COVID-19: What’s better for our economy, more frequent testing at home or more accurate testing at the doctor’s office?

John C. Roach

Our nation’s fight with coronavirus disease 2019 (COVID-19) posed many challenges in 2020 and beyond. COVID-19 is not the first challenge with a virus that the United States and the world have faced. COVID-19 was preceded by, among others, severe acute respiratory syndrome (SARS), Ebola virus disease (Ebola or EVD), and acquired immunodeficiency syndrome (AIDS), which is caused by the human immunodeficiency virus (HIV). The earlier experience raised several critical questions as we move forward. Specifically, what structures should be in place amid the current pandemic, when will a vaccine be available, how effective will it be, and how quickly will it be available to the public? The COVID-19 pandemic has increased the interest in diagnostic testing. Many observers also believe that a lack of information about the virus has exacerbated the pandemic’s disruption of the U.S. economy.

In their article, “A theory of voluntary testing and self-isolation in an ongoing pandemic” (National Bureau of Economic Research, Working Paper 27941, October 2020), economists Thomas F. Hellmann and Veikko Thiele examine the voluntary self-testing by private individuals and the economic impact as we transition into the “new normal” in our economy. As the authors explain, there are two points of view at play, one being the clinical mainstream view, which is that testing should be performed by healthcare professionals in a medical setting, such as hospitals or clinics. The theory here is that testing accuracy will be increased, thereby reducing the number of false positives that occur. The second point of view is that of public health, which views accuracy as less important than identifying as many infected people as early and as quickly as possible in order to prevent (or slow down) the virus’s spread.

From an economic perspective, if people understand the limitations of self-testing, such as the greater possibility of false positives and false negatives, is accuracy as important as availability, price, and ease of use? What happens if people who test at home do not understand the limitations of testing outside of a medical facility? Although less accurate, new testing technology is being developed that is faster and cheaper than the earlier testing methods. Symptomatic individuals are tested by qualified medical staff, unlike home-based tests designed for asymptomatic individuals. Self-testing allows people to decide whether to go out or self-isolate at home. The term “going out” would include work, socializing, shopping, and eating out. The decision to self-isolate reduces the spread of infection but hurts the economy, while going out helps the economy but increases the spread of infection.

Hellmann and Thiele obtained three main sets of results. First, people who self-test fall into two categories—those who would self-isolate without testing, and those who will go out regardless. Cheaper and easier-to-use home-based testing would increase self-testing by both groups. Second, there is economic value in home-based tests,
even if they are not as accurate as clinical tests. Clinical tests will warn against false-negative results, which otherwise would likely result in people going out while possibly being infected. In other words, with self-testing, there tends to be an assumption of perfect tests with no false negatives. Realistically, though, the alternative to an imperfect test is no test at all. As mentioned previously, some people with false-positive tests will self-isolate, whereas others will go out anyway. Finally, although it is less accurate, self-testing provides some useful information, which is better than none at all. The information from self-testing will help keep more high-risk people at home while allowing low-risk people to go out and contribute to the economy. People who do not fully understand test accuracy tend to self-test more, which reduces infection risk. The authors argue that reducing the price of testing reduces the infection risk, which aids the U.S. economy.
What happened to temps? Changes since the Great Recession

The temporary help services (THS) industry has grown in absolute and relative terms since 1990, and also since the Great Recession, from 2008–18, the period covered in this article. THS employment levels have fluctuated in advance of broader economic changes, providing a method for employers to scale employment up and down to meet changing conditions. As the economy has changed, so too has the deployment of THS employees. Trends in the THS industry follow overall employment trends and shine a light on changes in the regional, occupational, and industrial utilization of THS employees. These trends in THS employment underscore the key features of the labor market that underlie the overall employment trends. THS employment is, in many ways, a barometer for the employment changes in the U.S. economy.

In August 2010, we published a Monthly Labor Review article titled “The expanding role of temporary help services from 1990 to 2008.”[1] In the study, we reported that employment in temporary help services (THS) more than doubled from 1990 to 2008 and the industry came to include a larger share of jobs in highly skilled occupations. In addition to observing fast growth in legal, business, financial, computer, and other highly skilled occupations, we also observed a relative decline in transportation and material moving occupations and a rise in production occupations.

The United States experienced a financial crisis followed by the Great Recession from 2007 to 2009—the largest recession since the Great Depression. The Great Recession gave rise to a massive loss of jobs in nearly every industry and the largest post-World War II levels of unemployment on record, barring the recent employment changes from the 2020 coronavirus pandemic. Surely, the massive shifts in employment and methods of
production in the increasingly global value chain since the Great Recession would affect the employment levels and occupational types within the temporary help services industry.

Once again, we observed that employment movements in the temporary help services industry preceded employment movements in the overall economy. Although temporary workers (temps) account for just 2 percent of total nonfarm employment in the United States, employers have increasingly relied on temps—typically supplied by temporary help agencies—to provide greater flexibility in meeting their staffing needs. When the economy expands, employers are able to ramp up quickly by using temporary workers until permanent staff are hired. Also, temporary help agencies offer flexible staffing, candidate screening, and the opportunity to try out potential hires before committing to a permanent employment contract. Conversely, when the economy contracts, flexible labor arrangements provided by temp agencies allow firms to scale down their operations readily and without the added expense of separation pay or having to let go of their best workers. For these and other reasons, temporary help jobs are widely viewed as an important port of entry to permanent employment from the candidate’s perspective and a flexible staffing tool for employers.

The idea that temps have enhanced labor flexibility for firms was most evident during the most recent recessions (1990–91, 2001, and 2007–09) and subsequent recoveries. During the Great Recession, for example, temps experienced a larger share of job losses—34-percent decline for temps compared with 8-percent decline for all private employment—and during the recovery, a larger share of the job gains—75-percent growth for temps, 19-percent growth for all private jobs. Declines in THS employment preceded those in the overall labor market by 6 to 12 months in all three of the aforementioned recessions prior to the 2020 pandemic. Temp services also added jobs several months before the overall labor market began to recover following these recent recessionary periods.

As mentioned above, in recent years, the THS industry has supplied large numbers of jobs in production, construction, and similar occupations and in a wide variety of professional and technical occupations. Some studies have shown that the relationship between temp employment and employment in specific industries has strengthened in recent years. The THS industry has supplied large numbers of jobs in production, construction, and similar occupations, yet relatively little is understood about the dispersion and utilization rates of temp jobs across industries, occupations, and regions. By analyzing data on industries and occupations from the Occupational Employment Statistics (OES) survey and the Current Population Survey (CPS), this study provides a detailed profile of temps and the jobs, types of businesses, and parts of the United States where temps provided labor in the decade following the Great Recession.

**Growth of temps**

After the bottoming out of THS employment during the Great Recession, temp jobs had grown by approximately 75 percent, or 1.3 million jobs, across the United States by the end of 2018. Although the 6.2-percent annual growth of temps in the post-recession expansion outpaced the 2.0-percent annual growth for all employment, growth of temp jobs has decelerated in recent years. (See figure 1.)
While the overall number of temp jobs has continued to grow, the average hours worked in a week per temp job have generally declined since 2014. (See figure 2.)
In 2014, temp workers worked an average of 35 hours per week. That figure dropped below 34 hours per week by 2017, nearly approaching the level seen during the last recession. Therefore, as the economy continued to expand, the growth of temp jobs slowed and the average hours worked by temps declined. Nonetheless, the overall wage bill, as represented by the index of total wages paid (figure 3), still increased at a similar pace as all private employment. This suggests that since the growth in the number of temp jobs slowed while average hours declined, the average wage may have increased.
Regional growth

Since THS employment bottomed out in 2009, all regions—Midwest, Northeast, South, and West—have experienced substantial growth in the industry.[2] Employment of temps grew the fastest during the 2010–14 period, led by the West region. With the exception of the West region, temp employment growth decelerated between 2014 and 2015.

During the 1990–2008 period, temp employment grew in the South by 4.6 percent per year and in the West by 3.6 percent. From 2010 to 2018, however, the lead reversed. Temp employment in the West (up 5.6 percent per year) grew 20 percent faster than temporary jobs in the South (4.6 percent), the second fastest growing region in the United States for temporary help. (See figure 4 and table 1.) From 2010 to 2018, temps in the Midwest grew by 3.9 percent annually, markedly lower than the 4.3-percent annual growth rate from 1990 to 2008. Temps in the Northeast grew by 3.8 percent per year from 1990 to 2008 and by 3.6 percent annually from 2010 to 2018. Thus, compared with the 1990–2008 period, THS employment growth was greater in the West and South relative to the Midwest and Northeast.

These regional differences follow the overall and specific employment trends in the United States. Since the Great Recession, both overall employment growth and employment growth in temporary help have been greater in the West than in any other region.
Another measure of the regional importance of temps is the utilization rate: the percentage of all jobs in a region that are temps. While employment growth for temps was highest in the West, utilization rates for temp jobs were highest in the Midwest and South regions. (See table 1.) Overall, utilization rates for temps ranged from 1.9 percent in the Northeast to 2.7 percent in the Midwest in 2018.

Table 1. Percent change in employment, temporary help services, by region

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Midwest</td>
<td>4.3%</td>
<td>3.9%</td>
<td>2.7%</td>
</tr>
<tr>
<td>Northeast</td>
<td>3.8</td>
<td>3.6</td>
<td>1.9</td>
</tr>
<tr>
<td>South</td>
<td>4.6</td>
<td>4.6</td>
<td>2.5</td>
</tr>
<tr>
<td>West</td>
<td>3.6</td>
<td>5.6</td>
<td>2.2</td>
</tr>
</tbody>
</table>


**Occupational growth**

Data from the OES program show the growth and dispersion of temp jobs across occupations.[3] Since the end of the Great Recession, among the fastest growing groups of temp worker occupations has been the life, physical, and social science group, which grew 10.7 percent. Three other occupational groups of temps—computer and mathematical; arts, design, entertainment, sports and media; and education, training, and library—exceeded 9
percent annual growth during the 2010–18 timeframe: computer and mathematical; arts, design, entertainment, sports, and media; and education, training, and library. All but one occupational group in the employment services industry—education, training, and library—had increases in wages from 2010 to 2018.

In our previous analysis, employment in the employment services industry grew fastest between 2004 and 2008 in the legal; business and financial operations; computer and mathematical; community and social service; and arts, design, entertainment, sports, and media occupational groups.[4] Of the 22 occupational groups, 7 declined in employment from 2004 to 2008 and 10 declined in wages. The overall declines were expected as the Great Recession began in late 2007. Following the Great Recession, a shift in temp employment away from legal and financial occupations—which were more prominent during the 2004–08 period—to science, computer, and arts and media occupations during the 2010–18 period was observed.

