ARTICLE

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Projections overview and highlights, 2021–31

Employment and real output are projected to grow during the 2021–31 decade, reflecting both cyclical recovery from the 2020 coronavirus disease 2019 (COVID-19) pandemic-induced recession, and structural growth. About one-fourth of the population will be age 65 or older in 2031, contributing to slow projected growth in the labor force and a continued decline in the labor force participation rate. The aging population is also expected to continue to drive strong demand for a variety of healthcare services, with 2.6 million jobs projected to be added in the healthcare and social assistance sector through 2031.

The U.S. Bureau of Labor Statistics (BLS) projects 0.5-percent annual growth in employment over the 2021–31 decade, slower than the 1.0 percent growth that occurred over the 2011–21 decade.[1] This growth reflects recovery from the recession associated with the coronavirus disease 2019 (COVID-19) pandemic and low base-year employment for 2021. This cyclical growth, which occurs as the economy returns to full employment, comes in addition to long-term structural growth.[2] Between 2021 and 2031, the total U.S. economy is projected to add about 8.3 million jobs, with employment reaching a level of 166.5 million in 2031. Various demographic trends, including an aging population and slower growth in the civilian noninstitutional population, are expected to impact labor force growth and the labor force participation rate over the projections period. These demographic trends, combined with the pandemic recovery, in turn affect aggregate demand, industry output and employment, and occupational employment projections.

This article presents an overview of the 2021–31 projections. Highlights include the following:

- Labor force growth is projected to be slower (0.5 percent annually) than the growth in much of recent history, which will constrain growth of the economy. The labor force grew by 462,000 to 161.2 million from 2020 to 2021, 2.3 million less than the level seen in 2019 prior to the onset of the pandemic, but the labor force is projected to grow to 168.9 million in 2031.
- The labor force participation rate is projected to continue to trend down, declining from 61.7 percent in 2021 to 60.1 percent in 2031, primarily because of an aging population. However, participation rates among older workers are projected to increase over the projections period.
- Real gross domestic product (GDP) is projected to continue to grow, at 2.1 percent annually. This is slightly higher than the two previous decades' respective annual rates of 2.0 percent and 1.8 percent, but much lower than the 3.0 percent and above rates seen in the 1980s and 1990s.
- Most employment gains over the 2021–31 period are expected to occur in the service-providing sectors, led by the large employment increase in the healthcare and social assistance sector. An aging population will continue to create strong demand for industries and occupations that provide healthcare and social assistance services.
- Ongoing recovery from the COVID-19 recession will lead to faster projected growth in many industries and occupations that lost jobs as a result of the pandemic. For example, leisure and hospitality is projected to be the fastest growing sector as consumption in food services and accommodation return to prepandemic patterns.

Compared with the prior decade, the 2021–31 period is expected to see slower population growth.[3] The median age of the population will trend upward, with all baby boomers reaching ages 67 and older by 2031.[4] (See publication tables 3.2 and 3.4 under source data.) This increase in the share of people of traditional retirement age is expected to contribute to a decline in the labor force participation rate through 2031.

Real output is projected to increase by $7.8 trillion from 2021 to 2031, and most of this growth is expected to occur in the service-providing sectors. The 2.0-percent annual output growth projected for the total economy is slower than the 2.1-percent annual growth from 2011 to 2021.

Total employment is projected to grow 0.5 percent annually from 2021 to 2031,[5] which is slower than the 1.0-percent annual growth recorded over the 2011−21 decade. Service-providing sectors are expected to account for most of the jobs added from 2021 to 2031.

Of the 8.3 million jobs projected to be added to the economy, nearly one-third (2.6 million) will be in the healthcare and social assistance sector. Employment increases in this sector are expected to stem from greater demand for a variety of healthcare services—demand driven by continued population aging and increasing rates of chronic disease.

Among all sectors, the leisure and hospitality sector is projected to see the fastest annual employment growth—1.3 percent. This rapid growth is driven primarily by recovery from the pandemic, as nearly three quarters of the jobs lost in this sector in 2020 had yet to be recovered in 2021. Professional and business services are projected to add 1.5 million jobs over the projections period, an increase including strong growth in computer systems design and related services and management, scientific, and technical consulting services.

Compared with service-providing sectors, slower employment growth is projected in the goods-producing sectors—and among these, the manufacturing sector is projected to decline. Increasing automation, combined with international competition, is expected to reduce employment demand in manufacturing and in many of the production occupations concentrated in this sector. Changing consumer preferences and increases in the use of technology are expected to lead to declines in employment in the postal service and retail trade industries, as well as in several information-related industries.

Effects of the COVID-19 pandemic on the 2021–31 projections

The COVID-19 pandemic prompted an economic recession from February 2020 to April 2020, leading to substantial declines in output and employment.[6] Although the recession only lasted a few months, the pandemic persisted through 2021 and continued to disrupt economic activity, prevent or discourage people from reentering the labor force, and impact other economic conditions that affect employment.[7] The economy rebounded in 2021, regaining approximately 4.6 million jobs; however, this equates to only about half of the jobs that were lost from 2019 to 2020. As a result, the 2021 annual average employment level, which forms the baseline for the 2021–31 projections, remained well below the prepandemic level. Employment in a majority of sectors continued to recover through the first half of 2022, and the 2021–31 projections do not reflect the employment recovery and reallocation that occurred during that time.[8]

Some industries that were disproportionately affected by the COVID-19 pandemic have lower base-year values and are expected to experience cyclical recoveries in the early part of the 2021–31 decade as industry output and employment normalize and return to their long-term trends, leading to higher projected employment growth. Projected rapid growth for industries in which employment fell in 2020 and remained low in 2021 is expected to result in strong growth for the occupations employed by those industries. For instance, many movie theaters were not operating at full capacity in 2021, resulting in a lower employment level in the motion picture and video exhibition industry in 2021 than in prepandemic recent history.[9] This industry is projected to grow 70.5 percent over the 2021–31 decade, on account of a cyclical recovery in employment rather than a long-term structural increase in demand for motion picture and video exhibition. In turn, motion picture projectionists as well as ushers, lobby attendants, and ticket takers—occupations highly concentrated in the industry—are also expected to experience strong cyclical growth.

In addition, some industries and occupations are projected to have altered long-term structural demand arising from economic changes spurred by the pandemic. For example, many computer occupations are expected to have elevated long-term demand, in part because of increased business demand for telework computing infrastructure and information technology (IT) security.[10]

Data users should therefore note that fast growth rates in this projections set can be cyclically driven, structurally driven (in the long term), or driven by a combination of cyclical and structural factors.

Preparing the projections—a methodological overview

BLS prepares projections in four areas: labor force, aggregate demand, industry output and employment, and occupational employment. Each step in the projections process affects subsequent steps. The projections for the labor force affect those for GDP growth. These projections further affect industry output and employment, which then feed into the occupational employment projections.

In the BLS labor force model, population and participation rates determine the outlook for labor force growth. Population projections, estimated by the U.S. Census Bureau and benchmarked to 2021 BLS Current Population Survey data, are heavily impacted by the Census Bureau's outlook for mortality rates and immigration. Immigration, in particular, is an important but uncertain factor affecting the size of the future labor force.

Because labor force growth is one of the major determinants of long-term economic growth, the labor force projections describe the future path of the economy and its capacity to create goods and services. The long-term gradual slowdown in labor force growth continues to be key in determining the growth of the economy and of employment.

BLS develops macroeconomic projections with a model licensed from Macroeconomic Advisers (MA) by IHS Markit.[11] The MA model assumes full employment in the target year. Data for energy prices come from the U.S. Energy Information Administration, and BLS determines other critical variables and supplies them to the MA model exogenously.[12] The MA model then projects economic aggregates, including total employment, output, productivity, prices, interest rates, and many other variables for the U.S. economy. These variables—most importantly nonfarm payroll employment, labor productivity, and GDP—serve as constraints for the industry output and employment projections.

BLS produces model-based projections for hundreds of detailed industries, and these projections are then summed to arrive at aggregate values for subsectors and sectors. Macroeconomic factors, such as the labor force, GDP and its components, and labor productivity, affect the growth in total employment. These factors, along with the projection models for individual industries, determine the final projections of industry employment and output.

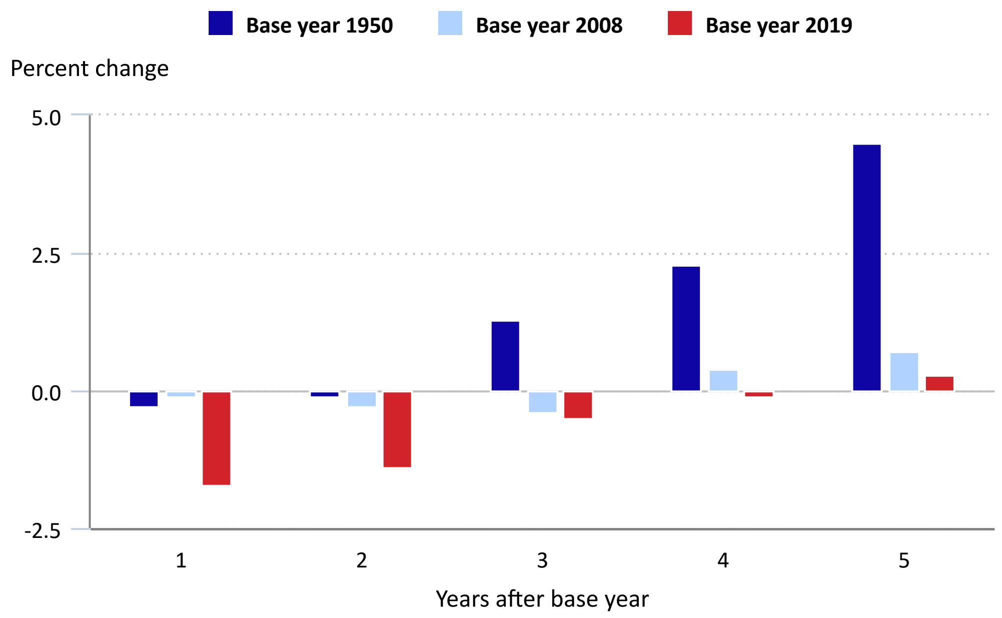
BLS produces occupational employment projections by analyzing current and projected future staffing patterns (the distribution of occupations within an industry) in an industry–occupation matrix. Changes in the staffing pattern for each industry are projected and applied to the final industry projections, yielding detailed occupational projections by industry. This projected employment matrix includes estimates for 832 occupations across 295 industries.[13]

Labor force, population, and labor force participation rate

The labor force went into a steep decline because of the COVID-19 pandemic and as of 2021 it had not yet fully recovered. Some portion of the labor force decline was voluntary, as individuals reevaluated their work–life balance, while another segment was involuntary, as COVID-19 and long COVID prevented individuals from working. Although the labor force grew by 462,000 in 2021, this is still 2.3 million less than in 2019. This decrease is a historically large reduction in the labor force relative to 2019.

A year-over-year labor force decline is an anomaly. In fact, including the current one, there were only three spans in which the labor force decreased since BLS began tracking this statistic in 1947.[14] These three spans are compared in chart 1. The magnitude of the 2020 through 2021 labor force decline is significantly larger than any other. Moreover, the labor force is not projected to fully recover until 2024. (See chart 1.) The ensuing discussion will describe the trends that account for this historical reduction as well as which trends are expected to continue in the future.

Chart 1. Labor force change, relative to base year



Click legend items to change data display. Hover over chart to view data.
Note: The horizontal axis indicates the number of years after the base year. The values in years 3, 4, and 5 after 2019 are projected.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Changes to the overall labor force stem from fluctuations to both the size of the population (from which the labor force is drawn) and the labor force participation rate (the percentage of the population working or actively looking for work). Although the participation rate trends up or down, population growth has virtually always been positive.[15] Population growth serves as a buffer for labor force growth—a steep participation rate drop is necessary for the overall labor force level to decline.

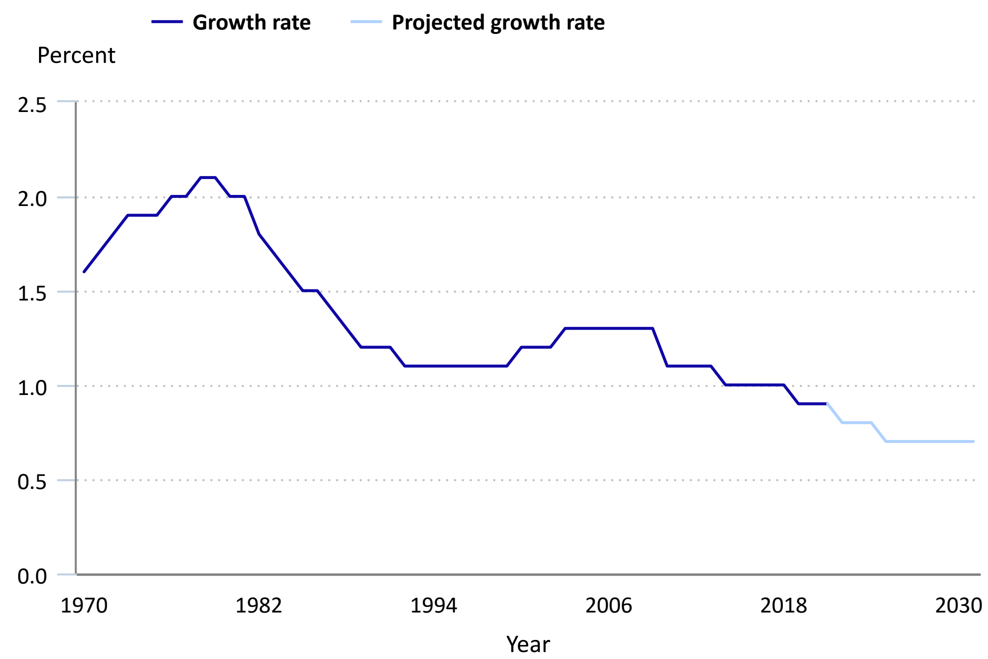
Population

Population growth has slowed recently, weakening the buffer against a shrinking labor force growth. (See chart 2.) In the late 1970s growth rates exceeded 2.0 percent, but growth rates slowed dramatically in the 1980s. More recently in the mid-2000s, the growth rate was 1.3 percent. It has slowed further to 0.9 percent and is projected to grow even slower, at 0.7 percent annually over the 2021–31 decade. (See publication table 3.2 under source data.)

Population growth is slowing primarily because of low fertility rates and because of an aging population, namely the baby boomers, who typically have higher mortality rates. The fertility rate fell significantly during the 1960s. The birth rate was 3.7 births per woman in 1960 as the baby-boom years peaked, followed by a decline through the mid-1970s. From 1972 to 2019, the birth rate hovered in a relatively narrow range between 1.7 and 2.1.[16]

Other trends contributing to slower population growth include reduced immigration and lower life expectancies. Net international migration to the United States has averaged around 1 million annually from 2000 through 2017, slightly over half of the 1.8 million it averaged annually in the mid-1990s.[17] That translates to 0.9 percent of the population in the mid-1990s compared to 0.4 percent in the mid-2010s. Since 2017, immigration declined dramatically, mostly because of the COVID-19 disruptions. Net migration between 2020 and 2021 added only 247,000, or 0.1 percent, to the nation's population.[18] Although immigration seems set to rebound, the extent is unknown. Immigration projections are highly uncertain as legislation can impact migration flows abruptly. Additionally, further developments in the ongoing COVID-19 pandemic could continue to affect immigration.

Chart 2. Population growth rates, 10-year compound annual average, 1971–2021 and 2021–31 projected



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

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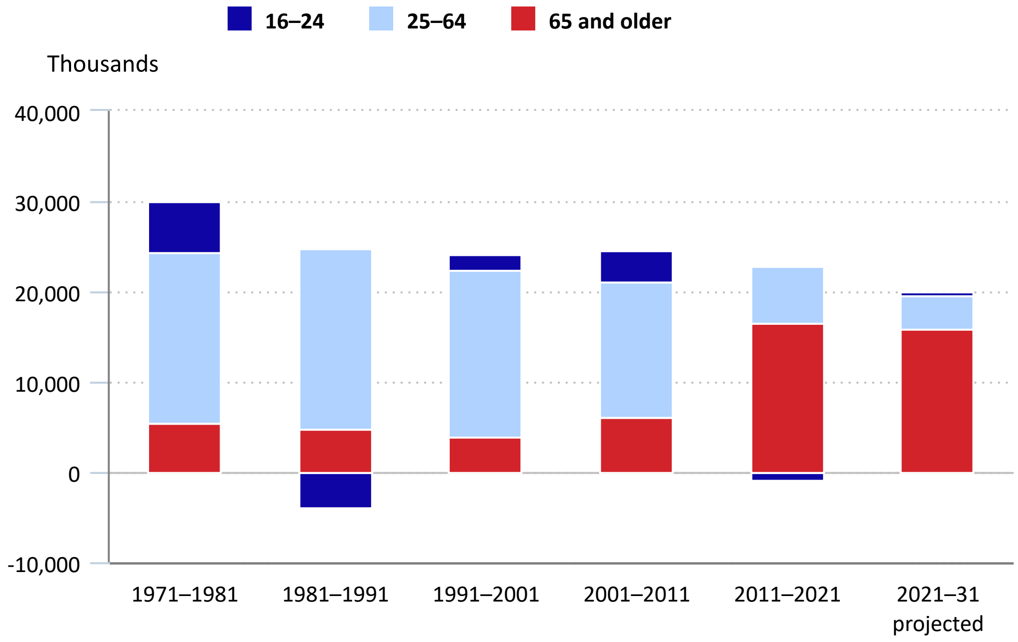
Changes in life expectancy are generally too slow to affect population growth. However, the effects of COVID-19 are more visible than most trends as it has quickly become the third leading cause of death as of 2021.[19] In May 2022, less than two and a half years since the first COVID-19 cases, the United States surpassed 1 million COVID-19 deaths, 0.4 percent of the population.[20] Consequently, life expectancy decreased from 78.86 years in 2019 to 76.60 years in 2021, a net loss of 2.26 years.[21]

As previously noted, the birth rate fell significantly during the 1960s. That drop is reflected now by the fact that the segment of the population growing the most is those born before 1960: the 65-and-older group. (See chart 3.) The 65 and older demographic grew by 16.5 million from 2011 to 2021 and is projected to grow by another 15.8 million over the projections decade. For comparison, the 25–64 age group grew by 6.3 million over the past 10 years and is projected to grow by an additional 3.7 million. The youngest age group, 16–24, negatively factored into population change over the past 10 years, declining by 0.9 million. That group is projected to grow by 0.1 million over the next 10 years. This low growth is due to the same dynamic as the overall population change: the distribution of the 16 to 24 subset of the population is changing. The 20–24-year-old age group is projected to grow slightly, while growth of the 16–19-year-old population is projected to remain flat. (See publication table 3.2 under source data.)

Those 65 and older are more likely to be retired and have a lower propensity to work than the rest of the population. (See the participation rate section for a more thorough discussion). This difference in propensity to work is the other reason the population growth buffer against a declining labor force has diminished.

Chart 3. Population change, by age group, for selected periods and 2021–31 projected



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

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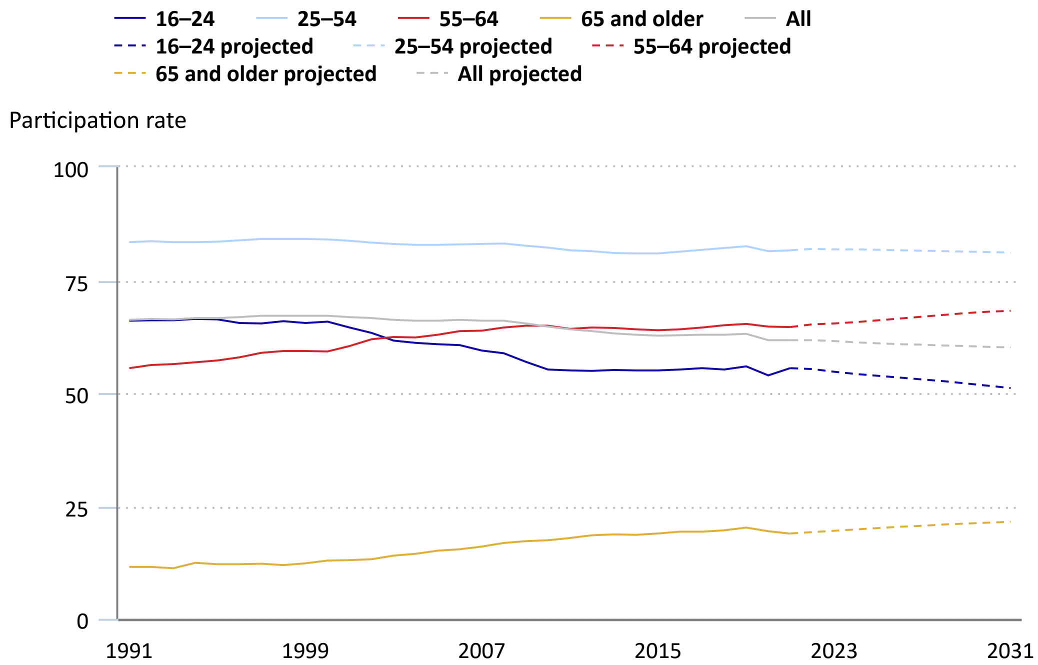
Labor force participation rate

The labor force participation rate fell substantially from 63.1 percent in 2019 to 61.7 percent in 2021. Based on current trends, the participation rate is projected to be 60.1 percent in 2031. (See publication table 3.3 under source data.) Some of the 2019 to 2021 decline is due to COVID-19, though much of it is due to the aging of the population. It remains to be seen to what extent COVID-19 effects will be short-term cyclical versus long-term structural.

Although COVID-19 impacts were sudden and steep, the effect of the aging population on the overall participation rate has been going on for over a decade. Since older individuals have a lower propensity to work, the more a population is comprised of older individuals the lower the overall labor force participation rate.

Chart 4. Labor force participation rate, by age group, historic and projected



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

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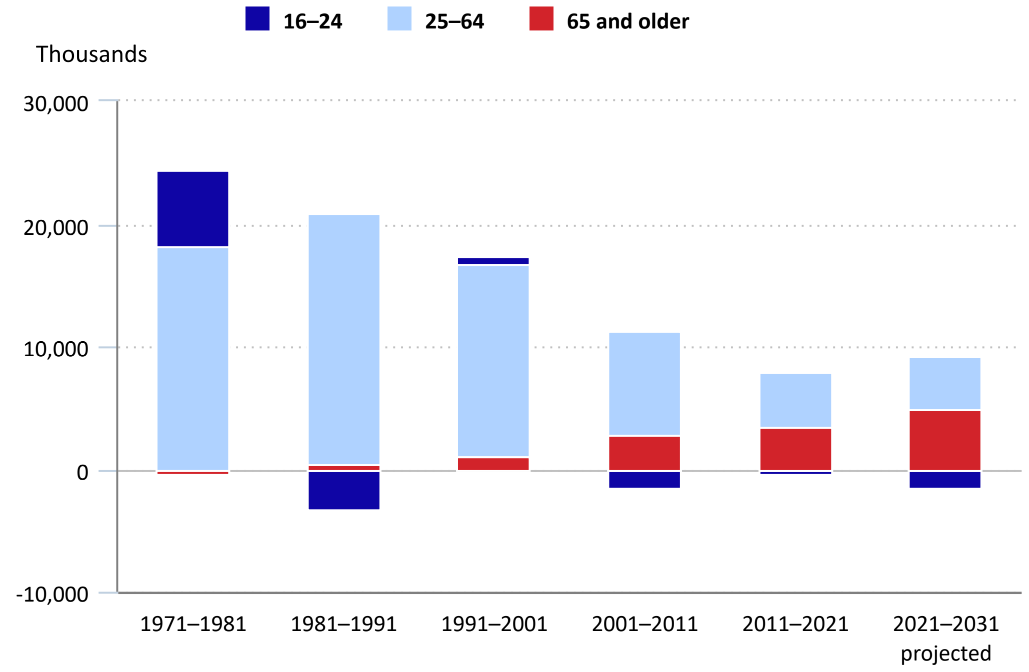
The aging of the population is projected to continue, resulting in a continued decline in the overall labor force participation rate to 60.1 percent in 2031. This is a slower rate of decline than that of 2019 to 2021. Partially offsetting the aging population effect is an increase in the participation rates for older workers. (See chart 4.) Although still low relative to the prime-working-age group (ages 25 to 54), the 65-and-older participation rate has been increasing and is projected to increase further from 18.9 percent in 2021 to 21.5 percent in 2031. Similarly, the participation rate for the 55-to-64 age group is projected to increase from 64.6 to 68.2 percent in 2031. The result of these trends is over half of the labor force growth from 2021 to 2031 is projected to come from the 65-and-older age group. (See chart 5.)

Chart 5. Labor force change, by age group, for selected periods and 2021–31 projected



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

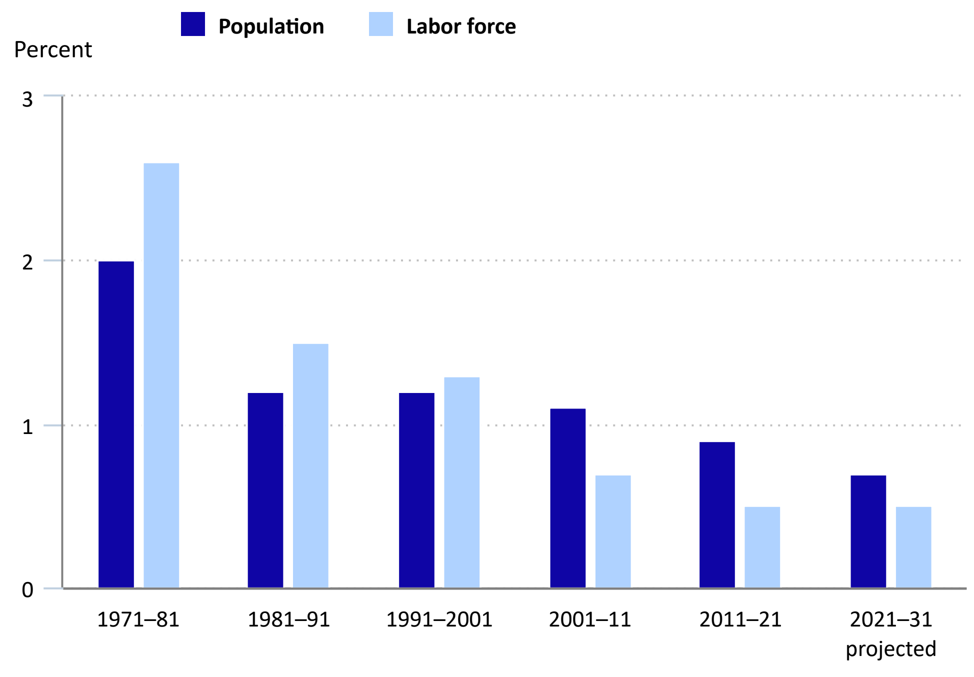
View Chart Data

Performing evaluations on these demographic data allows us to estimate how much of the decrease in the labor force participation rate from 2019 to 2021 is due to aging. This calculation yields an estimate that aging accounted for approximately 0.8 percentage point, over half of the 63.1- to 61.7-percent decrease.[22] This estimated aging effect of 0.8 percentage point decline of the overall participation rate leaves an additional 0.6 percentage point of decline. It is likely that much of this 0.6 percentage point is due to the widespread effects of COVID-19 on the economy and healthcare system.

Aside from the very youngest, every age group behaved similarly in the labor market over the COVID-19 pandemic, with participation rates declining between 0.5 and 1.9 percentage points from 2019 to 2021. COVID-19 caused many people to make different choices about whether to work. Some have decided to retire early while others report being out of the labor force because of home care and family care.[23] Additionally, long COVID appears to be keeping some of the population out of the workforce.[24]

The extent to which the pandemic effects are long-term structural or short-term cyclical in nature is still unknown. Workers who voluntarily left the workforce during the pandemic may be enticed back with increased wages and benefits. Record high profits in 2021,[25] with the widest margins since 1950,[26] suggests there is room to raise wages. COVID-19 and long COVID are likely to continue being a drag on the labor force, although investment in public health arenas and scientific breakthroughs could mitigate this drag to some degree.[27]

Chart 6. Population and labor force growth, 10-year compound annual rates of change, for selected periods and 2021–31 projected



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

View Chart Data

Although as of 2021 the labor force was still down relative to 2019 levels, it is projected to continue recovering, growing 0.5 percent annually over the next decade (See table 3.1 and chart 6.) This rate is slower than projected population growth. Population growth is responsible for all labor force growth as the continued participation rate decline will act as a drag on the labor force.

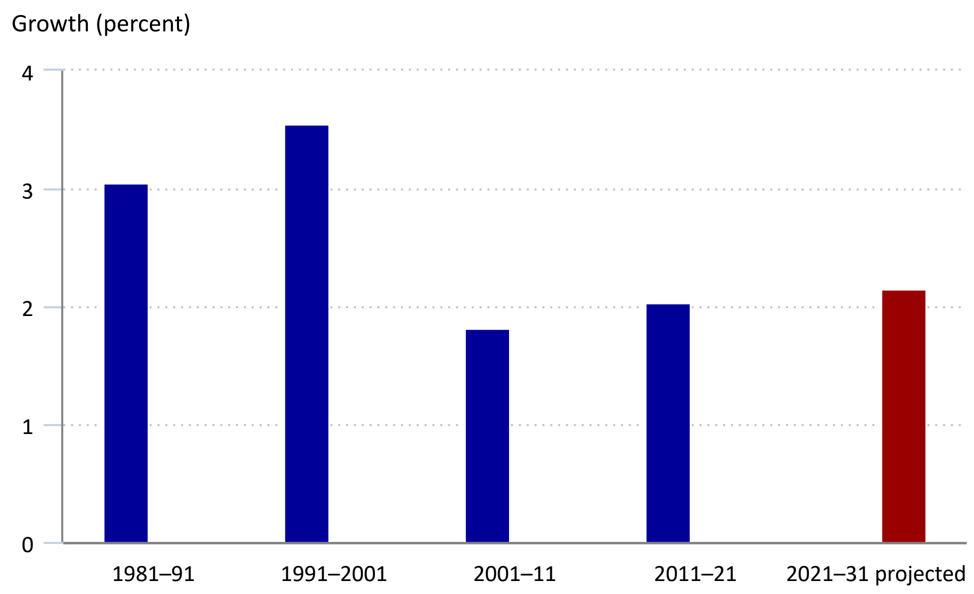
Macroeconomic projections

Changes to the size and composition of the labor force impact economic output (here measured in gross domestic product). Reduced labor force growth over the next decade will be a drag on GDP growth. However, GDP may still increase as the labor market recovers to full employment.[28] The 2021 GDP level was below potential as it had still not recovered from the 2020 recession. Other factors besides the labor force will also affect GDP.

Growth rates for GDP and its components will be expressed in real terms rather than nominal terms throughout this article. GDP is projected to grow 2.1 percent annually over the projections decade. This growth rate is higher than the prior two decades although significantly below growth in the decades prior to those. (See chart 7.) The difference in growth between this projection and the 1980s and 1990s is due to the slowing of labor force growth.

GDP growth can be disaggregated into its subcomponents: personal consumption expenditures (PCE), investment, government, and net exports. Historically, PCE accounts for the majority of GDP growth while investment also accounts for a smaller, though still significant, amount of growth. Net exports and government generally account for a minimal amount of growth. (See chart 8 for historical and projected GDP contributions).

Chart 7. Gross domestic product, 10-year compound annual growth rates, 1981–2021 and projected 2021–31



Hover over chart to view data.
Source: Historic data are from the U.S. Bureau of Economic Analysis, and projected data are from the U.S. Bureau of Labor Statistics.

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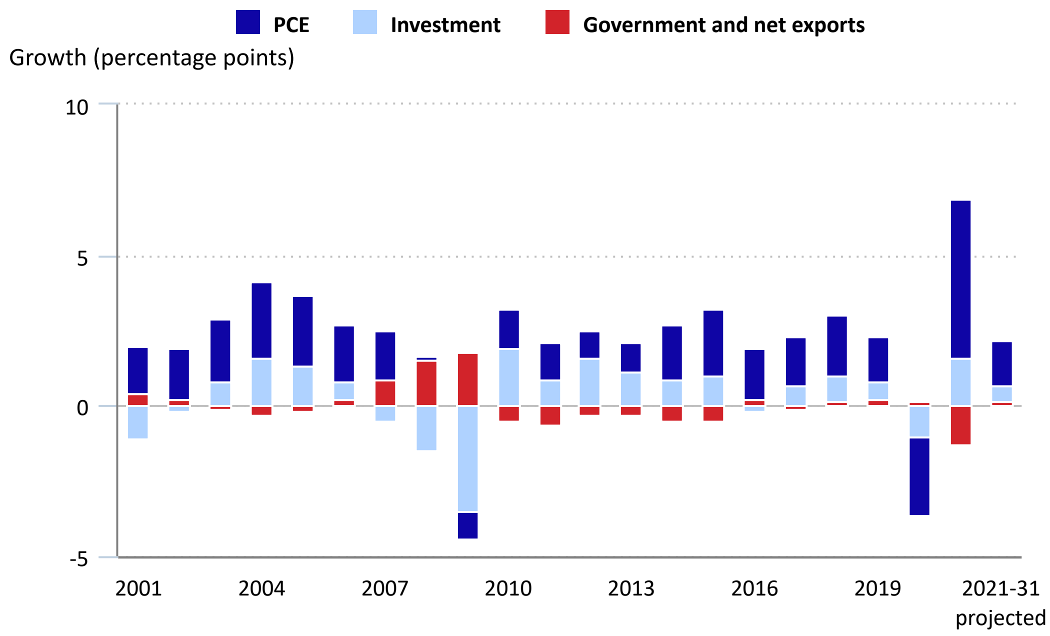
PCE and investment growth plummeted—and were in fact negative—in 2020 because of the COVID-19 pandemic; they have since rebounded dramatically. PCE and investment accounted for 5.3 and 1.6 percentage points of GDP growth respectively in 2021. Growth and contributions are projected to return to more normal levels through 2031: PCE will account for 1.5 percentage points of projected GDP growth while investment will account for another 0.6 percentage point over the next decade. Government spending will account for an additional 0.1 percentage point. Net exports will account for a negligible amount, rounding 0.0 percentage point.

Chart 8. Contributions to growth in real gross domestic product, 2001–21 and projected 2021–31



Click legend items to change data display. Hover over chart to view data.
Note: PCE = personal consumption expenditures.
Source: Historic data are from the U.S. Bureau of Economic Analysis, and projected data are from the U.S. Bureau of Labor Statistics.

