNAP and with imputed NSLP participation. For 2020 only, reduced lunch NSLP benefits were assigned to CUs with imputed NSLP participation but no SNAP benefits. There were no reduced benefits assigned for 2021. For 2020 and 2021, we only assign NSLP benefits to CUs with school-age children when they are expected to be in school, in person. Because many schools were closed during the pandemic in 2020 and 2021, the USDA used EBTs to administer NSLP benefits. For our measure of consumption, when EBTs were received, we assign a zero value to the NSLP benefit because we assume expenditures based on the use of the EBTs are already reflected in reported food expenditures. This is the same assumption that underlies the treatment of SNAP in the CE because SNAP benefits are administered via EBTs and thus are considered “like cash”; adding SNAP values to reported food expenditures would be double counting.[58]

For 2019 to 2021, if children in CUs were not assigned as receiving free or reduced lunch and were in school, in person, they were assumed to eat a hot lunch and to have received the NSLP-benefit values for paid meals. For 2019, the new BLS consumption measure used the average number of school days in an academic year, by state, to produce benefits for those who paid for their meals. For 2020 and 2021, we employed the method developed by the Census Bureau that accounted for school closings and changes in the NSLP when imputing NSLP benefits for those who paid for their meals.

For WIC, once participation receipt is imputed to the CE, WIC benefits are assigned. Average quarterly WIC-benefit values imputed to the CE are based on the benefits, infant-formula rebates, and infant participation. For those CE-respondent CUs who are imputed to have participants, the values for the in-kind benefits are assigned on the basis of state level per-beneficiary averages for WIC food benefits and infant-formula rebates, as well as timing of the adoption of WIC being electronically administered via EBT.[59] For consumer units living in states that have fully implemented the distribution of WIC food benefits by EBT, only the infant-formula rebate is added to consumption. To produce quarterly WIC benefits, average monthly values are produced and then multiplied by 3. For example, to compute the average monthly value for 2019 (represented by the CE data for 2019 quarter two to 2020 quarter one), three-quarters of 2019 fiscal-year monthly averages are pooled with one quarter of the 2020 fiscal-year monthly average. In contrast, for our earlier measure, fiscal year 2019 monthly averages were used. Average WIC food benefits are assigned to women and children. In addition, average infant-formula rebates are added to WIC food benefits. The infant-formula rebate benefit is assigned to the fraction of all infants who are assumed to be only formula fed.[60] WIC benefits and participation rates are based on administrative data published by the USDA.[61]

Consumption of rental shelter

For the consumption measure, there are several cases for which we expect the CE-reported out-of-pocket shelter expenditures not to reflect the full consumption value of this shelter. These include CUs receiving government rent subsidies, those living in public housing or those living in rent-controlled units, and those assumed to be paying less than market rents for other reasons. The CE asks about participation in the government programs, but not about the value of the difference in what renters pay for shelter and the market value of similar units, or about the market value of their units. Others who may pay less than the full consumption value of shelter include CUs consisting of people who are living rent free and those who are paying less rent because they are providing services to the landlord in lieu of paying the full rent. In addition, it is unlikely that the rents reported by college students living in dormitories reflect their consumption of shelter.

To impute rents for those receiving government rent subsidies, living in public housing, or living in rent-controlled units, we use the CE-participation variable for each program. In addition, we impute rents for renters who we assume are not paying full market rents: specifically, those reporting expenditures for maintenance and repairs in addition to reported rents. We also use the fact that some CUs consist of people living in dormitories to assign shelter consumption values.

We estimate a model of the full market rental value as a function of demographic, geographic, and housing-unit characteristics using a censored normal regression model, where the observed rental payment is censored from above if the CU received rental assistance (i.e., received government rental assistance, lived in public housing, or lived in a rent-controlled unit), or paid additional rent-related expenses. The estimation sample is restricted to traditional renters (i.e., respondents who report renting and do not report participating in a government rental assistance program, and who do not report out-of-pocket expenditures beyond rent alone). The estimation sample also excludes CUs consisting of people living in college or university dormitories. The rent used in the estimation model as the dependent variable is the logarithm of rent paid for the last month in the reference period, rather than the quarterly reported rent. This last month's rent is used so that the period more closely matches that of the period covered in owners' reports of rental equivalence: how much owners think their homes would rent for currently (at the time of the interview) without furnishings and without utilities.[62] The imputed market rent multiplied by 3 is used in place of the CE-recorded rent for the last 3 months (the reference period) for all respondents who are identified as participating in a government rental assistance program, occupying their residence without payment of rent, and those with out-of-pocket maintenance and repair expenditures in addition to their reported rents. To derive shelter consumption for renters, out-of-pocket expenditures for tenant's insurance are added to the rents reported by CUs assumed to be paying full market rents, and to the imputed rents for all other renters.

The consumption shelter value for CUs that consist of people living in college or university dormitories is imputed differently. Because dormitories are distinctly different from other rental units, we cannot apply our market-rent imputation model to these cases. Instead, we assign the national average dormitory cost, which we obtained from the National Center for Education Statistics.[63] We use this value to calculate an average monthly cost, which is then adjusted to reflect the 3-month cost for the reference period. Because we do not expect dormitories to be rented year round, to get the 3-month reference-period cost, the monthly value is scaled by the number of months in the reference period that overlap with the August–May school year. For example, a CU interviewed in July has a reference period of April, May, and June. This reference period has 2 months that overlap with the August–May school year, so the consumption value for dormitories during this reference period is twice the average monthly cost for a dormitory. The same adjustment is made for the cost of board while living at college.

Health insurance

The CE Interview asks about different types of insurance coverage and measures the out-of-pocket insurance premium associated with each type of insurance. The CE also measures out-of-pocket expenditures on medical goods and services. For people with insurance, out-of-pocket expenditures on medical goods and services will reflect copayments and coinsurance. One limitation of the CE data on health insurance coverage is that for types of insurance other than Medicare, the only questions asked are whether anyone in the CU is covered and the number of people who are covered. So, there is no way to identify the specific individuals covered.

For the consumption measure with health insurance, we first impute the full value of health insurance on the basis of insurance type. For private health insurance, the full value is based on the market price. This includes the out-of-pocket premiums that are captured by the CE and the employer contribution for employer-provided plans, or the value of any subsidy received for individual plans. For public insurance programs, the full value is based on the cost to the government (including administrative costs).

The methods and data sources used for the imputation of the full value of health insurance are based on the work of Garner, et al. (2022).[64] For that project, imputed values were added to CE health insurance expenditures to match the scope of the U.S. Bureau of Economic Analysis personal consumption expenditures (PCE) data, which, by definition, include employer contributions to employer-provided health insurance and government insurance programs. The data sources used to impute the values for the CE-PCE project are the same as those used to produce the consumption measures with health insurance (capped and uncapped) presented in this article. However, the values for health insurance used in the production of these consumption measures and those used for the CE-PCE project are not directly comparable because the two measures differ in scope.[65]

For employer-provided health insurance, we use data from the Medical Expenditure Panel Survey Insurance Component (MEPS-IC).[66] MEPS-IC has data on the average employer contribution and average employer share. For employer-provided coverage, we impute different amounts on the basis of the type of plan: single coverage, plus one, and family. We assign individuals in the CE to different plan types on the basis of the number of people covered by the plan. So, individuals are assumed to have single coverage if the plan covers one CU member, plus one if the plan covers two CU members, and family coverage if the plan covers more than two CU members.

People who purchase individual health insurance plans can receive subsidies in the form of a tax credit. The CE asks individuals who purchase individual plans whether they receive a subsidy. We assign the average subsidy among those who receive a subsidy to CUs in the CE with individual plans who report receiving a subsidy. The data on the average subsidy amounts come from the Centers for Medicare & Medicaid Services (CMS).[67]

For public programs, the imputed amount is the per-enrollee cost to the government, including administrative costs. For Medicare, the average cost (including administrative costs) per beneficiary is calculated from the Trustee's report for each of the Medicare programs: traditional Medicare (includes Parts A and B), Medicare Part C, and Medicare Part D. These programs also have out-of-pocket premiums. There are two ways to account for out-of-pocket premiums. One way is to add the average cost less premiums to the out-of-pocket premium amount reported in the CE. The other approach is to assign the average cost and ignore the out-of-pocket amounts. Which approach is preferable depends on whether the variation in out-of-pocket premiums for these programs is due to variation in the amount of coverage purchased or to variation in the amount the premium subsidized. If the coverage is the same, then adding the average cost less average premium amount will lead to a lower value for individuals who have received subsidies for their premiums. This is the case for traditional Medicare, so we ignore the CE-reported premiums and impute a value on the basis of the average cost. We treat Part D the same; although there is variation in Part D plans, the variation in out-of-pocket premiums due to subsidies is likely much larger. Part C can be thought of as a bundle of traditional Medicare and supplemental coverage. For the traditional Medicare component, we impute an average cost and ignore the CE-reported Part B premiums. Then, we add any additional premiums paid to reflect the supplemental coverage.

Other public programs are more straightforward because there is less variation in the types of coverage offered. So, we assign a single average-cost value to participants in other public programs and ignore any out-of-pocket premiums. For Medicaid and the Children's Health Insurance Program, the per-enrollee average cost comes from the CMS

National Health Expenditures tables.[68] Per-enrollee costs for other public programs (e.g., TRICARE, Veterans Affairs benefits, and Indian Health Services) are calculated from the budgets for each of the programs.[69]

Depreciation and opportunity costs of owning vehicles

For vehicles, we employ a user-cost approach to assign a consumption value that is based on the flow of services. The user cost is defined as the depreciation plus the opportunity cost of capital (value of the car times the interest rate), plus maintenance and repair costs. We estimate the depreciation and opportunity costs; the other components of user costs are already included in consumption as nonvehicle-purchase-related expenditures. Depreciation and opportunity costs are imputed to CUs on the basis of vehicle ownership. For our research, we restrict vehicles to cars and trucks, with sport utility vehicles being categorized as trucks. For 2021, about 87 percent of vehicles reported in the CE as being owned were classified as cars or trucks. The remaining 13 percent are other vehicles such as planes, boats with motors, and motorized campers. Because the sample size for other vehicles is quite small and the CE does not collect data on characteristics for these vehicles, depreciation and opportunity costs for “other vehicles” are not calculated and thus are not included in the consumption measure.