In our current analysis, although employment in education, training, and library occupations has risen, average wages for temp jobs in the group as a whole have markedly declined. This pattern of rising employment and falling wages was evident during the 2004–08 period. However, the decline in wages was more pronounced during the 2010–18 period. The average decline from 2010 to 2018 is primarily due to the changing occupational mix rather than to declining wages for individual occupations. During the 2010 through 2018 period, teacher assistants, whose average wages were among the lowest in the occupational group, tripled in employment. While wages have generally grown for individual occupations within the group, the overall average wages within the education, training, and library group have declined because of the increasing number of teacher assistant temps.

The four highest paying occupational groups had average annual salaries for temps of more than $80,000 in 2018: management ($122,960), legal ($88,110), computer and mathematical ($88,070), and architecture and engineering ($83,280). The greater pay in these occupational groups is associated with the high concentration of these jobs in some of the highest paying sectors of the economy. Many of these jobs—particularly in the computer and mathematical occupations—require specialized skills and advanced education, experience, or training. (See table 2.)

Table 2. Changes in employment and wages in the employment services industry, by major occupational group, 2010–18

<table>
<thead>
<tr>
<th>Major occupational group</th>
<th>Employment</th>
<th>Annualized percent change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2010</td>
<td>2018</td>
</tr>
<tr>
<td>Life, physical, and social science</td>
<td>9,260</td>
<td>20,950</td>
</tr>
<tr>
<td>Computer and mathematical</td>
<td>64,360</td>
<td>135,600</td>
</tr>
<tr>
<td>Arts, design, entertainment, sports, and media</td>
<td>14,940</td>
<td>30,720</td>
</tr>
<tr>
<td>Education, training, and library</td>
<td>30,530</td>
<td>62,620</td>
</tr>
<tr>
<td>Farming, fishing, and forestry</td>
<td>5,780</td>
<td>11,040</td>
</tr>
<tr>
<td>Personal care and service</td>
<td>39,400</td>
<td>74,940</td>
</tr>
<tr>
<td>Community and social service</td>
<td>7,080</td>
<td>13,160</td>
</tr>
<tr>
<td>Transportation and material moving</td>
<td>508,790</td>
<td>890,660</td>
</tr>
<tr>
<td>Food preparation and serving related</td>
<td>56,180</td>
<td>91,480</td>
</tr>
<tr>
<td>Architecture and engineering</td>
<td>34,670</td>
<td>55,460</td>
</tr>
<tr>
<td>Business and financial operations</td>
<td>132,550</td>
<td>195,710</td>
</tr>
<tr>
<td>Production</td>
<td>490,070</td>
<td>719,720</td>
</tr>
</tbody>
</table>

See footnotes at end of table.
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</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2010</td>
<td>2018</td>
</tr>
<tr>
<td>Installation, maintenance, and repair</td>
<td>50,560</td>
<td>72,310</td>
</tr>
<tr>
<td>Legal</td>
<td>7,850</td>
<td>10,720</td>
</tr>
<tr>
<td>Sales and related</td>
<td>89,290</td>
<td>119,800</td>
</tr>
<tr>
<td>Management</td>
<td>53,360</td>
<td>67,890</td>
</tr>
<tr>
<td>Building and grounds cleaning and maintenance</td>
<td>76,310</td>
<td>91,990</td>
</tr>
<tr>
<td>Office and administrative support[1]</td>
<td>632,630</td>
<td>642,450</td>
</tr>
<tr>
<td>Healthcare support[1]</td>
<td>78,420</td>
<td>79,620</td>
</tr>
<tr>
<td>Construction and extraction[1]</td>
<td>128,760</td>
<td>129,110</td>
</tr>
<tr>
<td>Healthcare practitioners and technical[1]</td>
<td>135,300</td>
<td>129,500</td>
</tr>
<tr>
<td>Protective service[1]</td>
<td>21,100</td>
<td>17,530</td>
</tr>
<tr>
<td>All occupations</td>
<td>2,667,200</td>
<td>3,662,950</td>
</tr>
</tbody>
</table>

[1] Signifies that the occupations are not statistically significant at the 95 percent confidence level.

Note: All employment changes not accompanied by a footnote are statistically significant (different from 0) at the 95 percent confidence level. All salary changes are statistically significant at the 95 percent confidence level. Between May 2010 and May 2012, the OES program transitioned between the 2000 version of the Standard Occupational Classification (SOC) system and the 2010 SOC. As a result, data for some occupational groups and detailed occupations are not directly comparable over the analysis period. Comparability issues at the major group level should be relatively minor. Detailed occupational comparisons exclude occupations that are not defined comparably over the analysis period. Occupations that had major definitional changes in the 2010 SOC revision were excluded from the analysis. For more information, see https://www.bls.gov/oes/oes_ques.htm#qf8 and https://www.bls.gov/opub/mlr/2013/05/art3full.pdf.


High-growth temp occupations

Looking at the occupations within an occupational group provides specific insights into the temporary jobs that grew rapidly and those that declined.

Laborers and hand freight, stock, and material movers—within the transportation and material moving major occupational group—made up the largest number of temp jobs during the 2010–18 period. Between these years, their employment doubled from 300,000 to 610,000 and made up 17 percent of all national temp employment by 2018. (See tables 3 and appendix table A-1.) Employment of laborers and hand freight, stock, and material movers grew by 104 percent in employment services, compared with 43 percent across all industries. By 2018, over 1 in 5 laborers and hand freight, stock, and material movers were employed as temps.

Table 3. Percent change in employment for selected occupations, temporary workers (temps) and across all industries, 2010–18

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Temps</th>
<th>All industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food processing workers</td>
<td>604.3%</td>
<td>20.3%</td>
</tr>
<tr>
<td>Applications software developers</td>
<td>483.4%</td>
<td>80.9%</td>
</tr>
<tr>
<td>Life, physical, and social science technicians</td>
<td>154.2%</td>
<td>17.8%</td>
</tr>
<tr>
<td>Laborers and hand freight, stock, and material movers</td>
<td>104.3%</td>
<td>42.9%</td>
</tr>
</tbody>
</table>

See footnotes at end of table.
Industrial truck and tractor operators, also a relatively large group of temps, doubled employment, from 31,000 to 62,000 between 2010 and 2018. This occupation grew by 103 percent in temp employment services, while at the same time employment of industrial truck and tractor operators grew by 17 percent across all industries. In 2018, about 1 in 10 jobs in this occupation were employed as temps.

Food processing workers, which make up a relatively small share of all production jobs, had one of the highest rates of employment growth between 2010 and 2018. They added nearly 20,000 jobs and grew over 600 percent since 2010. The majority of these jobs added were food batchmakers and meat, poultry, and fish cutters and trimmers. All-industry occupational growth rose by 20 percent.

Applications software developers led the growth of temps within the computer and mathematical major occupational group, with nearly 500-percent employment growth and over 20,000 added jobs between 2010 and 2018. Compared with all-industry occupational growth, this occupation grew by 81 percent, but not nearly as fast as temp jobs in this occupation.

Life, physical, and social science technicians accounted for the majority of the temp job growth among the life, physical, and social science major occupational group, adding nearly 8,000 jobs between 2010 and 2018. Temps made up the majority of the nearly 10,000 life, physical, and social science technician jobs gained across all industries. By 2018, nearly 1 in 5 science technicians were hired as temps.

### Declining temp occupations

The construction laborers occupation was among the few construction occupations to have declined in temporary help. The level of temporary employment among construction laborers fell by about one-third or 24,000 jobs. (See table 4.) Across all industries, employment for construction laborers grew by 29 percent. This finding suggests that companies shifted from hiring construction laborers through temp agencies to hiring workers through more traditional employment.

### Table 4. Percent change in employment for selected occupations, temporary workers (temps) and across all industries, 2010–18

<table>
<thead>
<tr>
<th>Occupations</th>
<th>Temps</th>
<th>All industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Construction laborers</td>
<td>-31.6%</td>
<td>28.8%</td>
</tr>
<tr>
<td>Licensed practical and licensed vocational nurses</td>
<td>-30.9%</td>
<td>-3.9%</td>
</tr>
<tr>
<td>Receptionists and information clerks</td>
<td>-38.5%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Data entry keyers</td>
<td>-28.9%</td>
<td>-20.3%</td>
</tr>
<tr>
<td>File clerks</td>
<td>-57.2%</td>
<td>-37.1%</td>
</tr>
</tbody>
</table>

See footnotes at end of table.
Temp employment for licensed practical and licensed vocational nurses declined by over 30 percent, falling by nearly 12,000. Across all industries, employment in this occupation fell by 4 percent. Several office and administrative support occupations suffered job losses in temp help between 2010 and 2018:

- Receptionists and information clerks declined by 38 percent or 15,000 jobs, while across all industries, this occupation grew by 5 percent.
- Data entry keyers declined by 29 percent, losing over 9,000 jobs. Similarly, jobs for this occupation declined by 20 percent for all industries. Despite the decline, 1 in 8 data entry keyers were still employed as temps in May 2018.
- File clerks declined by 57 percent, losing nearly 9,000 jobs. Across all industries, jobs in this occupation declined by 37 percent.

**Industry distribution of temps**

THS is a unique industry in which workers are placed in companies across all industries. Because temporary firms do not report the specific industries in which temps are placed, the industry distribution of temps is not directly measured from the OES survey, a business establishment survey that measures employment and wages at the firm level. Instead, temp employment is captured under the temporary help services industry classification that falls within the professional and business services industry sector. To estimate the industries in which temps are placed, we use three methods, using CPS microdata alone, OES data alone, and a combination of CPS and OES data.

In contrast to OES, CPS is a national household survey of about 60,000 households collected by the Census Bureau. We use the May 2017 Contingent Worker Supplement microdata for our estimates on temporary workers.

We estimate two sets of results. First is the industry distribution of temps—that is what percent of temps are placed in which industries? And second, we estimate the industry utilization of temps—that is, the percentage of employment in each industry that are temp jobs.

For estimates using OES data, we exclude THS employment from the professional and business services industry throughout. Furthermore, to calculate industry utilization rates, we added the estimated temp employment in each industry to the total industry (e.g., utilization rate = [# temps in industry A]/[# temps in industry A + total employment in industry A]).

**Estimate 1: CPS microdata**

Using microdata from the CPS May 2017 Contingent Worker Supplement, we limit the scope to respondents who were paid by a temporary help agency.[5] The survey also collects the industry and occupation of the respondent. The distribution of temps is aggregated.[6] However, these published estimates include about one-quarter of respondents (from the microdata) who selected the “Employment Services” industry under the “Professional and business services” sector. For our purposes of estimating industry distribution for temps, this self-classification by household respondents as part of the “Employment Services” industry would overestimate the proportion of temps in the professional and business services industry, so we excluded these respondents and re-estimated the
industry distribution of temps. We assume here that no systematic assignment of individuals to employment services is related to any particular industry (i.e., individuals in employment services are “missing at random.”)

**Estimate 2: CPS microdata and OES data**

Similar to a method proposed by Dey, Houseman, Polivka for temps in the manufacturing industry,[7] we first use CPS microdata to estimate the distribution of employment to the 14 exclusive and exhaustive industry sectors for each of the 22 exclusive and exhaustive occupations. Then using OES occupational data for temps, we distribute the employment for each of these 22 occupations into the 14 industries based on the CPS estimates. We then sum cross all occupations for each industry.