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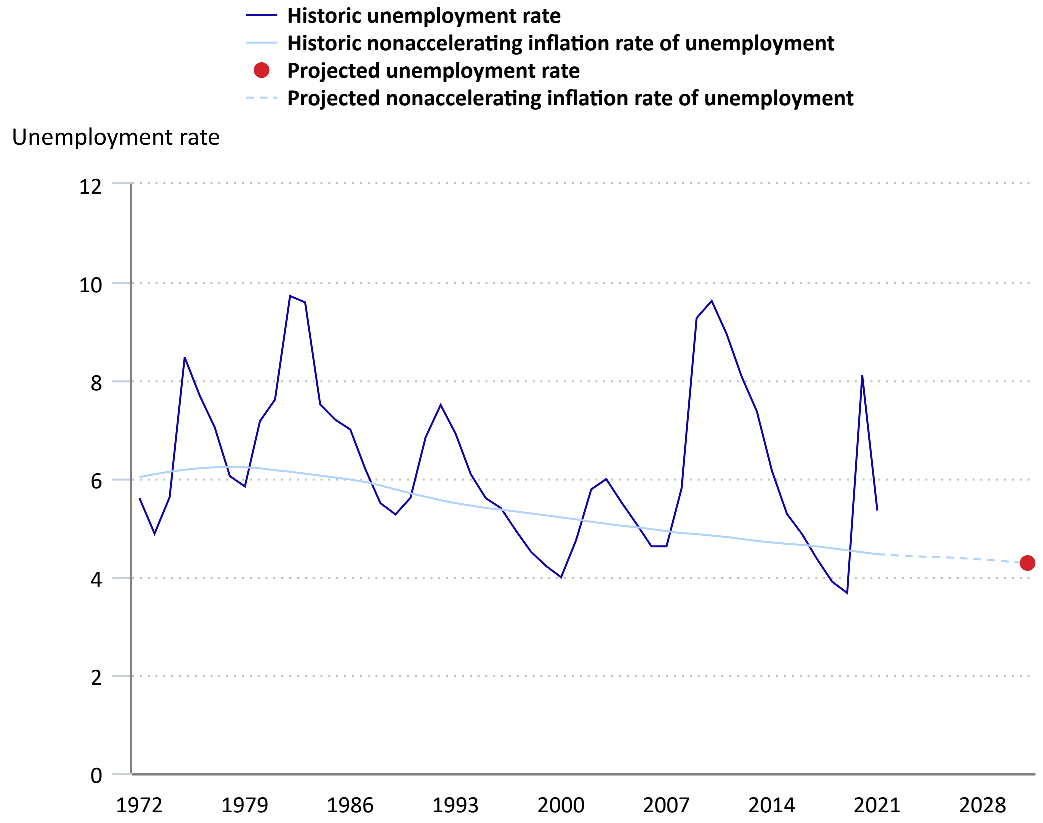
Employment, unemployment, and the nonaccelerating inflation rate of unemployment (NAIRU)

Employment consists of those who are working, while the labor force includes those who are working and actively searching for work. Therefore, while growth in the labor force influences GDP, it is employment that directly affects GDP. Those who are actively searching for work, but not working, are considered unemployed. Unemployment tends to be high during recessionary periods, although there is always some level of frictional unemployment as workers change jobs and are not working.

Chart 9. Unemployment rate and nonaccelerating inflation rate of unemployment, historic and projected



Click legend items to change data display. Hover over chart to view data.
Note: Unemployment rates calculated and used within the projection model are made with less precise values then those made and used by the Current Population Survey. Consequently, they may differ slightly from what is published by the Current Population Survey.
Source: Unemployment data are from the U.S. Bureau of Labor Statistics. Nonaccelerating inflation rate data are from the Congressional Budget Office.

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The natural level of unemployment that is frictional can be referred to as the nonaccelerating inflation rate of unemployment (NAIRU). At this level of unemployment, inflation is consistent, not accelerating. As of this writing, the monthly unemployment rate fell below the estimated 4.4 percent NAIRU level. Moreover, in recent months, inflation levels are spiking to levels not seen since the early 1980s.[29] However, in 2021 the annual unemployment level of 5.4 percent was above the 4.5 percent NAIRU, signaling the economy had not yet reached its potential.[30] (See chart 9.) As the economy was still below potential, there is additional room for GDP to grow over the projected period.

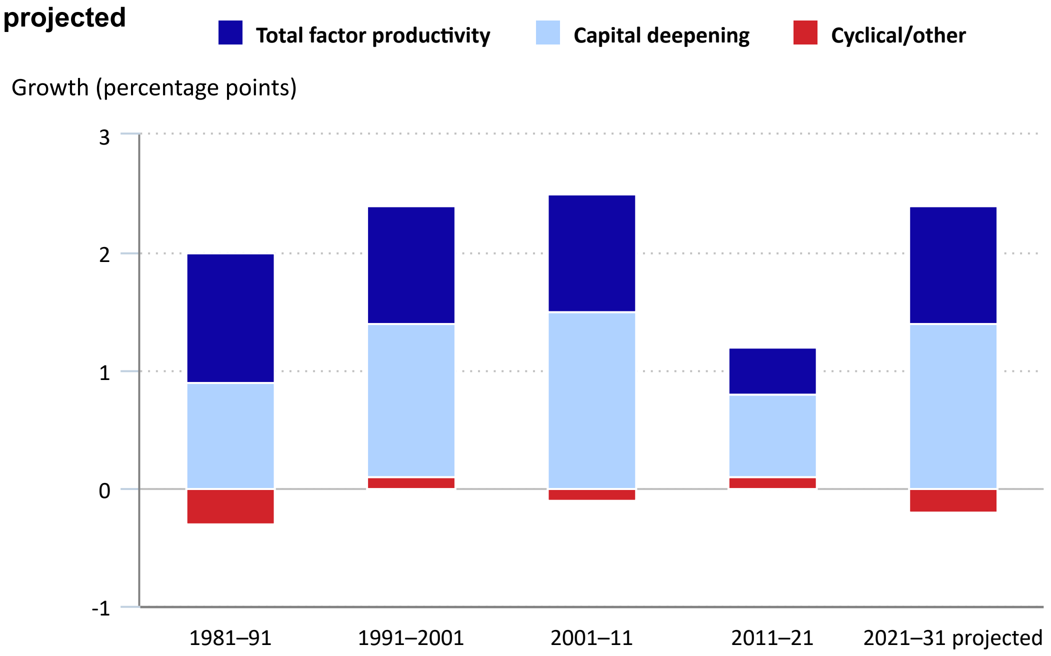
The flipside of unemployment is employment. As unemployment decreases, employment tends to increase.[31] Civilian household employment is projected to grow slightly faster than the labor force—0.6 percent annually compared to the 0.5 percent labor force growth. This difference in growth rates is due to the economy being below potential in 2021 as well as the estimated NAIRU declining slightly to 4.3 percent in 2031.

Productivity

The level of employment combined with productivity generates output. Productivity is influenced by capital deepening and total factor productivity (TFP). Capital consists of those durable produced goods that are in turn used as productive inputs for further production.[32] These inputs include computers, equipment, intellectual property, buildings, and the like. Capital deepening refers to an increase in the ratio of capital to labor. Greater investment increases this ratio, although capital naturally depreciates over time as well. TFP increases can be from technological improvements, increases in the education or quality of the workforce, improvements in management practices, and economies of scale.

Over the past 30 years, capital deepening has been responsible for approximately 60 percent of productivity growth while the remaining 40 percent can be attributed to TFP. This dynamic is projected to continue over the next 10 years. Productivity is projected to grow by 2.2 percent annually with capital deepening contributing 1.4 percentage points and TFP contributing 1.0 percentage point (capital deepening and TFP do not sum to total productivity growth due to some cyclicality). (See chart 10.)

Chart 10. Growth in labor productivity and its components, 10-year compound annual rates of change, for selected periods and 2021–31 projected



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

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Monetary and fiscal policy

Although monetary policy is undergoing significant changes as of this writing to combat inflation, it was relatively steady throughout 2021. No changes were made to the federal funds rate throughout the year as it hovered around 0.1 percent.[33] The Federal Reserve's balance sheet grew at a substantially slower rate than in 2020, from 7.3 trillion in January 2021 to 8.8 trillion in December.[34] From 2021 to 2031, the federal funds rate is projected to rise considerably to 2.6 percent—this rise is already underway, as the Federal Reserve announced a target range of 2.25 to 2.5 in their July 2022 meeting.[35]

As the economy recovered from its 2020 slump, fiscal stimulus packages ended. Over the course of 2021, Congress ended direct cash transfers to Americans in March,[36] ended the extended unemployment insurance program in September (for those states that had not already ended it),[37] and allowed the child tax credits to expire in December.[38]

Assumptions about fiscal policy, including tax policy and government spending, substantially affect expectations for government revenue, national debt, and economic growth. BLS generally assumes no major changes to current tax laws or other major legislation over the projections decade. Effective marginal tax rates also are held constant at their current levels.

Industry output and employment projections to 2031

Although GDP reflects final demand for goods and services, total output is comprised of intermediate goods in addition to GDP. Total industry output is used by BLS to develop industry employment projections because it better reflects the demand for labor, as workers are needed to produce intermediate as well as final goods and services. BLS projects that output will increase about the same in the 2021–31 decade as it did during the previous decade while employment growth will be slower. Industry output and employment projections were prepared using the North American Industry Classification System (NAICS). Major sectors—hereafter referred to as "sectors"—are aggregations of NAICS industries.

Industry output projections

BLS projects real output will increase from $34.9 trillion in 2021 to $42.7 trillion in 2031.[39] The $7.8 trillion increase from 2021 to 2031 is larger than the $6.4 trillion increase experienced during the previous decade. Most of the increase in real output (76.8 percent) is projected to come from service-providing sectors.

Sector output

Real output in the service-providing sectors is projected to grow at an annual rate of 2.2 percent per year from 2021 to 2031, slightly slower than the 2.4-percent annual growth experienced from 2011 to 2021. Over the 2021–31 decade, however, the projected 2.2-percent annual growth in output for service-providing sectors is slightly faster than the 2.0-percent projected annual output growth for the entire U.S. economy. All service-providing sectors are projected to experience real output growth over the 2021–31 decade, except for the federal government sector, which is projected to decline from $1.17 trillion in 2021 to $1.16 trillion in 2031. Whereas both the healthcare and social assistance sector and the information sector are projected to experience the fastest growth in output among service-providing sectors from 2021 to 2031, the utilities sector is projected to experience the slowest real output growth of all of the growing service-providing sectors during the same period.

As for the goods-producing (excluding agriculture) sectors, real output is projected to grow at a rate of 1.7 percent per year from 2021 to 2031; this growth is slower than the projected 2.0-percent annual growth for the overall economy, but faster than the 1.1-percent increase experienced by the goods-producing sector in the previous decade. In line with the previous four sets of projections, the mining sector is projected to experience the fastest output growth among the goods-producing (excluding agriculture) sectors, growing at an annual rate of 2.2 percent from 2021 to 2031.

Real output in the agriculture, forestry, fishing, and hunting sector is projected to grow at a rate of 1.9 percent per year for the 2021–31 projections period; a much slower growth compared with the prior decade, when this sector grew by 2.5 percent annually. (See table 1).

Table 1. Output by major industry sector, 2011, 2021, and 2031 projected

Industry Sector	Output (billions of chained 2012 dollars), 2011	Output (billions of chained 2012 dollars), 2021	Output (billions of chained 2012 dollars), 2031	Compound annual rate of change (percent), 2011–21	Compound annual rate of change (percent), 2021–31	Output (billions of dollars), 2011	Output (billions of dollars), 2021	Output (billions of dollars), 2031	Percent distribution, 2011	Percent distribution, 2021	Percent distribution, 2031
Total	28,475.0	34,893.3	42,696.0	2.1	2.0	28,045.9	40,232.4	50,455.6	100.0	100.0	100.0
Goods-producing, excluding agriculture	7,269.0	8,130.2	9,597.1	1.1	1.7	7,216.9	8,387.0	10,259.4	25.7	20.8	20.3
Mining	559.5	703.4	873.6	2.3	2.2	601.8	469.1	890.2	2.1	1.2	1.8
Construction	1,047.4	1,402.6	1,618.4	3.0	1.4	1,020.5	1,915.3	1,976.9	3.6	4.8	3.9
Manufacturing	5,663.8	5,986.4	7,062.4	0.6	1.7	5,594.6	6,002.6	7,392.2	19.9	14.9	14.7
Service-providing, excluding special industries	19,428.0	24,706.8	30,696.4	2.4	2.2	19,096.7	29,525.1	37,509.4	68.1	73.4	74.3
Utilities	465.2	512.1	541.5	1.0	0.6	484.9	586.2	600.2	1.7	1.5	1.2
Wholesale trade	1,567.3	2,020.1	2,544.3	2.6	2.3	1,530.8	2,380.3	3,046.7	5.5	5.9	6.0
Retail trade	1,368.7	1,996.9	2,593.6	3.8	2.6	1,335.9	2,385.4	3,230.0	4.8	5.9	6.4
Transportation and warehousing	985.2	1,229.1	1,561.6	2.2	2.4	958.8	1,366.2	1,732.5	3.4	3.4	3.4
Information	1,334.1	2,181.8	3,028.0	5.0	3.3	1,324.7	2,230.1	2,645.5	4.7	5.5	5.2
Financial activities	3,552.8	4,611.9	5,460.3	2.6	1.7	3,475.7	6,083.7	8,883.0	12.4	15.1	17.6
Professional and business services	2,902.3	4,120.6	5,366.6	3.6	2.7	2,868.6	4,737.9	6,037.1	10.2	11.8	12.0
Educational services	314.8	313.7	360.8	0.0	1.4	306.5	373.7	424.1	1.1	0.9	0.8
Health care and social assistance	1,897.5	2,323.8	3,218.6	2.0	3.3	1,867.8	2,753.0	3,614.9	6.7	6.8	7.2
Leisure and hospitality	1,059.8	1,232.0	1,529.1	1.5	2.2	1,030.0	1,469.2	1,771.0	3.7	3.7	3.5
Other services	561.4	598.2	733.4	0.6	2.1	548.9	761.7	910.0	2.0	1.9	1.8
Federal government	1,159.9	1,168.8	1,163.0	0.1	0.0	1,148.7	1,368.5	1,297.4	4.1	3.4	2.6
State and local government	2,258.2	2,480.9	2,817.8	0.9	1.3	2,215.2	3,029.3	3,317.0	7.9	7.5	6.6
Agriculture, forestry, fishing, and hunting	448.9	572.1	691.8	2.5	1.9	429.5	498.3	654.8	1.5	1.2	1.3
Special Industries[1]	1,329.3	1,405.8	1,585.9	0.6	1.2	1,302.9	1,822.0	2,032.0	4.6	4.5	4.0
Residual[2]	-0.2	78.5	124.8	[3]	[3]	[3]	[3]	[3]	[3]	[3]	[3]

Note:

[1] Consists of nonproducing accounting categories to reconcile the input-output system with National Income and Product Accounts.

[2] Residual is shown for the first level only. Subcategories do not necessarily add to higher categories as a by-product of chain-weighting.

[3] Not applicable.

Source: U.S. Bureau of Labor Statistics

Industries with fastest growing output

Of the 20 fastest growing real output industries for the 2021–31 projection period, growth is projected to be the fastest among industries in the leisure and hospitality sector and in the information sector. (See publications table 2.7 under source data.) Output in the museums, historical sites, and similar institutions; performing arts companies; and other amusement and recreation industries is projected to grow by 7.0-percent, 6.8-percent, and 4.7-percent per year, respectively. This growth is due to the expected continued recovery from the COVID-19 pandemic since many leisure and hospitality industries were particularly affected.

The information sector, which has remained one of the fastest growing output sectors for the past four projection cycles, includes software publishers; other information services; and data processing, hosting, and related services. Output in these industries is projected to grow between 4.3 percent and 5.3 percent annually for the 2021–31 decade, as demand for technological advancements to accommodate lifestyle needs (for example, increased remote work, online shopping, contactless finance, and overall internet and data usage) has been on an upward trend and is expected to remain robust.[40]

The healthcare and social assistance sector, which includes 5 of the 20 industries with the fastest growing real output for the 2021–31 projections period, includes home healthcare services, medical and diagnostic laboratories, offices of physicians, hospitals, and offices of dentists. These industries are projected to grow between 3.4 percent and 4.0 percent annually from 2021 to 2031, as the aging of the population and the continued expected rise in chronic health conditions, such as diabetes, is expected to drive demand for overall healthcare services.[41]

Industries with most rapidly declining output

Real output declines from 2021 to 2031 are mostly concentrated in the manufacturing sector. (See publication table 2.8 under source data.) Manufacturing industries with the fastest projected output declines over the projections decade include tobacco manufacturing; manufacturing and reproducing magnetic and optical media; apparel, leather, and allied product manufacturing; and other chemical product and preparation manufacturing. Among these most rapidly declining output industries, the tobacco manufacturing industry continues to lead in having the fastest output decline (4.0 percent annually). The rate of cigarette smoking has been on a steady decline over the last few decades for both adults and youths, and this trend is expected to continue from 2021 to 2031.[42] Moreover, rather than traditional rolled tobacco cigarettes, the prevalence and increased popularity in the use of electronic vapor cigarettes further contributes to the overall decline expected in the tobacco manufacturing industry.[43]

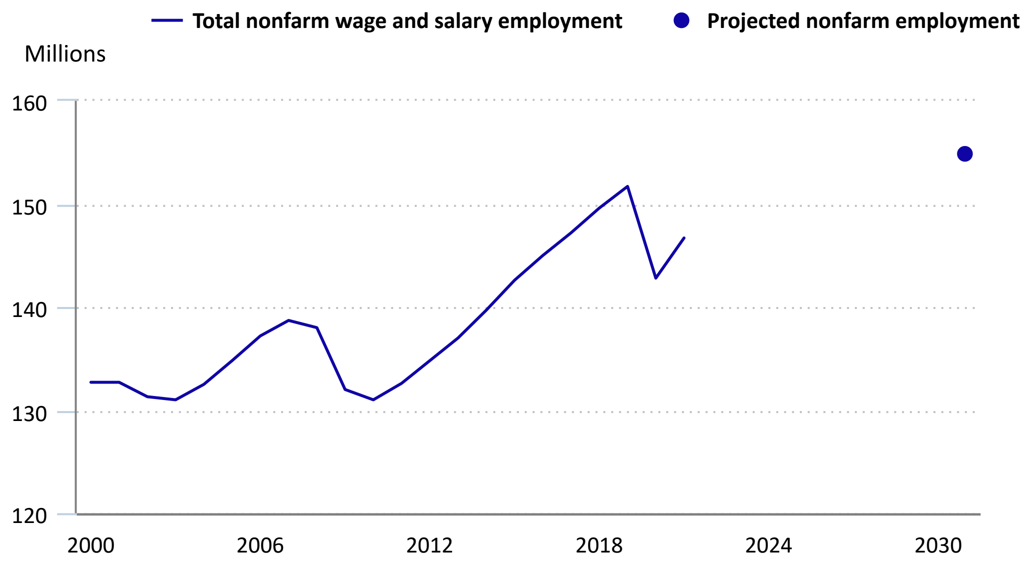
Coal mining, the third most rapidly declining output industry over 2021–31 decade, is projected to decline by 3.4 percent annually from 2021 to 2031. Declining demand for coal, coupled with a rise in the production of both low priced natural gas and alternative renewal energy such as wind and solar power are trends that are expected to continue from 2021 to 2031.[44]

Other sectors with the most rapidly declining output for the 2021–31 decade include industries from other services and the federal government sector, where industries are projected to decline by between 0.2 percent and 0.4 percent annually to 2031.

Industry employment projections

BLS projects total employment in 2031 to reach 166.5 million, an increase of about 8.3 million from 2021.[45] This growth represents a 0.5-percent annual growth rate. During the previous decade, total employment grew at 1.0 percent annually. Most of the increase in employment, 98.0 percent, stems from nonagricultural wage and salary jobs. Employment in nonagricultural wage and salary is projected to rise from 146.7 million in 2021 to 154.9 million in 2031, an increase of about 8.2 million jobs.[46] (See chart 11.) This increase is much less than the 14.1 million jobs that were added from 2011 to 2021. The projected slowdown in employment growth stems from both an aging population as well as lower population growth, as discussed earlier.

Chart 11. Total nonagricultural wage and salary employment, 2000–21 and projected 2031



Click legend items to change data display. Hover over chart to view data.
Note: Total nonagricultural wage and salary employment is the sum of private household employment data from the Current Population Survey and nonagricultural wage and salary employment data, excluding data for logging, from the Current Employment Statistics survey.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Sector employment

Employment in the service-providing sectors is projected to increase by 8.0 million jobs to reach about 134.5 million by 2031. This increase represents just over 96 percent of all jobs added from 2021 to 2031. Employment in the service-providing sectors is expected to grow by 0.6 percent annually over the 2021–31 decade, which is slower than the than the 1.0-percent annual growth rate experienced from 2011 to 2021, but slightly faster than the 0.5-percent projected annual growth for the overall economy. (See table 2.)

Table 2. Employment by major industry sector, 2011, 2021, and projected 2031

Industry Sector	Employment (thousands of jobs), 2011	Employment (thousands of jobs), 2021	Employment (thousands of jobs), 2031	Employment change (thousands of jobs), 2011–21	Employment change (thousands of jobs), 2021–31	Percent distribution, 2011	Percent distribution, 2021	Percent distribution, 2031	Compound annual rate of change (percent), 2011–21	Compound annual rate of change (percent), 2021–31
Total[1]	143,326.8	158,134.9	166,452.1	14,808.1	8,317.2	100.0	100.0	100.0	1.0	0.5
Nonagriculture wage and salary[2]	132,589.0	146,736.9	154,888.2	14,147.9	8,151.3	92.5	92.8	93.1	1.0	0.5
Goods-producing, excluding agriculture	17,999.6	20,279.5	20,408.6	2,279.9	129.1	12.6	12.8	12.3	1.2	0.1
Mining	739.2	519.6	583.4	-219.6	63.8	0.5	0.3	0.4	-3.5	1.2
Construction	5,533.4	7,413.3	7,618.0	1,879.9	204.7	3.9	4.7	4.6	3.0	0.3
Manufacturing	11,727.0	12,346.6	12,207.2	619.6	-139.4	8.2	7.8	7.3	0.5	-0.1
Services-providing, excluding special industries	114,589.4	126,457.4	134,479.7	11,868.0	8,022.2	79.9	80.0	80.8	1.0	0.6
Utilities	552.5	540.8	506.2	-11.7	-34.6	0.4	0.3	0.3	-0.2	-0.7
Wholesale trade	5,474.7	5,677.9	5,813.7	203.2	135.8	3.8	3.6	3.5	0.4	0.2
Retail trade	14,673.6	15,396.0	15,063.3	722.4	-332.7	10.2	9.7	9.0	0.5	-0.2
Transportation and warehousing	4,289.4	6,092.0	6,558.5	1,802.6	466.5	3.0	3.9	3.9	3.6	0.7
Information	2,673.3	2,831.4	3,041.2	158.1	209.8	1.9	1.8	1.8	0.6	0.7
Financial activities	7,696.6	8,777.0	9,113.2	1,080.4	336.2	5.4	5.6	5.5	1.3	0.4
Professional and business services	17,389.1	21,249.5	22,798.9	3,860.4	1,549.4	12.1	13.4	13.7	2.0	0.7
Educational services	3,249.6	3,589.3	4,026.5	339.7	437.2	2.3	2.3	2.4	1.0	1.2
Health care and social assistance	17,068.8	20,084.0	22,694.0	3,015.2	2,610.0	11.9	12.7	13.6	1.6	1.2
Leisure and hospitality	13,352.6	14,100.8	16,024.2	748.2	1,923.4	9.3	8.9	9.6	0.5	1.3
Other services	6,082.7	6,114.1	6,641.4	31.4	527.3	4.2	3.9	4.0	0.1	0.8
Federal government	2,858.5	2,885.7	2,780.7	27.2	-105.0	2.0	1.8	1.7	0.1	-0.4
State and local government	19,228.0	19,118.9	19,417.9	-109.1	299.0	13.4	12.1	11.7	-0.1	0.2
Agriculture, forestry, fishing, and hunting[3]	2,147.5	2,184.8	2,200.5	37.3	15.7	1.5	1.4	1.3	0.2	0.1
Agriculture wage and salary	1,304.9	1,460.2	1,520.1	155.3	59.9	0.9	0.9	0.9	1.1	0.4
Agriculture self-employed	842.6	724.6	680.4	-118.0	-44.2	0.6	0.5	0.4	-1.5	-0.6
Nonagriculture self-employed	8,590.3	9,213.2	9,363.4	622.9	150.3	6.0	5.8	5.6	0.7	0.2

Note:

[1] Employment data for wage and salary workers are from the BLS Current Employment Statistics (CES) survey, which counts jobs, whereas self-employed and agriculture, forestry, fishing, and hunting are from the Current Population Survey (CPS) household survey, which counts workers.

[2] Includes wage and salary data from the CES survey, except private households, which is from the CPS. Logging workers are excluded.

[3] Includes agriculture, forestry, fishing, and hunting data from the CPS, except logging, which is from CES survey. Government wage and salary workers are excluded.

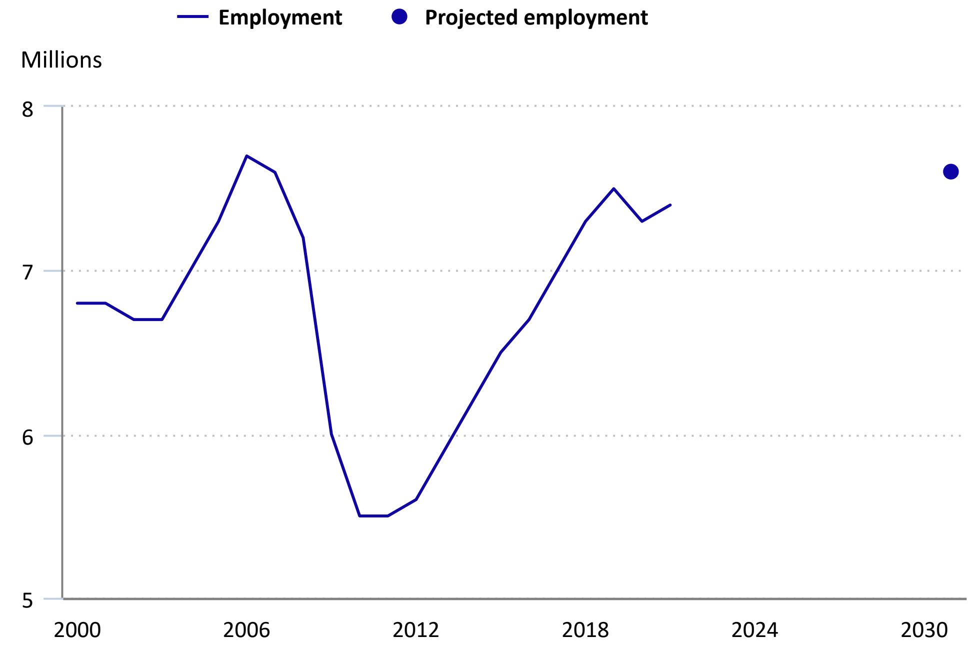
Source: U.S. Bureau of Labor Statistics

In line with the last seven sets of projections, the healthcare and social assistance sector is projected to add the most employment from 2021 to 2031. Employment in this sector is projected to add 2.6 million jobs over the 2021–31 decade, reaching a level of 22.7 million by 2031. This is a projected annual growth rate of 1.2 percent—slower than the 1.6-percent growth rate from 2011 to 2021, but faster than the 0.5-percent annual growth rate for the overall economy.

As with the last three sets of projections, the retail trade sector is projected to have the largest employment decline among all service-providing industries, projected to drop by 332,700 over the 2021–31 decade. This projected decrease in employment contrasts with the 722,400 jobs which were added during the previous decade. The declining employment trajectory in retail trade continues to be driven by several factors, most notably the shift of consumer-spending behavior in favor of e-commerce shopping.[47] In addition, while online purchases still support employment, relatively fewer jobs are in the retail sector; more jobs supported from online purchases are found in other sectors, including transportation and warehousing.

Overall employment in the goods-producing, excluding agriculture, sectors is projected to increase by 129,100 jobs during the 2021–31 decade to 20.4 million jobs. During the previous decade, employment in these sectors rose by 2.3 million, a much larger figure. The construction industry alone accounted for about 1.9 million of this employment growth, driven by recovery from the housing market crash and subsequent Great Recession of 2007–09. While growth is projected to slow considerably from 2021 to 2031, the construction sector is still projected to add the most employment (204,700 jobs) from 2021 to 2031 of all the goods producing sectors. (See chart 12.)

Chart 12. Construction wage and salary employment, 2000–21 and projected 2031

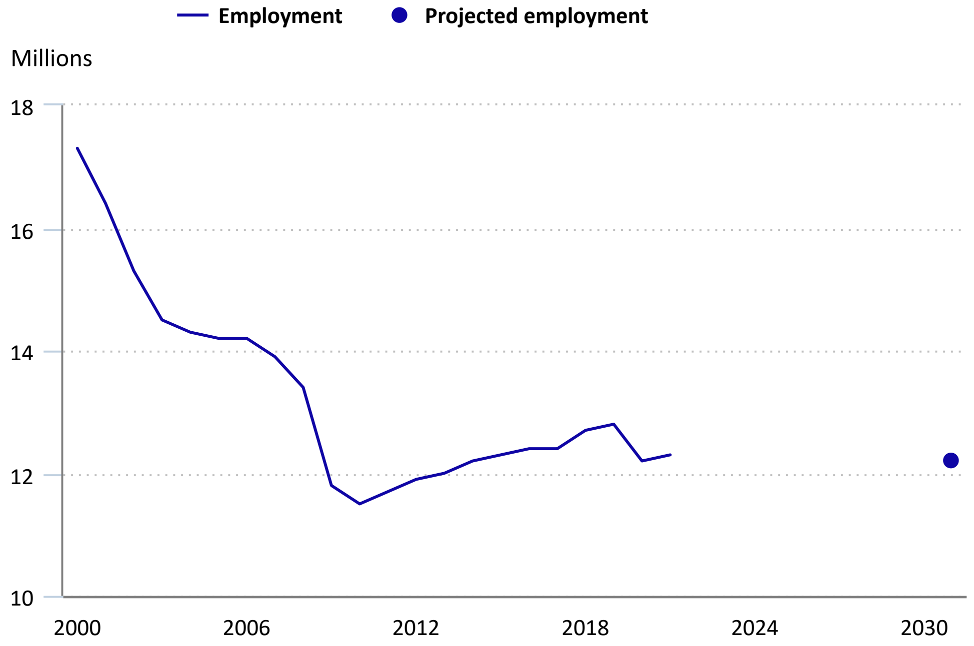


Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Manufacturing is the largest component of the goods-producing sector, accounting for over half of total employment in this sector. Manufacturing employment in the United States plummeted between 2001 and 2011 because of rapid productivity gains and offshoring of jobs to lower labor cost countries.[48] Although manufacturing did post a net gain of 619,600 jobs over the following decade, it is projected to decline slightly, by 139,400 jobs, over the 2021 to 2031 projection period. (See chart 13.)

Chart 13. Manufacturing wage and salary employment, 2000–21 and projected 2031



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

View Chart Data

At its lowest level in February 2021, mining jobs were down by 23.0 percent from prepandemic levels. Although employment in mining is projected to recover 63,800 of these jobs over the 2021–31 decade, it is still less than half of the number of jobs lost during the pandemic.

The agriculture, forestry, fishing, and hunting sector is projected to add 15,700 jobs from 2021 to 2031, less than half of the number of jobs it added from 2011 to 2021. The projected smaller increase is due, in part, to the continued employment slowdown in the crop production industry and the continued decline in the number of self-employed workers within the agriculture, forestry, fishing, and hunting sector. The number of self-employed workers in this sector is projected to decline by 44,200 from 2021 to 2031 (-0.6 percent annually).

Industries with fastest growing employment

Of the 20 fastest growing employment industries, 7 are within the leisure and hospitality sector. (See publication table 2.3 under source data.) This sector suffered substantial job losses during the COVID-19 pandemic. As sector output and employment normalize and return to their long-term growth trends, many industries within the leisure and hospitality sector are projected to experience rapid recoveries from low 2021 employment levels. Despite rapid growth rates, the majority of these industries are generally small in comparison to others on the fastest growers list; therefore, the magnitude of jobs added are also generally small in comparison to others on the list, such as industries in the healthcare and social assistance sector.

Within leisure and hospitality, the promoters of events, and agents and managers industry is projected to be the fastest growing industry, at 3.4 percent annually, followed by amusement parks and arcades at 3.2 percent annually; and performing arts companies is projected to be the third fastest with a 3.0-percent annual growth from 2021 to 2031. Other industries that appear on the fastest employment growth list because of pandemic-related recoveries include support activities for mining; state and local government passenger transit; motion picture, video, and sound recording industries; museums, historical sites, and similar institutions; travel arrangement and reservation services; support activities for agriculture and forestry; other educational services; private; and other personal services.

Employment in healthcare and social assistance industries has trended up in the last seven projection periods; demand for healthcare services is expected to continue to increase because of the aging baby-boom population and continued growth in the number of patients with chronic conditions.[49] Of the 20 fastest growing industries, 3 are within the healthcare and social assistance sector. The individual and family services industry is projected to be the fastest growing industry within this sector at an annual rate of 2.8 percent. Roughly three-quarters of the employment in the individual and family services industry is comprised of services for the elderly and persons with disabilities, which will see large increases in demand from the aging baby boom generation. Home healthcare services (2.0 percent annual growth rate) and offices of other health practitioners (1.9 percent annual growth rate) also make the fastest growers list. Healthcare and social assistance industries are expected to be not just amongst the fastest growers, but also within the largest employment gains, supporting an increasing share of U.S. total employment.

Industries with most rapidly declining employment

Of the 20 most rapidly declining employment industries, 14 industries stem from the manufacturing sector. (See publication table 2.4 under source data.) Increased international competition and continued automation that allows for an increase in overall production will continue to contribute to the loss of jobs for many industries within this sector.[50] The tobacco manufacturing industry is projected to have the most rapid declines in industry employment, falling by 7.4 percent annually from 2021 to 2031.

Other industries projected to be among those with the most rapidly declining employment over the 2021–31 decade include coal mining within the mining sector, projected to decline by 3.0 percent annually. In addition, newspaper, periodical, book, and directory publishers within the information sector is also projected to decline—by 2.7 percent annually from 2021 to 2031. Losses in print readership and ad revenue and readership migration to digital media, as well as an uptick in digital ad revenue are the driving forces behind this employment decline.[51]

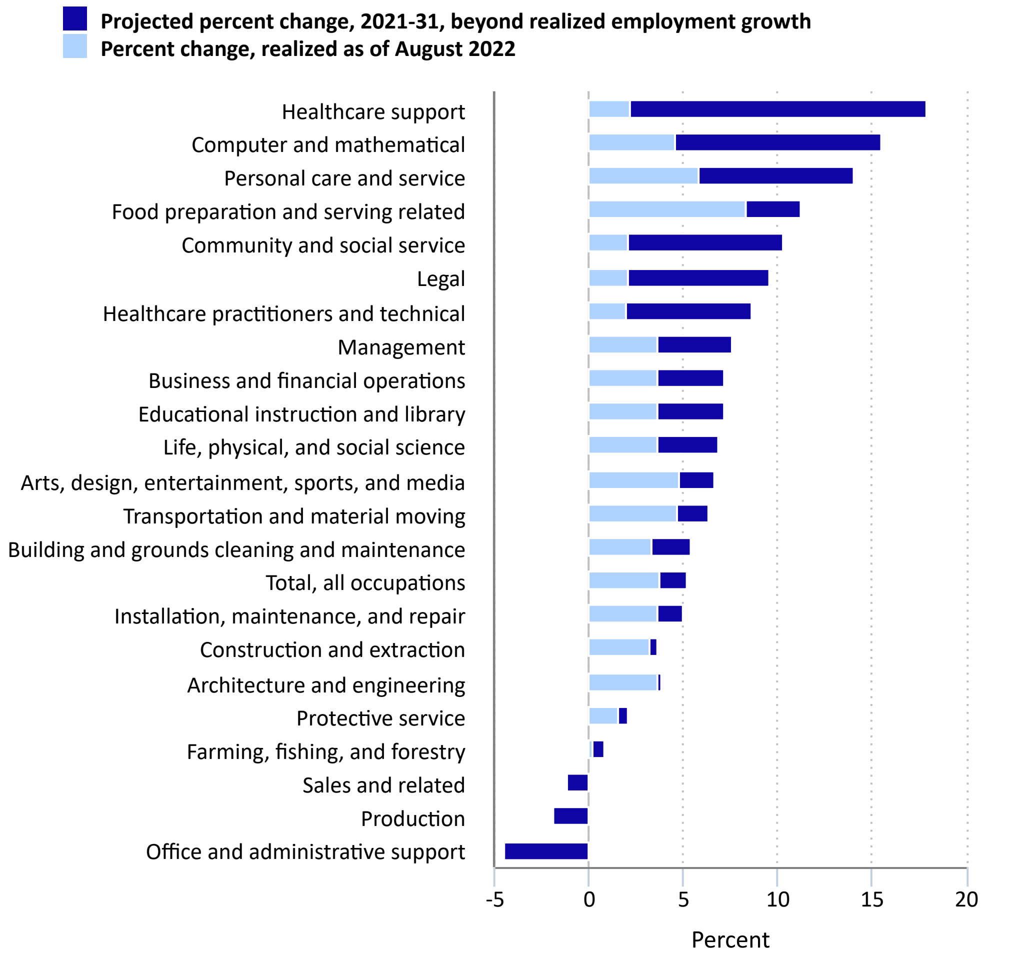
Occupational employment projections to 2031

This section begins with a discussion of BLS employment projections of major occupational groups. It then highlights detailed occupations that are expected to see the fastest employment growth over the 2021–31 decade, and then it ends with a review of occupations that are projected to experience employment declines over the same period.