We estimate the vehicle depreciation rate using data on vehicles owned as reported in the CE. For all vehicles owned, the CE collects data on the vehicle characteristics, including make, model, and year. The CE also asks when the vehicle was acquired and the purchase price of the vehicle. We estimate a depreciation rate by comparing the purchase price for vehicles purchased at different ages while controlling for vehicle characteristics. We estimate an age-specific depreciation rate for vehicles 10 years old or less. Vehicles over 10 years old are assumed to depreciate at a constant rate, as there are too few transactions involving older vehicles to estimate age-specific depreciation rates. The imputed depreciation value is calculated as the current market value of the vehicle times the age-specific depreciation rate. The current market value is calculated as the estimated new purchase price of the vehicle minus the estimated depreciation for prior years. The opportunity cost of capital is the product of an interest rate and the estimated current market value of each car and truck owned by the CU. The interest rates are the year-specific Treasury Long-Term Average (Over 10 Years), Inflation-Indexed annual rates, not seasonally adjusted, published by the Federal Reserve Bank of St. Louis.[70]

Table A-1. Nominal quarterly means of expenditures and consumption, by subcomponent, 2019 to 2021

Category	Total expenditures			Total expenditures, excluding gifts			Consumption without health insurance			Consumption with health insurance uncapped		
	2019	2020	2021[1]	2019	2020	2021[1]	2019	2020	2021[1]	2019	2020	2021[1]
Average quarterly expenditures or consumption	$14,717	$14,555	$16,196	$14,509	$14,386	$15,955	$12,395	$12,158	$13,562	$16,792	$16,767	$18,062
Percent of consumption that is imputed	[2]	[2]	[2]	[2]	[2]	[2]	12.16%	11.31%	10.95%	30.11%	31.87%	29.99%
Food[3]	$2,184	$2,139	$2,472	$2,175	$2,136	$2,462	$2,220	$2,142	$2,492	$2,220	$2,142	$2,492
Alcoholic beverages	134	112	142	134	112	142	134	112	142	134	112	142
Housing	4,862	5,037	5,367	4,815	4,995	5,312	[2]	[2]	[2]	[2]	[2]	[2]
Shelter	3,010	3,133	3,300	2,987	3,114	3,723	[2]	[2]	[2]	[2]	[2]	[2]
Owned dwellings[4]	1,662	1,849	1,861	1,662	1,849	1,861	3,246	3,518	3,762	3,246	3,518	3,762
Rented dwellings[5]	1,110	1,100	1,177	1,199	1,089	1,168	1,214	1,188	1,290	1,214	1,188	1,290
Other lodging[6]	238	184	263	224	176	244	332	308	362	332	308	362
Utilities, fuels, and public services[7]	1,012	1,049	1,058	1,008	1,044	1,052	1,012	1,047	1,056	1,012	1,047	1,056
Household operations	390	362	404	385	357	399	[2]	[2]	[2]	[2]	[2]	[2]
Child daycare expenses[8]	75	48	60	75	48	60	[2]	[2]	[2]	[2]	[2]	[2]
Out-of-pocket expenses, excluding child daycare	315	313	344	310	309	340	310	309	340	310	309	340
Household furnishings and equipment	451	493	604	435	480	588	[2]	[2]	[2]	[2]	[2]	[2]
Purchase of major kitchen appliances[9]	65	72	97	65	72	97	[2]	[2]	[2]	[2]	[2]	[2]
Out-of-pocket expenses, excluding household furnishings and equipment	386	422	508	371	408	491	371	408	491	371	408	491
Apparel and services	310	251	363	296	237	311	296	237	311	296	237	311
Transportation	2,649	2,430	2,776	2,616	2,404	2,751	[2]	[2]	[2]	[2]	[2]	[2]
Vehicle purchases (net outlay)[10]	1,135	1,208	1,281	1,116	1,188	1,268	[2]	[2]	[2]	[2]	[2]	[2]
Depreciation and opportunity costs of owning vehicles	[2]	[2]	[2]	[2]	[2]	[2]	854	829	794	854	829	794
Gasoline, other fuels, and motor oil	522	386	559	518	384	554	518	384	554	518	384	554
Other vehicle expenses	792	782	807	791	782	806	791	782	806	791	782	806
Public and other transportation	199	54	129	191	51	123	191	51	123	191	51	123
Health	1,225	1,227	1,301	1,217	1,225	1,296	[2]	[2]	[2]	[2]	[2]	[2]
Health insurance[11]	886	918	927	886	917	927	[2]	[2]	[2]	4,397	4,609	4,500
Medical services	239	217	274	231	215	270	[2]	[2]	[2]	[2]	[2]	[2]
Prescription drugs	66	65	68	66	65	68	[2]	[2]	[2]	[2]	[2]	[2]
Medical supplies	34	29	32	34	28	32	[2]	[2]	[2]	[2]	[2]	[2]
Entertainment	643	626	801	628	615	780	[2]	[2]	[2]	[2]	[2]	[2]
Motorized recreational vehicles (net outlay)	26	55	83	26	55	83	[2]	[2]	[2]	[2]	[2]	[2]
Out-of-pocket expenses, excluding motorized recreational vehicles	617	571	718	601	560	697	601	560	697	601	560	697
Personal care products and services	96	68	102	96	67	102	96	67	102	96	67	102
Reading	14	16	19	14	15	18	14	15	18	14	15	18
Education[10]	316	284	269	245	223	209	[2]	[2]	[2]	[2]	[2]	[2]
Tobacco products and smoking supplies	77	76	84	77	76	84	77	76	84	77	76	84
Miscellaneous	126	135	149	118	124	137	118	124	137	118	124	137
Personal insurance and pensions[10]	1,572	1,592	1,741	1,572	1,592	1,741	[2]	[2]	[2]	[2]	[2]	[2]
Life and other personal insurance[10]	129	121	119	129	121	119	[2]	[2]	[2]	[2]	[2]	[2]
Pensions and Social Security[10]	1,443	1,471	1,623	1,443	1,471	1,623	[2]	[2]	[2]	[2]	[2]	[2]
Cash contributions[10]	506	564	608	506	564	608	[2]	[2]	[2]	[2]	[2]	[2]
Income:												
CE-defined quarterly pretax income[12]	$20,726	$21,156	$21,890	$20,726	$21,156	$21,890	$20,726	$21,156	$21,890	$20,726	$21,156	$21,890
Census Bureau-defined quarterly pretax income[13]	$20,665	$21,094	$21,798	$20,665	$21,094	$21,798	$20,665	$21,094	$21,798	$20,665	$21,094	$21,798
Number of consumer units (in thousands)	132,068	131,542	133,653	132,068	131,542	133,653	132,068	131,542	133,653	132,068	131,542	133,653
Number of sample interviews	21,280	20,158	20,406	21,280	20,158	20,406	21,280	20,158	20,406	21,280	20,158	20,406
Consumer unit characteristics:												
Age of reference person	51.62	52.14	51.87	51.62	52.14	51.87	51.62	52.14	51.87	51.62	52.14	51.87
Average number in consumer unit:												
People	2.46	2.47	2.44	2.46	2.47	2.44	2.46	2.47	2.44	2.46	2.47	2.44

Category	Total expenditures			Total expenditures, excluding gifts			Consumption without health insurance			Consumption with health insurance uncapped		
	2019	2020	2021[1]	2019	2020	2021[1]	2019	2020	2021[1]	2019	2020	2021[1]
Children under 18	0.57	0.58	0.56	0.57	0.58	0.56	0.57	0.58	0.56	0.57	0.58	0.56
Adults 65 and older	0.4	0.42	0.42	0.4	0.42	0.42	0.4	0.42	0.42	0.4	0.42	0.42
Earners	1.3	1.29	1.28	1.3	1.29	1.28	1.3	1.29	1.28	1.3	1.29	1.28
Vehicles:												
Vehicles (owned)	1.84	1.82	1.8	1.84	1.82	1.8	1.84	1.82	1.8	1.84	1.82	1.8
Vehicles (leased)	0.08	0.08	0.07	0.08	0.08	0.07	0.08	0.08	0.07	0.08	0.08	0.07
Percent distribution:												
Reference person:												
Men	48	47	47	48	47	47	48	47	47	48	47	47
Women	52	53	53	52	53	53	52	53	53	52	53	53
Housing tenure:												
Homeowner	64	66	65	64	66	65	64	66	65	64	66	65
With mortgage	37	39	38	37	39	38	37	39	38	37	39	38
Without mortgage	27	27	27	27	27	27	27	27	27	27	27	27
Renter	34	33	33	34	33	33	34	33	33	34	33	33

[1] Data for 2021 are preliminary.

[2] Not applicable.

[3] For consumption, includes National School Lunch Program and Women, Infants, and Children program. Also includes an adjustment for board for students who report living in a dorm.

[4] For consumption, includes rental equivalence for primary residence.

[5] For consumption, includes market value of rental units. Consumer units residing in a college dorm were assigned the national average value for dorms based on data from the U.S. Department of Education.

[6] For consumption, includes rental equivalence for vacation homes. Consumption also includes an adjustment for expenditures on dorms for students who report living in a dormitory.

[7] For consumption, includes energy assistance using Low-Income Home Energy Assistance Program.

[8] Not included in consumption because considered part of education.

[9] Not included in consumption because considered part of rental equivalence and rent.

[10] Item not included in consumption.

[11] For consumption, only the imputation for the full value of health insurance is included. For 2021, the value of health insurance is based on 2020 imputations adjusted for inflation.

[12] Definition excludes food and rent as pay. This definition differs from the definition of income used in the published Consumer Expenditure Surveys tables, which includes food and rent as pay.

[13] Does not include the value of Supplemental Nutrition Assistance Program or food and rent as pay.

Source: U.S. Bureau of Labor Statistics.

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The poverty and inequality statistics presented in this article are meant to provide only an example of how the consumption measure can be used; BLS is not producing poverty or inequality statistics in an official capacity.

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Notes

1 The Luxembourg Income Study Database (LIS) and research series are excellent sources of information on income from household surveys; see the LIS Cross-National Data Center website at https://www.lisdatacenter.org/. For countries with developing economies, consumption and consumption expenditures are more meaningful concepts for household survey respondents than is income; thus, these measures are more often used for poverty and inequality analysis. See, for example, recent reports from the World Bank, including *Piecing Together the Poverty Puzzle*, Poverty and Shared Prosperity series (Washington, DC: World Bank, 2018), https://www.worldbank.org/en/publication/poverty-and-shared-prosperity-2018.