**Estimate 3: OES cross-industry data**

This method is the same as estimate 2, except that we replace the CPS estimate of the occupational-industry distribution of temps with those from OES data for all industries (i.e., we use the industry distribution of each occupation in place of the specific occupational-industry distribution estimates for temps.) This substitution assumes that the industry distribution for each occupation is the same for temps as it is for all industries.[8] For example, 76 percent of all production jobs across the United States were in manufacturing in May 2017, so we assume that 76 percent of production temp jobs are also in manufacturing. Just as we do in estimate 2, we then sum across all 22 occupations for each industry to estimate temps’ industry employment.

**Results**

From all estimates, it is clear that a large proportion of temp workers are placed in the manufacturing and education and health services industries. In terms of industry utilization rates, top industries include manufacturing and transportation and utilities. Considering that about 1 in 4 temp jobs are material moving workers and about 1 in 5 are assemblers and fabricators or in other production occupations,[9] it is not surprising that manufacturing and transportation and utilities are top industries for temp jobs. (See tables 5 and 6.)
Figure 5. Distribution of temporary help services by industry, 2017

Click legend items to change data display. Hover over chart to view data.
Note: Author's calculations based on Current Population Survey and Occupational Employment Statistics data.
Reliability of estimates

The CPS is a household survey, whereas OES is an establishment survey. While OES does not directly measure the industry distribution for the temp jobs, the CPS asks respondents whether an individual is hired through a temp agency and the industry and occupation in which he or she works. Because of the different natures of the surveys, differences may arise in how jobs are classified into an industry in the CPS, a household survey, versus how firms report their industry classification in the OES survey. Furthermore, for this article, we use a subset of the CPS data: individuals who have indicated they are hired through temporary staffing firms. This subset of the CPS data contains fewer than 300 relevant respondents. With this relatively small sample size, estimates from estimate 2 may have low coverage, especially for smaller industry and occupation intersections. On the other hand, although the OES survey provides much more robust estimates and we can take advantage of occupational data for temps (which is much more precisely estimated), we must rely on an assumption about occupation-industry distribution that is not directly testable, but reasonable to assume. We do not suggest which of these estimates are more reliable, as each has its strengths and underlying assumptions. However, taken together, they provide estimates that give an overall idea about industry distribution and utilization patterns of temps for which no one source can currently provide precise estimates.

Conclusions
Since the recovery from the Great Recession, temporary employment has increased by nearly 1 million jobs and at an annual rate more than triple that of private sector employment. In 2008, it represented 1.7 percent of total employment. By 2018, temp jobs represented 2 percent of all jobs. While the THS industry is small relative to retail trade, manufacturing, and other industry sectors, it is very important in a number of ways. First, temporary employment is the first resort of employers seeking to expand or contract their employment and it is essential in workforce level adjustment. It can immediately boost economic activity, or it can curb economic activity until firms are able to staff with confidence. For this reason, it is a bellwether for broader labor market and economic conditions and used as an indicator of potential changes in the economy.

Second, temporary employment provides insights as to change within economic regions and industry change. Similar to previous studies on temporary workers, this study found that both the largest number of temps and highest utilization rates were in manufacturing. For those temporary occupations that are changing the most, this reflects a shift in the broader themes of the economy. Prior to the last recession, the occupation growth patterns were dominated by jobs in legal, business and financial operations, and computer and mathematical occupations—all occupations that were associated with the rise of the financial sector. In recent years, the growth in jobs has shifted to science, computer and mathematical, and arts and media occupations—occupations that represent the emerging themes of biotechnology, data science, and expanding visual content in an increasingly connected world. Healthcare and construction industries, on the other hand, reduced their reliance on temps between 2010 and 2018.

Finally, temporary employment provides clues to changes in the type of temporary employment jobs, as we observe THS occupations growing rapidly in food, software, lab science, and logistics, which are all industry areas that share or support pop-up enterprises. One temp occupation on the rise, teacher assistants, has seen increased utilization but may also be dampening the average salary of temp workers in education. Meanwhile, those temp occupations in which employment is falling—construction laborers, licensed practical and licensed vocational nurses, and administrative support—relative to those occupations across all industries, appears to be reflecting a shift from temporary to permanent, full-time employment. Legal, business and financial operations, and computer and mathematical occupations represented the changes in the pre-recession period up until 2008; however, in the post-Great Recession expansion from 2010 and 2018, temps grew in science, computing, and arts and education occupations, representing the broader changes in a more highly technical and content-rich economy. Therefore, temp employment is much more significant in effect than its modest name implies—it quickly reflects changes in industry structure and emphasis over time and during periods of significant economic change.

The box below summarizes the changes in the temporary help services industry since the Great Depression.

**Summary of key changes in temporary services employment since the Great Recession**

- Temps grew by 75 percent (1.3 million jobs) across the United States compared to the total private employment change of 19 percent.
- The share of temps as a percent of all jobs grew from 1.7 in 2008 to 2.0 by 2018.
- Largest industry share of temps are concentrated in manufacturing.
- Manufacturing and transportation and utilities industries continue to have the highest utilization rates of temps.
- The West region led growth with annual rate of 5.6 percent, followed by the South at 4.6 percent.
- The highest utilization of temps were in the Midwest, the lowest in the Northeast.
- The life, physical, and social science; computer and mathematical; arts and media; and education, training, and library occupational groups were among the fastest growing occupations (over 9 percent per year).
- Applications software developer jobs grew by nearly 500 percent.
- Temp construction laborers fell by a third, contrary to its overall occupational growth.

**Appendix A. Comparison showing the changes in temporary help services employment between 2010 and 2018.**
Table A-1. Employment change in selected occupations in the employment services industry, 2010–2018

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Employment 2010</th>
<th>Employment 2018</th>
<th>Employment change</th>
<th>Percent change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laborers and hand freight, stock, and material movers (SOC 53-7062)</td>
<td>298,720</td>
<td>610,170</td>
<td>311,450</td>
<td>104.3%</td>
</tr>
<tr>
<td>Industrial truck and tractor operators (SOC 53-7051)</td>
<td>30,820</td>
<td>62,430</td>
<td>31,610</td>
<td>102.6%</td>
</tr>
<tr>
<td>Food processing workers (SOC 51-3000)</td>
<td>3,230</td>
<td>22,750</td>
<td>19,520</td>
<td>604.3%</td>
</tr>
<tr>
<td>Applications software developers (SOC 15-1132)</td>
<td>4,210</td>
<td>24,560</td>
<td>20,350</td>
<td>483.4%</td>
</tr>
<tr>
<td>Life, physical, and social science technicians (SOC 19-4000)</td>
<td>5,070</td>
<td>12,890</td>
<td>7,820</td>
<td>154.2%</td>
</tr>
<tr>
<td>Construction laborers (SOC 47-2061)</td>
<td>75,480</td>
<td>51,610</td>
<td>-23,870</td>
<td>-31.6%</td>
</tr>
<tr>
<td>Licensed practical and licensed vocational nurses (SOC 29-2061)</td>
<td>37,860</td>
<td>26,180</td>
<td>-11,680</td>
<td>-30.9%</td>
</tr>
<tr>
<td>Receptionists and information clerks (SOC 43-4171)</td>
<td>40,500</td>
<td>24,920</td>
<td>-15,580</td>
<td>-38.5%</td>
</tr>
<tr>
<td>Data entry keyers (SOC 43-9021)</td>
<td>31,840</td>
<td>22,640</td>
<td>-9,200</td>
<td>-28.9%</td>
</tr>
<tr>
<td>File clerks (SOC 43-4071)</td>
<td>40,500</td>
<td>24,920</td>
<td>-15,580</td>
<td>-38.5%</td>
</tr>
<tr>
<td><strong>All occupations</strong></td>
<td><strong>2,667,200</strong></td>
<td><strong>3,662,950</strong></td>
<td><strong>995,750</strong></td>
<td><strong>37.3%</strong></td>
</tr>
</tbody>
</table>


Appendix B. Comparison showing the changes in all industry employment between 2010 and 2018, and the percentage of all industry employment that are temporary help services workers.

Table B-1. Employment change in selected occupations, all industries, 2010–18

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Employment 2010</th>
<th>Employment 2018</th>
<th>Percent change</th>
<th>Temps as a percent of all industries (2018)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laborers and hand freight, stock, and material movers (SOC 53-7062)</td>
<td>2,024,180</td>
<td>2,893,180</td>
<td>42.9%</td>
<td>21.1%</td>
</tr>
<tr>
<td>Industrial truck and tractor operators (SOC 53-7051)</td>
<td>518,350</td>
<td>604,130</td>
<td>16.5</td>
<td>10.3</td>
</tr>
<tr>
<td>Food processing workers (SOC 51-3000)</td>
<td>666,430</td>
<td>801,770</td>
<td>20.3</td>
<td>2.8</td>
</tr>
<tr>
<td>Applications software developers (SOC 15-1132)</td>
<td>499,280</td>
<td>903,160</td>
<td>80.9</td>
<td>2.7</td>
</tr>
<tr>
<td>Life, physical, and social science technicians (SOC 19-4000)</td>
<td>55,360</td>
<td>65,220</td>
<td>17.8</td>
<td>19.8</td>
</tr>
<tr>
<td>Construction laborers (SOC 47-2061)</td>
<td>777,700</td>
<td>1,001,470</td>
<td>28.8</td>
<td>5.2</td>
</tr>
<tr>
<td>Licensed practical and licensed vocational nurses (SOC 29-2061)</td>
<td>730,280</td>
<td>701,690</td>
<td>-3.9</td>
<td>3.7</td>
</tr>
<tr>
<td>Receptionists and information clerks (SOC 43-4171)</td>
<td>997,080</td>
<td>1,043,630</td>
<td>4.7</td>
<td>2.4</td>
</tr>
<tr>
<td>Data entry keyers (SOC 43-9021)</td>
<td>219,530</td>
<td>174,930</td>
<td>-20.3</td>
<td>12.9</td>
</tr>
<tr>
<td>File clerks (SOC 43-4071)</td>
<td>174,910</td>
<td>110,020</td>
<td>-37.1</td>
<td>5.9</td>
</tr>
<tr>
<td><strong>All occupations</strong></td>
<td><strong>127,097,160</strong></td>
<td><strong>144,733,270</strong></td>
<td><strong>13.9</strong></td>
<td><strong>2.5</strong></td>
</tr>
</tbody>
</table>

Bibliography


NOTES


2 Regions are defined as follows: West (AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, WY); South (AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV); Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT); and Midwest (IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, WI).
Although we present selected employment comparisons using the Occupational Employment Statistics data, the data are not designed for making comparisons through time. Such comparisons should be interpreted with caution. For more information, see “Can the OES data be used to compare changes in employment and wages over time?” Occupational data for the temporary help services industry were not published until May 2014. In this section, for occupational comparisons between 2010 and 2018, we use employment services, a higher aggregate industry that includes temporary help, professional employer organizations, and employment placement and executive search services, as a proxy for temporary help services. Temp jobs typically make up over 80 percent of employment services industry employment. In particular, for the two largest temp occupational groups—transportation and material moving and production—over 90 percent of employment services employment were from temporary help services in the years 2014–18.