Employment projections of major occupational groups

BLS produces employment projections for 22 major occupational groups.[52] Chart 14 shows these groups' projected percent changes in employment between 2021 and 2031, including the share of projected employment growth that has already been realized as of August 2022.

Chart 14. Projected percent change in employment, by occupational group, 2021–31, including realized employment change as of August 2022



Click legend items to change data display. Hover over chart to view data.
Note: Data for percent change realized as of August 2022 are estimates of the employment change from the 2021 base year of the projections through the most recent historical data available as of August 2022, excluding occupational groups with a projected employment decline. Components may not add to total projected percent change because of rounding.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

The vast majority of occupational groups, 19 of 22, are expected to experience employment growth over the projections decade with the healthcare support, computer and mathematical, and personal care and service groups projected to be the three fastest growing groups. These groups' rapid employment growth is mainly attributable to structural factors in the economy that are expected to increase long-run demand for the occupations within these groups. This structural growth can be seen in chart 14, with job gains as of August 2022 accounting for only a minor share of their projected 2021−31 employment growth, indicating that structurally-driven, longer term gains in employment are mostly expected. The community and social service group, whose projected employment growth is also well above the all-occupation average, shows these characteristics as well.

On the other hand, some groups' projected employment growth largely reflects short-term cyclical growth rather than long-term expected job gains. This is the case for the food preparation and serving related occupational group, for example, which suffered heavy employment losses in 2020 because of the COVID-19 pandemic. As chart 14 shows, although it is projected to grow rapidly—the fourth-fastest of all groups—much of the employment growth projected over 2021−31 has been realized already, as employment grew substantially throughout the first half of 2022.

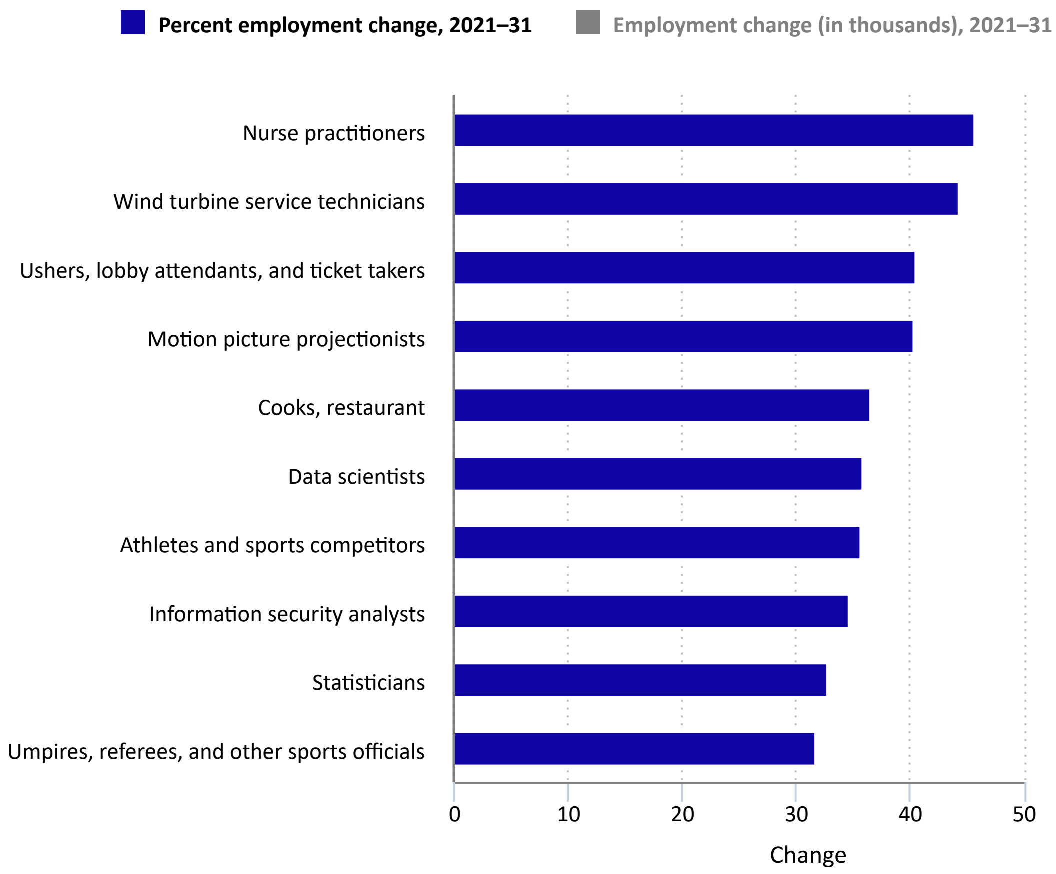
Meanwhile, three occupational groups are expected to see employment decline over the projections decade. These include the production, sales and related, and office and administrative support groups, groups that were also projected to lose jobs in the previous two projections sets.[53]

Occupations with fastest growing employment

As shown in the industry employment section, the healthcare and social assistance sector is projected to be the second-fastest growing sector between 2021 and 2031. This sectoral growth in turn is expected to drive rapid employment growth for several healthcare occupations, which are concentrated in both the healthcare support—the fastest growing of all occupational groups—and the healthcare practitioners and technical occupational groups. (See chart 14.) The growing size of the older adult population, who tends to have more healthcare needs and to require more complex care than younger people, is a major factor driving long-term structural demand for these occupations. In addition, the increasing prevalence of chronic conditions—such as heart disease, cancer, and diabetes—among the general population will bolster demand for healthcare services.

Employment of nurse practitioners is expected to grow 45.7 percent over the projections period, the fastest among all 832 detailed occupations. (See chart 15.) Along with physician assistants, this occupation is poised to see greater demand as the widely documented physician shortage prompts healthcare providers to increasingly adopt team-based models of care delivery.[54] Moreover, an aging population will result in an increased need for therapy services to treat a variety of age-related conditions, fueling demand for occupational therapy assistants and physical therapist assistants.[55] Similarly, an increasing number of seniors is expected to augment demand for long-term care services, including assistance with the activities of daily living. This increase, combined with the general preference of older adults to "age in place" and policy changes encouraging the provision of home- and community-based services, will boost demand for home health and personal care aides.[56]

Chart 15. Ten fastest growing occupations, projected 2021–31



Click legend items to change data display. Hover over chart to view data.
Note: 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. Some occupations are expected to experience cyclical recovery from the COVID-19 recession, which results in fast growth for these occupations.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

In all, healthcare occupations (including one managerial-type occupation tied to the healthcare industry) make up 6 of the 30 fastest growing occupations between 2021 and 2031. (See publication table 1.3 under source data.) In addition, healthcare occupations are expected to account for roughly one of every four new jobs added over the 2021–31 decade. (See publication table 1.1 under source data.) Notably, home health and personal care aides are expected to add the most jobs of any occupation. Employment is projected to grow by about 924,000 over this period, reaching an employment level of 4.6 million in 2031, which would make it the largest occupation in the economy. (See publication table 1.4 under source data.)

Employment in the computer and mathematical occupational group is projected to grow 15.4 percent from 2021 to 2031, the second-fastest of all groups. (See chart 14.) As with healthcare occupations, structural changes in the economy are set to drive long-term demand for computer and mathematical occupations, with 3 of them featuring among the 10 fastest growing occupations. (See chart 15.) The growth of the digital economy is the primary driver behind the strong demand expected for these workers.[57] Computer occupations will be at the forefront of developing and deploying the technological applications and solutions needed in an increasingly digitized economy, such as Internet of Things consumer and industrial devices, IT services including cloud computing and cybersecurity services, artificial intelligence (AI) tools and robotics, and other technologies.

Additionally, the onset of the COVID-19 pandemic accelerated the shift to online activity with the increased adoption of remote and hybrid work arrangements, a surge in consumer use of e-commerce and app-based services, and an expansion of telehealth services—trends that are expected to further support demand for computer occupations over the 2021–31 decade.[58] Parallel to the growth of the digital economy is the generation of massive amounts of data. This trove of data will drive up demand for mathematical science occupations as they will be needed to collect, organize, and analyze these vast quantities of data in order to derive insight and aid decision-making processes. In total, 3 computer occupations, namely information security analysts, web developers, and software developers, and 3 mathematical science occupations, specifically data scientists, statisticians, and operations research analysts, are among the top 30 fastest growing occupations for 2021–31. (See publication table 1.3 under source data.)

Food preparation and serving related occupations are projected to be the fourth-fastest growing occupational group, with growth of 11.2 percent. In contrast to healthcare and computer and mathematical occupations, whose expected growth is primarily driven by structural factors, the projected job growth for this group largely reflects cyclical recovery from the COVID-19 recession. This cyclical recovery is also seen in some occupations that are part of the third-fastest growing personal care and service group, such as motion picture projectionists as well as ushers, lobby attendants, and ticket takers. In general, these occupations are concentrated in industries that suffered steep employment losses during the pandemic, which, largely because of these industries' still-low employment base in 2021 and projected recovery growth, may lead to affected occupations featuring on the fastest growing occupations list.

For example, restaurant cooks, dancers, and athletes and sports competitors are among the 30 occupations projected to see the fastest job growth from 2021 to 2031. These occupations are highly concentrated in leisure and hospitality-tied industries that were severely impacted by the pandemic, such as the food services and drinking places, performing arts companies, and spectator sports industries. Although the leisure and hospitality sector saw some recovery in demand in 2021 amid the roll-out of vaccines and pandemic relief aid that coincided with improved consumer sentiment, the sector was hampered by the surge in infections caused by the Delta variant.[59] As a result, sector employment remained depressed in 2021. Thus, the rapid employment growth projected for the occupations employed within that sector reflects cyclical recovery effects. Of the 10 fastest growing occupations, 5 have a strong recovery growth component in their projections, with restaurant cooks also projected to add about 459,900 new jobs over the projections decade—the largest increase in employment after home health and personal care aides. In all, the 30 occupations with the largest projected job increases are expected to account for three of every five new jobs added through 2031. (See publication table 1.4 under source data.)

Meanwhile, wind turbine service technicians are projected to have the second-fastest employment growth over the 2021–31 decade. (See chart 15.) Along with solar photovoltaic (PV) installers, who are also featured among the top 30 fastest growing occupations, these workers are set to see strong structural demand going forward because of the continued expansion of wind and solar power generation capacity, which has been facilitated by the increasing cost competitiveness of renewables against fossil fuels.[60] As the adoption of renewable energy grows, more solar PV installers and wind turbine service technicians will be needed to install and maintain the associated infrastructure. Because these are small occupations, however, the fast projected growth will result in a limited number of jobs added over the projections decade, with less than 5,000 new jobs expected for each occupation. (See publication table 1.3 under source data.)

Occupations with declining employment

Over the 2021–31 decade, the office and administrative support occupational group is expected to see the strongest employment decline and to lose the largest number of jobs of any occupational group. (See table 3.) Automation of administrative and clerical tasks via the use of software and other technologies is expected to dampen demand for these workers. For instance, software tools for managing schedules and gathering customer information reduce the need for secretaries and administrative assistants,[61] while continued improvements in communication technologies, such as AI-based virtual assistants, opens up more room for displacing customer service representatives.[62] Of the 30 occupations expected to have the fastest drop in employment between 2021 and 2031, 7 are in the office and administrative support group, with word processors and typists' employment projected to decrease 38.2 percent—the sharpest decline of any occupation. (See publication table 1.5 under source data.) Moreover, four of the five occupations projected to lose the most jobs over the 2021–31 decade are office and administrative support workers. (See publication table 1.6 under source data.) These four occupations alone, which include office clerks and customer service representatives, in turn account for almost two-thirds of all the projected job losses for this occupational group.

Table 3. Occupational groups with projected declines in employment, 2021–31

Occupational group	Percent employment change, 2021–31	Employment change, 2021–31 (thousands)
Office and administrative support	-4.5	-880.8
Production	-1.9	-163.6
Sales and related	-1.1	-164.5
Source: U.S. Bureau of Labor Statistics.		

As noted in the industry employment section, many industries within the manufacturing sector are expected to experience rapid employment declines over the projections period, resulting in projected job losses for many occupations concentrated in manufacturing. The continued adoption of various automation technologies in manufacturing operations is expected to put downward pressure on employment of production occupations. For example, manufacturers are increasingly integrating collaborative robots (cobots) into their production lines, which, by performing repetitive tasks and freeing up workers to perform other higher-value tasks, leads to productivity gains.[63] Close to half of the 30 occupations expected to experience the fastest job losses in 2021–31 are tied to the production occupational group. (See publication table 1.5 under source data.)

Lastly, the growth of e-commerce, which has pressured margins and led to declining business at brick-and-mortar stores, is the main factor expected to weigh on employment in the sales and related occupational group.[64] Although the COVID-19 pandemic amplified the impact of this trend, retailers' adoption of various strategies to draw consumers to stores—for instance, improving the customer shopping experience or offering buy online, pick up in-store options—may support employment demand to some extent.[65] The bulk of the projected employment losses for the sales and related group stems from just three occupations primarily employed in retail settings, namely retail salespersons, cashiers, and first-line supervisors of retail sales workers. (See publication table 1.2 under source data.) Notably, cashiers—the second largest occupation within the group—is projected to lose more jobs than any other occupation, shedding a total of about 335,700 positions between 2021 and 2031. (See publication table 1.6 under source data.) The proliferation of self-check machines is a key driver behind this expected decline.[66]

Conclusions

Because of an aging population and slower population growth, labor force growth is expected to be slower in 2021–31 than in previous decades. Older people participate in the labor force less than younger people do, so an aging population shrinks the pool of workers available for employment. The ongoing effects of the pandemic translate to a low employment figure for the 2021 base year of the projections, producing cyclical growth as the economy recovers. Total employment is projected to grow 5.3 percent from 2021 to 2031.

Over the projections period, employment is projected to grow faster in the service-providing sector than in the goods-producing sector. Occupations that provide healthcare or services related to healthcare are projected to be among those with the fastest employment growth. An aging population is projected to drive demand for more healthcare and related services. In addition, the number of people with chronic health conditions is expected to continue to grow, adding to the demand for services provided by healthcare-related occupations. Other occupations projected to grow rapidly include those involving computers, data, and renewable energy. Fast growth is also projected for many occupations concentrated in industries expected to recover from pandemic-induced declines, namely those in the leisure and hospitality sector.

Although the extent of structural economic change arising from the COVID-19 pandemic remains uncertain, some industries and occupations are expected to see altered long-term growth trajectories because of pandemic impacts. These include computer-related industries and occupations, which are expected to see higher demand from expanded telework, and retail trade, which is expected to decline as a result of an accelerated shift from brick-and-mortar retail to e-commerce.

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Notes

1 All annual growth rates in this article refer to a compound annual growth rate.

2 In this discussion, cyclical change refers to short-term business cycle fluctuations around a trend. For example, employment may decline in a particular industry during a recession (cyclical decline) and grow during the recovery immediately following the recession (cyclical growth), eventually returning to the long-term trend. Structural change refers to the long-term trend and, in the case of employment, reflects changes in the allocation of employment by industry and occupation. Structural changes in industry or occupational employment are based on factors such as changes in consumer preferences that affect the demand for goods and services or new technology that affects production practices.

3 Population refers to the civilian noninstitutional population ages 16 and older, excluding "active duty members of the U.S. Armed Forces; people confined to, or living in, institutions or facilities such as prisons, jails, and other correctional institutions and detention centers; and residential care facilities such as skilled nursing homes." (https://www.bls.gov/cps/definitions.htm#population).

4 The baby boomer generation is defined as individuals born in years 1946 to 1964, and who will be between ages 67 and 85 years old in 2031.

5 Total employment is the sum of the employment figures for nonagricultural wage and salary workers; agricultural, forestry, fishing, and hunting workers; and self-employed workers. Nonagricultural wage and salary employment data are from the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey, excluding data for logging, and include private household employment data, which are provided by the Current Population Survey (CPS). The CPS also provides data for self-employed workers and agricultural, forestry, fishing, and hunting workers, except data for logging workers, which are provided by the CES survey.

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NOVEMBER 2022

Workers would rather work from home than get a raise

Summary written by: Eleni X. Karageorge

The ability to work remotely has become so valuable to workers that they are willing to trade off pay raises for the option to work from home, according to a recent study. In "The shift to remote work lessens wage-growth pressures" (National Bureau of Economic Research Working Paper 30197, July 2022), authors Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Brent H. Meyer, and Emil Mihaylov show that some workers are choosing to earn less by forgoing raises or taking pay cuts, as long as they can choose where they work at least a few days a week.

Barrero and colleagues base their research on the Federal Reserve Bank of Atlanta's Survey of Business Uncertainty. The authors estimate that remote work, which is considered a job amenity, slowed wage growth by 2 percentage points over the first 2 years of the pandemic. This finding may be good news for inflation since the remote-work-for-less wages tradeoff indicates that wages will not keep rising and businesses will stop passing those higher labor costs on to customers. The researchers argue that by employers capping wages, remote work has helped ease high inflation. The decrease in wage growth mostly occurred in the higher-paid white-collar positions that could be done remotely. Companies that were more likely to offer at-home work instead of raises were those in the finance, insurance, and real estate industries.

Barrero and coauthors surveyed more than 500 companies to determine if they had expanded their remote work over a 12-month period, ending in May 2022. Of these companies, 38 percent reported that to alleviate what they called "wage-growth pressures," they expanded opportunities for employees to work from home or from other remote locations. In addition, another 41 percent of companies expect to do the same over the next year. This percentage was particularly concentrated among larger companies, in which approximately 52 percent said that they made remote work more available to offset potential wage growth.

The researchers add that remote work is likely decreasing business costs and overall inflation in other ways. By offering remote work, companies may help lower the number of people who quit. Remote work can reduce potential turnover and in turn reduce hiring costs. Many companies are capitalizing on remote work by using it as a substitute for pay raises, to the point that it will help offset inflationary pressures. Companies found that offering remote work retains workers and keeps them happy. Barrero et al. also provide a glimpse into how employers are balancing their needs with workers' desires in the labor market. Many workers still prefer to work from home, and some will even quit if forced to return to the office.

The authors conclude that although many workers have enjoyed improved quality of life with less stress, commute-free workdays, and better work-life balance from expanding remote work opportunities, their employers have also benefited by paying lower wages to their employees than they may have otherwise.

ARTICLE

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Alternative capital asset depreciation rates for U.S. capital and total factor productivity measures

The U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS) use estimates of depreciation rates for structures and equipment to construct estimates of capital stock from data on capital investments. The depreciation rates are based on research by Frank C. Wykoff and Charles R. Hulten from the 1980s. More recent studies by Statistics Canada, from 2007 and 2015, use Canadian data on used asset transactions from Canada's Annual Capital and Repair Expenditures Survey of establishments. They found faster depreciation rates, especially for structures. Sheharyar Bokhari and David Geltner's 2019 study of U.S. used asset prices also found faster depreciation rates for structures. To illustrate the potential effects of implementing these estimates from newer studies, we created a concordance to match Canadian to U.S. asset categories. We reestimated BEA capital stock measures and the BLS capital and total factor productivity (TFP) measures using depreciation rates based on the Canadian Annual Capital and Repair Expenditures Survey. Using these faster depreciation rates results in substantially lower estimates of net capital stocks and higher estimates of depreciation in BEA accounts but has minimal effects on growth rates of TFP in the BLS accounts.

National accounts and productivity estimates require measures of capital stocks, capital asset depreciation, and capital services.[1] In the United States, the U.S. Bureau of Labor Statistics (BLS) constructs measures of capital services for its estimates of total factor productivity (TFP) growth for major sectors and detailed industries.[2] The U.S. Bureau of Economic Analysis (BEA) develops estimates of economic depreciation, or consumption of fixed capital (CFC), that are used in constructing measures of net fixed investment (gross fixed investment less CFC), business income (such as corporate profits), and net saving. Estimates of stocks of fixed assets, net of CFC, appear in BEA fixed assets accounts and in balance sheets for major sectors in the integrated macroeconomic accounts.[3]

BLS and BEA use similar approaches to estimate capital stocks, building from BEA estimates of fixed investment, with different assumptions. Because the owners and users of productive capital are in most instances the same, no market data exist on rental prices of capital or the quantity of capital used. To estimate capital stocks and capital input, BLS and BEA combine data on investment, depreciation, and other volume changes, with assumptions about how efficiency declines with age. Capital stocks are estimated from data on investment and asset service lives. The capital input (also known as capital services) in each period is found by multiplying capital stocks by imputed rental prices, which are obtained from data on changes in asset prices and taxes combined with estimates of depreciation.

This article reviews recent research on depreciation rates and compares published BEA capital measures and BLS capital and TFP growth measures with simulated measures constructed by using alternative depreciation rates. The depreciation rates used by BEA and BLS for equipment and structures are mostly based on studies by Frank C. Wykoff and Charles R. Hulten.[4] More recent studies by Statistics Canada estimated faster depreciation rates, especially for structures.[5] These studies use Canadian data from Statistics Canada's Annual Capital and Repair Expenditures Survey.[6] This mandatory establishment survey collects data on sales and disposals of fixed assets, including asset type, gross book value, asset sales price, and age. A recent 2019 study of U.S. data by Sheharyar Bokhari and David Geltner also found faster depreciation rates for structures.[7] In this article, we construct alternative estimates of BEA and BLS capital measures by using depreciation rates derived from the Statistics Canada data. Depreciation rates can differ across countries for many reasons, but the similarity of the results from Statistics Canada and Bokhari and Geltner suggests that the Statistics Canada rates can provide some useful insights for the United States. We present alternative estimates to test how the choice of depreciation rates matters for key statistics such as TFP, net capital stocks, and net investment and for international comparisons of these statistics.

Empirical studies of depreciation rates use the limited information available on used capital asset sales to capture depreciation rates of new and potentially improved capital assets, as well as changes in depreciation of existing capital assets. Depreciation is the decline in value of capital assets as they age and become less efficient in production because of wear and tear, increased maintenance requirements, obsolescence, accidental damage, and aging, including retirements.[8] As explained by Barbara M. Fraumeni,[9] "Obsolescence is a decrease in the value of an asset because a new asset is more productive, efficient, or suitable for production. A new asset might be more suited for production because it economizes on an input that has become relatively more expensive." Depreciation rates reflect the effects of both physical deterioration and obsolescence and may vary over time because of changes in the characteristics of capital assets and their uses in production and because of changes in economic conditions, including tax and regulatory laws. Rapid improvement in semiconductor and computer technologies gives owners a stronger incentive to replace earlier vintages of goods with newer versions, such as smart phones that have taken the place of many earlier devices by incorporating computer, GPS, camera, flashlight, and other functions. The relevance of these technologically sophisticated goods has grown in the contexts of cloud computing, the Internet of Things, 3D printing, robotics, virtual reality, and autonomous vehicles.[10] Manufacturing changes include smart factories capturing real-time data from sensors on machines, devices, and production systems to optimize production; improved industrial robots; and more agile automated production platforms that use, for example, innovations such as automated guided vehicles that can be reconfigured as production needs change, instead of fixed conveyer systems.[11] For some capital assets, these changes speed up rates of depreciation and obsolescence and reduce service lives. For others, service lives lengthen as newer vintages are built better and retain productive value longer.[12]

BEA depreciation rates are based on numerous studies conducted over many decades.[13] Although BEA measures of net stocks, net investment, and CFC are widely cited, economists have expressed concerns about slowdowns in net investment.[14] A recent study used BEA fixed assets accounts to estimate trends in net investment and stocks of infrastructure assets.[15] Following the 2008 financial crisis, the Data Gaps Initiative, led by the International Monetary Fund, has encouraged the development of sectoral accounts, such as the Integrated Macroeconomic Accounts, which present national balance sheets (including stocks of fixed assets) for key economic sectors. Possible biases in depreciation rates are also a concern in the context of the 2007–09 Great Recession and the slowdown in measured productivity growth.

In the next section, we describe the role of depreciation rates in estimates of BEA and BLS capital measures. Then we review the available studies of depreciation rates. And finally, we explain how we constructed alternative depreciation rates for U.S. capital stocks on the basis of the rates used by Statistics Canada and summarize the changes to the BEA and BLS capital measures that result from using these alternative rates. We refer to the official estimates by BEA and BLS as the "published" figures and compare them with our experimental estimates based on the services lives in the Statistics Canada data, which we call "simulated" estimates.

Capital stocks and rental prices

The input of a capital asset to productive output for a year is defined as its annual rental price multiplied by the productive capital stock of the asset. Before the role of alternative depreciation rates is considered, understanding the construction of each of these components may be helpful. This section describes the methods used by BEA and BLS to measure capital stocks and rental prices.

Capital stocks

Capital stocks are measured as indexes representing aggregates of equipment, structures, and other productive assets at a particular time. BEA and BLS use a method designed to produce annual indexes of capital stocks that correlate to how much output they will produce, as do statistical agencies in most Organisation for Economic Co-operation and Development (OECD) countries. This method, known as the perpetual inventory method (PIM) or vintage aggregation, combines past amounts of investment into productive assets with models of how they will decline in efficiency. The estimate of the flow of capital services provided in each period is modeled as the capital stock index multiplied by an annual rental rate.[16]

Under the PIM, productive capital stock at the end of a given period is a weighted sum of past investments, in which older investments are weighted less because they have declined in productive capacity.[17] The capital stock is equal to the accumulated productive capacity of past investments net of any depreciation and can be thought of as the amount of new investment that would be required to produce the level of capital services produced by existing assets of all ages.

Let K_t denote the (net) productive capital stock of an asset type in year t, I_{t-a} denote investment expenditures in year $t–a$, where a indexes the ages of investments into the asset and $t–a$ is called the vintage of each. Let S denote the maximum service life of the asset. Past investments are assumed to decline in productive capacity over time according to an assumed age-efficiency function, $\lambda(a,S)$, which declines from 1 (when the asset is new) to zero (when $a \geq S$) and represents the proportion of the investment's original productive capacity that remains at age a. The productive capital stock of a group of assets with a maximum service life of S years is given by

$$K_t = \sum_{a=0}^{S} \lambda(a,S) I_{t-a}\,. \tag{1}$$

The age-efficiency function accounts for the decline in the productive capacity of the assets due to physical deterioration or obsolescence. Therefore, the rates at which the productive capacity of the assets decline have a key role in these capital measures. While investment data are available, detailed quantitative information on how the efficiency of capital assets declines over time is not. Implementing the PIM requires assumptions about how asset efficiency declines over time and when assets are retired. BLS assumes a hyperbolic age-efficiency function for an asset class,[18] which is given by

$$\lambda(a,S) = \frac{S-a}{S-\beta a}, \tag{2}$$

where $\lambda(a,S)$ is the efficiency of an asset at age a relative to its performance when it was new; S is the asset service life; and β is a parameter that determines the shape of the age-efficiency function. When β is zero, an asset becomes less efficient, or deteriorates, by the same amount each year. When β is 1, the asset maintains the same level of efficiency until it reaches its service life, at which point it produces zero additional services. BLS uses a β value of 0.75 for structures assets and 0.50 for equipment assets.[19] The $\lambda(a,S)$ function models a slow initial decline in asset efficiency and a more rapid decline as asset age increases, a concave shape with respect to age.[20] To account for the heterogeneity of asset service lives, BLS assumes that, within each asset category and cohort, service lives are distributed according to a modified normal distribution centered on the mean for that category. This cohort age-efficiency function is less concave than the function in equation (2). For most capital assets, BLS uses BEA depreciation rates to determine asset service lives that are consistent with the BLS hyperbolic age-efficiency function.[21]

An alternative approach to estimating capital stocks, a modified version used by BEA, is to assume a geometric pattern of depreciation.[22] Under this assumption, the age-efficiency function becomes $\lambda(a) = (1 - \delta)^a$, where δ is the constant rate of depreciation and a is the age of the asset. Substituting $\lambda(a)$ for $\lambda(a,S)$ in the equation and rearranging terms, the PIM formula in equation (1) becomes

$$\lambda(a) = (1-\delta)^a \tag{3}$$

The assumption of geometric depreciation means that the service life does not enter the age-efficiency function, the age-efficiency function of the asset is convex, and a. An advantage of the geometric approach is that we do not need to track the vintages separately, but a disadvantage is that it imposes a convex aggregate age-efficiency shape regardless of the shape implied by the underlying empirical data.[23]

In addition to the assumption of geometric depreciation, BEA assumes that depreciation of current-year investment is one-half the annual depreciation rate, δ, because investment expenditures are distributed throughout the year.[24] BEA also accounts for other events, O_t, such as losses due to disasters. The modified version of the geometric PIM for an asset is given by

$$K_t = I_t + K_{t-1}(1-\delta)^a\,. \tag{4}$$

The annual change in the net stock of an asset equals the additional investment minus the additional depreciation, as estimated by BEA using assumed asset-specific depreciation rates, destruction of capital from disasters, and other volume changes. Depreciation, M_t, is estimated as a residual. Rearranging from the expression,

$$\lim_{a\to\infty} \lambda(a) = 0$$

(5)

BEA and BLS capital stocks are constructed from investment and service life data for similar categories of capital assets. BLS develops annual capital stocks that include 39 types of equipment assets, 32 types of private nonresidential structures assets, 11 tenant-occupied residential structures assets, 9 owner-occupied residential structures assets, 1 land asset, and 3 types of intellectual property assets. Intellectual property assets include software; research and development; and entertainment, literary, and artistic originals.[25] BLS uses BEA data on gross investment expenditures by asset type for private U.S. businesses. Depreciation rates for each type of capital asset are calculated by using primarily BEA asset service lives and a hyperbolic age-efficiency schedule.

In summary, the stock of capital each year is modeled as the sum of past investments, net of depreciation. BLS capital stock measures are calculated from BEA gross fixed investment data by implementing the PIM with a hyperbolic age-efficiency function and BLS service lives estimated for most assets based on BEA asset depreciation rates.[26] BEA measures of the market value of capital stock are based on accumulated fixed investment, net of depreciation. One difference between the BEA and BLS methods is that BEA assumes a geometric, rather than hyperbolic, pattern of depreciation.[27] In practice, the BLS and BEA methods result in very similar depreciation rate and service life values for most capital assets.[28]

Rental prices

As just noted, BLS assumes that capital services in each period are proportional to the productive capital stock, in which the proportion is the rental rate of capital. BLS productive capital stocks, constructed for various types of capital assets, are aggregated by asset type, by using capital cost shares as weights. Implicit rental prices are calculated by assuming that the purchase price of a capital asset is equal to the discounted stream of services (and implicitly, the rents) that the asset will provide in the future. Laurits R. Christensen and Dale W. Jorgenson modeled price and quantity components of capital services by capital compensation, [29] which is equal to rental price multiplied by the productive capital stock, as

$$Y_t = \sum_j c_{j,t} K_{j,t} \ , \tag{6}$$

where Y_t is total capital income in year t, $c_{j,t}$ is the rental price of capital, $K_{j,t}$ is productive capital stock, j represents the j^{th} asset, and t represents the year t.

In a simplified equation that disregards inflation and taxes, the rental price for an asset may be given by

$$c_t = p_{t-1} r_t + p_{t-1} \delta \ , \tag{7}$$

where p_t is the deflator for new capital goods, r_t is the nominal rate of return, and δ is the average rate of economic depreciation.[30] The rate of return r_t is a percentage rate of return that represents the income that is generated per $100 of physical capital assets. The rental price measures the opportunity cost of using the asset. It reflects the income the business could have earned by loaning its financial resources in the debt market rather than investing in physical capital. From equation (7), we can see that the rental price is positively related to rates of return and depreciation. If the depreciation rates used are slower than the true rates, then BEA estimates of net investment, net stocks of fixed assets available for production, net saving, and corporate profits usually will be overestimated and CFC will be underestimated. Depreciation rates that are biased downward would lead to underestimates of the amount of depreciation for a given stock.[31] The opposite biases in estimates of net stocks and depreciation will occur if the assumed depreciation rates are faster than the true rates.

The effect of underestimated depreciation rates on capital services and TFP is more complicated. Rates of return depend on the ratio of net capital income and the net capital stock, which is also affected by depreciation rates. One might expect that underestimating depreciation rates would lead to overestimating productive capital stock and capital services and, in turn, underestimating TFP. But there is an offsetting effect on capital rental prices. From equations (4) and (5), we can see that depreciation rates that are too low lead to lower rental prices and an underestimation of capital services. We examine the net impact of these two effects on the growth of capital services and TFP.

Both BLS and BEA capital measures rely on BEA estimates of fixed investment, and the definitions of investment are important for determining the relevant depreciation rate, especially for structures. Investment in private nonresidential structures is primarily based on value-put-in-place (VIP) data from the U.S. Census Bureau surveys of construction spending.[32] The survey collects data on construction costs rather than the eventual selling price of the asset. The VIP measure includes the cost of new structures as well as modifications to existing structures, such as additions, renovations, and major replacements (a new roof, for example). It also includes installation of mechanical and electrical systems, such as plumbing, heating, elevators, and central air-conditioning equipment. It excludes the cost of land and the cost of routine maintenance and repairs. Depreciation rates for each of these components of structures may differ. Improvements and mechanical components may, for example, depreciate or become obsolete faster than the original "brick and mortar" building. Depreciation rates for each type of structure should reflect an aggregation of the depreciation rates of these components.[33]

Overview of research on depreciation

Although depreciation is an essential concept in economics, it is difficult to measure empirically, and different studies produce different estimates. Based on path-breaking studies of used asset transactions by Hulten and Wykoff, depreciation rates for structures and equipment used by BEA and BLS were developed primarily by Fraumeni.[34] Recent studies by Statistics Canada and John Baldwin, Huju Liu, and Marc Tanguay, of Statistics Canada,[35] based on used asset transactions in Canada from 1985 to 2010, applied methods similar to the Hulten and Wykoff methods and obtained generally faster depreciation (higher depreciation rates), especially for structures. Many other OECD countries use depreciation rates that are faster than the U.S rates. Although these studies raise questions about the U.S estimates, true depreciation rates may differ across countries for many reasons, so one should be cautious about applying rates from other countries to U.S. assets. But a recent study by Bokhari and Geltner,[36] based on real estate transactions in the United States from 2001 to 2014, applied methods similar to the Hulten and Wykoff approach and also obtained faster depreciation rates for structures, similar to those found in the Statistics Canada studies. This section summarizes the data and methods used by these studies and discusses some key issues based on conversations with the authors and others who use these data.

The Hulten and Wykoff studies

The Hulten and Wykoff studies estimated depreciation patterns using samples of transactions of several types of used assets at market prices.[37] For machinery and equipment, they acquired data on machine tools, construction machinery, autos, and office equipment from a variety of sources.[38] For nonresidential structures, they used a sample of 8,066 observations of 22 types of buildings collected by the U.S. Department of the Treasury, Office of Industrial Economics (OIE), in 1972.[39] For this sample, the owner of a building was asked when it was constructed, when the owner acquired it, and the price paid for it exclusive of the value of the land. With these data, Hulten and Wykoff could determine market transaction prices by age and date of purchase.[40]

Hulten and Wykoff used these data to estimate age-price profiles for those assets that were included in the OIE sample.[41] Their estimation methods featured two key innovations. First, they made no assumption about the form of these profiles and used a flexible Box–Cox transformation instead to test whether the patterns resembled straight line, concave, or convex patterns. Second, because used asset prices reflect only surviving assets (a censored sample problem), Hulten and Wykoff weighted the used asset prices by the probability of survival before estimating the depreciation patterns. These weighted used asset prices thus reflect surviving and retired assets. The probability of survival depended on the mean and distribution of the service lives of assets. Service lives were based on the Department of the Treasury's "Bulletin F," and the distribution of retirements followed a Winfrey distribution.[42]

Hulten and Wykoff found that for most assets in their samples, the estimated age-price profiles were similar to a geometric (convex) form, with price declining more quickly early in the life of the asset before gradually diminishing to zero.[43] With a geometric form, age-price profiles can be approximated by using a single constant rate of depreciation, a feature that simplifies computations of net stocks. Based on their estimated age-price profiles, Hulten and Wykoff produced estimates of depreciation rates for the assets in their samples. This set of assets, which they labeled "type A assets," made up 55 percent of investment in equipment and 42 percent of investment in nonresidential structures in the National Income and Product Accounts (NIPA) in 1977.