2 See Bruce D. Meyer and James X. Sullivan, “Consumption and income inequality in the United States since the 1960s,” *Journal of Political Economy*, vol. 131, no. 2, February 2023, https://doi.org/10.1086/721702; and Jonathan Fisher, David S. Johnson, and Timothy M. Smeeding, “Inequality of income *and* consumption in the U.S.: measuring the trends in inequality from 1984 to 2011 for the same individuals,” *Review of Income and Wealth*, vol. 61, no. 4, December 2015, pp. 630–50, https://doi.org/10.1111/roiw.12129. In addition, researchers have promoted the use of the joint distribution of income, consumption, and wealth as a better measure of well-being; see, for example, Jonathan D. Fisher, David S. Johnson, Timothy M. Smeeding, and Jeffrey P. Thompson, “Inequality in 3-D: income, consumption, and wealth,” *Review of Income and Wealth*, vol. 68, no, 1, March 2022, pp. 16–42, https://doi.org/10.1111/roiw.12509.

[3] See Fernando Rios-Avila, "Quality of match for statistical matches using the American Time Use Survey 2013, the Survey of Consumer Finances 2013, and the Annual Social and Economic Supplement 2014," Working Paper 914 (Annandale-on-Hudson, NY: Levy Economics Institute of Bard College, September 2018), https://www.levyinstitute.org/pubs/wp_914.pdf; Laura Wheaton, "Underreporting of means-tested transfer programs in the CPS and SIPP," Research Report (Washington, DC: Urban Institute, February 2008), https://www.urban.org/research/publication/underreporting-means-tested-transfer-programs-cps-and-sipp; Graton Gathright and Tyler Crabb, "Reporting of SSA program participation in SIPP," Working Paper (U.S. Census Bureau, 2014); Jonathan L. Rothbaum, "Comparing income aggregates: How do the CPS and ACS match the national income and product accounts, 2007–2012," SEHSD Working Paper 2015-01 (U.S. Census Bureau, January 14, 2015); https://www.census.gov/library/working-papers/2015/demo/SEHSD-WP2015-01.html; Bruce D. Meyer, Nikolas Mittag, and Robert M. Goerge, "Errors in survey reporting and imputation and their effects on estimates of Food Stamp Program participation," Working Paper 25143 (National Bureau of Economic Research, October 2018), https://doi.org/10.3386/w25143; and Bruce D. Meyer and Nikolas Mittag, "Using linked survey and administrative data to better measure income: implications for poverty, program effectiveness and holes in the safety net," *American Economic Journal: Applied Economics*, vol. 11, no. 2, April 2019, https://www.aeaweb.org/articles?id=10.1257/app.20170478.

[4] See Bruce D. Meyer and James X. Sullivan, "Measuring the well-being of the poor using income and consumption," *Journal of Human Resources*, vol. 38, Special Issue on Income Volatility and Implications for Food Assistance Programs, 2003, pp. 1180-1220 https://www.jstor.org/stable/3558985; Bruce D. Meyer and James X. Sullivan, "Viewpoint: Further evidence on measuring the well-being of the poor using income and consumption," *Canadian Journal of Economics*, vol. 44, no. 1, February 2011, pp. 52–87, https://www.jstor.org/stable/41336351; and Bruce D. Meyer and James X. Sullivan, "Identifying the disadvantaged: official poverty, consumption poverty, and the new Supplemental Poverty Measure," *Journal of Economic Perspectives*, vol. 26, no. 3, Summer 2012, pp. 111–36, https://doi.org/10.1257/jep.26.3.111.

[5] See, for example, the World Bank's Multidimensional Poverty Measure, which draws from other prominent poverty measures, particularly the Multidimensional Poverty Index (MPI) developed by the United Nations Development Programme and Oxford University, https://www.worldbank.org/en/topic/poverty/brief/multidimensional-poverty-measure; and "Measuring well-being and progress: well-being research" (Organisation for Economic Co-operation and Development), https://www.oecd.org/wise/measuring-well-being-and-progress.htm.

[6] In the U.S. Bureau of Labor Statistics (BLS) Consumer Expenditure Surveys (CE), a consumer unit is defined as follows: "A consumer unit comprises either: (1) all members of a particular household who are related by blood, marriage, adoption, or other legal arrangements; (2) a person living alone or sharing a household with others or living as a roomer in a private home or lodging house or in permanent living quarters in a hotel or motel, but who is financially independent; or (3) two or more persons living together who use their income to make joint expenditure decisions. Financial independence is determined by the three major expense categories: Housing, food, and other living expenses. To be considered financially independent, at least two of the three major expense categories have to be provided entirely, or in part, by the respondent." See "Consumer Expenditure Surveys: Glossary," entry for "consumer unit" (U.S. Bureau of Labor Statistics, last modified February 13, 2015), https://www.bls.gov/cex/csxgloss.htm.

[7] See Nancy Folbre, "Care data infrastructure: a U.S. case study," *Review of Income and Wealth*, January 2023 (online version of record before inclusion in an issue), https://doi.org/10.1111/roiw.12633.

[8] Although we cannot trace the origin of this assumption, we have found examples of expenditures being used as a proxy for consumption as far back as Hall (1978), Sargent (1978), and Hall and Mishkin (1982). These authors state that they use expenditures as a measure of consumption, but they do not provide any justification for doing so. The lack of justification suggests that using expenditures as a measure of consumption was an accepted idea at the time. See Robert E. Hall, "Stochastic implications of the life cycle-permanent income hypothesis: theory and evidence," *Journal of Political Economy*, vol. 86, no. 6, December 1978, pp. 971–87, https://www.journals.uchicago.edu/doi/10.1086/260724; Thomas J. Sargent, "Estimation of dynamic labor demand schedules under rational expectations," *Journal of Political Economy*, vol. 86, no. 6, December 1978, pp. 1009–44, https://www.journals.uchicago.edu/doi/10.1086/260726; and Robert E. Hall and Frederic S. Mishkin, "The sensitivity of consumption to transitory income: estimates from panel data on households," *Econometrica*, vol. 50, no. 2, March 1982, pp. 461–81, https://www.jstor.org/stable/1912638?seq=8.

[9] For a review of these early efforts, see David S. Johnson, John M. Rogers, and Lucilla Tan, "A century of family budgets in the United States," *Monthly Labor Review*, May 2001, https://www.bls.gov/opub/mlr/2001/05/art3full.pdf.

[10] For an updated version of the conceptual framework for the CE, see Scott Curtin, Adam Safir, Thesia I. Garner, Brett Matsumoto, and Jake Schild, "A conceptual framework for the U.S. Consumer Expenditure Surveys" (U.S. Bureau of Labor Statistics, last modified October 7, 2022), https://www.bls.gov/cex/research_papers/garner-et-al-conceptual-framework-for-CE.htm. An earlier version (September 2000) is available from the authors upon request.

[11] For a select list of references, see those listed in "Consumer Expenditure Surveys: Consumption Research" (U.S. Bureau of Labor Statistics, last modified December 27, 2022), https://www.bls.gov/cex/consumption-research.htm.

[12] Fisher, Johnson, and Smeeding, "Inequality of income and consumption in the U.S.: measuring the trends in inequality from 1984 to 2011 for the same individuals."

[13] See Bruce D. Meyer and James X. Sullivan, "Winning the war: poverty from the Great Society to the Great Recession," *Brookings Papers on Economic Activity*, Fall 2012, pp. 133–83, https://www.brookings.edu/bpea-articles/winning-the-war-poverty-from-the-great-society-to-the-great-recession/; and Bruce D. Meyer and James X. Sullivan, "Consumption and income inequality and the Great Recession," *American Economic Review*, vol. 103, no. 3, May 2013, pp. 178–83, https://www.aeaweb.org/articles?id=10.1257/aer.103.3.178.

[14] See Grayson Armstrong, Caleb Cho, Thesia I. Garner, Brett Matsumoto, Juan Munoz, and Jake Schild, "Building a consumption poverty measure: initial results following recommendations of a federal interagency working group," *AEA Papers and Proceedings*, vol. 112, May 2022, pp. 335–39, https://doi.org/10.1257/pandp.20221041.

[15] See *Final Report of the of the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty*, p. 29, https://www.bls.gov/evaluation/final-report-of-the-interagency-technical-working-group-on-evaluating-alternative-measures-of-poverty.pdf. Although most of the work of the group was completed in 2020, the report was posted to the BLS website in January 2021.

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[18] Tullio Jappelli and Luigi Pistaferri, *The Economics of Consumption: Theory and Evidence* (New York, NY: Oxford University Press, 2017).

[19] David M. Cutler and Lawrence F. Katz, "Macroeconomic performance and the disadvantaged," *Brookings Papers on Economic Activity*, vol. 1991, no. 2, 1991, pp. 1–74, https://doi.org/10.2307/2534589; and Daniel T. Slesnick, "The standard of living in the United States," *Review of Income and Wealth*, vol. 37, no. 4, December 1991, pp. 363–86, https://doi.org/10.1111/j.1475-4991.1991.tb00379.x.

[20] David S. Johnson, Timothy M. Smeeding, and Barbara Boyle Torrey, "Economic inequality through the prisms of income and consumption," *Monthly Labor Review*, April 2005, https://www.bls.gov/opub/mlr/2005/04/art2full.pdf; Dirk Krueger and Fabrizio Perri, "Does income inequality lead to consumption inequality? Evidence and theory," *Review of Economic Studies*, vol 73, no. 1, January 2006, pp. 163–93, https://doi.org/10.1111/j.1467-937X.2006.00373.x; Orazio Attanasio, Erich Battistin, and Hidehiko Ichimura, "What really happened to consumption inequality in the United States?," in Ernst R. Berndt and Charles R. Hulten, eds., *Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches*, National Bureau of Economic Research Studies in Income and Wealth, vol. 67 (Chicago, IL: University of Chicago Press, 2007); Jonathan Heathcote, Fabrizio Perri, and Giovanni Violante, "Unequal we stand: an empirical analysis of economic inequality in the United States, 1967–2006," *Review of Economic Dynamics*, vol. 13, no. 1, January 2010, pp. 15–51, https://doi.org/10.1016/j.red.2009.10.010; Mark A. Aguiar and Mark Bils, "Has consumption inequality mirrored income inequality," Working Paper 16807 (Cambridge, MA: National Bureau of Economic Research, February 2011), https://doi.org/10.3386/w16807; Olivier Coibion, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia, "Innocent bystanders? Monetary policy in the U.S.," Working Paper 18170 (Cambridge, MA: National Bureau of Economic Research, June 2012), https://doi.org/10.3386/w18170; and Orazio Attanasio, Erik Hurst, and Luigi Pistaferri, "The evolution of income, consumption, and leisure inequality in the U.S., 1980–2010," Working Paper 17982 (Cambridge, MA: National Bureau of Economic Research, April 2012), https://doi.org/10.3386/w17982.