Temps are individuals who answered “Yes” to the following two questions “Are you paid by a temporary help agency on your job?” or “Even though you told me your job is not temporary, are you paid by a temporary help agency?”


We exclude temporary help services from the professional and business services industry, essentially re-estimating the industry distribution, as usual.

Based on OES May 2017 data for temporary help services.

Related Articles

Related Subjects
Labor force | Temporary work | Employment | Expansions | Temporary help | Recession
Many economists have long considered recessions a period of economic reorganization in which firms that have allocated their resources poorly are unseated by new, more productive firms. Does this belief still hold up today? In their paper “Flight to safety: how economic downturns affect talent flows to startups” (National Bureau of Economic Research, Working Paper 27907, October 2020), Shai Bernstein, Richard R. Townsend, and Ting Xu suggest that the tradition of new firms pushing out the old may no longer be true. One may think that during recessions, those who lose their jobs at established firms may realize a lower opportunity cost in joining a smaller startup. Alternatively, one might expect to observe a “flight to safety” as workers seek the believed relative security of a more established firm.

Using data from the recruiting site AngelList, the authors were able to evaluate the size and age of a firm as well as the experience and quality of a job candidate. To evaluate the talent flow to a startup, Bernstein and colleagues measured the number of job applications per job posting. They were also able to note how firms responded to job applications. Job candidate quality was assessed by the researchers on two metrics. The first was a candidate’s years of experience. The second metric, generated by AngelList, was a quality score that evaluated candidates based on their education, skills, experience, and actions taken on AngelList.

The authors found that during the economic downturn that resulted from the coronavirus disease 2019 (COVID-19), job seekers turned their attention away from smaller startups and toward larger, more established firms. This finding was especially true among higher skilled job seekers. After the beginning of the COVID-19 crisis, the quality and quantity of talent available to fledgling startups decreased markedly. But how were startups affected by this change? After the onset of the pandemic, firms overall received less applications to postings. This trend, however, was much stronger for smaller and younger firms. Although the researchers found that higher quality job candidates were more likely to pivot toward larger and older firms, they also note that the move by jobseekers away from startups has not been a general downward trend but instead a new development since the outbreak of COVID-19.

The authors discovered that a substantial “brain drain,” an emigration of the most qualified candidates, afflicted startups since the onset of the pandemic. How did smaller firms and younger firms respond? Do they hire the best candidate available to them? Or simply dial back on hiring altogether? The authors learned that startup firms were less likely to respond positively to a job application than before the pandemic because of the diminished talent pool. Conversely, established firms experienced a negligible change in their responses to job applications. This stark difference in application responses reveals the difficulty of a poorer talent pool for startups. When confronted with a diminished talent pool, startups chose to suspend recruitment as opposed to hiring an undesirable candidate.
How have jobs changed over time? The Industrial Revolution (1760 to about 1840) was a key turning point in the growth of the U.S. economy, as automation began replacing the tasks of unskilled workers. Twentieth century developments such as technological advances and outsourcing have only further transformed the labor force. Although more occupations are requiring individuals with higher skills, changes within specific occupations themselves are more difficult to study.

In “The evolution of work in the United States” (The American Economic: Applied Economics, 2 April 2020), Enghin Atalay, Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum attempt to quantify these shifts through a new data source: newspaper job advertisements (ads). The authors obtained a dataset of raw text files from The New York Times (1940 to 2000), The Wall Street Journal (1940 to 1998), and The Boston Globe (1960 to 1983), approximately 8.3 million total job ads. They then used a model to link each ad to a corresponding Standard Occupation Classification code, as well as a specific job title, through synonyms of words and phrases. This model was also implemented to identify and group any of the tasks or skills mentioned in an ad. The main method that the authors used to classify the ads followed that of Spitz-Oener (“Technical change, job tasks, and rising educational demands,” Journal of Labor Economics, April 2006), who created five categories of task content in occupations: “nonroutine analytic, nonroutine interactive, nonroutine manual, routine cognitive, and routine manual” tasks. In addition, the authors applied the findings of Deming and Kahn (“Skill requirements across firms and labor markets: evidence from job postings for professionals,” National Bureau of Economic Research, January 2018), as well as elements from the Occupational Information Network, to organize the ads based on skill content.

By comparing the prevalence of these five task groups over time for specific occupations and job titles, Atalay and colleagues found that more changes have occurred within jobs as opposed to between jobs. From 1950 to 2000, the number of mentions per 1,000 words in newspaper job ads fell for nonroutine manual tasks (from 0.91 to 0.75), routine manual tasks (from 0.97 to 0.06), and routine cognitive tasks (from 1.89 to 0.85). However, mentions of nonroutine analytic tasks (from 2.77 to 5.88) and nonroutine interactive tasks (from 5.06 to 7.39) increased over that same span. Once the authors accounted for movements in the overall proportions of jobs in the labor force, they concluded that “88 percent of the [economywide] task changes have occurred within job titles.”

The authors closed by drawing on four examples to show how tasks and job titles have changed over time. First, they examined the task content and the frequency of mentions of computer numerical control (CNC) technologies in job ads for machinists, further supporting a study by Bartel, Ichniowski, and Shaw (“How does information technology affect productivity?” 2007) that “the introduction of CNC technologies led to a reduction in the demand for worker-performed routine.” Second, the authors found that the frequency of words in managerial job ads related
to nonroutine interactive tasks increased from 1950 to 2000, confirming the findings of a 1999 study (The Changing Nature of Work) by the National Research Council. Third, a 2012 study ("Supersize it") by Basker, Klimek, and Van about retail cashiers was backed, as “the frequency of routine cognitive tasks in cashier jobs decreased from 4.3 mentions per 1,000 words in the 1950s (3.4 times the average across all ads and years) to 1.4 mentions per 1,000 words (1.1 times the sample average) in the 1990s. Conversely, the frequency of nonroutine interactive tasks nearly doubled over the sample period.” Finally, the authors found that the task content in job ads for real estate sales has not changed over time, which is similar to the job descriptions in the 1965 Dictionary of Occupational Titles and the present-day National Association of REALTORS.
A framework for the evaluation and use of alternative data in the Consumer Expenditure Surveys

As part of the implementation of its strategic plan, the U.S. Bureau of Labor Statistics (BLS) has increasingly studied the issue of using alternative data to improve both the quality of its data and the process by which those data are collected. The plan includes the goal of integrating alternative data into BLS programs. This article describes the framework used by the BLS Consumer Expenditure Surveys (CE) program and the potential these data hold for complementing data collected in traditional formats. It also addresses some of the challenges BLS faces when using alternative data and the complementary role that alternative data play in improving the quality of data currently collected. Alternative data can substitute for what is presently being collected from respondents and provide additional information to supplement the variables the CE program produces or to adjust the CE program’s processing and weighting procedures.

The U.S. Bureau of Labor Statistics (BLS) has intensified the examination of alternative data in order to improve both the quality of the data that BLS collects and the methods by which those data are collected. BLS has incorporated in its strategic plan the goal of integrating alternative data into its programs. This article describes the framework used by the BLS Consumer Expenditure Surveys (CE) program when it evaluates new data resources and the potential they hold for complementing data collected in traditional survey formats. The CE program must consider how best to use these data to meet its core measurement objectives and to do so within established constraints and considerations. This article examines (1) the definition of “alternative data,” (2) the ways that alternative data can assist in
Factors motivating the use of alternative data sources

Respondent data collected in the CE are used to produce the expenditure and demographic information necessary for the production of the Consumer Price Index (CPI), among other uses in government, academia, and the private sector. The CE program faces several challenges common to household survey operations. First, response rates are declining because of many factors, such as increasing distrust of government, privacy concerns among respondents, and the number of competing surveys. In addition, the increasing length and complexity of the CE interview contribute to higher nonresponse rates and poorer quality responses. Second, data collection costs have been increasing because of an erosion over time of respondents’ willingness to participate in the CE and the additional time and effort required to contact potential respondents and secure their cooperation. Finally, diminishing data collection resources created by increasing costs without commensurate budget increases result in fewer survey participants and less data on expenditures collected in the survey, which negatively affects the quality of the CE data.

These factors have led the CE program to consider how alternative data—that is, data collected from sources other than CE respondents—could enhance estimates currently produced. For example, alternative data sources could improve both expenditure data and other information collected by the survey, such as demographic data and various household characteristics. CE stakeholders recognize the potential value of using alternative data. For example, a Committee on National Statistics report entitled “Measuring What We Spend: Toward a New Consumer Expenditure Survey” includes recommendations for exploring the use of alternative data sources:

The ability to link CE data to relevant administrative data sources (such as IRS data or data on program participation) could provide additional richness for economic research as well as providing potential avenues to investigate the impact of nonresponse on the survey results. . . . For economic analyses, data on income, saving, and employment status are important to be collected on the CE along with expenditure data. Aligning these data over time periods, and collecting information on major life events of the household, will help researchers understand changes in income and expenditures of a household over time. Linkage of the CE data to relevant administrative data (such as the IRS and program participation) would provide additional richness, and possibly provide avenues to investigate the effect of nonresponse. . . . BLS should pursue a long-term research agenda that integrates new technology and administrative data sources as part of a continuous process improvement. The introduction of these elements should create reductions in data
collection and processing costs, measurement error, and/or the statistical variance and complexity of the CPI estimate. The agenda should address the robustness of new technology and a cost/quality/risk trade-off of using external data [emphases added].

Similarly, there is an awareness within the federal government of the need to facilitate the use of alternative data by federal agencies. In its 2017 report, the Commission on Evidence-Based Policymaking called on policymakers to consider removing statutory impediments to the sharing of data for evidence building. Other researchers have also recognized that data collected through different mechanisms can complement traditional survey data by helping address old questions using new means.

Exploring alternative data in the CE

In line with these recommendations, the CE program continues to explore alternative data, including linking survey data with administrative records and using data compiled by commercial vendors. For ease of discussion, we grouped alternative data into the following categories on the basis of the data source: (1) administrative data or administrative records data, which the Office of Management and Budget describes as “data collected by government entities for program administration, regulatory, or law enforcement purpose”; (2) consolidated data (e.g., data from credit card companies, data aggregators, or other private sector companies); and (3) operational data that are used to conduct routine agency activities but often are not available for research or statistical uses (e.g., the Statistics of Income program of the Internal Revenue Service transforms tax data into derived records from tax returns that are thus not subject to usual destruction requirements).