To produce estimates of depreciation for the NIPA assets not included in the OIE sample, Hulten and Wykoff analyzed each asset on a case-by-case basis.[44] These assets were then classified as either "type B" or "type C," depending on whether empirical evidence was available regarding the depreciation pattern of the asset. The Hulten and Wykoff rates for both type B and C assets were based more on judgment than evidence. Depreciation rates for assets labeled type B were supported by data from existing empirical studies conducted by others as well and by using information available at the time on the treatment of depreciation by BEA, Dale Jorgenson, and Jack Faucett Associates.[45] Little or no data were available for type C assets, and rates were developed based on inferences from similar type A category assets, where possible. Hulten and Wykoff assumed the depreciation pattern for these other assets was also geometric. To estimate depreciation patterns for the type C assets, Hulten and Wykoff used the relationship between the geometric depreciation rate (δ), the service life (S), and the declining balance rate (R) as

$$\delta = \frac{R}{S}. \tag{8}$$

The value of the declining balance rate determines the shape of the depreciation pattern minus the extent to which asset values fall more rapidly early in the lifecycle.[46] Higher values of R imply higher reductions in asset value earlier in the service life and more convex (such as geometric) depreciation profiles. For the assets for which data were available, Hulten and Wykoff estimated R values of 1.65 for equipment and 0.91 for nonresidential structures.[47] These estimates contrast with an R value of 2.00 (double-declining balance), a rate often assumed by accountants to allow taxpayers to write off more depreciation expenses in the earlier years of asset ownership. Use of a double-declining balance rate for accounting purposes typically does not reflect the true decline in the efficiency of the assets. Hulten and Wykoff then estimated geometric depreciation rates for type C assets by dividing these declining balance rates by the existing estimates of service lives.

The Hulten and Wykoff studies became the standard, and subsequent studies used a similar method to estimate depreciation.[48] In 1996, BEA released estimates of depreciation rates based largely on the Hulten and Wykoff studies.[49] These updated depreciation estimates replaced previous estimates that were generally based on straight-line depreciation, by using available service lives, and Winfrey retirement patterns.[50] For structures, the updated depreciation rates based on the Hulten and Wykoff studies were slower than the previous estimates and led to lower estimates of depreciation and higher estimates of net capital stocks. With few exceptions, BEA continues to use these rates for estimates of CFC and net stocks of nonresidential structures and equipment.[51]

Statistics Canada studies

Statistics Canada studies, like the Hulten and Wykoff studies, estimated depreciation patterns using samples of used asset transactions.[52] Both sets of studies employed flexible specifications to test the shape of the age-price pattern (straight line, concave, convex, etc.), experimented with alternative assumptions regarding the retirements and discards, and estimated values of structures net of land values.

The data used for the Statistics Canada studies are based on their Annual Capital and Repair Expenditures Survey.[53] The survey provides detailed information on asset type, gross book value, sale price, and age of each asset that is sold or discarded. The gross book value includes the original investment value plus the capitalized improvements over the life of the asset. Investment deflators were used to express all data in constant prices. The data in the 2007 Statistics Canada study cover the period from 1985 to 2001 (30,350 observations and 43 assets), and the 2015 Statistics Canada study extends the sample to cover the period from 2002 to 2010 (an additional 22,129 observations on 32 assets). These studies cover a more recent period and use larger samples of a wider range of assets than the Hulten and Wykoff studies.[54] The Statistics Canada studies also include data on the ages of discarded assets and on the value of capitalized improvements, whereas the Hulten and Wykoff studies use market transaction prices to reflect the remaining present value of capital assets because these prices are affected by discards and capitalized improvements.[55]

The Statistics Canada researchers edited the survey data to screen and adjust outlier observations that seemed unrealistic. Some sale prices close to zero were classified as discards.[56] Some long-lived assets that sold close to their original purchase price were excluded from the sample.[57] When reported asset durations were concentrated on rounded values like 5, 10, and 20 years, the authors employed a correction to apply a distribution to the rounded values. The estimates were limited to those assets with active resale markets.

The key variable in the Statistics Canada studies is the ratio between the asset price when sold (SV) and its gross book value (GBV), SV/GBV, where both numerator and denominator are expressed in constant prices.[58] Using this ratio and the age of the asset when sold, the studies estimated an age-price relationship that can be converted to a depreciation profile. The Statistics Canada studies jointly estimated asset survival and decline in value and the discard function using a flexible Weibull distribution that controls for price changes and other factors. They confirmed that the depreciation profiles generated by these econometric techniques produced convex age–price curves, consistent with geometric depreciation. The Statistics Canada studies also confirmed that the estimated depreciation rates changed little over the years in the sample.

A novel feature of the Statistics Canada studies was their comparison of these rates ("ex post rates") and the anticipated length of service life reported by survey respondents for initial investments ("ex ante rates").[59] The Statistics Canada studies used these service lives and the declining balance rates obtained from their econometric analysis of depreciation to estimate alternative depreciation rates. The two sets of depreciation rates were generally very similar.

For many assets, especially structures, the Statistics Canada studies estimate faster depreciation than do the Hulten and Wykoff studies. The Hulten and Wykoff studies estimate an average rate of depreciation for structures of 3.7 percent, with a range of 1.9 percent to 5.6 percent, whereas the Statistics Canada studies estimate 6 percent to 8 percent.[60] The declining balance rates from the Statistics Canada studies were generally 2 or higher, in contrast to the declining balance rates in the Hulten and Wykoff studies, which were below 2; higher declining balance rates imply more rapid depreciation earlier in the life of an asset. Both sets of studies used the available declining balance rates and data on service lives to estimate depreciation rates for some remaining assets. In its *Measuring Capital* manual, the OECD concluded, "This underlines the need for comprehensive and regular studies on depreciation patterns, lest there be a danger of ending up with biased values for depreciation and capital inputs."[61]

Studies from other countries

The Economic and Social Research Institute, Cabinet Office, Government of Japan, initiated the Survey on Capital Expenditures and Disposals (CED) in 2006.[62] The CED consists of three questionnaires focused on capital and repair expenditures, financial leases, and disposals. The CED has a detailed classification for more than 600 types of assets. In the disposal survey of the CED, assets are classified into four broad asset groups: buildings and accompanying equipment, machinery and equipment, transportation equipment, and other equipment. For each of these 4 asset groups, 15 observations of disposed assets, randomly selected by corporations, are reported, yielding a total of 60 observations of disposed assets covering all 4 asset groups if a firm fully responds. From these survey data, Japan's Economic and Social Research Institute estimates depreciation rates and average service lives. In general, depreciation rates are found to be similar to the rates estimated by Statistics Canada and are faster than those used in the United States.[63]

Statistics Netherlands has estimated depreciation rates and service lives based on direct capital stock observations. In a study by Myriam van Rooijen-Horsten, Dirk van den Bergen, Ron de Heij, and Mark de Haan, the capital stock survey data were supplemented with discard data collected from an annual Survey on Discards.[64] The study was conducted for all enterprises in the manufacturing industry with 100 or more employees and with annual Investment Survey data on additions to the capital stock in manufacturing industry enterprises with 20 or more employees. Combining data from the capital stock survey, discard survey, and investment surveys, the authors present estimated service lives for six asset categories by manufacturing industry: industrial buildings, civil engineering works, external transport equipment, machinery and equipment and internal means of transport, computers, and other tangible fixed assets. On the basis of the estimated depreciation rates and service lives, the authors of the study concluded that the discard survey may have missed a substantial portion of discards and that care needed to be taken in identifying reliable results. They also found the service life of an asset varied substantially depending on the manufacturing industry using the asset. Industry-specific service lives are developed by type of capital asset for NACE (Nomenclature of Economic Activities) two-digit-level industries. Because they assume different functional forms of depreciation, comparing their overall rates of depreciation with U.S. rates is not easy.

A 2016 Eurostat and OECD study reported on depreciation rate assumptions used by several national statistical agencies to estimate net stocks of structures.[65] Canada, Japan, the Netherlands, and about two dozen other countries responded to the survey. Consistent with the studies just discussed, the study found that U.S. statistical agencies assume slower depreciation rates than do most OECD countries.

Depreciation rates from another country may not suit the United States because true depreciation rates vary across countries for many reasons. Differences in the mix and scale of industries, relative prices of capital and labor, capital utilization, economic and financial conditions affecting investment, tax policies, and climate across countries may affect capital asset depreciation rates. Depreciation rates for structures reflect differences in building standards and land-use regulations.[66]

Bokhari and Geltner study

A study by Bokhari and Geltner applied the Hulten and Wykoff method to a large sample of over 100,000 commercial real estate transactions in the United States from 2001 to 2014 and also found faster depreciation rates for structures, consistent with the Statistics Canada studies.[67]

The Bokhari and Geltner study used three data sets. The first data set, from Real Capital Analytics (RCA), consisted of transaction prices and other data from commercial and apartment property transactions, making possible estimation of property values or age profiles. The RCA data did not include information on investment in improvements, which BEA and BLS also capitalize.[68] The other two data sets in the Bokhari and Geltner study measured investment in improvements. Data from the National Council of Real Estate Investment Fiduciaries (NCREIF) included over 15,000 properties (apartments, office, retail, and warehouses), with detailed information on rents and operating expenses, and separately identified capital improvement expenditures. Bokhari and Geltner write that their capital expenditures data include "only routine capital improvements and upkeep of the type that almost all commercial building owners must undertake on a regular basis (roof replacement, painting, carpeting, new appliances, new HVAC systems, landscaping, tenant custom fit-outs, etc.")[69] Thus, the data omitted major renovations and understated total investment in improvements. Data from Green Street Advisors on capital improvement expenditures for 1,299 apartment properties owned by real estate investment trusts were used to corroborate the findings from the NCREIF data set.[70]

The Bokhari and Geltner study defined "gross depreciation" as the sum of "net depreciation" (the depreciation of the original structure) plus capital improvement expenditures.[71] Bokhari and Geltner illustrate the significance of this definition by using the following example: ". . . suppose a property with a 10-year-old building has market value of $100, and an otherwise identical 11-year-old property has market value of $97 as of the same time. Now suppose that during the previous year the owner of the 11-year-old building put $1 of capital improvement into the building, increasing its market value to $98. (This $1 of capital improvement expenditures would have to some extent mitigated the wear and tear and the functional obsolescence of the building.)"[72] ". . . our estimated value/age profile based on our transaction price data would show 11-year-old properties selling for only 2 percent less than 10-year-old properties, even though the total capital consumption occurring between age 10 and 11 is 3 percent of the property value." As the authors state, "this example illustrates why we need to separately estimate the cost of capital improvements and add that cost to the net depreciation that we observe in our empirically estimated value/age profile, in order to quantify total capital consumption."[73]

To estimate net depreciation using the RCA data, Bokhari and Geltner used methods generally similar to those in the Hulten and Wykoff studies.[74] They regressed the log of the expected price (the actual price times the survival probability) on age dummy variables, location characteristics, and a set of year dummy variables to control for factors such as changes in land and construction prices. The coefficients of the age dummy variables provided a nonparametric estimate of a depreciation pattern that is nearly geometric for nonresidential and apartment buildings. The authors also removed the effects of land values from their estimated depreciation rates by using their estimates of the share of land in the total property value. Their estimated net depreciation rates were 3.1 percent for nonresidential structures and 3.9 percent for apartment structures, higher than the Hulten and Wykoff estimates.[75]

The Bokhari and Geltner study then used the NCREIF data to estimate patterns of capital improvement expenditures by age.[76] They regressed annualized capital improvement expenditures as a share of the market value of the building on age, age squared, and several controls for building characteristics. They found that capital improvement expenditures as a fraction of property value tended to increase over much of the lifespan of the property (and they may be underestimating capital improvement expenditures). The gross depreciation rate was calculated by using estimates of net depreciation and capital improvement expenditures. For a 25-year-old building, their estimate of gross depreciation was 6.61 percent for nonresidential buildings (3.14-percent net depreciation plus 3.47 percent for capital improvement expenditures) and 7.30 percent for apartments (3.94-percent net depreciation plus 3.36 percent for capital improvement expenditures). These gross rates of depreciation are close to those measured by the Statistics Canada studies.

Summary

The Statistics Canada and Bokhari and Geltner studies used the Hulten and Wykoff methods with recent data samples of used asset transactions and found faster depreciation than the Hulten and Wykoff studies, especially for structures. Possible explanations for these conflicting findings were discussed with the authors of the Hulten and Wykoff, Statistics Canada, and Bokhari and Geltner studies as well as users of BEA and BLS data at the Federal Reserve and other agencies. Overall, the authors remained confident in their own results and expressed some concerns about the other studies. Some of the capital specialists providing comments expressed concerns about using depreciation rates from other countries, because true depreciation rates could differ across countries for many reasons, although the Statistics Canada and Bokhari and Geltner estimates were similar. All were sympathetic to efforts to update research on the depreciation rates currently used by BEA and BLS. Regarding future updates of depreciation rates, the general recommendation was to proceed cautiously, given the numerous challenges in estimating depreciation. Some experts recommended BEA and BLS begin a new program of studies to develop updated rates by using the Hulten and Wykoff methods and new data. However, developing appropriate data sets of used asset transactions is difficult and demanding. There are active global markets for many types of used capital investment goods, including truck tractors, hydraulic excavators, dozers, backhoes, mobile cranes, machine tools, and conveyor belts. In principle, statistical agencies could therefore gather market prices for numerous specific types of used assets.[77] However, considerable resources would be required to gather these data and develop contemporary depreciation rates for each asset type.

One of the key differences between these studies is how they incorporate data on improvements. Since the BEA estimates of fixed investment in structures include the cost of the original structures and subsequent improvements, depreciation rates for the capital stock also reflect depreciation of these improvements. The Bokhari and Geltner and Statistics Canada studies include data on improvements, while the Hulten and Wykoff studies do not. The Bokhari and Geltner study finds that improvements make up a substantial share of investment in structures. As the Bokhari and Geltner study points out, the omission of data on improvements may bias downward the estimate of cumulative investment in a structure and, given initial and subsequent sale prices of the building, may bias downward the estimate of total depreciation.[78] In the Hulten and Wykoff studies, the effect of (unmeasured) improvements would be reflected in the resale price of the building, but the total investment in the building prior to resale, and perhaps total depreciation, may be understated.[79] Improvements such as wiring, heating and cooling, and renovations may experience depreciation and obsolescence at rates different from the original structure. Uncertainty exists about how well the data on improvements in the Statistics Canada and Bokhari and Geltner studies measure investment that should be capitalized and depreciated. It is difficult to differentiate in the data between “improvements” that should be capitalized and “maintenance and repairs” that should not. Still another question is whether the respondents to the U.S. Census Bureau construction surveys (the basis for BEA estimates of investment) fully and accurately report these improvements, although the U.S. Census Bureau questionnaires clearly request these data.

Other considerations include a range of issues about the methods and conclusions of these studies. For the Statistics Canada studies, questions were raised about the econometric specifications, the price measures used, and reporting problems with their survey data. For example, firms might report expected service lives as round numbers or numbers developed for tax purposes rather than based on actual observation. The authors of the Statistics Canada studies did not share these concerns and questioned some details about the Hulten and Wykoff studies. For example, they expressed concern that the data on building prices may have included the value of land, resulting in unrealistically low estimated declining balance rates. The building price data used in the Hulten and Wykoff study were obtained from U.S. Department of the Treasury surveys of building values, conducted in 1972 and 1973.[80] These surveys asked building owners to provide “cost or other tax basis of property *(less land),*” among other items. To the extent that building owners responding to these surveys complied with this direction, the Hulten and Wykoff building price data exclude the value of land.

One difficulty in comparing across studies is that depreciation rates are not necessarily stable over time. For example, when fiber optics were adopted for communication networks, copper wire telephone networks were replaced as a whole. That event caused sudden obsolescence, that is, faster depreciation for a brief time.

Simulation of U.S. capital accounts using Canadian service life data

In this section, we consider the potential impact of using alternative depreciation rates on several key BEA and BLS capital measures. We use Statistics Canada data on equipment and structures and assume that fixed asset depreciation and economic and technological trends are broadly similar in the U.S. and Canadian economies.

Asset service lives may differ because of country-specific factors such as variations in capital utilization, relative prices of capital and labor, economic and financial conditions affecting investment decisions, and climate.[81] The secondary market for productive assets may also differ substantially between countries, for example, because of tax differences. These factors could lead to different sale and discard prices in the two countries and different efficiency curves and depreciation rates.

However, the similarity of results from the Statistics Canada studies and the recent Bokhari and Geltner study, which only includes U.S. data on structures, suggests that the Statistics Canada rates are plausible proxies for the United States. Our goals are to describe the potential impact of using the Statistics Canada or Bokhari and Geltner rates in BEA and BLS capital measures, to enable cross-national comparisons of these outcomes, and to encourage further research on depreciation rates.

We developed a concordance between the asset classification systems of the two countries. Statistics Canada uses an asset classification system that features more detailed asset categories in general than the U.S. asset classification system.[82] While some asset categories are direct matches, other categories include more detailed assets in the Canadian system.

An example of a direct match between the Canadian and U.S. asset classification schemes is the BLS category autos (asset 22), which has a depreciation rate of 0.2165, and the Canadian category passenger cars (asset MPG336111), which has a faster depreciation rate of 0.2990. The U.S. category medical equipment and related instruments (asset 27) is classified as a direct match with the Canadian category medical, dental and personal safety supplies, instruments and equipment (asset MPG339100), which has more than double the published U.S. depreciation rate, at 0.301.

In most cases, the asset categories are similar but do not match exactly. We carefully reviewed the categories to match the Canadian asset categories to the U.S. asset categories on the basis of a detailed study of each asset description. This matching process typically resulted in a combination of Canadian asset categories being related to a single broader U.S. asset category. For example, the U.S. asset category other fabricated metal products (asset 3) corresponds to five detailed Canadian asset categories. A new depreciation rate for the broader U.S. asset category was developed by weighting the depreciation rates for the more detailed Canadian categories with the use of detailed nominal investment data from BEA benchmark (economic census year) estimates.[83]

In a few instances, to build up the underlying asset detail matches to the U.S. broader categories, we assigned a detailed Canadian asset category to multiple U.S. asset categories. For example, the BLS steam engines and turbines (asset 4) category is matched with the Statistics Canada category turbines and turbine generator set units (asset MPG333601). The BLS category internal combustion engines (asset 5) is also matched with turbines and turbine generator set units (asset MPG333601), as well as other engine and power transmission equipment (asset MPG333609). This matching was done selectively, in those instances in which the Canadian category—while not a perfect match—was the best match to detailed assets in more than one U.S. fixed investment expenditure category. In the case of internal combustion engines (asset 5), the investment weighted depreciation rate becomes 0.0929 rather than the BLS value of 0.1972. This asset is one of the few for which the service life obtained from Canadian data is greater than the published U.S. value.

The published U.S. asset classification scheme includes a few assets in which the service lives depend on industry of use. For example, the U.S. classification scheme includes different depreciation rates for 22 industries under the asset category metal working machinery (11). These service lives range from a low of 12 years in North American Industry Classification System (NAICS) code 321, wood products industry, to a high of 28 years in NAICS code 331, primary metal manufacturing industry. Special industry machinery (12) and general industrial equipment including materials handling (13) also have multiple service lives based on the industry in which the asset is used. These industry-specific depreciation rates for selected asset categories were developed on the basis of industry studies conducted during the 1970s by the former OIE of the U.S. Department of the Treasury and from industry studies conducted during the 1980s and 1990s by the Office of Tax Analysis of the U.S. Department of the Treasury.[84] To obtain revised depreciation rates for these asset-industry breakouts beneath assets 11, 12, and 13, we first noted that each of these three assets included industry-specific depreciation rates for 21 specific manufacturing industries and also for the nonmanufacturing industry category. For each of these three assets, we used the relationship between the depreciation rates for each specific industry and the nonmanufacturing industry category to adjust the Statistics Canada depreciation rate for the overall asset category.[85]

Generally, we found that the concordance of the U.S. and Canadian asset categories provided a reasonable scaffold on which to develop experimental depreciation rates for this analysis.

Using the asset category concordance, Canadian asset service lives, and Canadian declining balance rates, we conducted two simulations with different sets of service lives.[86] For the "set 1" simulation, we estimated new depreciation rates for 38 of the 39 U.S. equipment categories, all 32 private nonresidential structures categories, and 9 of the 11 tenant-occupied residential structures categories.[87] Where a U.S. asset category was matched to multiple more detailed Statistics Canada assets, an overall depreciation rate was developed as a weighted average of the Statistics Canada depreciation rates, in which the weights used are the shares of 2007 U.S. fixed investment in the more detailed assets. Table 1 summarizes the published BEA and BLS depreciation rates and our set 1 alternative rates, derived from Statistics Canada data, for each U.S. asset category. (See source data under related content.) For most categories of equipment, the rates from Statistics Canada are higher, implying a faster rate of depreciation. Only three U.S. equipment asset categories have slower revised depreciation rates than published U.S. rates:

1. Asset 5: internal combustion engines
2. Asset 19: other electrical equipment
3. Asset 21: other trucks, buses, trailers in the transit and ground passenger transportation industry

For structures, the depreciation rates from Statistics Canada are typically faster. For many types of buildings, the published BEA and BLS depreciation rates are in the range of 2 percent to 3 percent, whereas the alternative Statistics Canada based estimates are 6 percent to 8 percent.

To obtain revised service lives from the set 1 depreciation rates, we assumed a geometric age-efficiency function and used the relationship between the depreciation rate and the ratio of the declining balance rate to the service life as described in equation 8. We combined the Statistics Canada-derived depreciation rates in set 1 with BEA declining balance rates to obtain the corresponding set 1 service lives for each U.S. asset category, on the basis of the use of a geometric age-efficiency function. For the BLS simulations, these revised set 1 service lives were adjusted to equivalent hyperbolic age-efficiency function service lives, and the associated depreciation rates were calculated.

We also used the Canadian data to estimate a second simulation of depreciation rates, "set 2." Rather than using weighted averages of the Canadian depreciation rates to obtain rates for U.S. assets, we combined data on U.S. service lives with Statistics Canada declining balance rates. Using this approach allowed us to retain some of the information from historical U.S. studies of average service lives and to investigate the effect of more recent findings of Statistics Canada on the pattern of depreciation over time. For each U.S. asset category, we constructed estimates of declining balance rates from Statistics Canada data using our concordance between the U.S. and Canadian capital asset classification systems. The Statistics Canada declining balance rate value for each U.S. asset was divided by the BEA service life for each asset to obtain a revised depreciation rate. We then estimated the effect of the set 2 depreciation rates on BEA and BLS capital measures and BLS TFP measures.

In general, the set 2 depreciation rates fell between those in set 1 and the published BLS and BEA rates. Table 2 provides a more detailed comparison of the published and revised depreciation rates and service lives. (See source data under related content.)

When assessing the results of these simulations, note that the values of BLS and BEA capital stock measures are not directly comparable for several reasons. BLS capital stocks are consistently higher than BEA capital stocks, in part because BLS uses a hyperbolic age-efficiency function, which retains capital assets in capital stock for a relatively longer time than the BEA geometric depreciation function. Also, BLS capital stocks include land and inventories, while BEA fixed assets accounts do not. BLS also has relatively higher estimates of stocks of structures, equipment, and intellectual property products because BLS uses slower depreciation rates for some types of assets and because BLS and BEA use different functional forms for depreciation. BEA and BLS estimate capital stocks for different purposes: BEA estimates the market or replacement value of stocks for national accounts and balance sheets, whereas BLS estimates the value of productive capital and its capital services.

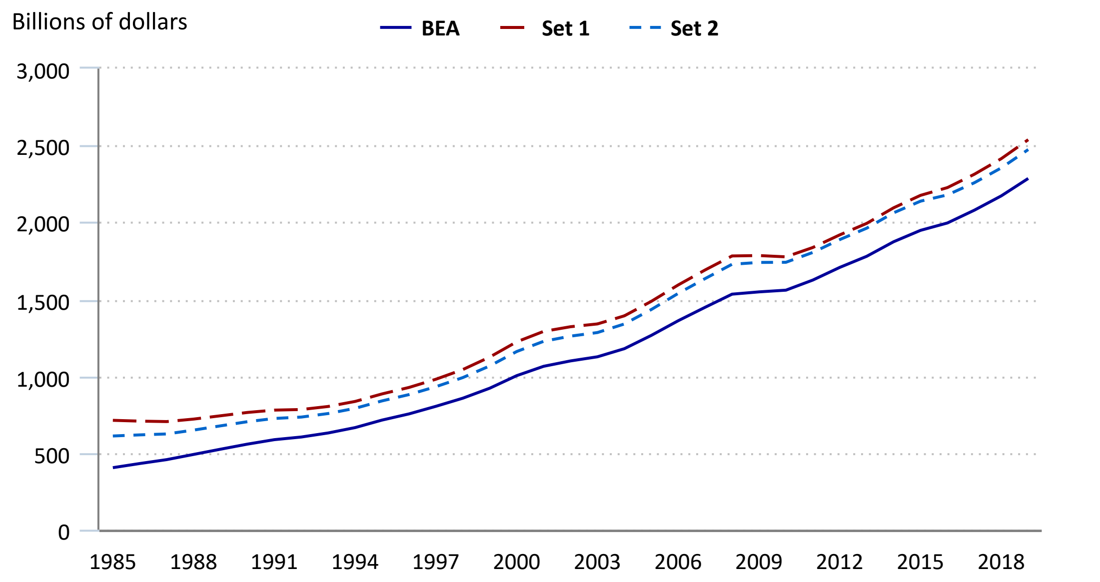
Simulation of capital measures using the revised service lives

To describe the potential effect of using these alternative depreciation rates, we substituted the revised rates into the BEA and BLS PIM and rental rate calculations to estimate simulated capital stock and capital services measures. We estimated our capital measures using both the set 1 and set 2 depreciation rates. In each simulation, we maintained the existing depreciation rates through 1984 and introduced the revised rates for all assets beginning in 1985. This approach simulated changing depreciation rates by assuming that the newer Statistics Canada rates are more appropriate for later years, whereas the published BEA and BLS rates are more appropriate for earlier years. Real depreciation rates most likely change gradually.

BEA-simulated capital measures

The use of the faster depreciation rates from Statistics Canada resulted in an upward revision to estimates of CFC (consumption of fixed capital), relative to BEA published estimates. (See chart 1.) Under the set 1 simulation, which implements revised rates starting in 1985, CFC is revised upward by $308 to $170 billion annually for 1985–94, $170–$214 billion for 1995–2004, and $222–$249 billion for 2005–18. When the generally slower depreciation rates from set 2 are used, CFC is revised upward by $206–$125 billion annually for 1985–94, $125–$163 billion for 1995–2004, and $168–$195 billion for 2005–19. In most years, the upward revision to CFC is larger for structures than for equipment because differences in depreciation rates and the capital stocks are larger for structures. (This detail is not shown in the chart.) As a percentage of the published CFC values, the upward revision to CFC declines from about 25 percent in 1994 to about 11 percent in 2019 (set 1) and declines from about 19 percent in 1994 to 8 percent in 2018 (set 2). Faster depreciation rates result in upward revisions to CFC that decline in percentage terms over time because the faster depreciation rates also result in downward revisions to net stocks. These lower net stocks lead to a partly offsetting decline in estimates of CFC. The notable upward revision to depreciation in 1985 results from our abrupt introduction of new rates in that year. A gradual transition in which rates were slowly revised upward over several years before 1985 is more realistic.

Chart 1. Consumption of fixed capital: published BEA estimates of private nonresidential fixed assets compared with revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985), in billions of dollars, 1985 to 2019

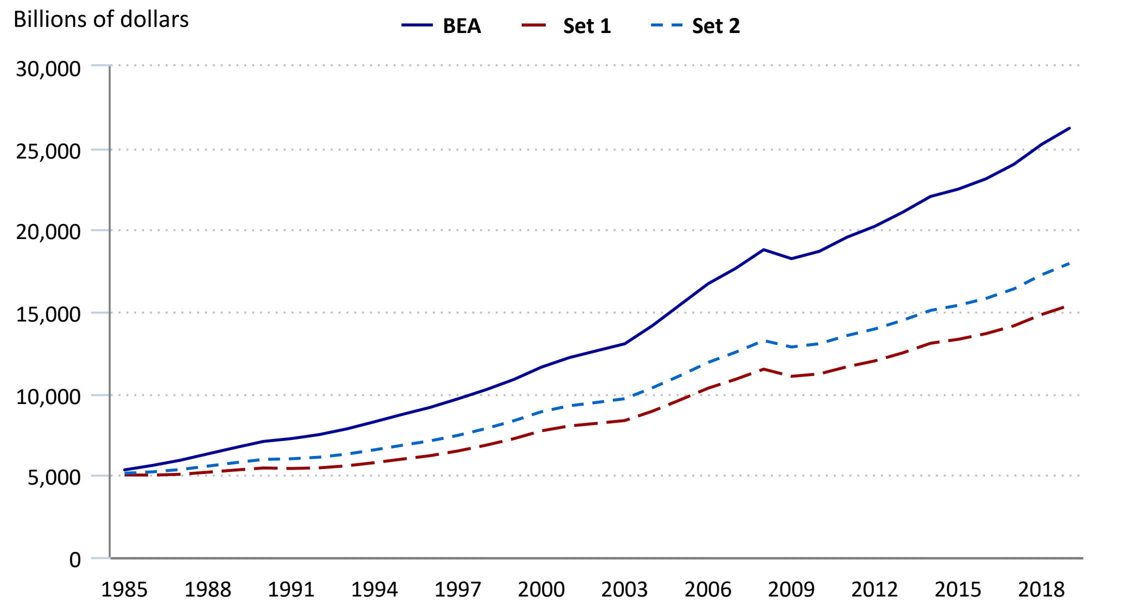


Click legend items to change data display. Hover over chart to view data.
Note: BEA = U.S. Bureau of Economic Analysis.
Source: U.S. Bureau of Economic Analysis and authors' calculations.

View Chart Data

These upward revisions to CFC lead to downward revisions to net stocks, as shown in chart 2. When the revised set 1 depreciation rates are used, net stocks (in current dollars) are reduced by $309 billion in 1985. This downward revision grew to over $10.4 trillion in 2018—a downward revision of 39.7 percent in current dollars. The downward revision to net stocks in 2018 is about $2.4 trillion for equipment and $8.0 trillion for structures. These downward revisions imply reductions in estimates of the value of fixed assets in the balance sheets of the business sector in the integrated macroeconomic accounts (sectoral accounts).[88] When the set 2 depreciation rates are used, net stocks are reduced in 2018 by $8.0 trillion (30.4 percent).

Chart 2. Net capital stocks: published BEA estimates of private nonresidential fixed assets compared with revised sets 1 and 2 depreciation rate estimates (applied beginning in 1985), in billions of dollars, 1985 to 2019



Click legend items to change data display. Hover over chart to view data.
Note: BEA = U.S. Bureau of Economic Analysis.
Source: U.S. Bureau of Economic Analysis and authors' calculations.

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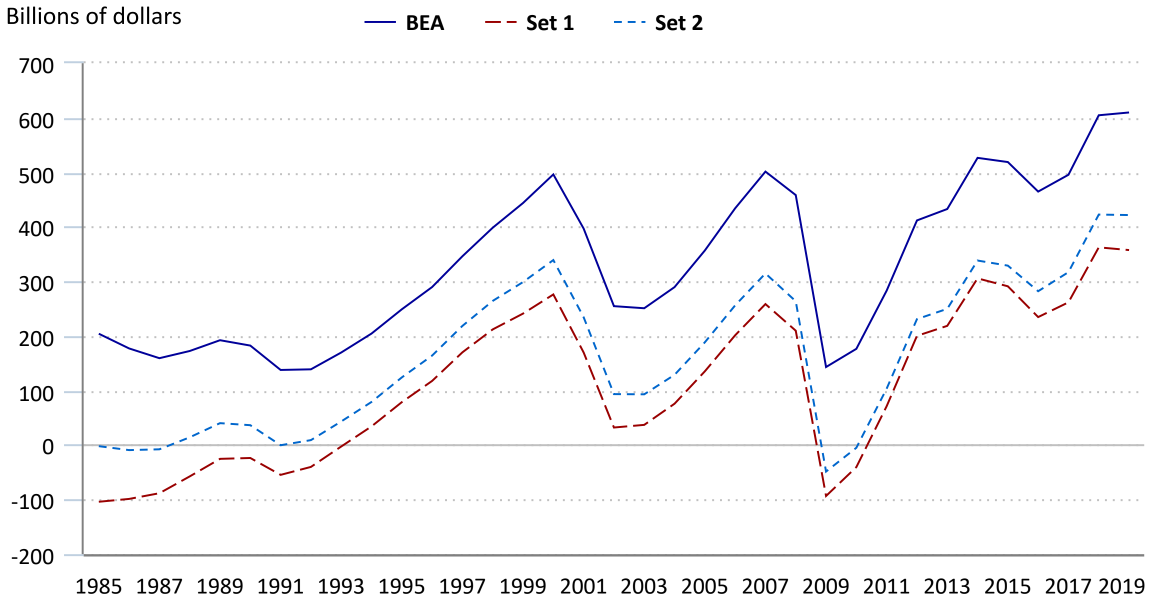
Downward revisions to net stocks reflect downward revisions to several categories of equipment and structures. Within equipment, downward revisions occurred for information processing equipment such as computers, communications equipment, and instruments ($0.6 trillion); industrial equipment ($0.9 trillion); transportation equipment ($0.4 trillion); and all other equipment ($0.5 trillion). Within structures, downward revisions occurred for commercial and healthcare ($3.2 trillion), manufacturing ($0.9 trillion), power and communication ($1.5 trillion), mining exploration ($0.6 trillion), and all other structures ($1.8 trillion).

As chart 3 shows, net investment is lower when simulated with the faster Statistics Canada depreciation rates, reflecting the upward revisions to CFC. These revisions to net investment do not shed any new light on the reasons for the timing of the productivity slowdown that began around 2004 because the capital simulations begin several years before the slowdown started. Nevertheless, the downward revisions to net investment and net stocks are noteworthy.[89]

Chart 3. Net fixed investment: published BEA estimates of private nonresidential fixed assets compared with revised sets 1 and 2 depreciation rate estimates (applied beginning in 1985), in billions of dollars, 1985 to 2019



Click legend items to change data display. Hover over chart to view data.
Note: Net fixed investment is gross fixed investment minus consumption of fixed capital. BEA = U.S. Bureau of Economic Analysis.
Source: U.S. Bureau of Economic Analysis and authors' calculations.