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[22] See the following sources for the international publications: *Report II: Household Income and Expenditure Statistics*, Seventeenth International Conference of Labour Statisticians, November 24–December 3, 2003 (International Labour Organization, 2003), https://www.ilo.org/public/libdoc/ilo/2003/103B09_182_engl.pdf; *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth* (Paris: Organisation for Economic Co-operation and Development, 2013), https://dx.doi.org/10.1787/9789264194830-en; United Nations Economic Commission for Europe, *Guide on Poverty Measurement* (New York: United Nations, 2017), https://unece.org/DAM/stats/publications/2018/ECECESSTAT20174.pdf; and Giulia Mancini and Giovanni Vecchi, *On the Construction of a Consumption Aggregate for Inequality and Poverty Analysis* (Washington, DC: The World Bank, March 2022), https://documents1.worldbank.org/curated/en/099225003092220001/pdf/P1694340e80f9a00a09b20042de5a9cd47e.pdf. For further background information, see the following two studies cited in the World Bank report: Angus Deaton and Salman Zaidi, "Guidelines for constructing consumption aggregates for welfare analysis," Living Standards Measurement Study Working Paper 135 (Washington, DC: The World Bank, May 2002), https://documents1.worldbank.org/curated/en/206561468781153320/pdf/Guidelines-for-constructing-consumption-aggregates-for-welfare-analysis.pdf; and Jean Olson Lanjouw and Peter Lanjouw, "How to compare apples and oranges: poverty measurement based on different definitions of consumption," *Review of Income and Wealth*, vol. 47, no. 1, March 2001, pp. 25–42, https://doi.org/10.1111/1475-4991.00002.

[23] See *Final Report of the of the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty*. See also Bruce Meyer and David Johnson, "Poverty measurement for the next generation: findings from the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty," W75-2021, webinar from Institute for Research on Poverty, University of Wisconsin-Madison, April 21, 2021, https://www.irp.wisc.edu/resource/poverty-measurement-for-the-next-generation-findings-from-the-interagency-technical-working-group-on-evaluating-alternative-measures-of-poverty/

[24] See Curtin et al., "A conceptual framework for the U.S. Consumer Expenditure Surveys."

[25] Not collected in the Interview but in the Diary are items such as postage and prescription drugs.

[26] The definition of pretax income used in the microdata differs from the definition of pretax income used in the published CE tables. Specifically, the definition used in the published CE tables includes income from food and rent as pay, whereas the microdata definition of pretax income does not include these sources of income. Both definitions include Supplemental Nutrition Assistance Program (SNAP) benefits.

[27] See "Income and Poverty" (U.S. Census Bureau, last modified July 6, 2022), https://www.census.gov/topics/income-poverty.html.

[28] See *Report II: Household Income and Expenditure Statistics* (International Labour Organization); *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*; and *Final Report of the of the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty*.

[29] For owned primary residences and owned vacation homes, we use the CE variable that is created for use in the production of the CPI based on quarterly rental equivalence values adjusted for ownership. For owned timeshares, we use the same comparable variable but with the addition of an adjustment for duration of usage.

[30] See *Final Report of the of the Interagency Technical Working Group on Evaluating Alternative Measures of Poverty*.

[31] Meyer and Sullivan, "Winning the war: poverty from the Great Society to the Great Recession"; Meyer and Sullivan, "Consumption and income inequality and the Great Recession"; and Johnson and Smeeding, "Inequality of income and consumption in the U.S.: measuring the trends in inequality from 1984 to 2011 for the same individuals."

[32] In addition to the differences noted above, there are also differences regarding the samples used to create the consumption measures. For example, Meyer and Sullivan included consumer units that participated in the CE Interview during quarters that correspond to a calendar year (e.g., they use CE Interview data collected in the first calendar quarter of 2019 through the fourth calendar quarter of 2019 for their 2019 consumption measure). Fisher, Johnson, and Smeeding restrict their sample to only those respondents with four consecutive interviews and create annual consumption values by summing the quarterly values. Specifically, the estimation sample includes consumer units whose last interview was between April of the current year and March of the following year, with the restriction that there were to be four interviews (e.g., 2009 annual estimates of consumption are estimated as the sum of quarterly values, with their last interview as early as April 2009 or as late as March 2010). For the BLS measure, we base our sample on CE interviews conducted in the second quarter of the current calendar year through the first quarter of the following calendar year to create quarterly measures of consumption for the current year (e.g., we use CE Interview data collected from second quarter 2019 through first quarter 2020 for our 2019 consumption measure). Data collected in each calendar quarter reference expenditures made during the previous 3 months; for example, data collected in the second quarter of 2019 refer to expenditures made in the period from January through March 2019. Thus, our measure covers expenditures from January of the current year through February of the following year (i.e., the 2019 consumption measure covers January 2019 through February of 2020).

[33] Meyer and Sullivan, "Winning the war: poverty from the Great Society to the Great Recession"; Meyer and Sullivan, "Consumption and income inequality and the Great Recession"; and Fisher, Johnson, and Smeeding, "Inequality of income and consumption in the U.S."

[34] Meyer and Sullivan, "Winning the war: poverty from the Great Society to the Great Recession"; Meyer and Sullivan, "Consumption and income inequality and the Great Recession."

[35] Ibid.

[36] Fisher, Johnson, and Smeeding, "Inequality of income and consumption in the U.S."

[37] Meyer and Sullivan, "Winning the war: poverty from the Great Society to the Great Recession"; Meyer and Sullivan, "Consumption and income inequality and the Great Recession."

[38] The Interagency Technical Working Group on Evaluating Alternative Measures of Poverty (ITWG) recommends that health insurance be no more than half of total consumption. We chose to use 50 percent, rather than 30 percent or some other value, because it is the least binding cap that is still consistent with the ITWG recommendations.

[39] Fisher, Johnson, and Smeeding, "Inequality of income and consumption in the U.S."

[40] This discrepancy occurs because the published tables use integrated data from both the Interview and Diary Surveys, whereas the results presented in this article are strictly based on the Interview Survey. Additionally, the published tables show calendar-year estimates—meaning, the expenditures used in the calculation are all within a specified calendar year. This study defines the measure on the basis of a collection year, which we defined as the second quarter of a specified year through the first quarter of the following year; therefore, the quarterly average means also include expenditures from outside a given calendar year. Finally, the adjustment to the quarterly weights, in order to produce the publication tables, is not exactly equivalent to the adjustment made in this study.

[41] For example, see table 1800, "Region of residence: Annual expenditure means, shares, standard errors, and coefficients of variation, Consumer Expenditure Surveys, 2021," https://www.bls.gov/cex/tables/calendar-year/mean-item-share-average-standard-error/cu-region-1-year-average-2021.pdf. Food and rent as pay are included in the "other income" category in the table.

[42] This equivalence is the same one used by BLS to produce the Supplemental Poverty Measure (SPM) thresholds. See "Price and Index Number Research: 2021 Research Supplemental Poverty Measure Thresholds" (U.S. Bureau of Labor Statistics, last modified June 23, 2022), https://www.bls.gov/pir/spm/spm_thresholds_2021.htm.

[43] See "Consumer Price Index: Chained Consumer Price Index For All Urban Consumers (C-CPI-U)" (U.S. Bureau of Labor Statistics, last modified December 3, 2021), https://www.bls.gov/cpi/additional-resources/chained-cpi.htm.

[44] For further evidence of the impact of the pandemic, see "Changes to expenditures during the COVID-19 pandemic," *The Economics Daily*, May 3, 2022, https://www.bls.gov/opub/ted/2022/changes-to-consumer-expenditures-during-the-covid-19-pandemic.htm: "After the COVID-19 pandemic began, consumer spending in the second quarter of 2020 was down 9.8 percent from the same period in 2019. One year later, in the second quarter of 2021, the pandemic was still affecting the economy, but businesses and consumers had begun to adapt. That resulted in consumer expenditures that were 15.7 percent higher in the second quarter of 2021 than a year earlier."

[45] These contrast with estimates of poverty rates based on CE pretax income data and official poverty thresholds; rates are estimated to be 12.2 percent for 2019, 11.4 percent for 2020, and 11.7 percent for 2021. These rates are not much higher than the rates based on the relative thresholds and consumption with health insurance, both capped and uncapped. The CE-based income poverty rates using official thresholds are similar to the official poverty rates published by the U.S. Census Bureau.

[46] In this study, we do not examine whether the differences in poverty rates are statistically significant because no standard errors have been produced for these measures. BLS expects to produce standard errors for them in the future.

[47] This result is in line with the change in child poverty as measured by the SPM. See Kalee Burns and Liana E. Fox, "The impact of the 2021 expanded Child Tax Credit on child poverty," SEHSD Working Paper 2022-24 (U.S. Census Bureau, November 22, 2022), https://www.census.gov/content/dam/Census/library/working-papers/2022/demo/sehsd-wp2022-24.pdf.

[48] Receipt of these payments resulted in increased expenditures, which will lead to an increase in consumption. See Jonathan Parker, Jake Schild, Laura Erhard, and David Johnson, "Economic Impact Payments and household spending during the pandemic," *Brookings Papers on Economic Activity: BPEA Conference Drafts, September 8–9, 2022* (Washington, DC: Brookings Institution, August 2022), https://www.brookings.edu/wp-content/uploads/2022/09/Parker-et-al-BPEA-Conference-Draft-BPEA-FA22.pdf; and Sophie M. Collyer, Thesia Garner, Neeraj Kaushai, Jiwan Lee, Jake Schild, Jane Waldfogel, and Christopher T. Wimer, "Effects of the expanded Child Tax Credit on household expenditures: preliminary intent-to-treat estimates from the Consumer Expenditure Survey," BLS Working Paper 549 (U.S. Bureau of Labor Statistics, April 2022), https://www.bls.gov/osmr/research-papers/2022/pdf/ec220040.pdf.

[49] This release would be similar to the release of state weights for the CE public-use data file. See "CE research products: State Weight files" (U.S. Bureau of Labor Statistics, last modified May 6, 2022), https://stats.bls.gov/cex/csxresearchtables.htm#stateweights.