Alternative data also can be organized by the forms they take, ranging from structured data (e.g., most of the federal administrative data produced) to semistructured data, such as those downloaded from the internet, and finally to unstructured data (e.g., open response text data requiring some type of language processing). A related categorization is based on the purpose of the data collection, distinguishing between data collected for a statistical purpose—“designed data”—and data that have arisen for other purposes—“organic data.” To date, most of the alternative data pursued by the CE program have been structured administrative data. Regardless of their categorization, alternative data require the CE program to employ varying degrees of effort to feed the data into the BLS information technology systems. The CE program must ensure that data from each alternative source meet the following criteria: (1) they are consistent with the CE program’s core measurement objectives and are representative of the target population; (2) they meet BLS requirements for data continuity—a sudden loss of an alternative data source cannot cause a disruption in production schedules, and the data elements and structure of alternative datasets cannot cause a sudden and urgent reworking of BLS information technology infrastructures; and (3) they uphold the agency’s ability to be transparent.

Of note, this article focuses exclusively on alternative data sources. In parallel, the CE program is also pursuing the investigation of alternative collection modes in an effort to meet the changing needs of the respondent population. As part of the Gemini Project to redesign the CE, for example, the CE program recently designed, developed, and field tested an online diary to complement the existing paper diary.

Potential uses of alternative data in CE programs
Alternative data have a variety of uses, including direct variable substitution, addition of auxiliary variables for information beyond respondent-collected data, validation of collected estimates, and as an input in processing (e.g., blended imputation and weighting). Three specific applications that the CE program has explored or is exploring are detailed in the subsections that follow.

**Nonresponse adjustment**

Alternative data could be used to improve the calculation of nonresponse adjustment weights by linking the alternative data to the CE’s sampled addresses in the calculations. Presently, the CE program uses publicly available aggregated federal tax data on income at the Zip-Code level to create nonresponse income weighting groups. The CE is exploring the possibility of improving the nonresponse weighting groups through the use of household-level income estimates from linked federal tax data instead of income data based on the respondent’s Zip Code. Brummet et al. found that there was little agreement between these nonresponse weighting groups assigned on the basis of Zip Code and those assigned on the basis of linked household-level tax information. Income data linked from Internal Revenue Service (IRS) Form 1040 and Form W-2 could be used to place responding and nonresponding units into the appropriate nonresponse weighting groups.

**Imputation**

Administrative data linked to the CE sample could be used for imputation in two ways. First, a linked variable could be used either directly to provide a value when the respondent fails to provide one or as an input into models used to impute missing values. One example is to use income from linked federal tax data in a multiple imputation model for different income variables. Second, the CE could also use alternative data on housing to improve estimates such as the rental-equivalent value of respondents’ owned homes. Multiple commercial sources contain housing characteristics that could be used to model rental equivalence and selectively replace questionable respondent-provided rental-equivalent value estimates.

**Question replacement**

In some instances, it may be possible to use alternative data to replace CE questions entirely. For example, instead of asking respondents for information on housing subsidies, the CE could obtain this information from U.S. Department of Housing and Urban Development (HUD) administrative data records. In some cases, this could not only reduce respondent burden by asking fewer questions but also reduce measurement error, if the assumption that the administrative sources are more accurate proves to be correct.

Adopting alternative data in survey processes may allow BLS to mitigate or resolve methodological and operational challenges. The observations provided by alternative data sources and collection methods often far outnumber those from traditional data collection; that is, a larger number of observations increases the likelihood that a missing respondent value can be replaced with a value from an alternative data source. Furthermore, alternative data may help BLS reduce and better manage respondent burden, address survey nonresponses, reduce collection costs, and allow for publication of data at a more detailed level. To evaluate the benefits of alternative data, regardless of their potential applications, the CE program needs to assess the suitability of the data before they can be used. These considerations are discussed in the next section.

**Evaluating the suitability of alternative data**
When evaluating alternative data for its fitness for use, the CE program uses criteria similar to those considered by Seeskin et al. to guide decisions about their suitability. These criteria are discussed in the subsections that follow.

Relevance

What data are contained in the alternative source, and would they provide a measure that matches the concept that the CE collects or intends to collect?

Timing

When are the alternative data available for the CE program’s use in a given year? The process of collecting and processing these data, especially with Federal Tax Information (FTI) that refers to the prior tax year, could add months to the CE program’s production timeline. The CE program must adhere to CPI program timeliness requirements, and it cannot incorporate business operation changes that result in lengthening the time the data are delivered to the CPI program. Depending on how the data are used in processing, the timing of available data could affect their utility. For example, if FTI were to be used to replace CE income data, then the delay in accessing tax records could prevent BLS from publishing CE data in a timely manner. However, this is not as much of a concern for data that help construct the CE sample frame or model income estimates for which earlier tax data could be used. Additionally, static data (e.g., data on housing construction) are less time sensitive than dynamic data (e.g., unemployment benefits receipts or participation in in-kind benefit programs such as subsidized housing or Medicaid).

Representativeness

Whether we are considering alternative data for data validation, adjustment, or replacement, it is critical that we assess the representativeness of the source relative to the CE’s target population. We must also consider factors such as the intended coverage of the alternative data, systematic inclusions or exclusions of various population subgroups, and any additional adjustments made by alternative data vendors.

Barriers to access and release

Are there any additional constraints on the linkage of data? Current use of certain data, such as FTI (protected under title 26 of the U.S. Code) requires participating staff to submit to a background investigation and travel offsite to use the data, because such data cannot be transferred to BLS. Nevertheless, the CE program pursues research using FTI, with the expectation that future laws or negotiated agreements with data owners will be more favorable to data linkage and will remove some of the barriers listed. For data collected by private sources, providers may require nondisclosure agreements, and the reuse of outside linked data may be limited (e.g., restricted from public microdata release), depending on the terms of the agreement. Additionally, some variables from aggregated data sources are derived by using models that are proprietary, limiting the ability of the CE to share source information with end users.

Administrative dataset availability

Linking CE data to other federal survey data requires the use of the CE’s sample frame information and personally identifiable information that is stored on U.S. Census Bureau servers and not available at BLS. Therefore, this linkage must be performed at the Census Bureau, where the Center for Economic Studies (CES) is engaged in
linkage research. The CE program currently relies on administrative datasets acquired and linked by the Census Bureau, many of which cover a different number of years in the past.

### Identifier availability

Some variables useful for improving match rates (e.g., date of birth and social security number) are not collected by the CE and therefore are not available for use in effective matching procedures. Although data on these variables could be collected, asking for such information may raise privacy concerns among respondents. Data can still be matched without those identifiers; however, the match rates are lower overall, which may reduce the utility of the matched data.

### Challenges to using alternative data in the CE production system

While evaluating various data sources that could be incorporated into the CE Quarterly Interview Survey and the Diary Survey, the CE program staff have identified several challenges that accompany alternative data: (1) constraints on accessing the data (e.g., background investigations), (2) difficulties in assessing the value of the data that would be provided, (3) the high costs of data acquisition, and (4) the potential for instability among data providers because of contract recompetition.

Additionally, there are requirements related to the CE production system and technical skills required to integrate alternative data into the system. As noted by Brett McBride in his 2018 study, past reviews of data sources have highlighted the importance of data relevance, and few available data sources have been found to be viable, most being tangential to the content collected by the CE.

The CE program is evaluating the specific ways in which the challenges involved in using alternative data affect their potential use in CE production.

### Match rate

The CE no longer asks respondents to provide their date of birth. Some respondents consider this to be sensitive information, but not having that information leads to a notable reduction (estimated at roughly 10 percent) in the number of respondents that can be linked to other (survey and administrative) records by using person-level matching.

### Conceptual differences

Another challenge to using alternative data in the CE involves how to reconcile inevitable differences between what the survey is trying to measure and the information provided by administrative records. For example, the CE program needs income information corresponding to the period in which expenditure information is collected. The CE interview asks about work and income levels over the “past 12 months,” whereas IRS data on income is for each calendar year. As a result, for most of the 12 months, conceptually, there is some misalignment between IRS data and the responses collected from the CE. In practice, however, past research has shown that the measures track consistently from month to month.

### Timing
Yet another challenge involves the timing of when the administrative data become available for use. The CE program’s mission is not only to provide data of high statistical quality, but also to do so in a timely manner. The CE program has semiannual releases of expenditure estimates. A project linking IRS data to CE data, discussed in the article by Brummet et al., illustrates how the timing of when data become available complicates the need to produce timely estimates. For interviews that were fielded in the year 2014, respondents reported on income received anywhere from January 2013 to November 2014 (depending on their interview month). The filing deadline for the corresponding IRS data was April 2015, which was after the fielding period for the CE. The IRS data did not become available until 2016, which was far past the publication date for 2014 CE data, in September 2015.

Legal limitations

Current legal limitations on accessing data also present challenges for the CE program. According to title 26 of the U.S. Code, IRS data can currently be shared for research purposes directly with a few agencies, including the Census Bureau but not BLS. Furthermore, once any administrative data are combined with survey data protected under another statute, it becomes more difficult to share the data with end users (in the form of microdata).

For any source of alternative data, collection presents its own set of challenges, many of which result from BLS not having control over the data. Only by first obtaining and then working with alternative data will BLS be able to determine if it can resolve the methodological and operational challenges mentioned earlier in order to use alternative data in the production of its estimates.

The CE program continues to explore linkage projects that represent a net benefit for the accuracy of data quality in light of the complications (e.g., timeliness and data confidentiality) associated with using alternative data. To ensure that each alternative dataset meets the needs of the CE program’s core measurement objectives, the CE staff evaluates the data’s fitness for use and the tradeoffs necessary to use the data. These tradeoffs may require changes to data collection, review procedures, and information technology applications.

Over time, the CE program will consider the need for introducing new estimation and imputation techniques that are appropriate for these data, just as it continues to do for data collected in the traditional way. More generally, the CE program will consider all of the effects on business processes and develop a standardized approach to handle alternative data. Finally, senior program management, along with other BLS executives, will pay special attention to identifying any necessary staffing and training gaps related to the research and use of alternative data.

Alternative data projects

The CE program has worked on several applications of alternative data, mostly carried out by the Census Bureau’s CES. This section discusses these applications.

Commercial housing data vendor X

The CE program worked with the CPI Housing Survey staff to allow BLS access to free-of-charge, consolidated data on housing from commercial housing data vendor X. This exploratory benchmarking project provided housing information on property square footage, number of rooms, property type, and an estimate of property value. In addition, address data were made available so that these addresses could be matched to those housing...
units included in the CPI Housing Survey. BLS and commercial housing data vendor X signed a legal agreement that permitted the transfer of these data for research purposes only.

**Commercial housing data vendor Y data linkage**

CES linked 2014 CE interview response data with aggregated data from a commercial housing data vendor, which we designate here as commercial housing data vendor Y.\(^{20}\) Datasets containing property tax and deed information were linked by using the Census Bureau's Master Address File and CE data on housing characteristics and mortgages. The findings indicated strong agreement between sources on home ownership, property tax, and some housing characteristics, but weaker agreement for home values and data from the deeds file. This project provided information about the alternative data's potential use for filling missing CE values in an imputation model (e.g., estimated market value of the owned home) or potentially replacing questions (e.g., property tax, for which missing rates in the CE were elevated). However, recompetition of the contract with the Census Bureau highlighted the risk that using aggregated data vendors can pose to the stability of the data source, as a different provider of data was ultimately awarded the contract. A change in vendor requires that the CE program learn and understand the new vendor's underlying methodology of data aggregation, and risks a break in data series, especially if the change in methodology is large.