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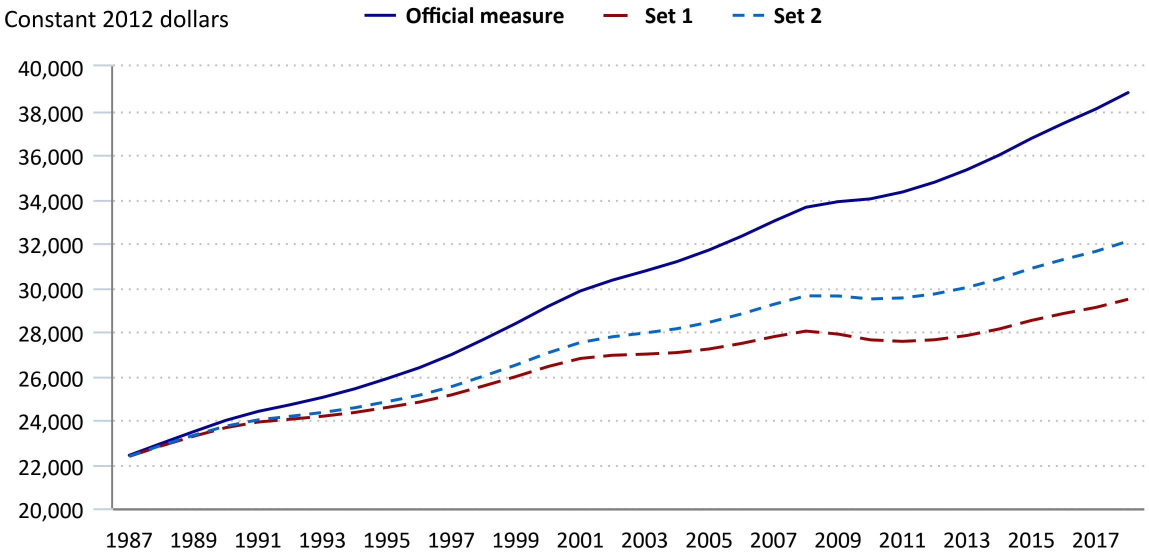
BLS-simulated capital measures

We used the revised depreciation rates to construct capital stock and capital services measures for major sectors, including the private business, private nonfarm business, and manufacturing sectors, and for 60 NIPA industries, roughly three-digit level, industries. Chart 4 presents the BLS official capital stock levels, in constant 2012 dollars, for the private nonfarm business sector along with the capital stock measures constructed with the use of the published BLS depreciation rates and the revised depreciation rates for both set 1 and set 2. The introduction of new rates in 1985 reduces the capital stock growth rate substantially over the 1987–2018 period, from the official value of 1.8 percent to 0.9 percent and 1.2 percent, for set 1 and set 2, respectively.

Chart 4. BLS official productive capital stock measures compared with BLS revised sets 1 and 2 depreciation rate estimates (applied beginning in 1985) for the private nonfarm business sector, constant 2012 dollars (in billions), 1987 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS productive capital stock is an unweighted direct aggregate of underlying asset productive capital stocks. BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

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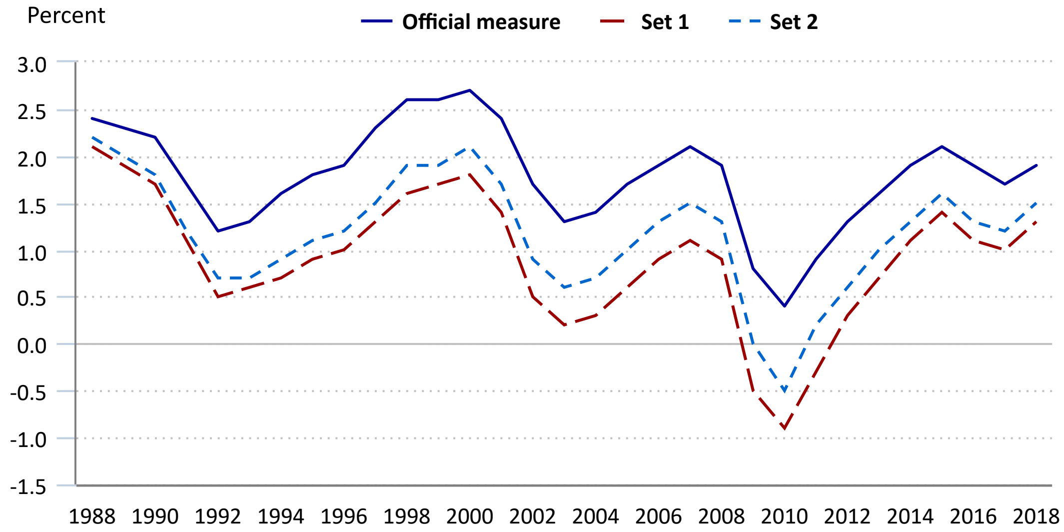
Chart 5 presents annual growth rates of the BLS official capital stock for the private nonfarm business sector and the simulated capital stock measures based on published BLS depreciation rates for both sets 1 and 2.[90] As just noted, BEA and BLS capital stock measures differ in terms of the assumptions made about asset depreciation rates and patterns of decline over time, as well as the types of assets included in each agency's measures. Comparisons between the BEA and BLS capital stock measures as a result are somewhat problematic. Regardless, we see that the use of the Statistics Canada depreciation rates results in lower stocks for both sets of estimates.

Chart 5. BLS official productive capital stock annual growth rates (in percent) compared with BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for the private nonfarm business sector, 1988 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS productive capital stock is an unweighted direct aggregate of underlying asset productive capital stocks. BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

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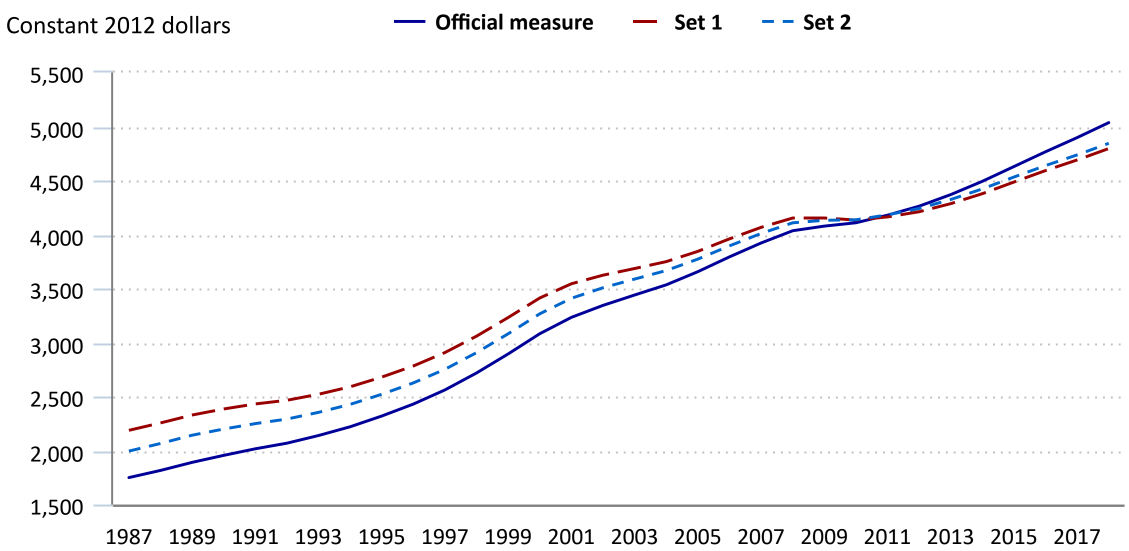
The change in service lives and depreciation rates is expected to reduce capital stocks, but the effect on capital services is less obvious. BLS measures of capital services are calculated as proportional to the capital stock, in which the proportion is the rental price of the asset.[91] Capital services measures, in constant 2012 dollars, for the private nonfarm business sector under set 1 and set 2 scenarios and those for the BLS official measures are presented in chart 6. All set 1 and set 2 simulated capital services series values are greater than the official values during the first two-thirds of the time series. The official value of capital services starts lower than that of the other two series but surpasses those of the two set 1 capital services series by 2011. The trend lines for all three series are similar though, with relatively steady growth except for a slowdown during and following the Great Recession (December 2007 to June 2009).[92]

Chart 6. BLS official capital services measures compared with BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for the private nonfarm business sector, constant 2012 dollars (in billions), 1987 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

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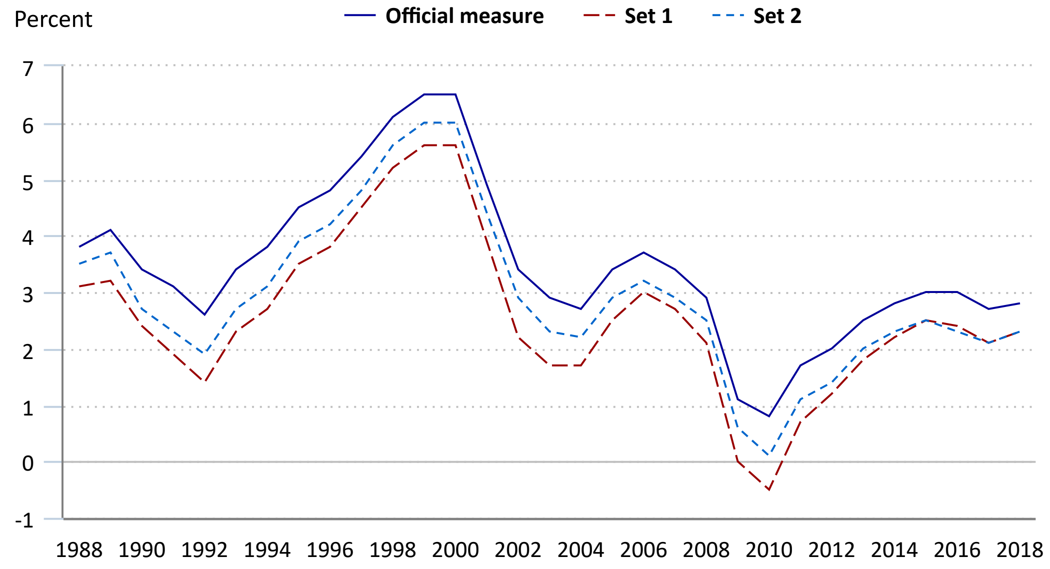
The revised and generally faster depreciation rates used in our capital services simulations had little effect on the estimates of capital services. This outcome can be explained by the offsetting effects of faster depreciation rates on capital stock and capital services measures. Changes in depreciation rates directly affect both productive capital stock measures and rental price measures. Faster depreciation rates lead to increases in rental prices and capital services per dollar of stock, which offset the reduction in productive stocks. The net effect on capital services is small. However, rental prices also function as a means of allocating capital income among capital assets. A change in depreciation rates may result in a change in the productive capital stock measures by asset type as well. Therefore, simulated asset prices may alter the allocation of capital income among the assets by modifying the weights used to aggregate detailed capital assets into the broader capital stock measures.

Faster depreciation rates also have offsetting effects on rates of return and capital stocks in the corporate sector. This offsetting effect occurs because the BLS capital measurement method adopts BEA corporate capital income and total capital income as given. Only BLS noncorporate capital income changes relative to depreciation rates and rental price fluctuations. For example, a change in depreciation rates may change the distribution of proprietors' income to labor and capital. Thus, the impact of changes in the depreciation rates on capital services would be minimal and reflect only changes in the distribution and weighting of assets and changes in noncorporate capital income.

Differences were substantial between the 1987–2018 annual growth rates of the BLS official capital stock measure and capital stock measures based on revised rates for 1985 forward by NIPA industry, with about a percentage-point difference for set 1 and slightly less for set 2. (See chart 5.) Similar effects are observed in chart 7 (which displays annual growth rates of capital services measures) for the BLS official capital services measure and the simulated capital services measures. Note that the updated capital services measures have very similar annual growth-rate movements, with level shifts that remain relatively consistent among the separate series. Again, with new service lives applied beginning in 1985, the growth rates of capital services series simulated by using set 1 and set 2 are lower than the published BLS series. For the major sectors, capital stock levels and growth rates are affected by the revised service lives. The reductions in the level of capital stock are expected given the generally downward revisions in service lives and upward adjustments in depreciation rates. On the other hand, little difference exists in capital services levels and growth rates at the aggregate level, because of the updated depreciation rates. However, the impact on detailed NIPA industry capital stock and capital services measures appears to be larger for many industries and warrants additional investigation.[93] The revised depreciation rates result in greater capital stock differences at the more detailed NIPA industry level than at the aggregate major sector level.

Chart 7. BLS official capital services annual growth rates (in percent) compared with BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for the private nonfarm business sector, 1988 to 2018



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

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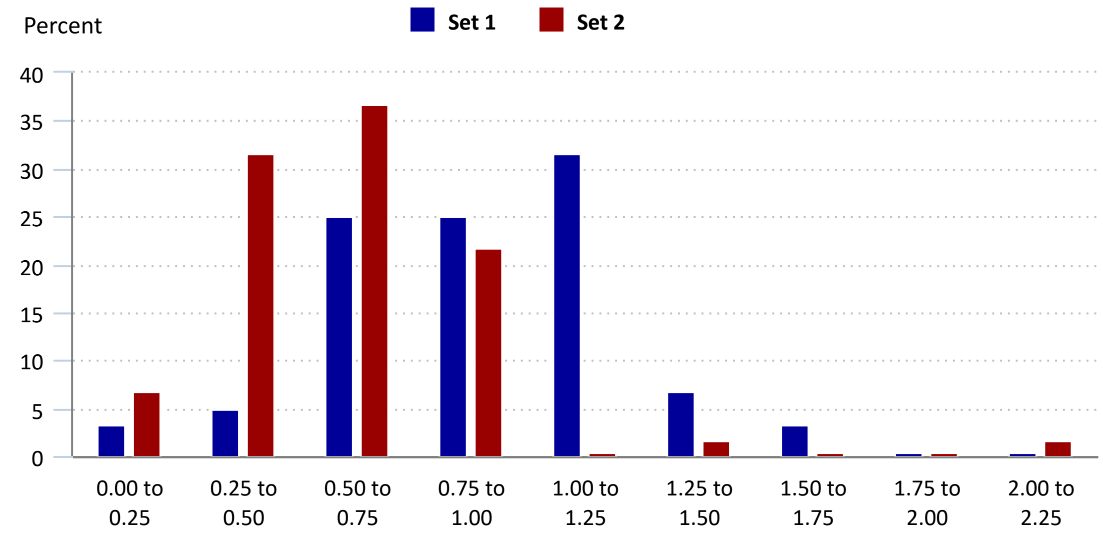
Variation across industries is summarized in charts 8 through 11, illustrating how the data from set 1 and set 2 differ from published BLS capital stock and capital services growth-rate data. Each chart presents the distribution of industry average deviations from published BLS average growth rates for the years 1988–2018. For example, in chart 8, the industry average deviation between the BLS and set 1 capital stock growth rates is calculated as the average annual growth rate of capital stock for each industry under the current BLS method minus the average growth rate of capital stock for each industry by using the set 1 service lives.

Chart 8 illustrates the distribution of these differences in capital stock growth rates by industry when set 1 or set 2 asset service lives are used. For set 1 service lives, the modal difference is between 1.00 and 1.25 percentage points. For all these industries, the average growth rates of published BLS capital stocks are greater than the average growth rates resulting from the set 1 service lives. When set 2 service lives are used, the distribution of differences is shifted leftward with the modal value now falling between 0.50 and 0.75. Again, all differences are greater than zero, indicating that growth rates of capital stock are reduced when the shorter service lives of set 2 are used in place of published BLS service lives.

Chart 8. Distribution of percentage-point differences between capital stock growth rates: BLS published capital stock growth rates minus BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for 60 National Income and Product Accounts industries, compound growth rates, 1987 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

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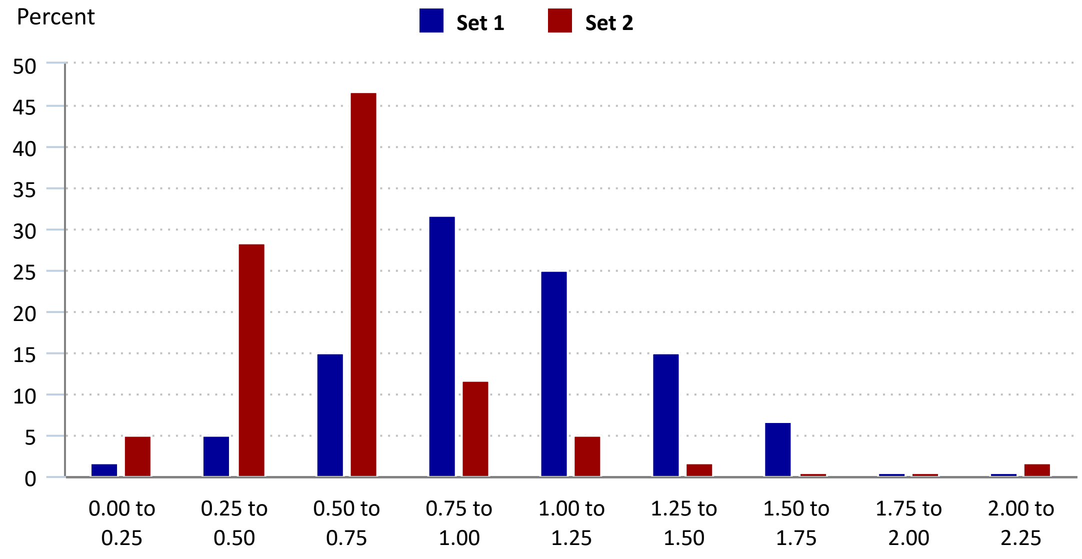
Chart 9 illustrates the distribution of the differences between the published BLS capital services average growth rates and the set 1 and set 2 growth rates for 1987–2018 of 60 NIPA industries. When the Statistics Canada set 1 growth rates are used, about three-quarters of industries deviate from the published BLS capital services growth rate by more than 0.75. The currently calculated BLS average capital services growth rate is also higher in every industry compared with the average growth rates, when the generally shorter service lives of set 1 are implemented beginning in 1985. When the more moderate set 2 service lives are used, about 80 percent of industries have simulated capital services growth rates that are up to 0.75 percentage points slower than the published BLS capital services average annual growth rates, from 1987 to 2018.

Chart 9. Distribution of percentage-point differences between capital services growth rates: BLS published capital services growth rates minus BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for 60 National Income and Product Accounts industries, compound growth rates, 1987 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

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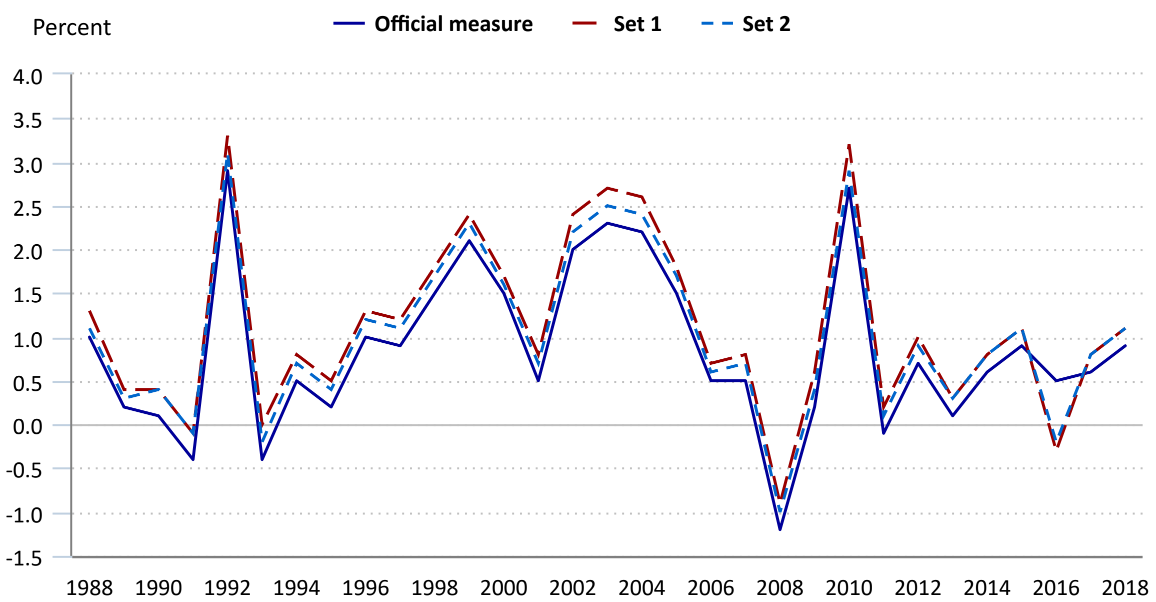
Chart 10 shows the impacts of the revised depreciation rates on BLS TFP growth estimates for the private nonfarm business sector over the 1988–2018 period. The simulated TFP growth rates, based on our simulated capital services measures, are very similar. The series with set 1 service lives results in larger differences with the published TFP growth values. Looking at year-to-year differences, we found that the published TFP series is consistently lower, by 0.3 percentage points in 15 years, 0.4 percentage points in an additional 6 years, and 0.5 in 1 year. The set 2 TFP growth values are closer to the published values but are often smaller than the set 1 values, usually about 0.1 or 0.2 percentage points lower, and greater than the published BLS values. In part, the difference between the published and simulated set 1 and set 2 TFP growth rates reflects a difference in the underlying capital stock measures. Growth rates for the capital stock derived by using the set 1 service lives beginning in 1985 also exhibit the largest deviation from published BLS capital stock growth rates. (See chart 5.) Over time, the levels of capital stock indicated by the set 1 and set 2 rates converge to a new lower level. (See chart 4.)[94]

Chart 10. BLS official total factor productivity annual growth rates (in percent) compared with BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for the private nonfarm business sector, 1988 to 2018

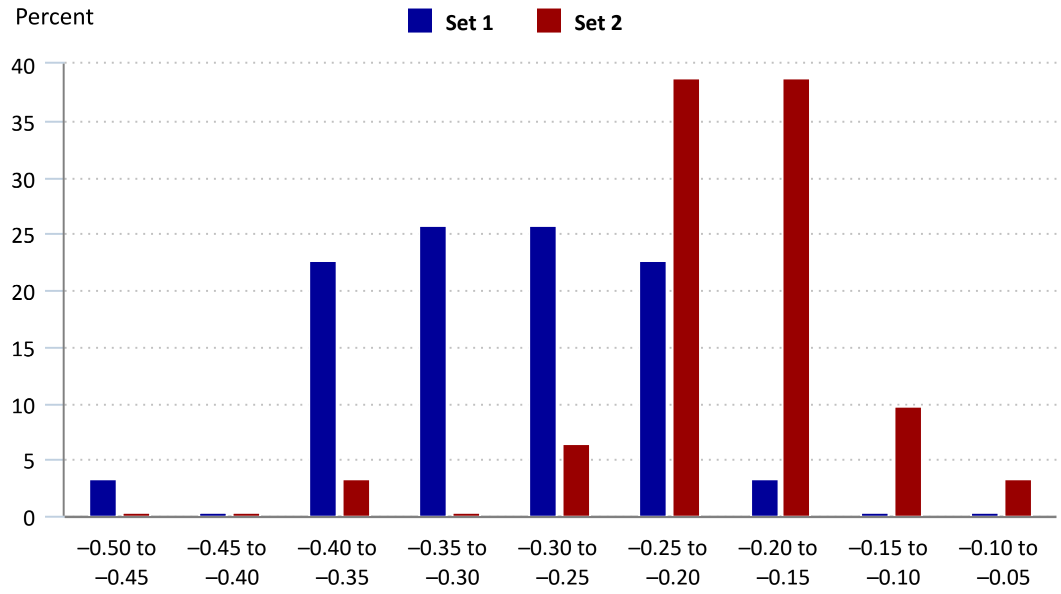


Click legend items to change data display. Hover over chart to view data.
Note: BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

View Chart Data

Chart 11 shows the distribution of the differences between the published and simulated BLS TFP growth rates for the private nonfarm business sector, from 1988 to 2018. By examining the deviation of simulated TFP growth rates from the published BLS growth rates when implementing the set 1 service lives beginning in 1985, we see that the simulated TFP growth rates for all years are higher than the published BLS rates. Of the 31 years in this period, 23 have rates up to 0.35 percentage points above the published BLS TFP rates. Using the more moderate set 2 service lives results in simulated TFP average annual growth rates for 1988–2018 that are mildly faster than the published BLS TFP growth rates in each year. TFP growth rates are up to 0.25 percentage points above the published BLS TFP average annual growth rates for 28 of the 31 years.

Chart 11. Distribution of percentage-point differences between total factor productivity growth rates: BLS published total factor productivity growth rates minus BLS revised set 1 and set 2 depreciation rate estimates (applied beginning in 1985) for 60 National Income and Product Accounts industries, compound growth rates, 1988 to 2018



Click legend items to change data display. Hover over chart to view data.
Note: BLS = U.S. Bureau of Labor Statistics.
Source: U.S. Bureau of Labor Statistics and authors' calculations.

View Chart Data

Conclusion

The published BEA and BLS capital measures use depreciation rates for equipment and structures that are mostly based on the widely respected Hulten and Wykoff studies from the early 1980s.[95] These depreciation rates are important in BEA estimates of net capital stocks, net investment, and net saving and in BLS measures of productivity and capital services. Because the estimation of depreciation rates is difficult and requires specialized data sets of used equipment transactions, BEA and BLS have not updated most of these rates, although technological and other changes may cause depreciation patterns to change over time. Unfortunately, few resources are devoted to gauging the accuracy of these rates. As a step toward improving the accuracy of U.S. capital depreciation rates, BEA and BLS might consider selective revisions to depreciation rates of a subset of these asset categories, depending on the prevailing assessment and availability of empirical evidence.

In this article, we estimate simulated capital measures using alternative, typically faster, depreciation rates based on studies by Statistics Canada that principally apply the Hulten and Wykoff method to more recent data from Canada's Annual Capital and Repair Expenditures Survey.[96] The Statistics Canada results are consistent with those of Bokhari and Geltner who apply a similar approach to estimate depreciation rates for commercial buildings in the United States in recent years.[97] Both studies find faster depreciation rates than those used by BEA and BLS, in which the largest differences in rates are for structures. While true depreciation rates vary across countries, the similarity of findings in these studies suggests that the U.S. rates—based on a patchwork of vintage research—may no longer adequately capture the depreciation of U.S. capital assets.

In this research, we evaluated the effect of using the Statistics Canada estimates in U.S. capital and TFP measures. Our results show that using the alternative depreciation rates produces substantial revisions to BEA capital measures. When we incorporate the faster depreciation rates from 1985 forward, we find that CFC is revised upward by $242 billion in current dollars (11 percent) in 2018, net investment is revised downward by the same amount, and net capital stocks are revised downward by $10.4 trillion (40 percent), with a $2.4 trillion downward revision to stocks of equipment and an $8.0 trillion downward revision to stocks of structures.

Capital stock levels that underlie U.S. productivity data are similarly affected. Constructing estimates of BLS private nonfarm business capital stock by using the Statistics Canada set 1 rates from 1985 forward results in substantial declines, from 0.002 to 24 percent, because much of the value of previous capital stock remains in place, particularly in structures. However, capital services, growth rates in capital services, and TFP growth rates for major sectors show a relatively small impact from using the Statistics Canada set 1 revised rates. The effects on capital stocks, capital services, and TFP are larger with the new depreciation rates implemented abruptly in 1985 than if they were introduced gradually.

We hope this comparison encourages additional research and discussion regarding the depreciation rates and service lives of U.S. equipment and structures used by BEA and BLS when constructing capital and related measures. Because the collection of survey data on used asset transactions can be costly, we especially encourage studies based on automated records of used asset transactions. In the meantime, users of these capital measures should be aware of the sensitivity of these measures to the choice of depreciation rates.

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Notes

[1] The U.S. Bureau of Economic Analysis (BEA) is responsible for the national accounts, while the U.S. Bureau of Labor Statistics (BLS) is responsible for the productivity statistics.

[2] For information on BLS capital services data for major sectors and National Income and Product Accounts (NIPA)-level industries, see "Annual capital details: total factor productivity" (data released March 24, 2022), https://www.bls.gov/productivity/tables/total-factor-productivity-capital-details-major-sectors-and-industries.xlsx.

[3] BEA fixed assets accounts can be found at "Fixed assets" (U.S. Department of Commerce, BEA), https://www.bea.gov/itable/fixed-assets. The integrated macroeconomic accounts can be found at "Integrated macroeconomic accounts for the United States" (U.S. Department of Commerce, U.S. Bureau of Economic Analysis, last modified September 23, 2022), https://www.bea.gov/data/special-topics/integrated-macroeconomic-accounts.

4 These classic articles include Frank C. Wykoff and Charles R. Hulten, “Tax and economic depreciation of machinery and equipment: a theoretical and empirical appraisal,” Phase II report, *Economic Depreciation of the U.S. Capital Stock: a First Step* (Washington, DC: U.S. Department of the Treasury, Office of Tax Analysis, July 26, 1979), https://home.treasury.gov/system/files/131/WP-28.pdf; Charles R. Hulten and Frank C. Wykoff, “The estimation of economic depreciation using vintage asset prices: an application of the Box–Cox power transformation,” *Journal of Econometrics*, vol. 15, no. 3, April 1981, pp. 367–96, https://www.sciencedirect.com/science/article/abs/pii/0304407681901019; and Charles R. Hulten and Frank C. Wykoff, “The measurement of economic depreciation,” ed. Charles R. Hulten, *Depreciation, Inflation & the Taxation of Income from Capital* (Washington, DC: The Urban Institute Press, 1981), pp. 81–125, http://econweb.umd.edu/~hulten/WebPageFiles/Original%20Hulten-Wykoff%20Economic%20Depreciation%20Study.pdf.

5 Statistics Canada, “Depreciation rates for the productivity accounts,” *The Canadian Productivity Review*, Catalogue no. 15-206-X, no. 5, February 2007; and John Baldwin, Huju Liu, and Marc Tanguay, “An update on depreciation rates for the Canadian Productivity Accounts,” *The Canadian Productivity Review*, Catalogue no. 15-206-X, no. 39, January 26, 2015, http://www.statcan.gc.ca/pub/15-206-x/15-206-x2015039-eng.htm.

6 For further information on Statistics Canada’s Annual Capital and Repair Expenditures Survey, see https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=2803.

7 Sheharyar Bokhari and David Geltner, “Commercial buildings, capital consumption, and the United States National Accounts,” *The Review of Income and Wealth,* series 65, no. 3, September 2019, p. 561–591, https://onlinelibrary.wiley.com/doi/epdf/10.1111/roiw.12357.

8 Charles R. Hulten, “Getting depreciation (almost) right” (paper presented at the meeting of the Canberra II Group and Joint Nesti-Canberra II Session on R&D Capitalization, April 24–27, 2007, OECD, Paris), https://www.econ.umd.edu/publication/getting-depreciation-almost-right.

9 Barbara M. Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts,” *Survey of Current Business*, July 1997, p. 8, https://apps.bea.gov/scb/pdf/national/niparel/1997/0797fr.pdf.

10 “Disruptive” technologies change existing industries meaningfully; they do not just add products or slightly reduce costs. See, for example, Bernard Marr, “Why everyone must get ready for the 4th Industrial Revolution,” *Forbes* (blog), April 5, 2016, https://www.forbes.com/sites/bernardmarr/2016/04/05/whyeveryone-must-get-ready-for-4th-industrial-revolution/#4816522279c9; Clayton M. Christensen, Michael E. Raynor, and Rory McDonald, “What is disruptive innovation?” *Harvard Business Review*, December 2015, pp. 44–53, https://hbr.org/2015/12/what-is-disruptive-innovation; and Airini Ab Rahman, Umar Zakir Abdul Hamid, and Thoo Ai Chin, “Emerging technologies with disruptive effects: a review,” *PERINTIS eJournal*, vol. 7, no. 2, December 2017, pp. 111–128, https://www.researchgate.net/publication/321906585_Emerging_Technologies_with_Disruptive_Effects_A_Review. The “Internet of Things” refers to the idea that vast numbers of devices might be connected and exchange data through the internet. To the extent vehicles, medical devices, warehouses, homes, and other physical objects are connected, greater automation of industry is possible. A formal definition of the Internet of Things as “objects that are readable, recognizable, locatable, addressable, and/or controllable via the internet, irrespective of the communication means (such as) RFID (radio frequency identification), wireless LAN, wide area networks, or other” and further discussion are available in P. Ravi and A. Ashokkumar, “Internet of Things: a great wonder,” *International Journal of Advanced Networking and Applications*, special issue of the UGC Sponsored National Conference on Advanced Networking and Applications, March 27, 2015, pp. 113–119, http://www.ijana.in/Special%20Issue/file25.pdf.

11 Jonathan Tilley, “Automation, robotics, and the factory of the future” (New York: McKinsey and Company, September 7, 2017), https://www.mckinsey.com/business-functions/operations/our-insights/automation-robotics-and-the-factory-of-the-future.

12 Organisation for Economic Co-operation and Development, “*Measuring Capital: OECD Manual*, 2nd ed. (Paris, France: OECD Publishing, 2009), pp. 111–112, http://www.oecd.org/sdd/productivity-stats/43734711.pdf.

13 The concepts, methods, and empirical studies underlying BEA depreciation rates are described in Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts,” pp. 7–23; and U.S. Department of Commerce, U.S. Bureau of Economic Analysis, *Fixed Assets and Consumer Durable Goods in the United States, 1925–97* (Washington, DC: U.S. Government Printing Office, September 2003), pp. M-6–M-8 and M-29–M-33, https://www.bea.gov/node/24441. BEA estimates the perpetual inventory method using real (inflation-adjusted) series and then reflates to obtain current-dollar net stocks and depreciation. For a summary of BEA depreciation rates and a brief overview of the studies on which they are based, see “BEA depreciation estimates,” https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf.

14 See, for example, Richard Peach and Charles Steindel, “Low productivity growth: the capital formation link,” *Liberty Street Economics* (blog) (New York Federal Reserve, June 26, 2017), http://libertystreeteconomics.newyorkfed.org/2017/06/low-productivity-growth-the-capital-formation-link.html.

15 See Jennifer Bennett, Robert Kornfeld, Daniel Sichel, and David Wasshausen, “Measuring infrastructure in BEA’s national accounts,” Working Paper 27446 (Cambridge, MA: National Bureau of Economic Research, June 2020), http://www.nber.org/papers/w27446.

16 For further discussion, see Eurostat and Organisation for Economic Co-operation and Development, “Estimating inventory stocks by using the perpetual inventory method,” chapter 6.4 in *Eurostat-OECD Compilation Guide on Inventories,* 2017 ed. (Luxembourg: Publications Office of the European Union, September 2017), pp. 107–119, http://ec.europa.eu/eurostat/documents/3859598/8228095/KS-GQ-17-005-EN-N.pdf/12e80726-35a3-46a9-869a-8f77ca3be742.

17 A second capital concept, the wealth stock of capital, represents its asset value at a point in time, not its productive value. The wealth stock is estimated by weighting real investment by an age/price profile, reflecting observed new and used asset prices and retirement patterns of capital assets over time.

18 For further discussion on the BLS choice of the hyperbolic age-efficiency function, including a comparison with the geometric age-efficiency function, see Michael J. Harper, “The measurement of productive capital stock, capital wealth, and capital services,” Working Paper 128 (BLS, June 1982), https://www.bls.gov/osmr/research-papers/1982/pdf/ec820020.pdf; Michael J. Harper, “Estimating capital inputs for productivity measurement: an overview of concepts and methods” (paper presented at the Conference on Measuring Capital Stock, OECD, March 1997), https://www.oecd.org/sdd/na/2666894.pdf; and U.S. Department of Labor, BLS, *Trends in Multifactor Productivity, 1948–81*, Bulletin 2178 (Washington, DC: U.S. Government Printing Office: September 1983), pp. 39–65, https://www.bls.gov/productivity/articles-and-research/trends-in-total-factor-productivity-1948-1981.pdf.

19 See Hulten and Wykoff, “The measurement of economic depreciation”; and Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices.” These values are consistent with their research that modeled the functional form of used asset prices for a variety of capital assets, by using an extensive database of used asset prices. This research determined that structures depreciate more slowly than equipment assets.

20 Light bulbs are a common example—they often work at 100-percent effectiveness until they suddenly turn dark permanently. This aging effect is a concave shape.

21 See “BEA depreciation estimates,”https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf; and Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts,” for a description of data sources and estimation methods underlying the BEA depreciation rate and service life computations. BLS also assumes variation in the service lives of each cohort of investments; this variation is called a service life distribution. This distribution was not varied in the simulations to be discussed later in the article.