[50] The imputations of National School Lunch Program (NSLP) and Women Infants and Children (WIC) benefits that we use in this article are similar to those developed by Garner and Gudrais; however, for the Low-Income Home Energy Assistance Program (LIHEAP), the methods differ. Garner and Gudrais did not use the reported LIHEAP values from the Current Population Survey Annual Social and Economic Supplement (CPS ASEC); rather, they assigned benefits based on heating and cooling degree days by geography. See Thesia I. Garner and Marisa Gudrais, "Alternative poverty measurement for the U.S.: Focus on Supplemental Poverty Thresholds." Working Paper 510 (U.S. Bureau of Labor Statistics, September 25, 2018). https://www.bls.gov/osmr/research-papers/2018/pdf/ec180100.pdf. References to earlier work that focused on estimating and including in-kind benefits in SPM thresholds follow: Thesia I. Garner, Marisa Gudrais, and Kathleen S. Short, "Consistency in Supplemental Poverty Measurement: adding imputed in-kind benefits to thresholds and impact on poverty rates for the United States," Working Paper (U.S. Bureau of Labor Statistics, October 2015), https://www.bls.gov/osmr/research-papers/2015/st150120.htm; Thesia I. Garner and Charles Hokayem, "Supplemental Poverty Measure thresholds: imputing School Lunch and WIC benefits to the Consumer Expenditure Survey using the Current Population Survey," Working Paper 457 (U.S. Bureau of Labor Statistics, July 2012), https://www.bls.gov/osmr/research-papers/2012/ec120060.htm; and Thesia I. Garner and Charles Hokayem. Supplemental Poverty Measure thresholds: imputing noncash benefits to the Consumer Expenditure Survey Using Current Population Survey—Parts I and II," Working Paper, (U.S Bureau of Labor Statistics, 2011), https://www.bls.gov/osmr/research-papers/2011/st110100.htm.

[51] The U.S. Census Bureau research focuses on the assignment of NSLP benefits to CPS ASEC households to produce the SPM resource measure. See the following research papers for the methods used to produce NSLP benefits during the COVID-19 pandemic: Em Shrider, "Alternative school lunch valuation in the CPS ASEC during COVID-19," SEHSD Working Paper 2021-20 (U.S. Census Bureau, September 2021), https://www.census.gov/library/working-papers/2021/demo/SEHSD-WP2021-20.html; and Shrider, "School lunch and P-EBT valuation in the 2021 Supplemental Poverty Measure," SEHSD Working Paper 2022-15 (U.S. Census Bureau, September 2022), https://www.census.gov/library/working-papers/2022/demo/SEHSD-wp2022-15.html. To see the impact on poverty rates of including imputed in-kind benefits in resources, see John Creamer, Emily A. Shrider, Kalee Burns, and Frances Chen, *Poverty in the United States: 2021*, Current Population Reports, P60-277 (U.S. Census Bureau, September 2022), https://www.census.gov/content/dam/Census/library/publications/2022/demo/p60-277.pdf.

[52] According to Em Shrider of the U.S. Census Bureau, when the March 2020 CPS ASEC was administered (with reference period 2019), if the respondent asked, "'Usually'?" or "What do you mean by 'usually'?" the field representative (FR) would explain that it meant more than 50 percent of the time. For the CPS ASEC administered in March 2021 (reference period 2020) and March 2022 (reference period 2021), the FR notes say that the word "usually" refers to days when school was held in person, such as during the prepandemic period, or in areas where schools remained open during the pandemic. These directions are in the FR notes and are presented during training, but they are not made available to the public. Emily A. Shrider, email communication with Thesia I. Garner, March 29, 2023.

[53] A monotone regression method is used to impute NSLP, WIC, and LIHEAP participation and ordinary least squares regression is used to impute LIHEAP benefits to the CE. We use SAS PROC MI for these imputations. For program participation, after the predicted probabilities are produced, a random number is then drawn for each respondent and imputation. If the random number is less than the participation probability, the respondent is identified as participating in the respective program. For example, suppose the estimated model predicts that consumer unit *j* has a 20-percent chance of participating in the NSLP. The SAS procedure will draw a random uniform [0,1] variable *u*. If *u* is less than 0.2, consumer unit *j* will be assigned a value of 1, and if *u* is greater than 0.2, consumer unit *j* will be assigned a value of 0. SAS repeats this for every observation with missing values for NSLP. See "The MI procedure," chap. 2 in *SAS/STAT 14.1 User's Guide* (Cary, NC: SAS Institute, 2015), https://support.sas.com/documentation/onlinedoc/stat/141/mi.pdf.

[54] Although NSLP benefits are based on data from the U.S. Department of Agriculture (USDA), the benefit values that we use are those calculated by the Census Bureau and combine the NSLP values for meal reimbursement, bonus commodities, and entitlements. For USDA information about these programs, see "National School Lunch Programs: Rates of Reimbursement" (U.S. Department of Agriculture, Food and Nutrition Service, last modified July 26, 2022), https://www.fns.usda.gov/cn/rates-reimbursement; and "USDA Foods in Schools: Value of Donated Foods Notices" (U.S. Department of Agriculture, Food and Nutrition Service, last modified December 26, 2019), https://www.fns.usda.gov/usda-fis/value-donated-foods-notices. The USDA values are presented by academic year; the Census Bureau uses data from 2 academic years to produce benefit values that align more closely with a calendar year.

[55] Shrider, "Alternative school lunch valuation in the CPS ASEC during COVID-19"; see note in figure 1, p. 7.

[56] For the estimation of 2019 NSLP benefits in the consumption measure, we use the average number of school days in the 2018–19 academic year, by state. For the most recent data available relative to 2019, see table 234.20, "Minimum amount of instructional time per year and policies on textbooks, by state: selected years, 2000 through 2020," in *Digest of Education Statistics: 2019* (National Center for Education Statistics, February 2021), https://nces.ed.gov/programs/digest/d19/tables/dt19_234.20.asp .

[57] Shrider, "Alternative school lunch valuation in the CPS ASEC during COVID-19"; and Shrider, "School lunch and P-EBT valuation in the 2021 Supplemental Poverty Measure."

[58] Ibid. In contrast to the treatment of NSLP benefits that are administered by electronic benefit transfer (EBT) being set to zero, when producing the SPM resource measure, the Census Bureau method assigns NSLP benefits that were administered by EBTs during months when schools were assumed to be closed.

[59] See "WIC EBT Activities" (U.S. Department of Agriculture, Food and Nutrition Service, last updated December 2022), https://www.fns.usda.gov/wic/wic-ebt-activities.

[60] This fraction is calculated as the number of WIC infants who are fully formula fed divided by the total number of infants participating in WIC. As evidence that most WIC infants are formula fed and receive the fully formula-fed package and not the partially formula-fed package, in their 2018 food package report, authors Nicole Kline, Kevin Meyers Mathieu, Jeff Marr write, "Fully formula-fed packages were prescribed for 30.9 to 66.0 percent of infants younger than 6 months old (800 ounces or more), and 54.5 percent of infants aged 6 months or older (at least 600 ounces). Quantities prescribed in the fully formula-fed [full nutrition benefit to maximum monthly allowance] ranges were most common across all infant age groups. Partially breastfed packages were prescribed for 8.5 percent of 0- to 0.9-month-old infants (less than 200 ounces), 13.7 percent of 1- to 3.9-month-old infants and 10.9 percent of 4- to 5.9-month-old infants (at least 200 but less than 600 ounces), and 4.8 percent of infants aged 6 months or older (at least 200 but less than 400 ounces)." See Kline, Mathieu, and Marr, *WIC Participant and Program Characteristics 2018 Food Packages and Costs Report* (Alexandria, VA: U.S. Department of Agriculture, Food and Nutrition Service, 2020), p. 21, https://fns-prod.azureedge.us/sites/default/files/resource-files/WICPC2018FoodPackage-1.pdf.

[61] For 2019 through 2021, see "WIC Data Tables: Monthly Data—State Level Participation by Category and Program Costs" (U.S. Department of Agriculture, Food and Nutrition Service, last updated February 10, 2023), https://www.fns.usda.gov/pd/wic-program.

[62] In the CE, owners are asked the following question: "If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?" To derive the quarterly consumption of owner-occupied shelter using responses to this question, we multiply by 3.

[63] The data we used are from table 330.10, "Average undergraduate tuition and fees and room and board rates charged for full-time students in degree-granting postsecondary institutions, by level and control of institution: 1963–64 through 2015–16," *Digest of Education Statistics: 2016* (National Center for Education Statistics, February 2018), https://nces.ed.gov/programs/digest/d16/tables/dt16_330.10.asp.

[64] Thesia I. Garner, Robert S. Martin, Brett Matsumoto, and Scott Curtin, "Distribution of U.S. personal consumption expenditures for 2019: a prototype based on Consumer Expenditure Survey data," Working Paper 557 (U.S. Bureau of Labor Statistics, August 8, 2022), https://www.bls.gov/osmr/research-papers/2022/ec220120.htm.

[65] For example, care provided in government-operated facilities is out of scope in the personal consumption expenditures data, so the imputed values for Department of Veterans Affairs (VA) services, TRICARE (the health care program for uniformed service members, retirees, and their families), and Indian Health Services (IHS) only include the cost of care purchased from private providers. By contrast, the cost of the care provided in government facilities is in scope for the BLS consumption measure presented in this article. For more information on the personal consumption expenditures data, see "Consumer Spending" (U.S. Bureau of Economic Analysis, last updated February 24, 2023), https://www.bea.gov/data/consumer-spending/main.

[66] See "Medical Expenditure Panel Survey Insurance Component" (Agency for Healthcare Research and Quality), https://datatools.ahrq.gov/meps-ic.

[67] See U.S. Department of Health and Human Services, Centers for Medicare & Medicaid Services, https://www.cms.gov/.

[68] Ibid.

[69] For budget information on TRICARE, see "Under Secretary of Defense (Comptroller): Defense Budget Materials" (U.S. Department of Defense, last updated April 12, 2022), https://comptroller.defense.gov/Budget-Materials/; for VA benefits, see *Department of Veterans Affairs FY2022 Appropriations*, Report 46964 (Congressional Research Service, last updated June 28, 2022), https://crsreports.congress.gov/product/pdf/R/R46964; for IHS benefits, see U.S. Department of Health and Human Services, Indian Health Services, "Congressional Justifications," https://www.ihs.gov/budgetformulation/congressionaljustifications/.

[70] See "Economic Research," Federal Reserve Bank of St. Louis, https://fred.stlouisfed.org.