**IRS data linkage project**

This project involved linking CE interview responses from the 2014–15 period to IRS administrative records (e.g., IRS Form 1040, Form W-2, and Form 1099).\(^{21}\) The CES was able to link 77 percent of interviewed respondents to 1040 forms by using Master Address File identifiers and 70 percent using Protected Identification Keys. Research found very small differences in reported average wages from the CE, compared with those from IRS records. Where misreporting occurred, it tended to be CE respondents reporting higher amounts at the bottom of the wage distribution and lower amounts at the top. The CE program's income imputation process was found to make up for the failure of some respondents to report wages, but it also was sometimes found to impute wages for respondents that did not have Form W-2 wages. As noted in prior studies, this project showed evidence of higher nonresponse rates among household sample units with higher income levels than those contained in the IRS records (when income is defined as adjusted gross incomes).\(^{22}\)

**HUD administrative data project**

The CES has matched CE interview responses from the 2013–17 period to U.S. Department of Housing and Urban Development (HUD) records (i.e., voucher recipient information and residence in public housing) to investigate (1) misreporting of the receipt of rental assistance and (2) misalignment in reported values of rents and rental subsidies.\(^{23}\) In addition, the CES is now investigating how estimates of rent burden and the Supplemental Poverty Measure thresholds are affected when replacing survey-reported rent and rental subsidy values with HUD administrative data.\(^{24}\)

**Conclusion**

In this article, we have addressed some of the challenges faced by the CE program when using alternative data and the complementary role that alternative data could play in improving the data currently collected from respondents. Alternative data can substitute for what is presently being collected from respondents, as well as provide additional information to supplement the variables the CE program produces or to adjust the CE program’s
processing and weighting procedures. Nevertheless, we acknowledge the set of challenges common to these new data sources—from conceptual issues to practical timing and legal constraints. Moving forward, the CE program will continue to work on projects that seek to identify ways that alternative data can benefit various components of the survey.


NOTES

1 For more information on the Consumer Price Index (CPI) program, see the CPI home page at https://www.bls.gov/cpi/.


9 For more information on the Gemini Project to Redesign the Consumer Expenditure Surveys (CE), see https://www.bls.gov/cex/geminiproject.htm.


12 For more information on title 26 of the U.S. Code, see https://uscode.house.gov.
The Census Bureau’s Center for Economic Studies was formerly known as the Center for Administrative Records Research and Applications (CARRA).


Ibid.

See Brummet et al., “Investigating the use of administrative records in the Consumer Expenditure Survey.”

Under title 26 of the U.S. Code, Internal Revenue Service data can also be shared with the Congressional Budget Office, the U.S. Bureau of Economic Analysis, and the National Agricultural Statistics Service of the U.S. Department of Agriculture.


Corporation name redacted for confidentiality reasons. This was a collaboration between the CPI and CE programs during the 2015–17 period.


Brummet et al., “Investigating the use of administrative records in the Consumer Expenditure Survey.”


The Supplemental Poverty Measure uses CE data on housing as part of the food, clothing, shelter, and utilities expenditures, which are, in turn, used to calculate poverty thresholds.

Related Articles


Consumer spending in World War II: the forgotten consumer expenditure surveys, Monthly Labor Review, August 2015.

Related Subjects
| Survey methods | Statistical methods | Expenditures | Consumer expenditures | Experimental methodology | Survey procedures |
Finding the meaning and the music in your work


In this time of global pandemic, one would be hard pressed to find a more aptly titled vocational book than Work Reimagined: Uncovering Your Calling. With millions of Americans being out of work, working from home, or contemplating the next chapter of their careers, the U.S. workforce is at an inflection point. In the introduction to their 2015 book, authors Richard J. Leider and David A. Shapiro presciently herald “the end of work as we know it.” This is their way of describing the fluidity of work, with innovation as the driving force. The authors observe, for example, that teleworking was relatively rare 20 years ago, whereas now entire industries have arisen to connect the workforce remotely via the internet and satellites. In a work world where change is a “new normal” marked by continual downsizing, restructuring, new technologies, globalization, automation, and robotics, Leider and Shapiro assert that reimagining work has become “a critical life skill.”

So what is work reimagined? The book’s thesis is that despite the ever-changing landscape of the work world, people remain “hungry” to find meaningful work that allows them to express their gifts and core values and to find a purpose greater than themselves. This is the concept of “calling.” The authors caution, however, that there is “no such thing as meaningful work; the meaning is what we bring to it.” Leider and Shapiro thus insist that when people work out of a sense of calling, they are not simply “making a living” but “making a life.”

The authors take great pains to distinguish a “calling” from a job or a career, explaining that people who have a “job” are primarily focused on gaining material benefits from work and do not expect any other type of reward. People who have a “career,” Leider and Shapiro contend, have a greater personal investment in their work, viewing their achievements not solely in monetary terms, but also in
terms of professional advancement that often brings higher status, higher self-esteem, and more power. By contrast, people with a calling “find that their work is inseparable from their lives,” and thus they value it not just for monetary gain or career advancement, but for the fulfillment it brings them. Best of all, according to the authors, when people discover and heed their calling, they “never have to work again” because they have found what they want to do.

While the book contains exercises to help readers uncover their calling, it is not merely a collection of all-too-familiar occupational personality tests. Indeed, as the authors observe, an inquiry into one’s life calling “is not something that can be answered with simple checklists or standardized formulas.” Rather, the book invites readers on an inward, contemplative journey to discover (or rediscover) those things that motivate and energize them—and for which they are particularly suited. Like the professional and academic backgrounds of the authors themselves, the book is part life coaching and part philosophy. Not surprisingly, then, it is liberally sprinkled with references to an eclectic mix of thinkers and writers ranging from Aristotle and Immanuel Kant to Ralph Waldo Emerson and Dylan Thomas.

Leider and Shapiro have skillfully divided the book into six thought-provoking chapters. In chapter 1, “Reimagining Work—What Do You Do?” readers are invited to reflect upon their career choices and gain a deeper understanding of what they are drawn to, good at, and inspired by. Chapter 2, “Reimagining Calling—Should You Quit Your Day Job?” encourages readers to consider whether they should be working in a different job, or simply working differently. In chapter 3, “Reimagining Gifts—How Do You Do It?” the authors use an exercise to help readers explore their gifts. Chapter 4, “Reimagining Passions—Why Do You Do It?” explores people’s efforts to find inspiration and purpose in their work and identify the beneficiaries of those efforts. Chapter 5, “Reimagining Values—Where Do You Do It?” encourages readers to find a “working environment that fits” and is aligned with their deepest values. Finally, chapter 6, “Reimagining Legacy—Have You Played Your Music?” explores the meaning of success and “the good life.”

People can uncover their unique calling at any stage of life, according to the authors. This should be welcome news for readers, given that, whether by necessity or choice, many people are working well past retirement age. It is equally reassuring for those who have found themselves unemployed, underemployed, or furloughed because of the pandemic. Leider and Shapiro suggest that by uncovering their calling, such individuals can readily retool their skills and adapt to a new work environment, arming themselves with greater “clarity and confidence” about their professional passions and strengths.

Fittingly, the book concludes by focusing on legacy. The authors state that our legacy emerges from a life lived in a manner consistent with our calling, describing it as “the music that plays after we are gone.” They quote Supreme Court Justice Oliver Wendell Holmes’s poignant observation that “most people go to their graves with their music still inside them.” The most common reason for this predicament, according to Leider and Shapiro, is that people never truly identify their song—in other words, they never really identify their calling. For this reason, the authors urge readers to consider carefully the legacy they want to leave from their working lives—and to finish that song.

Many of the concepts discussed in the book are not new. The Greek word that succinctly sums them up is “meraki,” which means to do something with soul, creativity, or love, and to put something of yourself into your work. What is new is the enthusiasm, wit, and wisdom that Leider and Shapiro display as they offer readers a roadmap to uncover their calling. This makes the book an enjoyable read, which I highly recommend.
Employment projections in a pandemic environment

This article examines the impact of the coronavirus disease 2019 (COVID-19) pandemic on the U.S. Bureau of Labor Statistics 2019–29 employment projections through two alternate scenarios: a moderate impact scenario and a strong impact scenario. The purpose of these projections is to estimate potential long-term structural changes in the U.S. labor market that are caused by changes in consumer and firm behavior as a result of the pandemic. Given the pandemic’s unprecedented impact on public health and social behavior, and in light of the still-evolving health crisis, the objective of this effort is to identify industries and occupations whose employment trajectories are subject to higher levels of uncertainty. The intent is not to produce precise estimates of employment change over the projections period.

This article examines two alternate scenarios (moderate impact and strong impact) to estimate some of the long-term labor market changes that may result from the coronavirus disease 2019 (COVID-19) pandemic. The article first explores the conceptual differences between these sets of projections and the baseline projections released in September 2020. This discussion is followed by a description of the methodology for how the two sets of pandemic projections were produced. Finally, the article presents the resulting employment projections for both scenarios for selected industries and occupations.

Concept

The COVID-19 pandemic has caused massive short-term disruptions to the U.S. economy and labor market, but its long-term impacts remain unclear. The U.S. Bureau of Labor Statistics (BLS) employment projections capture
long-term structural changes in the labor market, and the 2019–29 projections, released on September 1, 2020, reflect data preceding the pandemic.

As the pandemic took hold in the United States, total nonfarm employment dropped from 152.5 million to 137.8 million between February and June 2020, for a loss of 14.7 million jobs and a 9.6-percent employment decline. Some sectors were particularly hard hit, with hotels and motels employment declining 38.6 percent, air transportation employment declining 25.9 percent, and food services and drinking places employment declining 25.6 percent. Meanwhile, employment in grocery stores grew 3.5 percent.² (See figure 1.)

Teleworking also became more common as a result of the pandemic. In August 2020, 24.3 percent of all employees reported having teleworked at some point in the prior month because of the pandemic.³

Since the pandemic has already had a major impact on employment in the United States, users of projections data may be interested to know how BLS is assessing the long-term impacts of the pandemic on the distribution of occupational and industry employment. Therefore, BLS developed alternate projections for the 2019–29 period as a first attempt to identify industries and occupations subject to comparatively high uncertainty as a result of the pandemic.

**Conceptual difference between the baseline and alternate projections**

The BLS Employment Projections program estimates employment and occupational trends over a 10-year projections period. The employment projections for 2019–29 represent the baseline estimate of employment trends for the period, with no employment impacts stemming from the pandemic. A comparison of these baseline
projections with the alternate scenarios presented here can demonstrate how changes in consumer and firm behavior caused by the pandemic may alter the projections for detailed occupations and industries over the same period.