22 BEA uses geometric depreciation for most assets, with some exceptions. Computers and peripheral equipment and private autos use actual empirical depreciation profiles, and missiles and nuclear fuel rods use a straight-line pattern. For more information, see U.S. Department of Commerce, BEA, “A guide to the National Income and Product Accounts of the United States,” https://apps.bea.gov/scb/pdf/misc/nipaguid.pdf.

23 An advantage of assuming geometric depreciation is that the productive capital stock is equal to the wealth stock, which is used to estimate depreciation in the rental price formula.

[24] BLS uses a half-year convention to address this issue of new investment coming into service at different times during the year: “Since the investment figures received from BEA count investment at the time it is finished and ready to use, it seems reasonable to count about half of a given year’s new investment, efficiency loss, and depreciation toward the annual average measures of stocks. Therefore, a half-year convention is used in the BLS measures. A given year’s output is matched to the arithmetic mean of the current year-end stock and the year-end stock for the previous year. Thus, capital services are assumed proportional to the *annual average* productive stock of a given asset.” For further discussion, see U.S. Department of Labor, BLS, *Trends in Multifactor Productivity, 1948–81*, pp. 48–49.

[25] For a detailed list of the capital assets included in BLS capital stock measures, see U.S. Department of Labor, BLS, “Overview of capital Inputs for the BLS multifactor productivity measures,” “Table 1. BEA and BLS mean asset service lives—NAICS-based (revised August 20, 2013),” June 2, 2017, pp. 2–3, https://www.bls.gov/productivity/technical-notes/methods-capital-inputs-total-factor-productivity-2017.pdf.

[26] See U.S. Department of Labor, BLS, *Trends in Multifactor Productivity, 1948–81*.

[27] The hyperbolic function used by BLS is flatter early in the asset’s life and then falls sharply as the asset approaches its end of life. For further discussion of BLS capital measurement methods, see U.S. Department of Labor, BLS, *Trends in Multifactor Productivity, 1948–81*, appendix C, pp. 39–65; and Harper, “The measurement of productive capital stock, capital wealth, and capital services.”

[28] BLS obtains depreciation rates for most capital assets from BEA. These depreciation rates are then translated into slightly different depreciation rates and related service lives from those which result from the BEA geometric age and/or efficiency pattern, because of BLS use of a hyperbolic age-efficiency function rather than a geometric age and/or efficiency function.

[29] See Laurits R. Christensen and Dale W. Jorgenson, “The measurement of U.S. real capital input, 1929–1967,” *Review of Income and Wealth*, vol. 15, no. 4, 1969, pp. 293–320, https://onlinelibrary.wiley.com/doi/10.1111/j.1475-4991.1969.tb00814.x.

[30] Robert E. Hall and Dale W. Jorgenson, “Tax policy and investment behavior,” *The American Economic Review*, vol. 57, no. 3, June 1967, pp. 391–414, https://www.researchgate.net/publication/243780098_Tax_Policy_and_Investment. Note that depreciation and deterioration are conceptually different. “Deterioration” refers to the decline in the productive capacity of the asset from wear and tear, whereas “depreciation” refers to the decline in the financial value of the asset. These movements are the same when a geometric decline is assumed but not when a hyperbolic age-efficiency function is assumed.

[31] A small offsetting effect of slower depreciation rates also occurs that leads to higher levels of net stocks over time and thus higher levels of annual depreciation.

[32] The U.S. Census Bureau defines construction to include new buildings and structures; additions, alterations, conversions, expansions, reconstruction, renovations, rehabilitations, and major replacements (such as the complete replacement of a roof or heating system); mechanical and electrical installations, such as plumbing, heating, electrical work, elevators, escalators, central air-conditioning, and other similar building services; site preparation and outside construction of fixed structures or facilities such as sidewalks, highways and streets, parking lots, utility connections, outdoor lighting, railroad tracks, airfields, piers, wharves and docks, telephone lines, radio and television towers, water supply lines, sewers, water and signal towers, electric light and power distribution and transmission lines, petroleum and gas pipelines, and similar facilities that are built into or fixed to the land; installation of boilers, overhead hoists and cranes, and blast furnaces; fixed, largely site-fabricated equipment not housed in a building, primarily for petroleum refineries and chemical plants, but also including storage tanks, refrigeration systems, etc.; and cost and installation of construction materials placed inside a building and used to support production machinery. Examples of construction materials include concrete platforms, overhead steel girders, and pipes to carry paint, etc., from storage tanks. Exclusions from construction include maintenance and repairs to existing structures or service facilities; cost and installation of production machinery and equipment items not specifically covered above, such as heavy industrial machinery, printing presses, stamping machines, bottling machines, and packaging machines; special purpose equipment designed to prepare the structure for a specific use, such as steam tables in restaurants, pews in churches, lockers in school buildings, beds or x-ray machines in hospitals, and display cases and shelving in stores; drilling of gas and oil wells, including construction of offshore drilling platforms; digging and shoring of mines (construction of buildings at mine sites is included); work that is an integral part of farming operations such as plowing and planting of crops; and land acquisition. For more information on the U.S. Census Bureau construction statistics, see https://www.census.gov/construction/c30/definitions.html.

[33] For private equipment, BEA estimates are prepared using the “commodity-flow method.” This method begins with a value of domestic output (manufacturers’ shipments) based on data from the 5-year Economic Census and the Annual Surveys of Manufacturers. Next, the domestic supply of each commodity—the amount available for domestic consumption—is estimated by adding imports and subtracting exports, both based on international trade data from the U.S. Census Bureau. The domestic supply is then allocated among domestic purchasers—business, government, and consumers—on the basis of Economic Census data.

[34] Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices”; Hulten and Wykoff, “The measurement of economic depreciation”; and Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts.”

[35] Statistics Canada, “Depreciation rates for the productivity accounts”; and Baldwin, Liu, and Tanguay, “An update on depreciation rates for the Canadian Productivity Accounts.”

[36] Bokhari and Geltner, “Commercial buildings, capital consumption, and the United States National Accounts.”

[37] Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment”; Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices,” pp. 367–96; and Hulten and Wykoff, “The measurement of economic depreciation,” pp. 81–125.

[38] Hulten and Wykoff, “The measurement of economic depreciation.” Hulten and Wykoff acquired data of sales of machine tools from a private source, and data on sales of construction machinery, autos, and office equipment from several sources, including the *Forke Brothers Bluebook, Ward Automotive Yearbooks, Kelly Bluebooks*, and auction reports from the General Services Administration.

[39] Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices,” pp. 382–383.

[40] For further discussion, see Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices.” The Hulten and Wykoff studies did not have data on renovations, which in principle would be capitalized. A major contribution of the Hulten and Wykoff studies was their refutation of the “lemons problem” of used asset studies. Because sellers and buyers of used assets may have asymmetric information about the quality of the asset (only sellers may know about the “lemons”), depreciation estimates based on used asset markets may suffer from bias. Hulten and Wykoff made the point that most of these assets are bought and sold by professional buyers with extensive knowledge and expertise so that problems of asymmetric information and resulting biases are likely to be minimal. The “lemons problem” is explained in the classic article by George A. Akerlof, “The market for ‘lemons’: quality uncertainty and the market mechanism,” *The Quarterly Journal of Economics*, vol. 84, no. 3, 1970, pp. 488–500.

[41] Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices.”

[42] See U.S. Department of the Treasury, U.S. Bureau of Internal Revenue, “Bulletin ‘F’ (revised January 1942): income tax depreciation and obsolescence, estimated useful lives and depreciation rates” (Washington, DC: U.S. Government Printing Office, 1948), https://openlibrary.org/books/OL22951093M/Bulletin_F_(revised_January_1942); and Robley Winfrey, “Statistical analyses of industrial property retirements,” Bulletin 125 (Iowa Engineering Experiment Station, 1935), https://babel.hathitrust.org/cgi/pt?id=mdp.35128000776532&view=1up&seq=14. Winfrey curves are widely used in depreciation studies. An L0 Winfrey curve was used to estimate the pattern of retirements about the mean for structures. The L0 curve is an asymmetrical distribution that allows for some assets to survive to very old ages. An S3 curve, a bell-shaped distribution centered around the mean, was used for metalworking and general industrial machinery.

[43] Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices,” pp. 383–386.

[44] Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment,” pp. 11–14.

[45] For further information, see Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment,” p. 32.

46 “For additional information, see Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts,” p. 11.

47 For further discussion, see Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment,” p. 36; and Hulten and Wykoff, “The measurement of economic depreciation,” p. 94.

48 See, for example, Statistics Canada, “Depreciation rates for the productivity accounts,” pp. 8–15; Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts”; and U.S. Department of Commerce, U.S. Bureau of Economic Analysis, *Fixed Assets and Consumer Durable Goods in the United* States*, 1925–99*.

49 Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts.”

50 Ibid.

51 See “BEA depreciation estimates,” https://apps.bea.gov/national/pdf/BEA_depreciation_rates.pdf; and Fraumeni, “The measurement of depreciation in the U.S. National Income and Product Accounts,” for more details. BEA estimates of depreciation for computers and peripheral equipment are based on work by Stephen D. Oliner, “Constant-quality price change, depreciation, and retirement of mainframe computers,” in *Price Measurements and Their Uses*, eds. Murray F. Foss, Marilyn E. Manser, and Allan H. Young (Chicago, IL: University of Chicago Press, January 1993), pp. 19–61, https://www.nber.org/books-and-chapters/price-measurements-and-their-uses/constant-quality-price-change-depreciation-and-retirement-mainframe-computers. The service life for nuclear fuel was obtained from Professor Madeline Feltus of Pennsylvania State University. Beginning with 1992, light trucks were assigned a service life of 17 years on the basis of data from private sources, while other trucks, buses, and truck trailers were assigned separate service lives that varied by industry. The derivation of stocks of autos is based on a method that does not require an explicit service-life assumption. In 2003, the service lives of aircraft for several industries for 1960 forward were raised from 20 to 25 years. The service life for railroad equipment and structures is derived from reports of individual railroads submitted to the Interstate Commerce Commission. For communication, electric light and power, gas, and petroleum pipelines structures, the service lives are derived by comparing book value data provided by regulatory agencies with perpetual inventory estimates calculated by using alternative service lives. For petroleum and natural gas exploration, shafts, and wells, the lives are based on data from the U.S. Census Bureau annual surveys of oil and gas for 1979–1982.

52 Statistics Canada, “Depreciation rates for the productivity accounts”; Baldwin, Liu, and Tanguay, “An update on depreciation rates for the Canadian Productivity Accounts”; Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment”; Hulten and Wykoff, “The measurement of economic depreciation”; and Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices.”

53 For more information, see the Statistics Canada’s Annual Capital and Repair Expenditures Survey, https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=2803.

54 See Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment”; Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices”; and Hulten and Wykoff, “The measurement of economic depreciation.”

55 Hulten and Wykoff, “The measurement of economic depreciation,” pp. 84–90.

56 Baldwin, Liu, and Tanguay, “An update on depreciation rates for the Canadian Productivity Accounts.”

57 Ibid, p. 44.

58 Ibid, p. 19.

59 Ibid, pp. 33–39.

60 Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment,” p. 33; and Hulten and Wykoff, “The measurement of economic depreciation,” pp. 95–96.

61 Organisation for Economic Co-operation and Development, “*Measuring Capital,”* p. 100.

62 Organisation for Economic Co-operation and Development Working Party on National Accounts, “Measurement of depreciation rates based on disposal asset data in Japan,” STD/CSTAT/WPNA(2008)9, September 30, 2008 (paper presented by Koji Nomura at Tour Europe, Paris la Défense, October 14, 2008), http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?doclanguage=en&cote=std/cstat/wpna(2008)9.

63 For example, see Koji Nomura and Yutaka Suga, “Measurement of depreciation rates using microdata from disposal survey of Japan,” July 28, 2018 (paper presented at 35th IARIW General Conference in Copenhagen, Denmark, August 24, 2018), http://old.iariw.org/copenhagen/suga.pdf. Nomura and Suga report that “Japan’s rates of geometric depreciation estimated in this study are broadly similar to the estimates at Statistics Canada (Baldwin, Liu, and Tanguay, 2015), but considerably higher than those used in the U.S.” See endnote 26 for more information.

64 See Myriam van Rooijen-Horsten, Dirk van den Bergen, Ron de Heij, and Mark de Haan, “Service lives and discard patterns of capital goods in the manufacturing industry, based on direct capital stock observations, the Netherlands,” Discussion Paper 08011 (Statistics Netherlands, Voorburg/Heerlen, August 2008), https://www.cbs.nl/-/media/imported/documents/2008/27/2008-11-x10-pub.pdf.

65 Eurostat and Organisation for Economic Co-operation and Development, *Eurostat-OECD Survey of National Practices in Estimating Net Stocks of Structures,* 2016, pp. 11–12, http://ec.europa.eu/eurostat/documents/24987/4253483/Eurostat-OECD-survey-of-national-practices-estimating-net-stocks-structures.pdf.

66 See for example Jiro Yoshida, “The economic depreciation of real estate: cross-sectional variations and their return implications,” *Pacific-Basin Finance Journal*, vol. 61, June 2020, https://www.sciencedirect.com/science/article/pii/S0927538X18304505; and Nolan Gray, “Why is Japanese zoning more liberal than US zoning?” *Market Urbanism*, March 19, 2019, https://marketurbanism.com/2019/03/19/why-is-japanese-zoning-more-liberal-than-us-zoning/.

67 Bokhari and Geltner, “Commercial buildings, capital consumption, and the United States National Accounts”; Wykoff and Hulten, “Tax and economic depreciation of machinery and equipment”; Hulten and Wykoff, “The estimation of economic depreciation using vintage asset prices”; and Hulten and Wykoff, “The measurement of economic depreciation.”

68 Investment in structures by private business includes improvements (additions, alterations, and major structural replacements) to nonresidential and residential buildings. For additional information, see “Private fixed investment,” chapter 6 in *Concepts and Methods of the U.S. National Income and Product Accounts* (U.S. Department of Commerce, U.S. Bureau of Economic Analysis, December 2020), pp. 6–3, 6–6.

69 Bokhari and Geltner, “Commercial buildings, capital consumption, and the United States National Accounts.” In the National Council of Real Estate Investment Fiduciaries (NCREIF) data, the distinction between “operating expenses” (not included in capital improvement expenditures) and routine “capital improvement expenditures” is that the latter expenditures are for items that last longer than 1 year. This definition is similar to the definitions used in national accounts. The NCREIF properties are professionally appraised, enabling the authors to quantify capital improvement expenditures as a fraction of property value.

70 Bokhari and Geltner, “Commercial buildings, capital consumption, and the United States National Accounts.” The Bokhari and Geltner study used the Green Street Advisors data as a check on the NCREIF data and found that routine capital improvement expenditures in the two data sets were similar. The authors found that for over 700 properties in the Green Street Advisors sample that were held at least 16 years, real estate investment trusts performed major renovations (not included in routine capital improvement expenditures) that amounted to 37 percent of the value of the routine capital improvement expenditures over the period.

71 Bokhari and Geltner, “Commercial buildings, capital consumption, and the United States National Accounts,” p. 562.

72 Ibid, p. 572.

73 Ibid.

74 Bokhari and Geltner, "Commercial buildings, capital consumption, and the United States National Accounts," p. 572; Wykoff and Hulten, "Tax and economic depreciation of machinery and equipment"; Hulten and Wykoff, "The estimation of economic depreciation using vintage asset prices"; and Hulten and Wykoff, "The measurement of economic depreciation."

75 Bokhari and Geltner, "Commercial buildings, capital consumption, and the United States National Accounts," p. 581.

76 Ibid, p. 570.

77 See, for example, an analysis of global machine tools by market size, share, growth, by 2027, at https://www.marketsandmarkets.com/Market-Reports/machine-tools-market-168345068.html; a summary of used equipment market trends by Ritchie Bros. at https://s24.q4cdn.com/560830410/files/doc_downloads/2020/Ritchie-Bros-Used-Equipment-Market-Trends-Summary-US-CA-Edition.pdf; a report of global mobile cranes market size, share, and trends analysis, 2020–27 at https://www.grandviewresearch.com/industry-analysis/mobile-cranes-market; and an analysis of conveyor belts market size, industry share, and trends, 2022–32, at https://www.futuremarketinsights.com/reports/conveyor-belts-market.

78 Bokhari and Geltner, "Commercial buildings, capital consumption, and the United States National Accounts," p. 571.

79 Hulten and Wykoff, "The estimation of economic depreciation using vintage asset prices," p. 382.

80 U.S. Department of the Treasury, Office of Industrial Economics, "Business building statistics: a study of physical and economic characteristics of the 1969 stock of non-residential non-farm business buildings and depreciation practices of building owners," August 1975, p. 4, https://babel.hathitrust.org/cgi/pt?id=mdp.39015051123365&view=1up&seq=2. The U.S. Department of the Treasury, Office of Industrial Economics, conducted three mail surveys in 1972 and 1973 to test whether the depreciation periods used by owners of buildings were shorter than the guideline depreciation periods in force for tax purposes.

81 Organisation for Economic Co-operation and Development, "Measuring capital," p. 110.

82 Note that although the 2014 Canadian classification had 153 asset classes, a revision in 2018 had slightly fewer.

83 For example, U.S. asset (1), household furniture and fixtures, was matched to three more detailed asset categories of the Statistics Canada asset classification system. After the three detailed Statistics Canada assets to similar U.S. detailed input–output commodity items were matched, the 2007 investment expenditure values for the three U.S. input–output commodity items were used to weight the depreciation rates for the three Statistics Canada detailed assets and create an overall weighted average rate for asset (1).

84 See U.S. Department of Commerce, U.S. Bureau of Economic Analysis, *Fixed Assets and Consumer Durable Goods in the United States, 1925–97*, p. M-32, footnote 69, for a further description of these industry studies.

85 For example, under asset 11, metalworking machinery, the wood products industry's revised BLS depreciation rate was calculated as the BLS published rate (0.1671) for wood products divided by the BLS nonmanufacturing industries rate for metalworking machinery (0.1203), resulting in a ratio of 1.38903. The calculated set 1 depreciation rate based on Statistics Canada data for asset 11 is 0.1970. The Statistics Canada set 1 industry-specific rate for wood products under metalworking machinery is then 1.38903 × 0.197, or 0.27364.

86 This article describes two of several simulations used to analyze the impact of alternative depreciation rates on BEA and BLS capital stock. Additional simulations, including historical trials with depreciation rates altered in 1901 and boundary runs, with extreme high and low depreciation rates, are discussed in a related work by Michael D. Giandrea, Robert J. Kornfeld, Peter B. Meyer, and Susan G. Powers, "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measures," Working Paper 539 (U.S. Department of Labor, BLS, April 9, 2021), https://www.bls.gov/osmr/research-papers/2021/pdf/ec210050.pdf.

87 Because one equipment category, nuclear fuel (asset 31), uses a depreciation rate based on recent U.S. data, we did not revise this rate. Owner-occupied residential capital asset rates also are unrevised because BLS obtains the related capital stock estimates directly from BEA and does not use the perpetual inventory method to develop capital stock measures for these structures assets. We also did not revise rates for intellectual property products because these rates have been more recently developed. Land, inventory, and tenant- and owner-occupied acquisition and disposal costs assets were also left at published BLS depreciation rates.

88 One ongoing issue with the balance sheets in the business sector of the integrated macroeconomic accounts is that the estimates of total real estate assets (including structures and land) and BEA estimates of total structures (not including land) can sometimes imply (by subtraction) unrealistic estimates of land owned by the business sector. The use of faster depreciation rates may reduce this problem.

89 The data underlying charts 1, 2, and 3 are presented in tables 3a and 4a in Giandrea et al., "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measures."

90 The BLS published and simulated capital stock growth rates for the major sector and NIPA industries are presented in tables 5a and 5b for selected periods, in Giandrea et al., "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measures."

91 The methods are further explained in U.S. Department of Labor, BLS, *Trends in Multifactor Productivity, 1948–81*, p. 40.

92 Capital services growth rates for the major sector and NIPA industries are presented in tables 6a and 6b, for selected periods, in Giandrea et al., "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measures." Tables 6a and 6b include both the BLS published rates and the simulated rates.

93 The differences in both major sector and NIPA industry capital stock and capital services measure growth rates when constructed with the published and revised set 1 and set 2 depreciation rates are presented in Giandrea et al., "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measures," tables 7a, 7b, 8a, and 8b.

94 Based on published BLS depreciation rates and set 1 and set 2 rates, multifactor productivity indexes, growth rates, and differences in growth rates for the private nonfarm business sector are presented in Giandrea et al., "Alternative capital asset depreciation rates for U.S. capital and multifactor productivity measure," table 9.

95 See Wykoff and Hulten, "Tax and economic depreciation of machinery and equipment"; Hulten and Wykoff, "The estimation of economic depreciation using vintage asset prices"; and Hulten and Wykoff, "The measurement of economic depreciation."

96 See Statistics Canada, "Depreciation rates for the productivity accounts"; Wykoff and Hulten, "Tax and economic depreciation of machinery and equipment"; Hulten and Wykoff, "The estimation of economic depreciation using vintage asset prices"; Hulten and Wykoff, "The measurement of economic depreciation"; and Statistics Canada's Annual Capital and Repair Expenditures Survey, https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getSurvey&SDDS=2803.

97 Bokhari and Geltner, "Commercial buildings, capital consumption, and the United States National Accounts."

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ARTICLE

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Empirical evidence for the “Great Resignation”

This article empirically assesses the observed increase in job resignations during the coronavirus disease 2019 (COVID-19) pandemic and examines the pandemic's uniqueness from prior macroeconomic events. The article shows that, compared with the dot-com recession of 2001 and the 2007–09 Great Recession, the pandemic produced unique quits rates, and this finding holds across U.S. census regions. In addition, the results show that, during the pandemic, quits rates in firms with fewer than 1,000 employees were higher than quits rates in firms with more than 1,000 employees. A regression analysis assessing the antecedents of the pandemic's quits rate also reveals that while the rates for hires and job openings had a positive effect on quits rates, hourly earnings and the unemployment rate exerted a negative effect. The article empirically confirms the "Great Resignation" phenomenon, which is characterized by record job quitting during the pandemic, and suggests that this phenomenon may be ameliorated by increasing hourly earnings, thereby increasing employees' switching costs. However, if the phenomenon persists, it is conceivable that labor-saving investments that were hitherto economically infeasible will become feasible, altering the nature of work and the workplace.

The coronavirus disease 2019 (COVID-19) pandemic had a sudden, rapid, and unprecedented impact on many national and local economies. In response to the pandemic, governments shut down many segments of their economies, except those deemed “essential.”[1] In the United States, the economy “troughed” for a few months immediately after the implementation of these policies. However, the persistence of the pandemic through new COVID-19 variants, coupled with multiple waves of infection, kept the U.S. economy from returning to its prepandemic condition.

A major observation associated with the COVID-19 pandemic is the “Great Resignation” phenomenon, which has received significant attention. This phenomenon, whose moniker was coined by Anthony Klotz, involves record rates of job quitting during the pandemic.[2] As noted by one author, return-to-office mandates, attractive job offers from competing employers, and revelations about better work–life balance have motivated a “record-breaking departure from jobs in a shockingly small window of time.”[3] Using a global survey of 4,000 companies and more than 9 million employee records, a recent study found that resignations increased the fastest among midcareer employees (i.e., those between 30 and 45 years of age).[4] These resignations have also been attributed to people making changes to their work–life balance.[5] A Public Broadcasting Service documentary on the future of work explored the potential effect of the COVID-19 pandemic on “American ‘workism,’” observing that, compared with men, women are leaving the workforce more rapidly and in larger numbers for a variety of reasons, including gaining access to childcare and providing care for family.[6] However, research conducted prior to the pandemic shows that hires, job openings, and quits all reached new highs in 2018.[7] This finding challenges the attribution of the Great Resignation to the pandemic, demanding further empirical investigation that would confirm this attribution.

Consistent with this goal, this article compares U.S. labor market dynamics during the COVID-19 pandemic (here, the pandemic period spans from March 2020 to January 2022) with those from the two previous recessions—the Great Recession (December 2007 to June 2009) and the dot-com recession (March 2001 to November 2001). Because it has been reported that the 9/11 terrorist attack, which occurred prior to the end of the dot-com recession, adversely affected people's work attitudes, the end of the dot-com recession is extended to March 2002.[8]

The COVID-19 pandemic, the Great Recession, and the dot-com recession all had significant adverse economic impacts on individuals and organizations. Although the pandemic added sickness, death, and economic shutdowns to its toll, financial challenges and job losses during the previous two downturns produced their own mental anguish.[9] The extent to which these impacts might have affected people's willingness to quit their current employment has not been fully investigated, but there is some evidence that they might have engendered changes to the nature and type of work some people were willing to consider.[10] Adding to the fallout from the dot-com recession, the impact of 9/11 exacerbated the ongoing financial challenges faced by some people, especially white-collar workers in certain parts of the country.[11] In addition, it has been reported that the increased xenophobia that emerged in some areas after 9/11 has affected the sense of security of workers of certain religions and ethnicities.[12]

In comparing the aforementioned macroeconomic events, the article does not compare the pandemic's labor market dynamics with those associated with other recent coronaviruses, because none of these viruses had comparable reach and economic impact. Neither the severe acute respiratory syndrome (SARS), which broke out in China in 2002–03, nor the Middle East respiratory syndrome (MERS), which was first observed in Saudi Arabia in 2012, produced a macroeconomic response comparable to that of COVID-19. SARS occurred in only five countries and registered less than 8,500 cases, including 73 in the United States.[13] MERS occurred in 27 countries and recorded 2,519 cases and 866 deaths.[14] No SARS-related deaths and only two MERS-related deaths occurred in the United States. In contrast, as of March 2022, the COVID-19 pandemic had caused nearly a million deaths and infected about 80 million people in the United States.[15] Globally, COVID-19 had infected more than 455 million people and killed over 6 million by March 2022.[16]

For its main analyses, the article uses monthly data from the U.S. Bureau of Labor Statistics (BLS) Job Openings and Labor Turnover Survey (JOLTS).[17] The JOLTS dataset includes information on job openings, hires, and separations. Separations are organized into three major components: (1) layoffs and discharges, which cover involuntary separations initiated by the employer, (2) quits, which are employee-initiated voluntary departures from current positions, and (3) other separations, defined as departures arising from retirements, transfers to other locations, disability, or death. The period of analysis, which spans from December 2000 through January 2022, is chosen to capture the three macroeconomic events of interest.

The article's research question is addressed along three dimensions: national level, regional level, and firm size class. The national-level analyses test the hypothesis that the average quits rate during the pandemic was the same as the rates for the other macroeconomic events. To ascertain the Great Resignation phenomenon, the alternative hypothesis is that the average quits rate during the pandemic was higher. The analyses use the JOLTS dataset, whose data elements are defined in the BLS *Handbook of Methods*.[18] Consistent with these definitions, the term "level" refers to a total number associated with a data element (e.g., job openings, hires, total separations, quits, layoffs and discharges, or other separations), whereas the term "rate" involves dividing the level for a data element by total employment and multiplying the quotient by 100, facilitating accounting for economic growth. The regional comparisons consider differences in quits rates across four U.S. census regions: Northeast, South, Midwest, and West.[19] Finally, the comparisons by firm size use six BLS firm size classes (detailed later), hypothesizing that the quits rate during the pandemic was the same across the six firm size classes and across the three macroeconomic events within each firm size class.

The literature on job quitting: a brief overview

An economic theory proposed by Kenneth J. McLaughlin suggests that flexible wage rates increase employees' desire to leave their current employers and employers' desire to keep current employees when the wage rate is below a certain level (and vice versa).[20] When an adverse economic event (e.g., a recession) occurs, the wage-to-profitability ratio increases and triggers layoffs. When the event abates and profitability begins to increase, the wage-to-profitability ratio decreases, motivating employers not only to keep their current employees but also to recruit new ones. Increasing demand for employees introduces a wrinkle in McLaughlin's theory, because employers' negotiations with employees become complicated by competitors' wage offers to the same employees, increasing the latter's options and strengthening their negotiating position.[21]

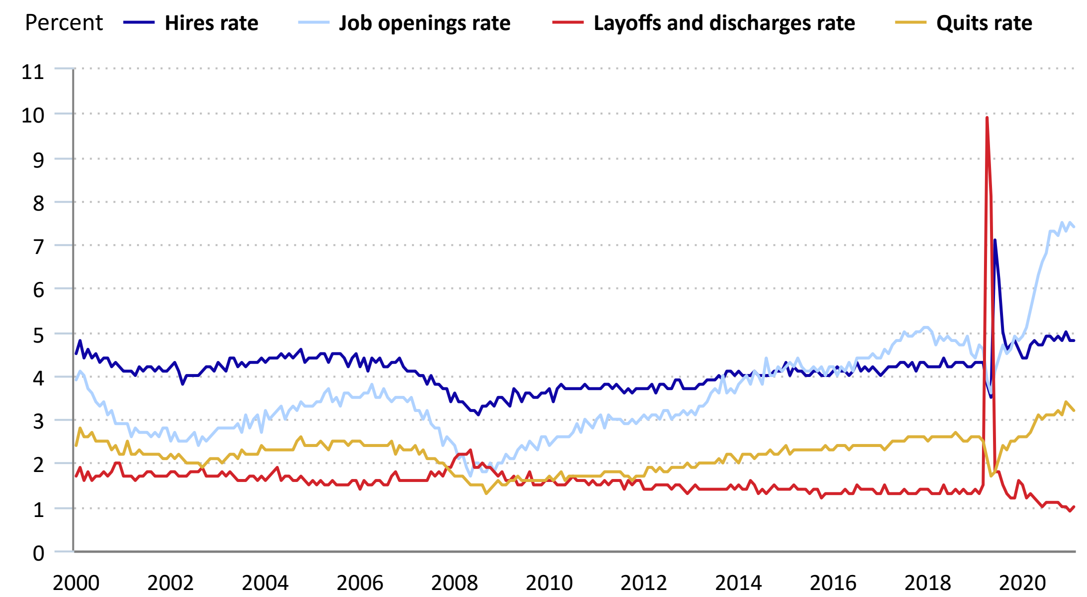
Better wage offers often motivate workers to change jobs without going through a period of unemployment.[22] Research has established a procyclical relationship between quits and wage rates, providing a good predictive power for inflation on the upswing.[23] However, the sticky-down nature of wages prevents wage adjustments and creates what George A. Akerlof, Andrew K. Rose, and Janet L. Yellen have described as a "vacancy chain."[24] Other researchers have showed that, besides wage rates, factors such as employment rates, employee job satisfaction, perceptions about compensation fairness, and ease of movement between jobs also contribute to job switching.[25] Arguing that the foregoing factors are important but insufficient variables in explaining quits, Tae Heon Lee et al. have focused on a different variable—unsolicited offers from competing employers in tight labor markets.[26] It has also been noted that quits may occur only after employees have reached certain milestones, such as receipt of stock options or retention bonuses.[27] In the context of the COVID-19 pandemic, additional factors emerging as covariates in explaining quits are employee burnout from daily routines (e.g., wake up at 5 a.m., fight traffic, and sit in a cubicle all day) and the conscious decision to change one's work–life balance.[28] These psychological factors, which have received little attention in the literature, may be partially responsible for the unprecedented number of business applications during the pandemic. For example, the average number of monthly business applications between March 2020 and January 2022 was nearly 418,000, compared with about 209,000 during the Great Recession.[29]

Studies of labor market dynamics commonly assume that wage rates drive labor force participation rates.[30] However, the relatively high number of people quitting their jobs and transitioning to self-employment during the pandemic challenges this assumption. It opens the possibility that the decision choice of employees takes into account not only working for wages but also working for self. Some market watchers believe that the challenges of sustaining business performance and income needs might entice some of those who quit their jobs to start their own businesses.[31] The foregoing discussion suggests that the factors influencing quits during the COVID-19 pandemic could differ from those of earlier periods, because of the pandemic's uniqueness in time, scope, and reach.

Quits trend in the United States

The COVID-19 pandemic ended the longest employment and economic expansion in U.S. history.[32] Uncertainty about the pandemic's potential public health effects unleashed an abrupt "closure" of the U.S. economy and the economies of most countries.[33] The policy response to the pandemic altered the wage-to-profitability ratio virtually overnight, leading to the most massive and rapid layoff in the last 100 years of U.S. history. Total nonfarm employment went down from about 152.5 million in February 2020 to about 130.2 million by April 2020, a decline of 14.62 percent.[34] Chart 1 shows the trends in monthly rates for hires, job openings, layoffs and discharges, and quits in the U.S. nonfarm sector from December 2000 through January 2022, a period that encompasses the three major macroeconomic disruptions considered in this article (the dot-com recession, the Great Recession, and the COVID-19 pandemic). The chart shows that, over the past two decades, the quits rate was higher than the rate for layoffs and discharges, except for the latter half of the Great Recession. The chart also shows that the gradient of the quits rate during the pandemic was steeper than in any prior period.

Chart 1. Rates for hires, job openings, layoffs and discharges, and quits, December 2000–January 2022



Click legend items to change data display. Hover over chart to view data.
Note: For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.
Source: U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

View Chart Data

The number of quits from February 2020 to January 2022 was forecast by using the historical trend from the period following the Great Recession, to assess what that number could have been without the pandemic. The results put the projected quits at about 3.9 million in January 2022, which compares with an actual quits level of almost 4.3 million. Thus, despite the massive drop in quits at the onset of the pandemic, the level of quits "recovered" rapidly, surpassing the number of quits that could have been expected under the historical trend, without the pandemic.

Hires include all additions to payroll during an entire month, including workers who have been rehired on a full-time, part-time, permanent, short-term, or seasonal basis. Job openings include all open positions (full time, part time, permanent, short term, or seasonal) on the last business day of the month and refer to positions for which the employer is actively recruiting from outside the establishment. Adding context to chart 1, job openings and hires averaged about 5 million per month from the end of the Great Recession to February 2020, growing at average monthly rates of 0.80 percent and 0.33 percent, respectively. From April 2020 to January 2022, job openings and hires averaged (respectively) 8.32 million and 6.20 million per month, with the former growing at an average monthly rate of 3.86 percent and the latter remaining virtually flat. Never in the last 20 years of data reviewed for this article has the gap between job openings and hires been this wide. The data show that job openings surpassed hires back in December 2014 and fell below the level of hires only in May and June 2020. Indeed, by January 2022, job openings had exceeded hires by 4.81 million, which is higher than the quits level of 4.20 million in the same month. To break this trend, real wages have to reverse their current downward trend, which would provide superior net benefits from working for wages and entice those working for self to consider switching back to working for wages.[35]

Table 1 reports summary statistics for the rates of different data elements, enabling an assessment of the effects of each examined macroeconomic event after accounting for economic growth. The job openings rate is computed by dividing the number of job openings by the sum of employment and job openings and multiplying that quotient by 100. The rates for hires, layoffs and discharges, and quits are computed by dividing these data elements' respective levels by employment and multiplying that quotient by 100. The hires rate for the entire period of analysis averaged 4.10 percent per month (a minimum of 3.10 percent and a maximum of 7.10 percent), with a standard deviation of 0.43 percent. The quits rate averaged 2.20 percent per month (a minimum of 1.30 percent and a maximum of 3.40 percent), with a standard deviation of 0.38 percent.