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April 2023

COVID-19 and employment outcomes of people with disabilities

Summary written by: Yavor Ivanchev

During economic downturns, people with disabilities suffer more severe labor market impacts than their counterparts without disabilities. During the 2007–09 Great Recession, for example, job losses were more prevalent among people with disabilities, and the postrecession employment recovery for that group was markedly slower. But did the same predicament reemerge during and after the 2020 recession caused by the COVID-19 pandemic?

This is the question addressed in Ari Ne'eman and Nicole Maestas' recent article titled "How has COVID-19 impacted disability employment?" (National Bureau of Economic Research, Working Paper 30640, November 2022). The authors note that, in theory, the effects of COVID-19 on the employment experiences of people with disabilities are not clear cut. On the one hand, fear of viral exposure in face-to-face interactions, coupled with job discrimination, may have put workers in this group at a disadvantage in the labor market. On the other hand, pandemic-induced increases in the use of telework, together with tight postrecession labor market conditions, may have given those workers a much-needed employment boost.

Considering these possibilities, the authors use data from the Current Population Survey to examine employment trends for people with and without disabilities before, during, and after the COVID-19 recession, focusing on the period from the first quarter of 2020 to the second quarter of 2022. The main dependent variable in the analysis is the employment-to-population ratio (employment rate) for each group, with the numerator of that variable capturing only people who are both employed and "at work" (rather than individuals who may be employed but furloughed). The authors' models also include a series of demographic control variables (age, gender, race, and education) and capture differences across occupational types (essential jobs, teleworkable jobs, etc.).

The empirical results presented in the article differ sharply from those reported for previous recessions, indicating that people with disabilities may have reaped employment benefits from the transformational effects of the pandemic. Although people with and without disabilities both experienced significant declines in their employment rates in the first half of 2020, the former's rate saw a strong recovery in the subsequent 2 years. By the second quarter of 2022, that rate had exceeded its prepandemic level by nearly 3.6 percentage points, whereas the rate for people without disabilities stood about 0.5 percentage point below the level recorded before the pandemic. Over the recovery period, people with disabilities also experienced faster employment growth in percent terms and a stronger rebound in their labor force participation rate.

Another important result reported in the article is that the relatively faster employment recovery for people with disabilities was driven mainly by those employed in essential, nonfrontline occupations amenable to telework. According to the authors, this finding indicates that this group of workers benefited from the sharp expansion of telework after the pandemic hit. However, the authors caution that it remains unclear how much of the group's employment recovery could be attributed to an increase in the number of people who became disabled because of the adverse health effects of the pandemic.

ARTICLE

April 2023

Federal government wage indexes

For nearly 50 years, the Employment Cost Index (ECI) has been providing the public with estimates of the change in employer labor costs. We explore the practicality of constructing federal wage indexes, in the spirit of the ECI, using Office of Personnel Management (OPM) salary data. To accomplish this task, we aggregate OPM records into occupation and industry groups. Although these salary data have a crosswalk for mapping OPM occupation codes into the Standard Occupational Classification system, no corresponding crosswalk exists for industries. A key hurdle, therefore, involves creating a crosswalk that assigns industry codes to OPM establishments. We create this crosswalk by developing an algorithm that uses Quarterly Census of Employment and Wages data and machine-learning tools to match agencies with a unique industry. With this agency-North American Industry Classification System crosswalk, we calculate annual Laspeyres, Paasche, and Fisher wage indexes for several aggregations. The resulting wage inflation rates are plausible and do not deviate substantially from the corresponding private industry and state and local wage inflation rates.

The Employer Cost Index (ECI) of the National Compensation Survey (NCS) has provided the public with estimates of changes in labor costs since December 1975. At the ECI launch, only private industry estimates were published; however, in June 1981, ECI expanded to include state and local government workers. The federal government, despite being the largest U.S. employer with over 3 million employees (see table 1), is presently out of scope for NCS data products. This article explores, as a proof of concept, the practicality of constructing federal wage indexes using Office of Personnel Management (OPM) salary data. Since this analysis is purely exploratory, we do not attempt to fully replicate ECI methodology, but instead use it as a guide.

Table 1. Number and percentage of civilian federal workers, by occupation and industry, second quarter of 2020, 2021, and 2022

Category	2020 second quarter		2021 second quarter		2022 second quarter	
	Number	Percent	Number	Percent	Number	Percent
Occupation						
Management, business, and financial	1,588,381	49.6	1,608,050	49.5	1,604,617	50.0
Professional and related	924,123	28.9	949,506	29.2	940,476	29.3
Sales and related	10,908	0.3	10,279	0.3	9,330	0.3
Office and administrative support	301,965	9.4	304,487	9.4	293,667	9.1
Service	251,655	7.9	255,296	7.9	244,730	7.6
Construction, extraction, farming, fishing and forestry	17,075	0.5	16,680	0.5	16,408	0.5
Installation, maintenance and repair	18,298	0.6	18,862	0.6	18,380	0.6
Production	12,549	0.4	12,496	0.4	12,115	0.4
Transportation and material moving	75,143	2.3	74,427	2.3	71,750	2.2
Industry						
Wholesale and retail trade	37,199	1.2	36,203	1.1	35,752	1.1
Transportation and warehousing	7,123	0.2	7,117	0.2	7,345	0.2
Elementary and secondary schools	9,012	0.3	9,176	0.3	9,299	0.3
Colleges, universities, and professional schools	3,273	0.1	3,330	0.1	2,774	0.1
Hospitals	39,908	1.2	40,945	1.3	49,224	1.5
Nursing and residential care facilities	875	0.0	878	0.0	852	0.0
Rest of health services	5,975	0.2	6,174	0.2	6,126	0.2
Rest of services	80,381	2.5	82,526	2.5	83,502	2.6
Public administration	3,005,275	93.9	3,052,558	93.9	3,005,394	93.6
Goods producing	11,076	0.3	11,176	0.3	11,205	0.3
Work schedule						
Full time	3,097,080	96.8	3,147,790	96.9	3,115,654	97.0
Part time	103,017	3.2	102,293	3.1	95,819	3.0
Total	3,200,097	100.0	3,250,083	100.0	3,211,473	100.0

Source: Authors' calculations using data from the Office of Personnel Management.

To construct federal wage indexes, we must overcome one major hurdle: records from the OPM data must be categorized into industry (see appendix table A-1) and occupation groups (see appendix table A-2) that are consistent with NCS aggregations used for the ECI.[1] The latter is straightforward because the U.S. Bureau of Labor Statistics (BLS) uses a crosswalk classification system to map OPM occupations into the Standard Occupational Classification (SOC) system. The former, in contrast, is more difficult because the OPM data do not contain industry codes. To address this problem, we use the department and agency information in the OPM data and machine-learning tools to match OPM and Quarterly Census of Employment and Wages (QCEW) establishments.[2] An algorithm is developed to select a unique North American Industry Classification System (NAICS) code for each agency observed in the OPM data. This final mapping yields a desired agency-to-NAICS crosswalk that we use to calculate Laspeyres, Paasche, and Fisher wage indexes for a variety of aggregations.[3]

Wage index number formulas

We have many index number formulas to choose from, including the commonly used Laspeyres and Paasche indexes and the less commonly used Dutot or Jevons indexes.[4] For exploratory purposes and brevity, we focus on the Laspeyres, Paasche, and Fisher indexes.

Given wages and employment for periods 0 (base period) and 1 (comparison period), the Laspeyres and Paasche wage index number formulas use a fixed "basket" of jobs (employment) to compute the ratio of total wage costs for period 1 to total wage costs for period 0. The Laspeyres index uses the fixed basket to be period-0 employment, whereas the Paasche index uses the fixed basket to be period-1 employment. These formulas are given by

$$I_L = \sum_{i=1}^{n} s_i^0 \frac{w_i^1}{w_i^0}$$

and

$$I_P = \left(\sum_{i=1}^{n} s_i^1 \left(\frac{w_i^1}{w_i^0} \right)^{-1} \right)^{-1},$$

where I_L and I_P are the Laspeyres and Paasche indexes, w_i^t is hourly wage, s_i^t is the expenditure share, and *i* is job 1, 2, ..., *n*. The expenditure share is given by

$$s_i^t = \frac{w_i^t e_i^t}{\sum_{j=1}^{n} w_j^t e_j^t},$$

where e_i^t is employment, *i* and *j* are jobs $1, 2, \ldots, n$, and *t* is period 0,1.[5] In theory, employers can be expected to substitute away from more expensive workers. Since the Laspeyres index uses a period-0 fixed-employment basket, the Laspeyres index theoretically overstates wage inflation. Conversely, since the Paasche index uses a period-1 fixed-employment basket, the Paasche index theoretically understates wage inflation.

The Fisher wage index is given by the geometric mean of the Laspeyres and Paasche indexes as

$$I_F = \sqrt{I_L I_P}\ .$$

Along with the Törnqvist index, the Fisher index is considered to be "superlative," with a base and comparison period treated symmetrically to better capture labor substitution effects.[6]

Data

BLS has four quarters of OPM data: first quarter of 2019 and second quarter of 2020, 2021, and 2022. For this analysis, we omit the data from the first quarter of 2019 for two reasons. First, 2019 (first quarter) to 2020 (second quarter) straddled the start of the COVID-19 pandemic, which saw large and uncharacteristic changes in the labor market. Second, 2019 (first quarter) to 2020 (second quarter) was a five-quarter period that included two federal salary increases. The data cover workers employed at the end of each quarter. Note that the data are reported to OPM by human resource offices across the federal government and may be subject to some error. If the federal workforce were incorporated into the ECI, data would need to be collected quarterly from OPM.

OPM data include individual federal employees, annual salary, OPM occupation, full-time or part-time status,[7] grade, agency, city, and state. BLS's OPM data include workers on military bases (which we exclude) but not postal service employees.[8] These data do not include any benefit-cost data (e.g., health insurance, retirement, nonproduction bonuses). All salaries are given as annual full-time salaries, so hourly wages are computed by dividing salary by 2,087.[9] Missing from OPM data are industry data (NAICS codes), so we use QCEW data and some machine-learning tools to construct an agency-to-NAICS concordance.

Also missing from the OPM data are establishment identifiers. So, we identify them by what we observe: agency, city, and state data, which can be used as imperfect proxies for an establishment. When an agency has just a single establishment within a city, city and state work as a perfect proxy. But if an agency has multiple establishments within a city, city and state are imperfect because multiple establishments are identified as a single establishment.