Like the baseline projections, the alternate projections are estimates of long-term structural changes to the economy. They model potential pandemic-induced structural changes to the economy and the labor market by taking into account changes in consumer spending behavior and workplace structural changes resulting from the pandemic.

**Explanation of the alternate scenarios**

Two alternate scenarios, moderate impact and strong impact, were modeled as possible paths for the U.S. economy for 2019–29. The terms “moderate” and “strong” refer to the extent of long-term economic changes resulting from the pandemic. The strong impact scenario assumes more widespread, permanent changes to consumer and firm behavior as a way to mitigate viral spread.

In the moderate impact scenario, increased telework is the primary force of economic change and has both direct and spillover effects. With more employees teleworking, the need for office space will decline, and so will nonresidential construction. Spending for employee trips to offices, including commuting costs, business travel, and lunchtime restaurant spending, are all lower here than in the baseline projections.

In addition, several industries and occupational groups are projected to see increased demand in the moderate impact scenario. Increased telework will drive demand for information technology (IT) and computer-related occupations, particularly those involved in IT security. Changes in food consumption as a result of lower restaurant spending will lead to more spending at and employment in grocery stores. Public demand for better prevention, containment, and treatment of infectious diseases is also expected to lead to increased scientific and medical research funding.

In the strong impact scenario, the changes detailed for the moderate impact scenario remain, although the consumer and firm behaviors associated with them are amplified. Consumer preference for avoiding interpersonal contact leads to further declines for restaurant dining, travel, and accommodation. Telework continues to expand, leading to further gains for associated IT support positions. Additionally, people’s desire to avoid large crowds leads to declines in employment demand for industries that depend on large gatherings, including live sporting events, theaters, and concerts. Further efforts to avoid interpersonal contact also lead to more virtual services than in-person services, including telehealth, and to the automation of many in-person customer service positions.

**How to interpret the alternate projections**

The alternate projections identify industries and occupations whose future employment trajectories are subject to high levels of uncertainty because of the pandemic. The goal is not to produce precise estimates of employment change over the projections period.

Occupations and industries whose alternate projections deviate the most from their baseline projections are those which are subject to the greatest pandemic-induced uncertainty over the next 10 years. Conversely, occupations with little difference between baseline and alternate projections have a narrower range of likely paths and are subject to less uncertainty.
For example, employment of hosts and hostesses is projected to grow 8.2 percent in the baseline scenario, but it is expected to decline 10.8 percent in the moderate impact scenario and 18.0 percent in the strong impact scenario. This wide range means that employment of hosts and hostesses is subject to a high degree of uncertainty over the next 10 years. If restaurants largely revert to their prepandemic staffing preference for hosts and hostesses, the occupation is expected to grow. However, permanent changes to consumer and firm preference for reducing interpersonal contact could lead to either moderate or strong declines for the occupation.

In contrast, employment of chief executives is projected to decline 10.0 percent in the baseline scenario, 9.9 percent in the moderate impact scenario, and 10.2 percent in the strong impact scenario. The likely structural changes to consumer and firm behavior resulting from the pandemic (outlined above) do not lead to any significant staffing changes for chief executives that differ from the baseline. Therefore, the pandemic-induced uncertainty in the employment trend for chief executives is expected to be small.

**Method of development**

This section presents the methodology used to develop the alternate projections, which involves adjustments to final demand, industry employment, and occupational staffing patterns.

**Baseline projections**

The 2019–29 projections were used as the baseline projections. These projections were developed in a process composed of six interconnected steps, each based on a different procedure (or model) and different assumptions. The six steps involve the labor force, the aggregate economy, industry final demand, industry output, industry employment, and occupational employment. The results obtained at each step are key inputs to subsequent steps, and the sequence may be repeated multiple times to allow feedback and ensure consistency. (See figure 2.)
Alternate projections

The alternate scenarios discussed in this article use the baseline scenario as their starting point. Two aspects of the employment projections process were changed in these alternate scenarios: final demand and occupational staffing patterns. The changes made to final demand flow through the rest of the process and change the output and employment results.

In the alternate scenarios, the major final-demand projections from Macroeconomic Advisers by IHS Markit are no longer used as constraints for the modeled final-demand sectors. Without constraints, the final-demand categories that would see uncertainty in the form of increased or decreased demand by consumers and firms can be changed directly. Changing final demand, however, implicitly changes aspects of the macroeconomic projections in the baseline scenario.

In the next step of the process, the staffing patterns used in the BLS National Employment Matrix, which distributes employment from industries to detailed occupations, were altered. These changes were made to address the impacts of the revised assumptions on structural changes in within-industry staffing decisions.

Changes to final demand

Final demand is split up into 11 different groups—personal consumption expenditures (PCE), private investment in equipment, private investment in intellectual property products, private investment in nonresidential structures, private investment in residential structures, change in private inventories, exports of goods and services, imports of goods and services, federal government defense consumption and investment, federal government nondefense
consumption and investment, and state and local government consumption and investment. The Employment Projections program uses 153 final-demand sectors in its projections.

The output in each final-demand sector is distributed to different commodity sectors with the use of a distribution matrix. A final-demand sector can have a 1-to-1 or 1-to-many mapping to commodity sectors. For example, PCE final-demand sector 19, telephone and related communication equipment, has a 1-to-1 mapping to commodity sector 71, communications equipment manufacturing. However, PCE final-demand sector 10, information processing equipment, has a 1-to-many mapping to seven different commodity sectors. The Employment Projections program defines 205 sectors to represent both industries and commodities. By distributing the final demand to different sectors, the program calculates total final demand for each commodity.

The input–output framework used for the projections describes relationships between the final demand for commodities and the output and employment needed in each industry to meet that demand. The first change made for the alternate scenarios is the change to final demand for commodities—that is, any pandemic-induced increase or decrease in consumer demand for a particular good or service. The input–output system, in particular the employment requirements matrix that is derived from the baseline projections, can be used to identify the employment impact on all industries, including those which supply intermediate goods and services, from a change in demand for a particular commodity.

By changing final demand, one can derive the structural changes resulting from people’s behavioral changes, seeking to find out what happens to employment when people change their spending practices because of the pandemic. Because this exercise focuses on how spending behaviors affect employment, most of the changes made to final demand are associated with the PCE grouping of final-demand sectors. The final-demand changes are the basis for the employment changes in the alternate scenarios.

Tables 1 and 2 show the intersection of the aforementioned final-demand sectors and the commodity sectors within the complete final-demand distribution matrix. For example, final-demand sector 120, private investment in nonresidential structures, is distributed to five different commodity sectors. Table 1, however, shows that the only commodity sector whose final demand was changed as a result of final-demand changes to sector 120 was commodity sector 15, construction. If the final demand at the intersection of final-demand sector 120 and commodity sector 15 is 100 in 2029 in the baseline scenario, a 5-percent decrease indicates that the output at that intersection in the moderate impact scenario is 95 in 2029.

### Table 1. Changes to final demand in the moderate impact scenario

<table>
<thead>
<tr>
<th>Sector number</th>
<th>Sector title</th>
<th>Final-demand number</th>
<th>Final-demand title</th>
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See footnotes at end of table.
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Table 2. Changes to final demand in the strong impact scenario

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<td>Computer systems design and related services</td>
<td>114</td>
<td>Private investment in software</td>
<td>10</td>
</tr>
<tr>
<td>131</td>
<td>Scientific research and development services</td>
<td>115</td>
<td>Private investment in research and development</td>
<td>10</td>
</tr>
<tr>
<td>137</td>
<td>Employment services</td>
<td>72</td>
<td>Professional and other services</td>
<td>3</td>
</tr>
<tr>
<td>139</td>
<td>Travel arrangement and reservation services</td>
<td>50</td>
<td>Ground transportation</td>
<td>-15</td>
</tr>
<tr>
<td>139</td>
<td>Travel arrangement and reservation services</td>
<td>56</td>
<td>Other recreational services</td>
<td>-15</td>
</tr>
<tr>
<td>147</td>
<td>Offices of physicians</td>
<td>43</td>
<td>Physician services</td>
<td>-1</td>
</tr>
<tr>
<td>148</td>
<td>Offices of dentists</td>
<td>44</td>
<td>Dental services</td>
<td>-2</td>
</tr>
<tr>
<td>151</td>
<td>Medical and diagnostic laboratories</td>
<td>45</td>
<td>Paramedical services</td>
<td>5</td>
</tr>
<tr>
<td>159</td>
<td>Performing arts companies</td>
<td>53</td>
<td>Membership clubs, sports centers, parks, theaters, and museums</td>
<td>-5</td>
</tr>
<tr>
<td>160</td>
<td>Spectator sports</td>
<td>53</td>
<td>Membership clubs, sports centers, parks, theaters, and museums</td>
<td>-10</td>
</tr>
<tr>
<td>161</td>
<td>Promoters of events, and agents and managers</td>
<td>53</td>
<td>Membership clubs, sports centers, parks, theaters, and museums</td>
<td>-10</td>
</tr>
</tbody>
</table>

See footnotes at end of table.
Some final-demand categories have contributed to growth or decline in demand for multiple commodity categories. For example, final-demand sector 114, private investment in software, is distributed to four different commodity sectors. Table 1 shows that final demand was changed for three of the four commodity sectors. When the output of a commodity sector changes, the distribution within the final-demand sector that sources that change is altered.

Generally, in the moderate impact scenario, demand at specific intersections of final-demand sectors and commodity sectors increases or decreases by 5 percent, with some exceptions. In the strong impact scenario, the magnitudes of many of these changes increase, with some new commodities being affected by additional demand changes. Tables 1 and 2 show all of the final-demand changes leading to the employment changes discussed in the analysis section.

**Changes to occupational staffing patterns**

The BLS National Employment Matrix apportions industry employment into detailed occupations. The matrix shows the distribution of occupational employment for wage and salary workers by industry, as well as the distribution of self-employed workers by occupation. These distributions are called staffing patterns. For the alternate projections, staffing patterns were altered in each scenario to account for the changes employers are expected to make under the alternate assumptions.

For example, in the moderate impact scenario, there was a projected final-demand increase in industry sector 131, scientific research and development services, because of increased demand for infectious disease research, treatments, and cures. Running that final-demand increase through the employment requirements matrix resulted in increased industry employment as well. That industry employment is distributed, with the use of staffing patterns, to different occupations. By changing staffing patterns, the overall increase in industry employment can be directed to occupations specifically involved in infectious disease research, such as epidemiologists and
microbiologists. If the staffing patterns were not changed, employment for all occupations in the industry would increase uniformly, which would result in comparable increases for occupations less related to infectious disease research, such as physicists.

Another example, this time from the strong impact scenario, involves the projected final-demand decrease in performing arts industries—a decrease caused by consumers’ wariness to gather in large groups, specifically when indoors. The final-demand decrease for these industries caused industry employment decreases, which resulted in occupational employment decreases. The occupations that are expected to see their employment decrease can be targeted specifically by making staffing pattern changes. In this case, ushers, lobby attendants, and ticket takers are taking a reduced share from the industry employment.