Table 1. Summary statistics for rates of hires, job openings, layoffs and discharges, and quits, by macroeconomic event, December 2000–January 2022

Macroeconomic event	JOLTS element	*N*	Mean	Standard deviation	Minimum	Maximum
None	Hires	199	4.05	0.30	3.30	4.80
	Job openings	199	3.44	0.81	1.80	5.10
	Layoffs and discharges	199	1.53	0.16	1.20	2.00
	Quits	199	2.15	0.33	1.30	2.80
Dot-com recession	Hires	13	4.28	0.18	4.00	4.60
	Job openings	13	3.13	0.33	2.60	3.70
	Layoffs and discharges	13	1.75	0.13	1.60	2.00
	Quits	13	2.41	0.17	2.20	2.70
Great Recession	Hires	19	3.67	0.34	3.10	4.10
	Job openings	19	2.62	0.55	1.70	3.50
	Layoffs and discharges	19	1.85	0.24	1.60	2.30
	Quits	19	1.93	0.30	1.50	2.40
Pandemic	Hires	23	4.82	0.69	3.50	7.10
	Job openings	23	5.74	1.34	3.60	7.50
	Layoffs and discharges	23	1.91	2.27	0.90	9.90
	Quits	23	2.71	0.48	1.70	3.40
Total	Hires	254	4.10	0.43	3.10	7.10
	Job openings	254	3.57	1.10	1.70	7.50
	Layoffs and discharges	254	1.60	0.70	0.90	9.90
	Quits	254	2.20	0.38	1.30	3.40

Note: For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic. JOLTS = Job Openings and Labor Turnover Survey.
Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

Because the macroeconomic events considered in the analysis are of different durations, the Scheffé test is used to test the hypothesis that the means of their quits rates are equal. The alternative hypothesis is that the mean for the pandemic is higher than the means for both the dot-com recession and the Great Recession. If the hypothesis of mean equality is not rejected, then the observed trends in quits rates during the pandemic have been merely a continuation of historical trends. Conversely, if the hypothesis is rejected, then the pandemic's effect on quits rates has differed from the effects of the two prior macroeconomic events.

Table 2 presents pairwise macroeconomic-event comparisons, showing contrast results for the average monthly rates of hires, job openings, layoffs and discharges, and quits. The results indicate that the pandemic's average monthly quits rate was higher than and statistically different from the average monthly quits rates for the other macroeconomic events ($p < 0.001$). The hypothesis of equality of average monthly quits rates across the different macroeconomic events is, thus, rejected in favor of the alternative hypothesis. Similar conclusions are reached for hires and job openings, but not for layoffs and discharges. These results suggest that the pandemic did not just alter the quits rate but also profoundly affected two of the three other data elements. However, the results also suggest that the rate for layoffs and discharges, unlike the rates for the other data elements, did not change because of the pandemic.

Table 2. Pairwise macroeconomic-event comparisons for rates of hires, job openings, layoffs and discharges, and quits, December 2000–January 2022

Macroeconomic-event pair	Contrast	Standard error	Scheffé *t*	Scheffé *P* > *t*	95-percent confidence interval		Significance
					Lower bound	Upper bound	
Hires rate							
Dot-com recession vs. none	0.23	0.10	2.25	0.171	-0.06	0.51	[1]
Great Recession vs. none	-0.38	0.08	-4.50	0.000	-0.62	-0.14	***
Pandemic vs. none	0.77	0.08	9.93	0.000	0.55	0.99	***
Great Recession vs. dot-com recession	-0.61	0.13	-4.79	0.000	-0.97	-0.25	***
Pandemic vs. dot-com recession	0.54	0.12	4.45	0.000	0.20	0.89	***
Pandemic vs. Great Recession	1.15	0.11	10.53	0.000	0.85	1.46	***
Job openings rate							
Dot-com recession vs. none	-0.31	0.24	-1.30	0.642	-0.99	0.36	[1]
Great Recession vs. none	-0.82	0.20	-4.08	0.001	-1.39	-0.25	***
Pandemic vs. none	2.30	0.18	12.45	0.000	1.78	2.82	***
Great Recession vs. dot-com recession	-0.51	0.30	-1.69	0.417	-1.36	0.34	[1]
Pandemic vs. dot-com recession	2.61	0.29	8.97	0.000	1.79	3.43	***
Pandemic vs. Great Recession	3.12	0.26	12.00	0.000	2.39	3.85	***
Layoffs and discharges rate							
Dot-com recession vs. none	0.23	0.20	1.14	0.731	-0.33	0.78	[1]
Great Recession vs. none	0.32	0.17	1.95	0.285	-0.14	0.79	[1]
Pandemic vs. none	0.38	0.15	2.52	0.098	-0.04	0.81	*
Great Recession vs. dot-com recession	0.10	0.25	0.40	0.984	-0.60	0.80	[1]
Pandemic vs. dot-com recession	0.16	0.24	0.66	0.932	-0.52	0.83	[1]
Pandemic vs. Great Recession	0.06	0.21	0.28	0.994	-0.54	0.66	[1]
Quits rate							
Dot-com recession vs. none	0.26	0.10	2.64	0.075	-0.02	0.53	*
Great Recession vs. none	-0.22	0.08	-2.72	0.062	-0.45	0.01	*
Pandemic vs. none	0.56	0.07	7.55	0.000	0.35	0.77	***
Great Recession vs. dot-com recession	-0.48	0.12	-3.92	0.002	-0.82	-0.13	***
Pandemic vs. dot-com recession	0.31	0.12	2.61	0.081	-0.02	0.63	*
Pandemic vs. Great Recession	0.78	0.10	7.47	0.000	0.49	1.08	***

[1] Not significant.

Note: **p* < 0.10; ***p* < 0.05; ****p* < 0.001. For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.

Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

Quits rates in U.S. regions

In its JOLTS dataset, BLS organizes U.S. states and territories into four census regions: Northeast, South, West, and Midwest.[36] This section explores differences in quits rates across these regions, testing two broad hypotheses: (1) in each region, the average quits rate during the COVID-19 pandemic was not statistically different from the quits rates during the dot-com recession and the Great Recession, and (2) the average quits rate during the pandemic was not statistically different across the four U.S. census regions.

The summary statistics for quits rates by region and macroeconomic event are presented in table 3. The table shows that the average quits rate during the pandemic was 2.78 percent in the South region, 2.49 percent in the Midwest region, 2.31 percent in the West region, and 1.83 percent in the Northeast region. Table 4 presents the test results for the two broad hypotheses. For the first hypothesis, the table shows that, in the Midwest region, the average quits rate during the pandemic differed statistically from the quits rates for the dot-com recession ($p < 0.05$) and the Great Recession ($p < 0.001$). The results are similar for the South region. For the Northeast and West regions, the average quits rate during the pandemic was not statistically different from the quits rate for the dot-com recession, but it was statistically different from the quits rate for the Great Recession ($p < 0.001$). The hypothesis that the average quits rates for the pandemic and the other macroeconomic events were equal was rejected in all cases for the Midwest and South regions, which suggests that the effect of the pandemic on quits rates in those regions was different from the effects of the two previous economic shocks. The results provide evidence that the pandemic produced statistically higher quits rates in all regions relative to the Great Recession and in two regions relative to the dot-com recession.

Table 3. Summary statistics for quits rates, by census region and macroeconomic event, December 2000–January 2022

Macroeconomic event	Region	Mean	Standard deviation	Minimum	Maximum
None	Midwest	1.87	0.31	1.10	2.60
	Northeast	1.50	0.23	0.80	2.00
	South	2.14	0.34	1.30	2.80
	West	1.96	0.34	1.10	2.60
Dot-com recession	Midwest	2.16	0.26	1.80	2.50
	Northeast	1.80	0.15	1.60	2.00
	South	2.27	0.10	2.10	2.40
	West	2.16	0.21	1.90	2.60
Great Recession	Midwest	1.62	0.26	1.20	1.90
	Northeast	1.35	0.24	1.00	1.80
	South	1.88	0.33	1.40	2.40
	West	1.78	0.29	1.20	2.20
Pandemic	Midwest	2.49	0.41	1.60	3.10
	Northeast	1.83	0.32	1.30	2.30
	South	2.78	0.46	1.80	3.40
	West	2.31	0.46	1.40	2.90
Total	Midwest	1.92	0.37	1.10	3.10
	Northeast	1.53	0.26	0.80	2.30
	South	2.18	0.40	1.30	3.40
	West	1.99	0.36	1.10	2.90

Note: For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.
Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

Table 4. Pairwise macroeconomic-event and regional comparisons for quits rates, December 2000–January 2022

Macroeconomic-event and regional pairs	Contrast	Standard error	Scheffé *t*	Scheffé *P* > *t*	Significance
Midwest region					
Dot-com recession vs. none	0.30	0.09	3.30	0.014	**
Great Recession vs. none	-0.24	0.08	-3.26	0.015	**
Pandemic vs. none	0.63	0.07	9.08	0.000	***
Great Recession vs. dot-com recession	-0.54	0.11	-4.80	0.000	***
Pandemic vs. dot-com recession	0.33	0.11	3.04	0.028	**
Pandemic vs. Great Recession	0.87	0.10	8.97	0.000	***
Northeast region					
Dot-com recession vs. none	0.30	0.07	4.49	0.000	***
Great Recession vs. none	-0.15	0.06	-2.70	0.066	*
Pandemic vs. none	0.34	0.05	6.51	0.000	***
Great Recession vs. dot-com recession	-0.45	0.08	-5.37	0.000	***
Pandemic vs. dot-com recession	0.03	0.08	0.43	0.980	[1]
Pandemic vs. Great Recession	0.49	0.07	6.71	0.000	***
South region					
Dot-com recession vs. none	0.13	0.10	1.34	0.616	[1]
Great Recession vs. none	-0.25	0.08	-3.04	0.028	**
Pandemic vs. none	0.64	0.08	8.44	0.000	***
Great Recession vs. dot-com recession	-0.39	0.12	-3.10	0.024	**
Pandemic vs. dot-com recession	0.51	0.12	4.25	0.001	***
Pandemic vs. Great Recession	0.89	0.11	8.35	0.000	***
West region					
Dot-com recession vs. none	0.20	0.10	2.08	0.232	[1]
Great Recession vs. none	-0.17	0.08	-2.09	0.228	[1]
Pandemic vs. none	0.35	0.08	4.64	0.000	***
Great Recession vs. dot-com recession	-0.38	0.12	-3.04	0.028	**
Pandemic vs. dot-com recession	0.15	0.12	1.23	0.679	[1]
Pandemic vs. Great Recession	0.52	0.11	4.91	0.000	***
Pairwise regional comparisons					
Midwest vs. Northeast	0.66	0.11	6.00	0.000	***
Midwest vs. South	-0.29	0.13	-2.22	0.032	**
Midwest vs. West	0.18	0.13	1.42	0.163	[1]
Northeast vs. South	-0.94	0.12	-7.99	0.000	***
Northeast vs. West	-0.47	0.12	-4.04	0.000	***
South vs. West	0.47	0.14	3.45	0.001	***

[1] Not significant.

Note: *$p < 0.10$; **$p < 0.05$; ***$p < 0.001$. For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.

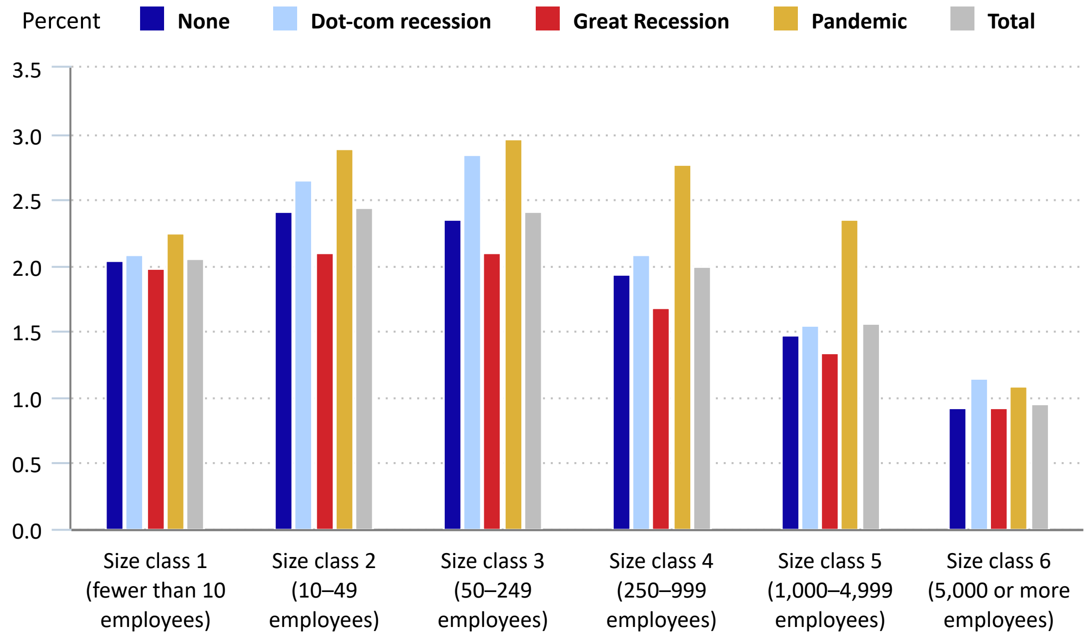
Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

Table 4 also shows that, during the pandemic, the average quits rate for the Midwest region was higher than the quits rates for the Northeast and West regions (by 0.66 and 0.18 percentage point, respectively), but it was lower than the quits rate for the South region (by approximately 0.29 percentage point). The difference between the pandemic's quits rate for the Midwest region and the quits rate for the Northeast region was positive and statistically significant ($p < 0.001$). The difference between the pandemic's quits rate for the Midwest region and the quits rate for the South region was negative and statistically significant ($p < 0.05$). However, the difference in average quits rates between the Midwest and West regions was not statistically significant. Therefore, the hypothesis that the Midwest region's average quits rate during the pandemic was equal to the quits rates of the Northeast and South regions is rejected, but the hypothesis concerning the pairwise comparison between the Midwest and West regions cannot be rejected. The results in table 4 also reject the hypothesis that the Northeast region's average quits rate during the pandemic was equal to the quits rates of the South and West regions, and the same finding holds for the hypothesized equality of average quits rates with respect to the South and West regions.

Quit rates by firm size

Firm size class is defined by number of employees. Firms of size classes 1, 2, and 3 are those with, respectively, fewer than 10 employees, 10–49 employees, and 50–249 employees. Firms of size classes 4, 5, and 6 are those with, respectively, 250–999 employees, 1,000–4,999 employees, and 5,000 or more employees. Using the average employee number by size class between 2010 and 2021, one finds that, over that period, firms of size classes 4, 5, and 6 accounted for less than 1 percent of the total number of firms and 53.7 percent of the total number of employees.[37] The monthly share of quits by size class is defined as the number of quits for each size class divided by the total number of quits in the nonfarm sector in each month. Chart 2 shows a positively skewed distribution of an increasing share of quits by size class. The distribution peaks at size class 3 for both the pandemic and the dot-com recession and at size class 2 for the "none" event. Firms of size classes 2 and 3 had the same average quits rates during the Great Recession. The chart confirms the findings of prior research indicating that firms of size class 6 tend to have lower quits rates, primarily because large firms are more likely to be unionized, have higher wages, and provide superior employment benefits.[38]

Chart 2. Average quits rates, by firm size class and macroeconomic event, December 2000–January 2022



Click legend items to change data display. Hover over chart to view data.
Note: For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.
Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

View Chart Data

Table 5 shows that, for firms of size classes 4 and 5, the quits rate during the pandemic differed statistically from the quits rates of all other macroeconomic events ($p < 0.001$). For firms of size classes 1, 2, and 3, the pandemic's quits rate did not differ statistically from the quits rate of the dot-com recession. For firms of size classes 2 and 3, the pandemic's quit rate differed statistically from the Great Recession's quits rate ($p < 0.001$). For firms of size class 6, there were no statistically significant quits-rate differences among the pandemic, the dot-com recession, and the Great Recession. The average pandemic quits rate for firms of size class 6 was statistically different from the rate for the "none" event, higher than the rate for the Great Recession, and lower than the rate for the dot-com recession. The same pattern holds for the average quits level for size class 6.

Table 5. Pairwise macroeconomic-event comparisons for quits rates, by firm size class, December 2000–January 2022

Macroeconomic-event pair	Contrast	Standard error	Scheffé *t*	Scheffé *P > t*	Significance
Size class 1 (fewer than 10 employees)					
Dot-com recession vs. none	0.03	0.10	0.34	0.990	[1]
Great Recession vs. none	-0.06	0.08	-0.78	0.894	[1]
Pandemic vs. none	0.21	0.08	2.77	0.056	*
Great Recession vs. dot-com recession	-0.10	0.12	-0.79	0.889	[1]
Pandemic vs. dot-com recession	0.18	0.12	1.47	0.538	[1]
Pandemic vs. Great Recession	0.27	0.11	2.57	0.088	*
Size class 2 (10–49 employees)					
Dot-com recession vs. none	0.23	0.11	2.07	0.234	[1]
Great Recession vs. none	-0.32	0.09	-3.43	0.009	***
Pandemic vs. none	0.47	0.08	5.53	0.000	***
Great Recession vs. dot-com recession	-0.55	0.14	-3.94	0.002	***
Pandemic vs. dot-com recession	0.24	0.13	1.80	0.357	[1]
Pandemic vs. Great Recession	0.79	0.12	6.59	0.000	***
Size class 3 (50–249 employees)					
Dot-com recession vs. none	0.49	0.11	4.38	0.000	***
Great Recession vs. none	-0.25	0.09	-2.59	0.084	*
Pandemic vs. none	0.62	0.09	7.15	0.000	***
Great Recession vs. dot-com recession	-0.74	0.14	-5.21	0.000	***
Pandemic vs. dot-com recession	0.13	0.14	0.93	0.835	[1]
Pandemic vs. Great Recession	0.87	0.12	7.09	0.000	***
Size class 4 (250–999 employees)					
Dot-com recession vs. none	0.16	0.11	1.56	0.490	[1]
Great Recession vs. none	-0.25	0.09	-2.81	0.051	*
Pandemic vs. none	0.84	0.08	10.30	0.000	***
Great Recession vs. dot-com recession	-0.41	0.13	-3.11	0.023	**
Pandemic vs. dot-com recession	0.67	0.13	5.25	0.000	***
Pandemic vs. Great Recession	1.09	0.11	9.49	0.000	***
Size class 5 (1,000–4,999 employees)					
Dot-com recession vs. none	0.06	0.09	0.72	0.916	[1]
Great Recession vs. none	-0.14	0.07	-1.97	0.278	[1]
Pandemic vs. none	0.87	0.07	13.09	0.000	***
Great Recession vs. dot-com recession	-0.20	0.11	-1.88	0.317	[1]
Pandemic vs. dot-com recession	0.81	0.10	7.72	0.000	***
Pandemic vs. Great Recession	1.01	0.09	10.82	0.000	***
Size class 6 (5,000 or more employees)					
Dot-com recession vs. none	0.22	0.07	3.18	0.019	**
Great Recession vs. none	0.01	0.06	0.15	0.999	[1]
Pandemic vs. none	0.16	0.05	3.04	0.028	**
Great Recession vs. dot-com recession	-0.21	0.09	-2.43	0.120	[1]
Pandemic vs. dot-com recession	-0.06	0.09	-0.69	0.923	[1]
Pandemic vs. Great Recession	0.16	0.08	2.04	0.247	[1]

[1] Not significant.

Note: *$p < 0.10$; **$p < 0.05$; ***$p < 0.001$. For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.

Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

While many organizations have implemented various forms of telework and remote work for years, the pandemic provided a different context for assessing these flexible work arrangements, affecting and giving voice to a broader group of workers and employers. Having no choice but to work at home, many employees had the time to assess their lifestyles and work–life balance. This introspection may have intensified with the large-scale death and disease unleashed by the pandemic, engendering a new reality about work—one probably not seen since the genesis of Taylorism.[39] Various employees—from those working on assembly lines and in cubicles to those occupying executive suites—had a chance, for the first time, to reflect on what they do, why they do it, and how they can balance their work–life choices given the pandemic's existential realities.[40] These considerations may explain why the pandemic has had a stronger effect on job quitting than the dot-com recession and the Great Recession, regardless of the level at which this effect is evaluated (national, regional, or firm size class).

However, the antecedents of higher quits levels and rates during the pandemic have also been influenced by practical constraints. For example, work exhaustion, fear of illness, and limited access to services such as childcare have contributed largely to the new situation.[41] Data from the U.S. Census Bureau Household Pulse Survey (May 26 to June 7, 2021) show that nearly a quarter of adults in responding households took unpaid leave, cut work hours, or used vacation or sick days for childcare. About 17 percent of responding households had an adult who quit a job for childcare reasons, and another 8.4 percent had an adult who lost a job for the same reasons.[42]

Many frontline and other essential workers reported exhaustion from being overworked, a condition partly resulting from coworker sickness, exposure to COVID-19, or taking time off to care for loved ones.[43] In all areas of essential work, replacing sick and deceased workers has become nearly impossible, even with increases in wages and signing bonuses.[44] This exhaustion burden, it turns out, has caused frontline and emergency workers to become the single largest segment of workers quitting their jobs.[45] For example, JOLTS data show that, during the pandemic, healthcare and social assistance workers quit their jobs at an average monthly rate of 2.71 percent, or 464,044 people per month. At the of end January 2022, more than 10.67 million healthcare and social assistance workers had voluntarily quit their jobs, compared with a total of 80.87 million workers for all industries combined. The share of total quits for this group of frontline workers during the pandemic was 13.20 percent, compared with 10.60 percent during the Great Recession and 9.24 percent during the dot-com recession. In addition to experiencing work burnout and exhaustion, many frontline workers now consider their compensation to be incommensurable with the risk in their workplace and the commitment being demanded from them during the pandemic.[46]

Hires, job openings, unemployment, wage and salary rates, and quits rates

Assessing whether the quits rate during the COVID-19 pandemic differed from the quits rates seen in prior macroeconomic disruptions was the primary motivation for this research. The results so far have shown that although the quits rate had been increasing since the end of the Great Recession, it accelerated soon after the onset of the pandemic. That the average quits rate during the pandemic differed statistically from the quits rates of earlier macroeconomic events (at the national and regional levels and by firm size class) confirms the Great Resignation phenomenon. This section identifies the antecedents of this phenomenon, providing insights into how it can be ameliorated.

Economies with flexible wages are susceptible to employees switching jobs when they receive superior offers from other employers.[47] It is argued here that, during the pandemic, the “freedom” employees had away from their traditional workspaces afforded them the opportunity to consider their work situation and explore alternatives, including working for self. The analysis that follows assesses whether the antecedents of the quits rate behaved differently during the three macroeconomic events considered for this article. Using insights from the relevant literature, one can hypothesize that the quits rate in period t, q_t, is determined by the hires rate, the unemployment rate, hourly earnings, and the job openings rate. It is conceivable that employees decide to quit their jobs by considering available information on these variables. The deployment of this information suggests a lag between the reception of the information and the quit decision. Experiments done for this article indicate that this lag consists of two 1-month periods (a two-period lag) for all independent variables, except for the categorical variable describing the macroeconomic events. The structural equation defining the problem is specified as follows:

$$q_t = \beta_0 + \beta_1 h_{t-2} + \beta_2 u_{t-2} + \beta_3 w_{t-2} + \beta_4 j_{t-2} + \beta_5 E_1 + \beta_6 E_2 + \beta_7 E_3 + \varepsilon_t,$$

where h, u, w, and j represent, respectively, the hires rate, the unemployment rate, hourly earnings, and the job openings rate; E_1, E_2, and E_3 represent the three macroeconomic events; and ε_t is the regression error term. The a priori expectation, based on the relevant literature and the foregoing statistical analyses, is that all coefficients are positive, except the coefficients on the unemployment rate and hourly earnings, which are predicted to be negative. This means that an increase in the hires rate is expected to increase competition among employers for working employees, leading to increasingly attractive offers from potential employers to entice workers from their current positions. Likewise, an increase in the job openings rate is expected to increase the pool of potential employers, signaling to current employees that the labor market is tightening and increasing their likelihood of quitting their current positions. The coefficient on the unemployment rate is hypothesized to be negative because an increasing unemployment rate signals a softening labor market, which encourages people to hold on to their current jobs. In addition, the coefficient on hourly earnings is hypothesized to be negative because increasing hourly earnings increase employees’ satisfaction with their current positions and reduce their likelihood of switching jobs.

While the hires rate and the job openings rate are taken directly from the JOLTS dataset, the monthly unemployment rate (from BLS) was obtained through the Federal Reserve Bank of St. Louis.[48] Hourly earnings are total earnings divided by the total number of hours for which private sector employees received pay during a pay period, and include overtime pay and recurring cash compensation. Data on monthly hourly earnings from December 2000 through January 2022 are from the Organisation for Economic Co-operation and Development and were retrieved from the Federal Reserve Bank of St. Louis.[49] All data are seasonally adjusted, rates are in percent, and hourly earnings are in U.S. dollars per hour.

To address any inherent serial correlation in the data, the model estimation used the Prais-Winsten procedure of Stata (version 17.0).[50] A VIF (variance inflation factor) test indicated the absence of multicollinearity in the model. However, a Ramsey RESET test suggested the presence of omitted variables ($p < 0.001$), an expected result given that the quits rate is associated with and determined by additional variables not included in the model. Stata’s link test, which tests the hypothesis that a properly specified model should not find additional predictors except by chance, indicated the absence of misspecification (_hat ($p < 0.001$); _hatsq ($p < 0.174$); _const ($p < 0.185$)).

The regression results, presented in table 6, show a coefficient of determination of 0.896 and an F-value (7, 243) of 322.40 ($p < 0.001$). The Durbin-Watson statistic (transformed) is 2.01, suggesting the absence of autocorrelation. The regression results show that all coefficients have the theoretically expected signs. Holding all other variables constant, a unit increase in the unemployment rate decreases the quits rate by about 0.08 percentage point ($p < 0.001$), whereas a unit increase in the two-period lagged job openings rate increases the quits rate by approximately 0.21 percentage point ($p < 0.001$). In addition, a unit increase in the two-period lagged hires rate is associated with a 0.10-percentage-point increase in the quits rate ($p < 0.007$), and a $1.00 increase in hourly earnings is associated with a 0.03-percentage-point decrease in the quits rate ($p < 0.001$). The results also show that the categorical variable for the COVID-19 pandemic shifted the intercept up by more than 0.3 percentage point ($p < 0.056$), producing a quits rate of 2.42 percent.

Table 6. Regression results for quits rate response to two-period lagged hires rate, job openings rate, unemployment rate, and hourly earnings

Variable	Coefficient	Semirobust standard error	*t*	*P* > *t*	95-percent confidence interval	
					Lower bound	Upper bound
Hires rate	0.10	0.04	2.71	0.007	0.03	0.18
Unemployment rate	-0.08	0.02	-4.40	0.000	-0.12	-0.05
Hourly earnings	-0.03	0.01	-4.63	0.000	-0.04	-0.02
Job openings rate	0.21	0.05	4.51	0.000	0.12	0.30
Dot-com recession	0.01	0.05	0.15	0.881	-0.09	0.10
Great Recession	-0.03	0.03	-1.16	0.248	-0.08	0.02
Pandemic	0.30	0.16	1.92	0.056	-0.01	0.62
Constant	2.13	0.31	6.82	0.000	1.51	2.74

Note: $N = 251$; $F(7, 243) = 322.40$; Prob > F = 0.000; R-squared = 0.869; Root mean squared error = 0.093; rho = 0.269; Durbin-Watson statistic (original) = 1.520; Durbin-Watson statistic (transformed) = 2.01. For this analysis, the dates of the three macroeconomic events of interest are March 2001 to March 2002 for the dot-com recession, December 2007 to June 2009 for the Great Recession, and March 2020 to January 2022 for the coronavirus disease 2019 (COVID-19) pandemic.
Source: Author's estimates based on data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey.

The elasticities associated with the explanatory variables provide more intuitive insight into the sensitivity of the quits rate to changes to those variables. The results indicate that, holding all other variables constant, a 1-percent increase in the two-period lagged hires rate increases the quits rate by about 0.19 percent ($p < 0.007$). Similarly, a 1-percent increase in the two-period lagged job openings rate increases the quits rate by nearly 0.34 percent ($p < 0.001$). Notably, a 1-percent increase in hourly earnings reduces the quits rate by 0.28 percent. This result suggests that employers are likely to succeed in reducing the quits rate by increasing hourly earnings, the only variable employers can manipulate directly. By increasing hourly earnings, employers increase the switching costs of current employees who may receive offers from other employers or who are considering self-employment. The hourly earnings elasticity of the quits rate for the pandemic period is −0.3 percent ($p < 0.001$), indicating a small absolute increase of about 6.4 percent from the estimated hourly earnings elasticity for the overall model. However, the job openings elasticity of the quits rate for the pandemic period is 0.43 percent, a 26.4-percent increase from the overall model's value of the same indicator. When estimated specifically for the pandemic period, the elasticities for the hires rate and the unemployment rate decrease by 5.04 percent and 7.49 percent, respectively. The foregoing results provide further evidence that the quits rate behaved differently during the pandemic than in prior macroeconomic events.

Conclusion

This article sought to verify the Great Resignation phenomenon that unfolded in the United States during the COVID-19 pandemic. After controlling for economic growth, the analysis showed that the levels and rates of quits during the pandemic (up to January 2022) were statistically different from those seen in the Great Recession and the dot-com recession. The higher levels of quits during the pandemic were established for the whole economy, for the four U.S. census regions, and by firm size class. A regression analysis assessing the collective effect of the hires rate, the job openings rate, hourly earnings, and the unemployment rate on the quits rate revealed regression coefficients that were statistically significant and carried theoretically expected signs.

Given the empirical veracity of the Great Resignation (relative to prior macroeconomic disruptions), a continuing pandemic pressure (at sustained or higher levels) on the wage-to-profitability ratio may motivate accelerated investments in labor-saving solutions, such as those driven by technology. Presumably having become sensitized to the possibility of another pandemic in the future, public and business leaders may increase their investments in labor-saving technologies that would prevent the recurrence of economic impacts similar to those of the current pandemic.[51] Therefore, organizations need to reimagine work and redesign the workplace to accommodate the postpandemic employee in a way that meets their risk management and performance objectives.

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BEYOND BLS

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NOVEMBER 2022

An economic look at child protection policies of the foster care system

Summary written by: Charlotte M. Irby

We know that foster care is the care that the government provides to protect those who cannot protect themselves, particularly children. But what does the term "foster care" really mean?

To many children in the United States, the term means fear, loss, and separation—a disconnect from all that they know. To the government, however, foster care means placing neglected or abused children in homes that will protect them with the ultimate goal of returning them to their families—a "protect and preserve" adage. However, as Anthony Bald, Joseph J. Doyle Jr., Max Gross, and Brian Jacob point out in "Economics of foster care" (National Bureau of Economic Research, Working Paper 29906, April 2022), these children grow up with higher depression rates and lower educational outcomes than children not placed in foster care. In their paper, Bald and his colleagues look at the child welfare system as a whole to determine whether economic research may benefit its policies that protect children.

Bald and coauthors breakdown their analysis into three primary areas: (1) the practices of the child welfare system—how it evaluates, investigates, and intervenes on behalf of the child; (2) the demand (need) of foster care; and (3) the supply (source) of foster care. They examine several local and state child welfare policies and their processes, in the 2000s. And then they look at the demand and supply of foster care during this period and how these areas can be improved.

Within the child welfare system is the Child Protective Services (CPS), the agency that assesses and investigates possible child abuse. Bald and his colleagues observe that at the end of 2019, CPS placed over 400,000 children in foster care (0.6 percent of the total U.S. child population). The main reasons for placement include maltreatment and neglect. The authors list several types of foster care placements: kinship (placed in a home of a relative), unrelated foster family, and congregate, such as a group home or an institution. Of these children, CPS placed nearly half in unrelated foster families, staying an average of 15 months.

Bald and his coauthors find that the child welfare policies that CPS follow in addressing possible child abuse or neglect vary substantially between state and local governments and within each authority. They note that some of these factors that cause this variance are number of children who must be placed, number of available placements, costs of maintaining placements, and racial disparities.

As for the demand and supply of foster care, Bald and his colleagues' analysis shows that these elements are also affected by government policies, both state and local that often vary from one to the other. Demand is affected by the level of abuse reported and the policies that dictate how CPS should respond. For supply, policies must cover assessing and obtaining foster care families, licensing homes, and selecting the right type of foster care.

Bald and his coauthors surmise that the foster care system policies and practices that direct the protection and preservation of children in the United States are inconsistent. They recommend that economic research is needed to improve the system's policies for the "wellbeing" of the children and their families. To address foster care demand, they recommend programs to help the welfare system understand why children are being mistreated and solutions to help stop the mistreatment. And for supply of foster care, the authors propose better quality of foster care through more modern recruitment processes. With these types of improvements and the policies that institute them, they find that economic research can protect children.

BOOK REVIEW

NOVEMBER 2022

Creating future career opportunities for African Americans

Upper Hand: The Future of Work for the Rest of Us. By Sherrell Dorsey, with a forward by Angela Jackson. Hoboken, NJ: John Wiley & Sons, Inc., 2022, 276 pp., $25 hardcover.

In *Upper Hand: The Future of Work for the Rest of Us*, author Sherrell Dorsey argues that early access to technology can create better career and economic opportunities for members of disadvantaged communities. Although African Americans and other minority groups have always been involved in leading technology forward, their contributions have not always been recognized. There are ways, including establishing community support groups and participating in team competitions, to provide minority youth with access to the jobs that will drive the nation's economic future. Dorsey lived these opportunities and, through her story, lets readers know how they, too, can plan their lives and careers.

The book's opening revolves around the author's family and early life, which set the stage for her subsequent growth and development. This story begins with Dorsey's grandfather moving the family from Detroit to Seattle and becoming a part of the technology-driven future. Dorsey's family recognized and respected the importance of technology and information, providing her with access to opportunities others did not have. Aiding these family efforts was the surrounding community, which valued learning and intellectual curiosity. Armed with educational CDs and insights into the history and technological contributions of African Americans, Dorsey was able to gain a deeper understanding of her community and find opportunities to grow. She took courses in computer programming and secured internships that would shape her understanding of the world and her place in it.

Dorsey's experience does not reflect that of many minority members of our society. The author notes that, according to a 2021 McKinsey study, more than half of Black workers are in low-paying but essential jobs in fields such as healthcare, food preparation, retail, and customer service. This situation is due, in part, to segregated locales having fewer economic opportunities than wealthier communities. In the case of Dorsey, she had the fortune to intern at Microsoft for 3 years while in high school, building a resume that college graduates would envy.

As noted in the book, one of the issues facing today's youth is related to credentialling expectations. Many jobs do not require a specific degree, but they do require technical knowledge, skills, and experience that are hard to demonstrate to potential employers. There are many existing initiatives that can help with this problem. Hackathons are one example, allowing members of collaborative teams to create programming solutions, network with peers, strengthen their resumes, and win prizes.

Dorsey spends some time discussing technology and how it is changing everyday life. She argues that advances in robotics and automation are not to be feared; instead, they allow workers to be more efficient, safer, and socially engaged. Rather than destroying jobs, robots create opportunities for upskilling and moving into higher paying occupations with lower physical demands. This insight is especially relevant to African Americans, many of whom are employed in jobs amenable to automation. However, Dorsey warns that while technology offers opportunities, some of its advancements, such as facial recognition software, can discriminate against minority groups. Such cases can create fear and have led to the banning of software over privacy concerns.

Another area that Dorsey dives into is wage negotiation. She recalls cases in which she undervalued her work and accepted wages lower than what she was worth. This is a problem that can persist during one's career and lead to lower savings. Students seeking jobs or internships need to learn how to negotiate wages by using available employment data and, if needed, be ready to move on to other opportunities. This skill is important in negotiating with both legacy and startup employers. A lack of understanding of the fundamentals of the stock market can also hold people back because they cannot get the most out of their opportunities in assessing stock options as a part of compensation.