With an agency-to-NAICS crosswalk and a method for identifying establishments, we then map SOC and NAICS codes into occupation and industry groups (sometimes referred to as pseudo-SOC [PSOC] and pseudo-NAICS [PNAICS]). (See appendix tables A-1 and A-2.) Mean wages and total employment are computed for each basic ECI cell (a grouping by PSOC, PNAICS, and job) or subcell (a grouping by PSOC, PNAICS, subcell category, and job). Summary statistics, including employment counts and percentages of total employment from the OPM, are presented in table 1.

Since this analysis is purely exploratory, we do not attempt to reproduce the method for computing the ECI but instead use its basic conceptual framework for computing wage cost indexes for common index number formula.[10] For the ECI, the unit of observation is a quote (such as an establishment, occupation, work status, or grade). These quotes are aggregated into cells consisting of an ownership sector, industry group (PNAICS), and occupation group (PSOC). Cells can be further divided into subcells that may include full- or part-time status, region, division, union status, and so forth.

NAICS codes

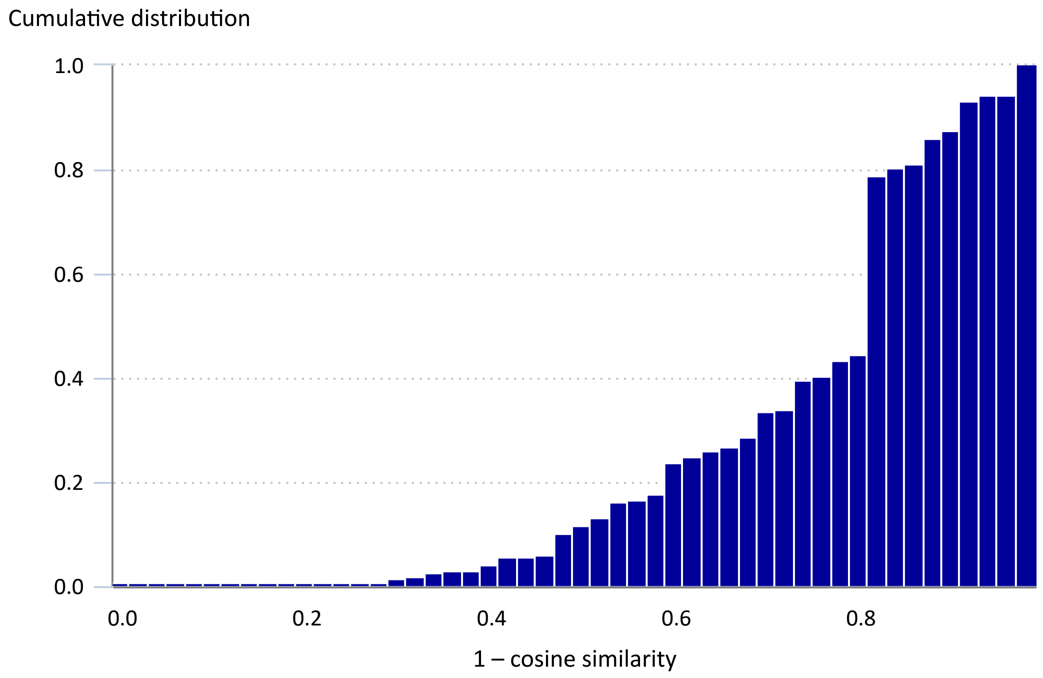
Missing from the OPM data are NAICS codes. We construct an agency-to-NAICS crosswalk using QCEW-reported NAICS codes for federal government establishments. The OPM data have standardized, descriptive text for each department and agency. In the QCEW, the department, agency, and NAICS codes are reported individually by each establishment. These reports are subject to variations in establishment practice and can include spelling errors and varying abbreviations. For these reasons, matching the OPM establishments with QCEW establishments is not straightforward.

To construct an agency-to-NAICS crosswalk, we begin by aggregating individual employee data in the OPM data to agency by location. We then match each OPM agency and location with each QCEW establishment by year or quarter, state, and county. For each of these matches, cosine similarities are then calculated for term frequency–inverse document frequency (or TF–IDF) vectorized department descriptions and agency descriptions. This approach essentially amounts to the construction of a cardinal measure of similarity between two vectors. A number of options exist for constructing these vectors for a given match's descriptions. We have explored bag-of-words unigrams (an unordered list of the individual words from the descriptions) and character n-grams (a contiguous sequence of *n* characters from a piece of text). We ultimately chose character n-grams because they account for the issue of spelling errors or variations. A key problem with selecting a vectorization strategy is the lack of an objective standard. That is, in the absence of an objective standard, any choice between vectorization strategies possesses some level of arbitrariness.

For a given vectorizer, we use the mean of the cosine similarities for department and agency, weighting by QCEW-reported mean employment and upweighting and downweighting by the relative deviation between employee counts in the OPM establishment-level data and QCEW-reported mean employment. We assume here that larger establishments are more reliable but may also be "punished" for large differences in the reporting of a variable that should be similar. The QCEW department or agency with the best weighted cosine similarity is chosen as the match.

Finally, since each department or agency should uniquely match a NAICS code, we compare the weighted cosine similarity among all establishments for a department or agency and select the NAICS code for the establishment with the best matching weighted cosine similarity. As constructed, the crosswalk is not without flaws, with a mean agency-size weighted score of 0.76 (standard deviation 0.161) and ranging from nearly the worst (0.002) to the best (1.000). The cumulative distribution of cosine similarity scores, weighted by agency size (see chart 1), shows that the bulk of matches are fairly reliable (>0.8), with very few that are clearly unreliable (<0.4). Moreover, the federal government distribution of PNAICS in the OPM dataset roughly matches that for the QCEW data (see chart 2).

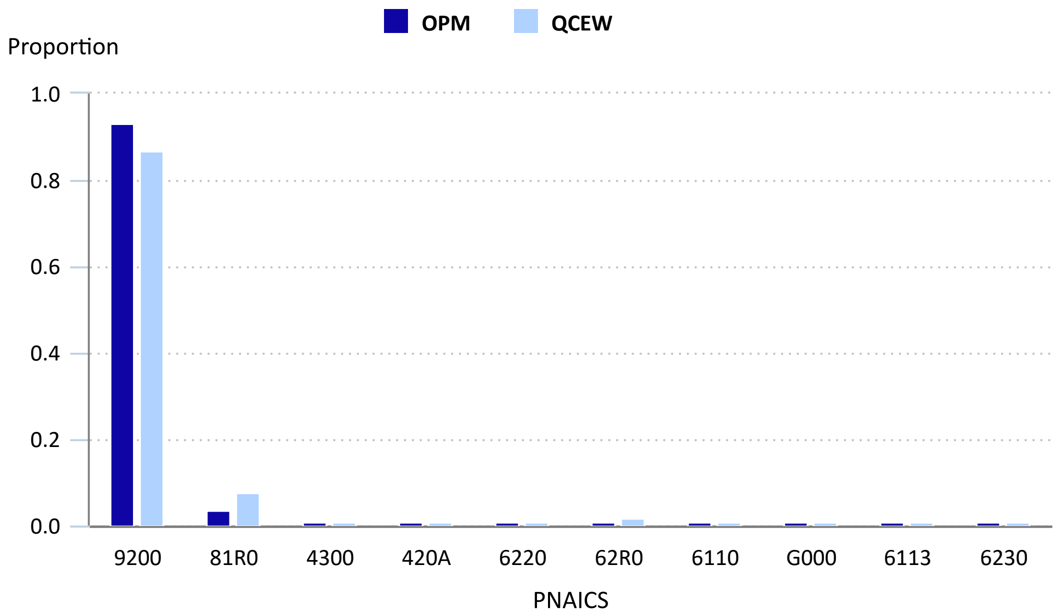
Chart 1. Distribution of cosine similarity scores for selected Quarterly Census of Employment and Wages matches, weighted by agency size



Hover over chart to view data.
Source: Author's calculations.

View Chart Data

Chart 2. Comparison of the distribution of PNAICS codes with OPM and QCEW data, second quarter of 2020



Click legend items to change data display. Hover over chart to view data.
Note: OPM = Office of Personnel Management, PNAICS = pseudo-North American Industry Classification System, and QCEW = Quarterly Census of Employment and Wages.
Source: Authors' calculations.

View Chart Data

For computing exploratory wage indexes, this imperfect crosswalk is sufficient. But to publish indexes using OPM data will require dedicated analyst labor to create a more accurate crosswalk.

Wage index calculations

To compute wage indexes, we first partition the OPM microdata into establishments (department, agency, and city and state) and jobs (occupation, full- or part-time status, and grade).[11] Next, we compute average hourly rates and number of employees for each job within an establishment. The establishment-job data are then matched between the second quarter of 2020 and the second quarter of 2021 and between the second quarter of 2021 and the second quarter of 2022. The resulting matched data are partitioned by cell (PNAICS and PSOC) and period. We then calculate weighted average wages and total employment. Finally, we aggregate these data into wage indexes with the use of the Laspeyres, Paasche, and Fisher formulas. To compute subcell wage indexes, we partition the matched establishment-job data by subcell (PNAICS, PSOC, subcell category). Then, we calculate weighted average wages and total employment and aggregate them into subcell wage indexes. Note that for the published ECI, the base period is fixed and all comparisons are relative to the current base quarter (currently the fourth quarter of 2005). In contrast, for each matched pair of OPM datasets (e.g., the first quarter of 2020 to the second quarter of 2021), the base period is the earlier time (e.g., the first quarter of 2020) so that the time series of indexes for each cell and subcell is what is termed "chained."

Laspeyres, Paasche, and Fisher wage index calculations are shown in tables 1 through 6 for the basic cell aggregation and for a variety of subcell aggregations. We find that our computed rates of inflation are reasonable. Note that the calculations of the Laspeyres, Paasche, and Fisher wage indexes are quite close and, in some instances, equal up to the fourth decimal. This result is similar to other research results.[12] This present research also showed that the expected pattern in which the Laspeyres index exceeds the Paasche index is frequently reversed.[13] Finally, a comparison of the federal Laspeyres index with the official ECI is given in table 7. Perhaps unsurprisingly, the exploratory federal ECI is more closely aligned with the state and local ECI.

Table 2. Wage index calculations of basic cell, 2020 second quarter to 2022 second quarter

Period	Laspeyres	Paasche	Fisher
2020 Q2 to 2021 Q2	1.0131	1.0131	1.0131
2021 Q2 to 2022 Q2	1.0342	1.0341	1.0341

Note: Q2 = second quarter. Wage index data are aggregated into basic cells consisting of ownership sector, industry group, and occupation group.
Source: Authors' calculations using data from the Office of Personnel Management.