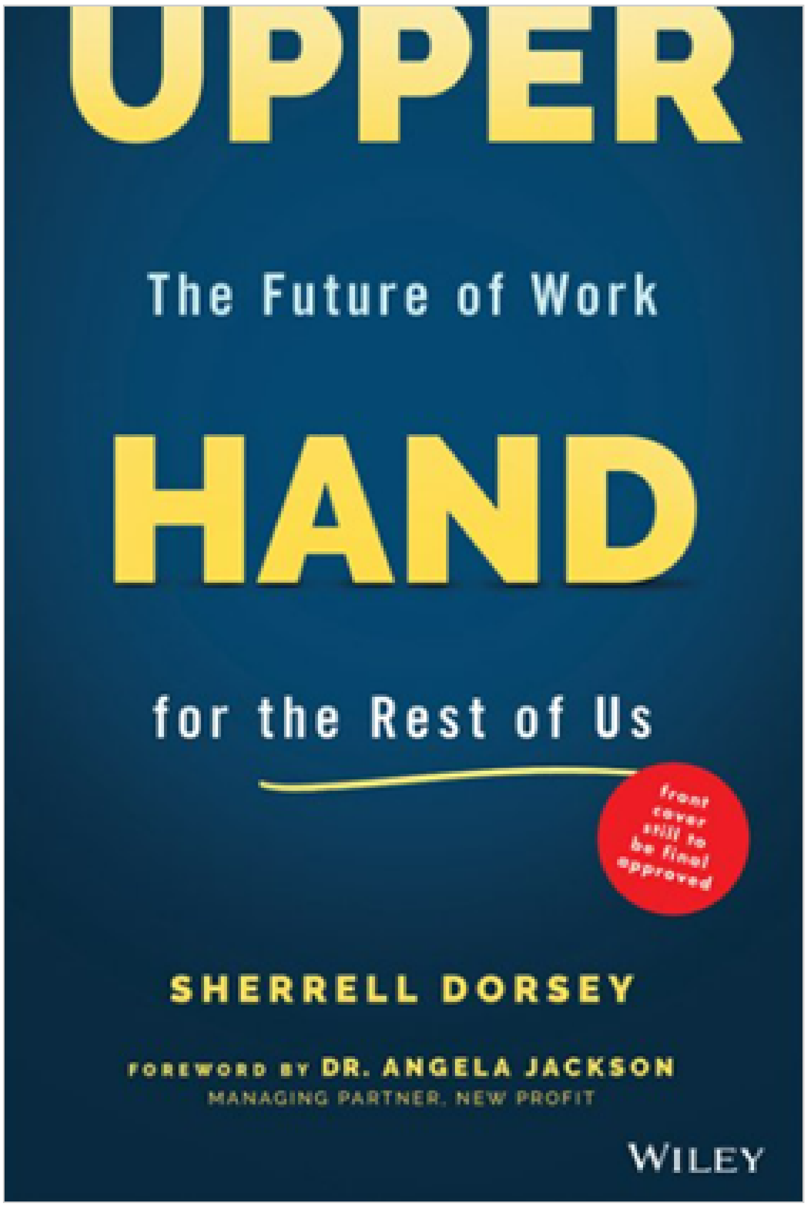
Unfortunately, opportunities can be limited by gatekeepers. According to Dorsey, connections are often very important for getting a foot in the door, and a look at the major companies in the high-technology field shows that most of their executives come from a very small subset of universities. This means that university choice can play a role in career planning and should be informed by knowledge of the target industry and the paths its leaders have taken. Also, spending time on skill-building activities is important. Learning how to run an effective meeting by taking on leadership roles in clubs and other organizations, for example, can pay long-term dividends.

The later chapters of *Upper Hand* focus on jobs, analyzing future employment opportunities. Much of the future of work may be about creating opportunities through self-run businesses. Dorsey describes how her many side hustles became the basis for her own career. She also discusses the groups she formed to help African-American and other minority members of her community develop their high-technology skills and connect with others. One example is BLKTECHCLT, a group Dorsey established in the Charlotte, NC, area, bringing together like-minded people who thought they were alone in their aspirations. The opportunities to establish connections of this kind can be limited by a lack of access to the digital tools that one needs to become a part of the future economy. Such tools and the internet are keys to the modern world, but many communities do not have access to them.

In the book's final chapter, Dorsey delves into the 2019–29 employment projections of the U.S. Bureau of Labor Statistics, supplementing base projections data with related information on professional certificates and specific degrees required for certain occupations. Consistent with the focus of the book, the chapter highlights employment opportunities in technology, although some technology-related jobs, such as those of CNC programmers, are not included. While *Upper Hand* was published in 2022, Dorsey's use of 2019 base-year projections data is reasonable because 2020 was heavily affected by the coronavirus disease 2019 (COVID-19) pandemic.

Upper Hand offers an interesting look into what work means to individuals, particularly those of minority status. As an analyst in the BLS Employment Projections program, I was drawn to the book by its title, expecting to learn about the types of jobs that will likely be available in a decade. Although the book does not identify any specific new jobs, it does examine what skills and abilities will be needed in the future. It also discusses existing occupations that will remain relevant and should be sought by young people.

Another strength of the book is its effort to identify specific steps, described at the end of each chapter, that can be taken to develop the potential of minority youth and find a path forward for disadvantaged communities. Rather than being derived from a simple thought exercise, these steps are based on a lot of supporting data that connect Dorsey's lived experiences with the rest of the world. This pragmatic approach makes the information presented in the book more accessible to readers, demonstrating how Dorsey developed through her personal and professional life, how she helped others, and how she plans to continue to contribute to society.



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ARTICLE

NOVEMBER 2022

Has the pandemic permanently changed job requirements?

The U.S. Bureau of Labor Statistics Occupational Requirements Survey publishes information on job requirements in four areas: education and training, cognitive and mental requirements, physical demands, and environmental conditions. This article reports on an examination of whether the pandemic led to changes in job requirements measured in this survey. Increased use of teleworking is evident, but the other job requirements do not generally show statistically significant changes since the onset of the coronavirus disease 2019 pandemic.

The Occupational Requirements Survey (ORS) is a survey of establishments in private industry and state and local government conducted by the U.S. Bureau of Labor Statistics (BLS). Sponsored by the Social Security Administration because of that agency's responsibility for disability adjudication, ORS publishes information on job requirements in four areas:

- Education and training
- Cognitive and mental requirements
- Physical demands
- Environmental conditions

Job requirements information is currently being collected over a 5-year reference period, 2019–23. This article reports on research conducted to assess whether job requirements have been permanently changed as a result of the coronavirus disease 2019 pandemic.

How can one determine if the job requirements measured by ORS changed permanently? If one could measure requirements for employers before the start of the pandemic and also remeasure requirements for those same employers after the impact of the pandemic, then one could attribute the change from "before" to "after" to the pandemic. In general, however, employers are in the ORS sample only once. That is, a nationally representative sample is chosen for each of the 5 years, 2019–23, and only a small number of establishments are in the sample for more than 1 year. Another approach would be to ask employers whether the pandemic affected their job requirements. For those employers who said it had, one could try to obtain measures of the current requirements and measures from before the pandemic. Unfortunately, this type of approach would be quite burdensome on the respondents and also rely on them to recall how job requirements have evolved in recent years.

Instead of using these methods, BLS relied on two different approaches, which were less direct than the two just mentioned. In the first approach, during the third year (August 2020–July 2021) of the 5-year reference period, BLS field economists asked each employer whether any job requirements changed. The field economists recorded the employer's response in one of four categories: (1) no change, (2) permanent change, (3) temporary change, and (4) other. To be clear, owing to response burden issues, this question was not asked for each requirement but for any requirement that might have changed. No information was collected on which requirement might have been involved.

The responses in the "other" category were excluded from the analysis. Prepandemic requirements were collected in the case of a temporary change. And those in the temporary-change category were grouped with those with no change. That is, a comparison of those in a combined no-change and temporary-change category with those in the permanent-change category could reveal which requirements were changing.

The second approach attempted to uncover the possible effects of the pandemic by comparing the requirements of jobs before the onset of the pandemic with the requirements of jobs after the impact of the pandemic. The ORS data that BLS economists collected between September 2018 and July 2021 were divided into the following three groups:

1. A baseline group composed of all jobs whose information was collected in the first year of the reference period (September 2018–August 2019)

2. A prepandemic group composed of all jobs in the second year of the reference period whose information was collected before March 1, 2020 (August 2019–February 2020)

3. A postpandemic group, which began after the start of the pandemic in the United States, composed of all jobs whose information was collected beginning on June 1, 2020, up to the end of the third year of the reference period (June 2020–July 2021)

A couple of clarifications are worth mentioning for the three groups. First, data collected in March, April, and May 2020 were not used. Employers were assumed to have adjusted to the pandemic's impact in this period. Second, though the third group is called a postpandemic group for brevity, this name does not imply that the pandemic is not still with us. Rather, the name signifies that the data were collected after the employers had time to adjust to the impact of the pandemic.

Of the two approaches just mentioned, only the second one is discussed in this article. For the first approach, not reported in this article, only about 1 percent of the analysis sample was in the permanent change group. This finding suggests that any changes in job requirements that are measured using this survey would have affected only a small portion of the economy. Of the analysis sample, 77 percent reported no change in requirements and 22 percent indicated only temporary changes.

In the rest of this article, the first section reviews the ORS elements (job requirements) that might have been changed by the pandemic. The second section briefly discusses the methods for determining which requirements may have changed significantly. The third section provides, as background, the levels and changes in each of the elements during the period. The fourth section contains the analysis, which assesses whether statistically significant changes in elements remain after controlling for differences in occupational composition.

Job requirements

Has the pandemic changed job requirements permanently or at least those job requirements that are collected in the ORS? In general, the onset of the coronavirus has led to two easily seen impacts on jobs. The first is increased use of personal protective equipment and attention to personal hygiene in order to minimize exposure to the disease. The second is expanded efforts to increase distance between workers, which could affect how workers communicate with each other. To create a list of job requirements potentially changed by the pandemic, one must review the full list of ORS elements and select those that may have been affected.

As indicated earlier, ORS collects information in four areas: education and training, cognitive and mental requirements, physical demands, and environmental conditions. The first impact of the coronavirus (people minimizing exposure to the coronavirus) on jobs is equivalent to minimizing exposure to biohazards, which is excluded from ORS collection. Thus, the focus when considering ORS elements for analysis is primarily on physical distancing and its impact.

Did education and training requirements change because of the pandemic? Given that such job requirements change quite slowly,[1] they likely did not change noticeably. In the analysis, BLS examines this presumption with respect to on-the-job training and prior work experience requirements. Among the cognitive demands, several elements had potential to change. Efforts to increase physical distance, which could be permanent, may affect the prevalence of such ORS requirements as teleworking, working with the general public, working around crowds, the frequency of work being reviewed, and whether a supervisor is present. Increasing distancing may also limit verbal interactions and reduce the level of people skills required. Also, the physical demand of speaking may be affected. The reorganization of work to increase distance may result in greater keyboarding. Lastly among physical demands, reaching at or below the shoulder is also examined. An increased use of plexiglass and other barriers might heighten the need for reaching.

For the final ORS area environmental conditions, no elements were examined. As noted, the use of personal protective equipment and personal hygiene steps to minimize exposure are excluded from the ORS. In addition, it is not apparent that the other elements in this category would be subject to permanent change.

Table 1 displays the elements selected for the analysis. Defining a categorical variable to correspond to each element is necessary. Within the education and training area, one variable is defined for prior work experience and another variable for on-the-job training to determine whether each element appears. Thus, if the element equals "Yes," the categorical variable will equal 1, while if the element equals "No," the categorical variable will equal zero.

Table 1. Elements from the Occupational Requirement Survey selected for analysis

Element	Response categories
1. Education, training, and experience	
Prior work experience	Yes/No and number of days if Yes
On-the-job training	Yes/No and number of days if Yes
2. Cognitive and mental requirements	
Teleworking	Yes/No
Working with the general public	Yes/No
Working around crowds	Yes/No
Frequency of work being reviewed	More than once per day; once per day; less than once per day, but at least once per week; and less often than weekly
Supervisor is present	Yes/No
Verbal interactions	Constantly, every few minutes; not constantly, but more than once per hour; not more than once per hour, but more than once per day; once per day or less often
People skills	Basic, more than basic
3. Physical demands	
Speaking	Not present, up to 2 percent, 2 percent up to 33 percent, 33 percent up to 66 percent, and 66 percent or more
Keyboarding	Not present, up to 2 percent, 2 percent up to 33 percent, 33 percent up to 66 percent, and 66 percent or more
Reaching at or below the shoulder	Not present, up to 2 percent, 2 percent up to 33 percent, 33 percent up to 66 percent, and 66 percent or more
4. Environmental conditions	
None	None
Source: U.S. Bureau of Labor Statistics.	

For the cognitive demand elements selected, teleworking, working with the general public, working around crowds, and a supervisor is present have response categories of "Yes" and "No." Therefore, variables are defined on the basis of whether these elements are present. For the frequency of work being reviewed, the variable is 1 for more than once per day, zero otherwise. For verbal interactions, the variable is 1 for interactions of once per hour or fewer, zero otherwise. Finally, for people skills, it is 1 for more than basic, zero otherwise.[2] For the three physical demand elements, the variable is set equal to 1 if the element is present. If otherwise, the variable is set to zero.

Methods

BLS uses two methods to determine which job requirements may have been changed significantly by the pandemic. Each method has advantages and disadvantages. The first method uses what is known as a logit regression, which is used in multivariate analysis when the dependent variable is categorical, as is the case here. One can use such a regression to address the following question: Has the pandemic led to significant changes in the proportion of the economy with each of the elements? Two types of comparisons are tried. The first, using just the pre- and postpandemic groups defined earlier as the analysis sample, has as independent variables an indicator for whether or not the job is in the postpandemic group and indicators for the occupations of the jobs. Variables are used for occupations so as to control for differences by group in occupational composition. If the coefficient on the indicator for the postpandemic group is statistically significant, then one might believe that the pandemic has changed the job requirement. This is the case because jobs in the postpandemic group may have changed their requirements as a result of the pandemic, while those in the prepandemic group will not have.

The baseline group should be examined as well in order to assess if the assumed difference between the groups can be attributed to the pandemic. In the second comparison, one expands the analysis sample to include the baseline group, and one adds to the logit regression specification an indicator for whether the job is in the baseline group. If trends noted between the pre- and postpandemic groups are also present between the baseline and the prepandemic groups, then one might suspect that assuming that the entire difference between pre- and postpandemic should be attributed to the pandemic is too strong. Accordingly, at least part of the change between the pre- and postpandemic groups should probably be attributed to a continuation of preexisting trends. On the other hand, if the change between the pre- and postpandemic groups marks a reversal of that between the baseline and prepandemic groups, then one's assurance that the more recent trend can be attributed to the pandemic will be enhanced.

The second method is occupation specific. For each element, the proportions in which the element is present for a given occupation is calculated for the pre- and postpandemic groups. A comparison of the two proportions, which uses a statistical hypothesis test, addresses the question of whether the proportion changed for an element for that occupation. One advantage of this method is that it facilitates making inferences for specific occupations. But a disadvantage is that assessing economywide changes is more difficult.

Levels and changes in selected elements

As background for the analysis of the next section, table 2 shows the percentage levels of each of the elements considered for the baseline, prepandemic, and postpandemic groups.[3] The fourth and fifth columns present the difference in percentage points between the prepandemic and the baseline groups and the pre- and postpandemic groups, respectively. The final column displays the difference between the fourth and fifth columns to show whether any tendencies observed between the baseline and prepandemic groups were continued between the pre- and postpandemic groups.

Table 2. Levels and changes in selected elements by group

Element	Baseline	Prepandemic	Postpandemic	Difference between prepandemic and baseline	Difference between postpandemic and prepandemic	Difference between (postpandemic and prepandemic) and (prepandemic and baseline)
Prior work experience	46.2	46.4	46.9	-0.2	-0.5	-0.3
On-the-job training	79.5	79.4	78.1	-0.1	-1.3	-1.2
Teleworking	9.6	7.6	11.4	-2.0[2]	3.8[1]	5.8[1]
Working around crowds	4.1	3.7	2.7	-0.4	-1.0[2]	-0.6
Working with the general public	75.1	80.5	80.4	5.4[1]	-0.1	-5.5[1]
Supervisor is present	66.2	63.9	64.4	-2.3	0.5	2.8
Frequency of work being reviewed	34.5	35.6	33.4	1.1	-2.2	-3.3
Verbal interactions	22.2	21.2	23.3	-1.0	2.1	3.1
People skills	62.0	61.2	59.5	-0.8	-1.7	-0.9
Speaking	93.5	95.0	95.4	1.5[2]	0.4	-1.1
Keyboarding	65.3	65.0	66.6	-0.3	1.6	1.9
Reaching at or below the shoulder	79.4	79.7	76.6	0.3	-3.1[2]	-3.4

[1] The value is significant at the 1-percent level.

[2] The value is significant at the 5-percent level.

Note: The baseline reference period is from September 2018 to August 2019. The prepandemic reference period is from August 2019 to February 2020. The postpandemic reference period is from June 2020 to July 2021.

Source: U.S. Bureau of Labor Statistics and the author’s calculations.

Examining the difference between the pre- and postpandemic groups first (table 2, fifth column), we can see that three changes are statistically significant. The proportion of jobs with teleworking increased by 3.8 percentage points from 7.6 percent to 11.4 percent, significant at the 1-percent level. The proportion working around crowds declined by 1.0 percentage point to 2.7 percent. The share of employment requiring reaching at or below the shoulder fell by 3.1 percentage points to 76.6 percent. The latter two changes are significant at the 5-percent level.

It turns out, however, that of these three requirements, only the pre- to postpandemic change in teleworking remains statistically significant when compared with the baseline to prepandemic change. That is, the 3.8-percentage-point increase in teleworking following the start of the pandemic closely follows a 2.0-percentage-point decline in teleworking in the prior period. The tendency to work less around crowds was already evident in the baseline period so that the difference between the pre- and postpandemic groups and between the prepandemic and baseline groups is not statistically significant. For the element reaching at or below the shoulder, the difference between the two changes is not statistically significant, even though the movement from baseline to prepandemic was slightly in the opposite direction. On the other hand, the element working with the general public has emerged as statistically significant in the final column. This element increased by 5.4 percentage points from the baseline group to the prepandemic group, so the fact that it declined slightly in the prepandemic and postpandemic periods represents a reversal.

Accounting for differences by group in occupational composition

In this section, logit regressions and occupation-specific hypothesis tests are conducted to assess changes in job requirements after accounting for differences in occupation composition across the groups. The first set of logit regressions is run on prepandemic and postpandemic groups. The second set of logit regressions is run on baseline, prepandemic, and postpandemic groups. The first set of occupation-specific hypothesis tests examines six-digit occupational groups. The second set of occupation-specific hypothesis tests examines two-digit occupational groups.

Logit regressions

As noted earlier, the logit regressions that are run have as dependent variables a categorical variable for each element that is subject to analysis. The specifications of the logit regressions focus on comparing the three groups: baseline, prepandemic, and postpandemic. In the first set of specifications, only the pre- and postpandemic groups are included, and a dummy variable is used when the observation comes from the postpandemic group. In the second set of specifications, all three groups are included, and in addition to the dummy variable for the postpandemic group, a dummy variable is used for the prepandemic group. The other independent variables in the regressions are dummy variables for occupations. Occupations are specified in two ways, each having its advantages and disadvantages. First, six-digit occupational groups, which are detailed identifications of occupations, are used, but to facilitate convergence of the logit regressions only occupations containing at least 30 jobs are used.[4] Second, two-digit major occupational groups are used, which allow the whole sample to be analyzed. The regressions on the two-digit occupations institute controls which impose the restriction that all six-digit occupations within two-digit occupations have the same impact on the dependent variable.

Table 3 displays, for both specifications, the estimated marginal effects applicable for each element’s regression. These effects are the average over the sample of moving from the prepandemic group to the postpandemic group, given the estimated coefficients. In other words, the marginal effects provide an estimate of how different the probability of an outcome would be, on average, if jobs were in the postpandemic group rather than in the prepandemic group. For most elements, the marginal effects are not statistically significant, suggesting that these requirements did not undergo major changes after the onset of the pandemic. Two notable exceptions are teleworking and working around crowds. Teleworking is 3 to 4 percentage points higher after the pandemic, depending on the specification, while working around crowds is 1 to 2 percentage points lower. Both these results are consistent with increased physical distancing. The only other element with statistical significance in either regression specification is people skills, in which the six-digit occupation specification suggests a reduced demand for advanced people skills.

Table 3. Logit regression results: sample of prepandemic and postpandemic groups

Element	Marginal effects from postpandemic to prepandemic: six-digit occupations	Marginal effects from postpandemic to prepandemic: two-digit occupations
Prior work experience	-0.5	-0.3
On-the-job training	-1.6	-1.1
Teleworking	4.1[1]	3.1[1]
Working around crowds	-1.9[2]	-1.2[1]
Working with the general public	0.7	0.5
Supervisor is present	-0.7	0.4
Frequency of work being reviewed	-0.8	-1.6
Verbal interactions	0.8	1.6
People skills	-3.4[1]	-2.2
Speaking	1.8	0.4
Keyboarding	0.6	1.3
Reaching at or below the shoulder	-2.0	-2.1

[1] The value is significant at the 1-percent level.

[2] The value is significant at the 5-percent level.

Note: The marginal effect is the average over the sample of the impact of moving from prepandemic to postpandemic, given the estimated coefficients. It is an estimate of how different the probability of an outcome would be, on average, if a job were in the postpandemic group rather than in the prepandemic group.
The prepandemic reference period is from August 2019 to February 2020. The postpandemic reference period is from June 2020 to July 2021.
Source: U.S. Bureau of Labor Statistics and the author's calculations.

As discussed in the methods section above, expanding the analysis sample to include the baseline group in the regressions is useful to determine if any differences between the pre- and postpandemic groups are merely the continuation of earlier changes. Table 4 displays, for both six-digit and two-digit occupation controls, two different columns of marginal effects and a column showing the difference between the two. In other words, the first column of each set of three columns provides the change between the baseline group and the prepandemic group, the second column of the three provides the change between the prepandemic group and the postpandemic group, and the third column of the three provides the difference between the two changes. A test of the hypothesis that this difference equals zero relies on an alternative scenario than did the earlier set of specifications (in table 3) about what job requirements may have been affected by the pandemic. The assumption is that the change noted between the baseline group and the prepandemic group would have continued were it not for the pandemic.

As shown in table 4, it is rare for the difference in the change between groups to be statistically significant. Only in the case of teleworking is this difference statistically significant for both occupational specifications. Because teleworking decreased between the baseline and prepandemic groups, the increase in teleworking between pre- and postpandemic registers as a reversal of a trend and thus is more likely attributable to the onset of the pandemic. A decrease in the baseline period for working around crowds rendered the difference in the change insignificant.

Table 4. Logit regression results: sample of baseline, prepandemic, and postpandemic groups

Element	Marginal effects from prepandemic to baseline: six-digit occupations	Marginal effects from postpandemic to prepandemic: six-digit occupations	Marginal effects from (postpandemic to prepandemic) to (prepandemic to baseline): six-digit occupations	Marginal effects from prepandemic to baseline: two-digit occupations	Marginal effects from postpandemic to prepandemic: two-digit occupations	Marginal effects from (postpandemic to prepandemic) to (prepandemic to baseline): two-digit occupations
Prior work experience	1.5	-0.6	-2.1	1.5	-0.3	-1.8
On-the-job training	-0.4	-1.6	-1.2	-0.6	-1.2	-0.6
Teleworking	-2.0	4.2[1]	6.2[2]	-1.6[2]	3.1[1]	4.7[1]
Working around crowds	-0.2	-1.7[2]	-1.5	-0.2	-1.2[2]	1.0
Working with the general public	5.0[1]	0.7	-4.3[2]	4.2[1]	0.7	-3.5
Supervisor is present	-1.0	-0.7	0.3	-2.5	0.4	2.9
Frequency of work being reviewed	0.8	-0.7	-1.5	0.3	-1.6	-1.9
Verbal interactions	0.2	1.0	0.8	-0.4	1.6	2.0
People skills	-0.4	-3.2[1]	-2.8	0.0	-2.0	-2.0
Speaking	-2.8[2]	1.2	4.0	-1.6[2]	0.4	2.0
Keyboarding	0.9	0.4	-0.5	0.8	1.3	0.5
Reaching at or below the shoulder	-1.1	-1.9	-0.8	-0.4	-2.1	-1.7

[1] The value is significant at the 1-percent level.

[2] The value is significant at the 5-percent level.

Note: The marginal effect is the average over the sample of the impact of moving one group to another (either baseline to prepandemic or prepandemic to postpandemic), given the estimated coefficients. It is an estimate of how different the probability of an outcome would be, on average, if a job were in the second group rather than in the first.
The baseline reference period is from September 2018 to August 2019. The prepandemic reference period is from August 2019 to February 2020. The postpandemic reference period is from June 2020 to July 2021.
Source: U.S. Bureau of Labor Statistics and the author’s calculations.

Comparisons by occupation

We divided the sample into six-digit and two-digit occupations and compared the proportion of a given element in the prepandemic group with the corresponding proportion in the postpandemic group. Restricting attention to six-digit occupations with at least 30 observations yields 252 occupations to assess. Table 5 summarizes the results of hypothesis tests for six-digit occupations. The hypothesis is that the proportion of a given element for each occupation in the prepandemic group is the same as the corresponding proportion in the postpandemic group. The result of each hypothesis test is distributed across four columns in table 5. A rejected hypothesis means that the difference between the periods is statistically significant. If the difference is statistically significant and the postpandemic group proportion is greater than the prepandemic category, then the first column is used. If it is less than the prepandemic group, then the second column is used. If the difference is not statistically significant, then the third column is used. In some cases, the statistic for the hypothesis test cannot be calculated, so the fourth column is used. This situation occurs if either both proportions equal 1 or both equal zero.

Table 5. Summary of hypothesis tests on 252 six-digit occupations

Element	Difference is statistically significant and positive	Difference is statistically significant and negative	Difference is not statistically significant	Test statistic could not be computed
Prior work experience	15	14	218	5
On-the-job training	9	21	218	4
Teleworking	10	1	126	115
Working around crowds	1	5	145	101
Working with the general public	5	8	165	74
Supervisor is present	13	13	223	3
Frequency of work being reviewed	12	10	193	37
Verbal interactions	12	8	211	21
People skills	5	13	143	91
Speaking	5	1	67	179
Keyboarding	7	5	120	120
Reaching at or below the shoulder	8	16	208	20

Note: The hypothesis is that the proportion of a given element for each occupation in the prepandemic group is the same as the corresponding proportion in the postpandemic group. Test statistic cannot be calculated when, for a given variable, either all values are equal to zero or all values are equal to 1 for both the prepandemic and postpandemic groups.
The prepandemic reference period is from August 2019 to February 2020. The postpandemic reference period is from June 2020 to July 2021.
Source: U.S. Bureau of Labor Statistics and the author's calculations.

Examining table 5, we can see that for each element, either a high share of the hypothesis tests is not significant, implying that one cannot reject the hypothesis that the proportion is the same for the two groups or the test statistic cannot be calculated, which occurs more frequently when the proportions of an element are close to zero or to 1. The high share of insignificant hypothesis tests is not surprising. This is the case given that job requirements tend to change slowly over time under normal circumstances. Thus, there may be little reason to expect significant changes by occupation.

In the two columns that display significant results, the teleworking element stands out because of the high proportion of significant and positive cases, suggesting that the rate of teleworking had been increasing. This result is consistent with the finding of the logit regressions.

Table 6 is the same statistical test as conducted in table 5, except the hypothesis tests are done for major occupations instead of detailed ones. Because of the greater aggregation of the occupations, a test statistic is rarely not computed, although a high proportion of the tests are statistically insignificant. Teleworking has the highest number of statistically significant cases, and all these significant cases are consistent with growing rates of teleworking over time.

Table 6. Summary of hypothesis tests on 22 two-digit occupations

Element	Difference is statistically significant and positive	Difference is statistically significant and negative	Difference is not statistically significant	Test statistic could not be computed
Prior work experience	2	0	20	0
On-the-job training	0	1	21	0
Teleworking	4	0	17	1
Working around crowds	0	2	18	2
Working with the general public	1	1	20	0
Supervisor is present	0	0	22	0
Frequency of work being reviewed	0	0	22	0
Verbal interactions	2	0	20	0
People skills	0	1	20	1
Speaking	0	0	18	4
Keyboarding	1	1	18	2
Reaching at or below the shoulder	0	1	21	0

Note: The hypothesis is that the proportion of a given element for each occupation in the prepandemic group is the same as the corresponding proportion in the postpandemic group. Test statistic cannot be calculated when, for a given variable, either all values are equal to zero or all values are equal to 1 for both the prepandemic and postpandemic groups.
The prepandemic reference period is from August 2019 to February 2020. The postpandemic reference period is from June 2020 to July 2021.
Source: U.S. Bureau of Labor Statistics and the author's calculations.

Conclusion

This article reports on an examination of whether the pandemic led to changes in job requirements measured in the ORS. Job-related data collected from the ORS between September 2018 and July 2021 are examined across three groups: baseline, prepandemic, and postpandemic. The methods rely on assumptions about what is behind job requirement differences across these three groups. That is, for much of the analysis, any difference between the prepandemic and the postpandemic groups are attributed to the pandemic. For part of the analysis, the assumption is that a change between the baseline and prepandemic groups would have continued had the pandemic not occurred. The results are generally consistent across the statistical approaches. Findings indicate that a pandemic-induced shift in a job requirement is rare. The exception to this conclusion is the element of teleworking, which moved toward increased use.

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Maury Gittleman, "Has the pandemic permanently changed job requirements?," *Monthly Labor Review,* U.S. Bureau of Labor Statistics, November 2022, https://doi.org/10.21916/mlr.2022.30

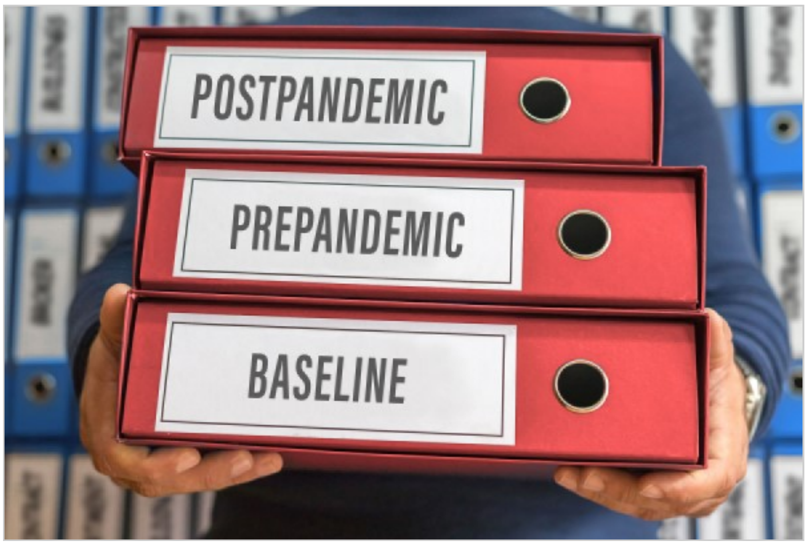
Notes

[1] Michael J. Handel, “Dynamics of occupational change: implications for the Occupational Requirements Survey,” unpublished report (U.S. Bureau of Labor Statistics, July 15, 2016), https://www.bls.gov/ors/research/sample-design/pdf/dynamics-occupational-change-2016.pdf.

[2] The element verbal interactions includes videoconferencing but does not include written communication. The element people skills includes not only verbal but also written communication. Both verbal interactions and people skills are coded for the highest level experienced.

[3] All computations from here on use survey weights. In addition, when appropriate, the relevant statistical software takes account of primary sampling units and strata in the Occupational Requirements Survey sample.

[4] Of the six-digit occupations, 252 meet this criterion.



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NOVEMBER 2022

Racial segregation and its educational ripples

Summary written by: Nicholas A. Schaffer

Racial segregation exists in neighborhoods across the United States for several reasons. Redlining, racial covenants, and discrimination in the real estate market have all contributed to segregated communities. Although some of these contributing factors have disappeared, many segregated communities remain. Research has shown that segregation contributes to negative outcomes for Black children, relative to their White cohorts. In their essay, "City segregation and the college degree gap" (Economic Synopsis no. 17, Federal Reserve Bank of St. Louis, June 23, 2022), authors Hannah Rubinton and Maggie Isaacson examine how the segregation level of a city affects the gap in college attainment between its Black and White children.

Rubinton and Isaacson use data from the U.S. Census Bureau and from Opportunity Insights, a not-for-profit organization based at Harvard University. The researchers use 2000 census data on census tracts and commuting zones. Census tracts are statistical subdivisions of a county. Commuting zones are areas intended to reflect the geographic relationship between where people live and work. In their essay, the authors consider commuting zones to be cities. Rubinton and Isaacson create a dissimilarity index to measure segregation. They create the index by calculating the proportions of Black and non-Black populations that live in each census tract. Then using data from Opportunity Insights, Rubinton and Isaacson assess the gap between races in college attainment. These data combine tax information with educational attainment data from the Census Bureau. From these datasets, the authors calculate the probability that a child who grew up in a given city obtained a college degree.

The authors find a positive correlation between segregation and the gap between Black students' and White students' levels of degree attainment. In other words, an increase in segregation increases the gap between the number of Black and White students obtaining college degrees. This correlation between college attainment and segregation matches the findings of other academic papers. The authors use new data sources to expound on those academic papers and create city-level perspectives on segregation and educational gaps.

Rubinton and Isaacson find from other studies that the link between segregation and the education gap may have a multitude of causes, as stated earlier. Several researchers have hypothesized that racial segregation can affect the frequency children interact with college-educated adults. Others argue that segregation can affect some groups' access to higher quality schools. Other mechanisms, such as redlining, have been removed from the legal framework in the United States. However, the gap in educational outcomes as a result of segregation may be a not-so-distant echo of redlining. Rubinton and Isaacson conclude that a renewed campaign to integrate schools and neighborhoods could help narrow the racial gap in educational attainment.

BEYOND BLS

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

NOVEMBER 2022

Why has targeted social insurance spending increased in the United States?

Summary written by: Justin Holt

Social insurance is a set of governmental transfers that increase the economic wellbeing of individuals. These transfers can be grouped into two main categories: universal and targeted. Universal programs provide a benefit to all individuals who qualify with no required means test (in essence, irrespective of wealth and income). Examples of universal programs in the United States are Social Security and Medicare. Targeted programs provide benefits to individuals who qualify based on a means test. In the United States, prominent examples of targeted programs include, Medicaid, the Supplemental Nutrition Assistance Program (SNAP), and the Earned Income Tax Credit (EITC).

In "Targeting, universalism, and other factors affecting social programs' political strength (The Hamilton Project, Brookings Institution, August 2022), Robert Greenstein considers the history, effectiveness, and longevity of targeted and universal programs in the United States. The main finding of Greenstein's research is that certain targeted programs have demonstrated greater growth in spending and in the number of beneficiaries served compared with universal programs. In general, targeted and universal programs have grown in both real dollar terms and in the number of beneficiaries. From 1979 to 2019, the average annual growth, in U.S. dollars (adjusted for inflation and population), for universal programs was 2.36 percent and for mandatory targeted programs was 3.39 percent.

Greenstein argues that there are three main reasons why particular mandatory targeted programs have increased in spending and scope in comparison with universal programs. First, targeted programs have lower total costs. Second, targeted programs have an increasing number of individuals benefiting directly or indirectly from program spending. Third, the targeted population is considered to deserve the transfer. Populations seen as more deserving (children, retirees, and the disabled) are more likely to receive continuous and increasing amounts of cash and in-kind transfers. Whereas populations seen as less deserving (working age adults who are not disabled) are less likely to receive continuous and increasing amounts of transfers.

Some targeted programs are no longer only for individuals with low incomes. For example, Medicaid currently covers three times the share of births as it did in 1985. Greenstein argues that this increase in coverage leads to broader support for a program. Also, programs can build secondary constituencies (groups that benefit from transfers without directly receiving them) that become interested in the continued existence and expansion of particular spending. For instance, food retailers have an interest in nutrition spending, and those who work for hospitals have an interest in healthcare spending.

In Greenstein's analysis of the effectiveness of social insurance, he documents the poverty reduction effects of various programs in 2017. Social Security lifted 26.9 million people of all ages above the poverty line. Targeted tax credits moved 5.1 million children out of poverty. SNAP helped 4.3 million people leave poverty conditions.

Greenstein has a set of concluding recommendations to improve the effectiveness of social insurance. One recommendation is to increase the enrolment rate of targeted programs. Enrollment rates can be increased by automatically providing benefits to eligible individuals. For example, in 2021, distribution of the Child Tax Credit increased when payments were sent out automatically to recipients based on their previous year's tax return.