Table 3. Wage index calculations of full-time and part-time work schedules, 2020 second quarter to 2022 second quarter

Work schedule	Period	Laspeyres	Paasche	Fisher
Full time	2020 Q2 to 2021 Q2	1.0130	1.0129	1.0129
	2021 Q2 to 2022 Q2	1.0337	1.0337	1.0337
Part time	2020 Q2 to 2021 Q2	1.0366	1.0361	1.0363
	2021 Q2 to 2022 Q2	1.0427	1.0425	1.0426

Note: Q2 = second quarter.
Source: Authors' calculations using data from the Office of Personnel Management.

Table 4. Wage index calculations, by Census divisions, 2020 second quarter to 2022 second quarter

Census division	Period	Laspeyres	Paasche	Fisher
New England	2020 Q2 to 2021 Q2	1.0123	1.0122	1.0122
	2021 Q2 to 2022 Q2	1.0491	1.0490	1.0490
Middle Atlantic	2020 Q2 to 2021 Q2	1.0144	1.0144	1.0144
	2021 Q2 to 2022 Q2	1.0355	1.0355	1.0355
East South Central	2020 Q2 to 2021 Q2	1.0183	1.0184	1.0184
	2021 Q2 to 2022 Q2	1.0370	1.0368	1.0369
South Atlantic	2020 Q2 to 2021 Q2	1.0097	1.0097	1.0097
	2021 Q2 to 2022 Q2	1.0320	1.0320	1.0320
East North Central	2020 Q2 to 2021 Q2	1.0159	1.0158	1.0159
	2021 Q2 to 2022 Q2	1.0341	1.0341	1.0341
West North Central	2020 Q2 to 2021 Q2	1.0152	1.0152	1.0152
	2021 Q2 to 2022 Q2	1.0378	1.0375	1.0377
West South Central	2020 Q2 to 2021 Q2	1.0145	1.0145	1.0145
	2021 Q2 to 2022 Q2	1.0345	1.0346	1.0345
Mountain	2020 Q2 to 2021 Q2	1.0150	1.0150	1.0150
	2021 Q2 to 2022 Q2	1.0398	1.0395	1.0397
Pacific	2020 Q2 to 2021 Q2	1.0207	1.0206	1.0206
	2021 Q2 to 2022 Q2	1.0437	1.0436	1.0437

Note: Q2 = second quarter.
Source: Authors' calculations using data from the Office of Personnel Management.

Table 5. Wage index calculations, by Census region, 2020 second quarter to 2022 second quarter

Census region	Period	Laspeyres	Paasche	Fisher
Northeast	2020 Q2 to 2021 Q2	1.0139	1.0139	1.0139
	2021 Q2 to 2022 Q2	1.0388	1.0388	1.0388
South	2020 Q2 to 2021 Q2	1.0155	1.0155	1.0155
	2021 Q2 to 2022 Q2	1.0361	1.0360	1.0360
Midwest	2020 Q2 to 2021 Q2	1.0111	1.0111	1.0111
	2021 Q2 to 2022 Q2	1.0322	1.0322	1.0322
West	2020 Q2 to 2021 Q2	1.0180	1.0179	1.0180
	2021 Q2 to 2022 Q2	1.0412	1.0411	1.0412

Note: Q2 = second quarter.
Source: Authors' calculations using data from the Office of Personnel Management.

Table 6. Wage index calculations by size class, 2020 second quarter to 2022 second quarter

Size class by number of employees	Period	Laspeyres	Paasche	Fisher
1 (<50)	2020 Q2 to 2021 Q2	1.0189	1.0189	1.0189
	2021 Q2 to 2022 Q2	1.0402	1.0402	1.0402
2 (51 to 100)	2020 Q2 to 2021 Q2	1.0117	1.0116	1.0116
	2021 Q2 to 2022 Q2	1.0407	1.0408	1.0408
3 (101 to 500)	2020 Q2 to 2021 Q2	1.0104	1.0104	1.0104
	2021 Q2 to 2022 Q2	1.0349	1.0349	1.0349
4 (>500)	2020 Q2 to 2021 Q2	1.0133	1.0132	1.0132
	2021 Q2 to 2022 Q2	1.0342	1.0341	1.0342

Note: Q2 = second quarter.
Source: Authors' calculations using data from the Office of Personnel Management.

Table 7. Comparison of federal Laspeyres index with official Employer Cost Index, 2020 second quarter to 2022 second quarter

Period	Private industry	State and local	Exploratory federal
2020 Q2 to 2021 Q2	1.0315	1.0202	1.0131
2021 Q2 to 2022 Q2	1.0554	1.0341	1.0342

Note: Q2 = second quarter.
Source: Authors' calculations using data from the Office of Personnel Management.

Conclusion

This analysis demonstrates the practicality of using OPM data to compute a federal government wage component of the ECI. Other elements of the ECI may also be feasible if benefit-cost and hours data can be acquired. Given the magnitude of the U.S. federal workforce, its inclusion would expand NCS coverage as well as filling a void in information about federal workers. Although the annually announced federal pay increase provides some information about federal employment cost growth, it is an imprecise indicator—actual cost growth depends on the flow of employees into and out of federal service and the mix of employee tenures. The calculation of a wage or employment cost index would provide BLS data users useful measures of the growth of federal employment costs.

Further exploration of OPM data for use with the NCS will be enhanced by access to benefit-cost data. Even though acquiring benefit-cost data might be infeasible, we believe that the construction of federal wage indexes would prove a valuable addition to the NCS. The addition of the federal workforce to the NCS will require an analyst-validated NAICS crosswalk, which we view to be an attainable goal considering the findings presented in this article.

Appendix: North American Industry Classification System codes by industry and Standard Occupational Classification codes by occupation

Table A-1. Government industry group definitions, including codes

PNAICS	NAICS	Industry
G000	21, 23, 31 to 33	Goods producing
4400	221	Utilities
420A	42 to 45	Wholesale and retail trade
4300	48, 49	Transportation and warehousing
6110	6111	Elementary and secondary schools
6112	6112	Junior colleges
6113	6113	Colleges, universities, and professional schools
61R0	61, excluding 6111 to 6113	Rest of educational services
6220	622	Hospitals
6230	623	Nursing and residential care facilities
62R0	621, 624	Rest of health services
9200	92, excluding 928	Public administration
81R0	51 to 56, 71 to 81, excluding 814	Rest of services

Note: PNAICS = pseudo-North American Industry Classification System, and NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics.

Table A-2. Occupation group definitions, including codes

PSOC	SOC	Occupation
110	11, 13	Management, business, and financial
120	15, 17, 19, 21, 23, 25, 27, 29	Professional and related
210	41	Sales and related
220	43	Office and administrative support
300	31 to 39	Service
405	45, 47	Farm, fishing, forestry, construction, and extraction
430	49	Installation, maintenance, and repair
510	51	Production
520	53	Transportation and material moving

Note: PSOC = pseudo-Standard Occupational Classification, and SOC = Standard Occupational Classification.
Source: U.S. Bureau of Labor Statistics.

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Notes

1 Each basic Employer Cost Index (ECI) "cell" is categorized into industry and occupation groups. ECI cells are further separated into subcategories or "subcells." These subcategories include full- or part-time work, Census division or region, establishment size, metropolitan or nonmetropolitan, New York–Chicago–Los Angeles area, union status, and time and incentive status. Our analysis includes only subcells for full- or part-time work, Census division, region, and establishment size.

2 An establishment is defined as an economic unit that produces goods or services, usually at a single physical location, and that is engaged in one or predominantly one type of economic activity. For more information, see U.S. Bureau of Labor Statistics glossary https://www.bls.gov/bls/glossary.htm#E.

3 U.S. Census, "General information about price indexes" (U.S. Census Bureau, n.d.), https:/www.census.gov/construction/cpi/pdf/generalinformationaboutpriceindexes.pdf.

4 For a list of index formulas, see *Wikipedia: The Free Encyclopedia*, "List of price index formulas," https://en.wikipedia.org/wiki/List_of_price_index_formulas; and U.S. Census, "General information about price indexes."

5 Typically, Laspeyres and Paasche index number formulas are expressed as a ratio of total wage costs, given period-0 and period-1 fixed employment baskets,

$$I_L = \frac{\sum_{i=1}^{n} w_i^1 e_i^0}{\sum_{j=1}^{n} w_j^0 e_j^0}$$

and

$$I_P = \frac{\sum_{i=1}^{n} w_i^1 e_i^1}{\sum_{j=1}^{n} w_j^0 e_j^1}.$$

After some manipulation of these formulas, the Laspeyres and Paasche indexes can also be expressed as the function of wage relatives and expenditure shares, as given in the main text.

6 Since the Törnqvist and Fisher indexes are close approximations of one another (formulas produce numbers that are close to one another), we do not use the slightly more complicated Törnqvist index number formula.

7 OPM defines part-time work as between 16 and 32 hours a week and full-time work as more than 32 hours a week. In addition to full-time and part-time work, a number of other work schedules include full-time seasonal, part-time seasonal, intermittent, and intermittent seasonal. Our analysis only includes full-time and part-time workers.

8 We excluded military bases because they can have establishments such as schools, hospitals, entertainment venues, and so forth. Although nurses and teachers might be straightforward to classify into hospitals and schools, occupations such as janitors and secretaries would be challenging. U.S. Postal Service employee data are separately available from OPM and potentially could be included in the future.

9 "Fact sheet: computing hourly rates of pay using the 2,087-hour divisor" (U.S. Office of Personnel Management, n.d.), https://www.opm.gov/policy-data-oversight/pay-leave/pay-administration/fact-sheets/computing-hourly-rates-of-pay-using-the-2087-hour-divisor/.

10 Underlying the ECI is the Laspeyres index number formula.

11 Technically, ECI jobs are also differentiated by union status and time or incentive status. Union status is unavailable in our data, and to our knowledge, incentive pay is not widely used in the federal government.

12 Michael K. Lettau, Mark A. Loewenstein, and Aaron Cushner, "Is the ECI sensitive to the method of aggregation?" *Monthly Labor Review*, June 1997, https://www.bls.gov/opub/mlr/1997/06/art1full.pdf; and Michael K. Lettau, Mark A. Loewenstein, and Steve P. Paben, "Is the ECI sensitive to the method of aggregation? an update," *Monthly Labor Review*, December 2002, https://www.bls.gov/opub/mlr/2002/12/art3full.pdf.

13 Ibid. For an explanation of this pattern reversal, see specifically Lettau et al. "Is the ECI sensitive to the method of aggregation?"

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