Results from the scenarios
This section examines the simulation results from the moderate and strong impact scenarios. The analysis highlights industries and occupations whose alternate projections diverge the most from their baseline projections. As mentioned previously, given uncertainty about the labor market outlook over the next decade, the purpose of these projections is to provide guidance on some of the potential long-term labor market impacts due to the pandemic rather than to provide specific values for any resulting changes in employment.

Industry employment projections
This subsection presents the results for the industry employment gains and losses expected under the two alternate scenarios.

Industry employment losses under the alternate scenarios
The retail trade industry is projected to experience the largest employment loss among all industries in both scenarios. In the moderate impact scenario, employment in the industry is projected to decline by 681,800 from 2019 to 2029, a decline of 4.4 percent, almost doubling the drop seen in the baseline projections. (See figure 3.) In the strong impact scenario, the industry is projected to lose 1.1 million jobs, a decline of 7.2 percent, erasing the job gains of the previous decade. With the exception of food and beverage stores and nonstore retailers, which are projected to see stronger employment under both alternate scenarios, employment in all retail industries is expected to weaken relative to the baseline projections. The deeper contractions in retail trade employment are due to an expected acceleration in a number of trends already set in motion prior to the COVID-19 pandemic.
Short-term consumer behavioral changes aiming to reduce human interaction and avoid crowded places have favored the e-commerce market and are likely to be “sticky,” further solidifying the existing trend toward more online shopping. Many traditional brick-and-mortar retailers have suffered from falling sales amid lockdown measures designed to reduce the spread of the virus, and several large department store chains have already announced nationwide store closures or declared bankruptcy. These developments suggest that the retail sector is likely to continue to see consolidation of big-box stores and that the overall physical retail footprint countrywide may shrink in the long term. This prospect could be exacerbated by the rise in telework, which may reduce foot traffic along traditional storefronts. Meanwhile, pandemic-related long-term changes to the in-store shopping experience of consumers will likely include an increase in contactless transactions through the use of mobile phone applications or self-service checkout kiosks.

One of the major assumptions underlying many of the most notable changes in the alternate projections is the expectation that telework will be offered on a more permanent basis. According to a BLS analysis, working from home is generally feasible in management, professional, and administrative support jobs, including those in the information, financial activities, professional and business services, and public administration industries. Consumer surveys also suggest that many American workers prefer to continue some form of telework arrangement even after the pandemic subsides. Telework has also been shown to increase employee happiness and not to hinder productivity. A higher prevalence of telework over the long term has ramifications for employment in various industries, including accommodation, food services, transportation, construction, and information and computer-related industries.
Working from home can greatly reduce consumers’ demand for dining out as the lunch-hour rush is replaced with more at-home dining. Consumers may also prefer to continue using delivery, takeout, or curbside pickup services after the pandemic dissipates, which would possibly reduce staffing requirements for restaurant dining rooms and food counters. Within this context, in the moderate impact scenario, employment growth in the food services and drinking places industry is projected to be relatively anemic, at 1.3 percent between 2019 and 2029, compared with a 7.3-percent rise in the baseline scenario. The estimates for the moderate impact scenario suggest that 156,200 jobs will be added to the food services and drinking places industry, an increase representing 720,600 fewer new jobs than those expected in the baseline scenario. In the strong impact scenario, on the other hand, employment is seen falling 3.1 percent over the 10-year projections period, dropping by 376,900, down to a level of 11.7 million in 2029. This decrease is the result of declines in employment in restaurants and other eating places, drinking places (alcoholic beverages), and special food services.

With a higher percentage of employees working from home, demand for transportation is expected to decline over the 2019–29 projections period. Demand for public transportation is expected to be stifled by fewer workers commuting to offices. Employment growth in the transit and ground passenger transportation sector is projected to moderate from 5.3 percent in the baseline scenario to 2.9 percent in the moderate impact scenario and 0.4 percent in the strong impact scenario. (See figure 4.) This projected slowdown is due to expected employment contractions in urban transit systems, interurban and rural bus transportation, and taxi and limousine services.

The pandemic also is expected to have consequences for business travel, because many companies are likely to see such travel as an avoidable cost at a time when virtual meetings are widely used. Business travel will continue, but with reduced prevalence. As a result, employment in air transportation is expected to be lower than that
estimated in the baseline scenario. In the moderate impact scenario, the air transportation workforce is projected
to increase 2.8 percent by 2029, compared with 5.9 percent in the baseline scenario. This translates into 15,300
fewer jobs being created because of increased telework and weaker business travel. In the strong impact scenario,
employment in air transportation is projected to drop 0.3 percent, down to a level of 501,300 in 2029, which is
31,200 fewer jobs than the level seen in the baseline projections.

Moreover, weaker business travel is expected to affect demand for accommodation. In the moderate impact
scenario, employment in the traveler accommodation industry is projected to decline by 82,800, or 4.2 percent,
compared with a 0.3-percent dip in the baseline scenario. In the strong impact scenario, the industry is expected to
suffer an additional loss of 89,400 jobs relative to the moderate impact scenario, with employment dropping from
2.0 million in 2019 to 1.8 million in 2029, a decrease of 8.6 percent. (See figure 3.)

Finally, the last sector expected to experience a substantial negative impact from the shift to telework is
construction. Because the rise in telework is expected to shrink demand for new office spaces, in the moderate
impact scenario, nonresidential building construction is projected to decline 2.0 percent between 2019 and 2029.
(See figure 5.) This decline contrasts with a 4.2-percent increase expected in the baseline projections. In the
strong impact scenario, the decline in employment is projected to deepen to 3.8 percent. Weaker demand for
nonresidential construction is likely to spill over into reduced demand for various construction industries (e.g., land
subdivision; building equipment contractors; electrical contractors; and plumbing, heating, and air conditioning
contractors), putting a damper on employment growth.

Figure 5. Projected percent change in employment, by selected construction industries, 2019–29

Click legend items to change data display. Hover over chart to view data.
On the other hand, employment growth in residential building construction is projected to be greater in the moderate impact scenario than in the baseline projections, which should partly offset some of the negative effects on the construction sector. Greater workplace flexibility and the disproportionate impact of COVID-19 on high-density urban areas are driving a “flight to the suburbs.” With telework becoming more prevalent, some Americans are choosing to migrate out of cities to areas where housing is more affordable, and low mortgage rates in the short term should further support housing demand. That said, the long-term sustainability of this trend will be determined by many factors, including the overall health of the economy, the trajectory of interest rates, and consumers’ access to credit.

All in all, construction is seen adding 197,300 jobs in the moderate impact scenario and 90,500 jobs in the strong impact scenario, down from the over 300,200 new jobs expected in the baseline scenario.

**Additional industry employment losses in the strong impact scenario**

In the strong impact scenario, several additional industries are expected to have notable employment changes that are not reflected in the moderate impact scenario. A 2005–06 Congressional Budget Office report noted that one of the largest macroeconomic impacts of a potential pandemic would be seen in the arts and recreation industries, and, in fact, data from the U.S. Bureau of Economic Analysis show that these industries were affected dramatically when the COVID-19 pandemic started. Altered social behaviors in the strong impact scenario are expected to reduce demand for and attendance at concerts, sporting events, amusement parks, and other entertainment offerings. Consequently, employment growth in the performing arts, spectator sports, and related industries is projected to stagnate in this scenario, adding only 5,300 new jobs over the 10-year projections period, compared with 27,600 new jobs in the baseline scenario.

**Industry employment gains due to the pandemic**

Several industries are expected to benefit from structural labor market changes caused by the virus and the health implications of the global pandemic. These industries are predominantly concentrated in scientific research and development and in IT and computer-related fields.

In the moderate impact scenario, employment growth in research and development in the physical, engineering, and life sciences is projected to more than double from the baseline projections, accelerating from 4.1 to 8.4 percent. This growth translates into 55,600 new jobs being added to the industry from 2019 to 2029, bringing its employment level to about 720,400, compared with 692,300 in the baseline projections. In the strong impact scenario, industry employment is expected to rise further, to 748,300, an increase of 12.6 percent. Increased demand for research into infectious disease properties, treatments, and cures underpins the projected rise in employment.

Likewise, employment in the pharmaceutical and medicine manufacturing industry also stands to benefit from increased preparation for pandemics and production of vaccines. Employment in this industry is seen growing roughly 19 percent in both alternate scenarios, accelerating from 5.4-percent growth in the baseline scenario. (See figure 6.) As a result, the industry’s employment level is projected to climb to 363,900 in the moderate impact scenario and to 365,200 in the strong impact scenario.
The increase in telecommuting over the long term should also benefit computer-related manufacturing and services. Stronger demand for computers, software, and related equipment to outfit home workstations is expected to drive an increase in computer and peripheral equipment manufacturing employment, which is projected to reach a level of 194,100 by 2029 in both alternate scenarios, up from 163,000 in 2019, rising 19.1 percent over the decade. (See figure 7.)
Moreover, increased telework should also strengthen demand for IT support systems and cyber security. In the baseline scenario, employment growth in the computer systems design and related services industry is projected to be much faster (26.1 percent) than the average for all industries (3.7 percent), with employment rising by 574,500 and reaching a level of 2.8 million in 2029. Under the moderate impact scenario, greater demand for computer systems design and related services is projected to boost the 10-year growth rate to 29.0 percent, adding an additional 65,200 workers to the industry’s workforce solely because of the aftereffects of the pandemic. Under the strong impact scenario, employment growth accelerates to 31.8 percent, representing 126,300 new positions due to increased demand relative to the baseline.

Figure 8 shows the differences in percent changes in employment between the baseline and alternate scenarios across all two-digit North American Industry Classification System industries.
Occupational projections

The aforementioned impacts of increased telework, weaker business travel, increased online shopping, expanded contactless ordering, greater demand for IT support systems, and more intensive medical research are expected to disproportionately affect some occupations in the industries discussed earlier. This section highlights some of the main occupations identified as more likely to experience long-term structural changes as a result of the
pandemic. This list is by no means exhaustive, but it highlights either occupations with substantial increases or substantial declines in employment or occupations with significant deviations from the baseline projections.

**Occupational employment losses associated with the alternate scenarios**

One pandemic impact identified as a driver of staffing pattern changes in the labor market is the accelerated use of contactless payments and transactions. This trend, along with the automation of checkout positions, was already in place before the pandemic hit and was partly responsible for the projected decline in sales and related occupations (such as cashiers) in the baseline projections. Checkout automation is expected to accelerate because of the pandemic, with businesses attempting to reduce direct interaction between staff and customers in the short term.

These factors, paired with a stronger displacement of brick-and-mortar retail by online shopping, are expected to sharply reduce the number of cashiers needed. In the baseline projections, cashiers are expected to lose 265,300 jobs by 2029, a decline of 7.4 percent. In the moderate impact scenario, the occupation’s job losses are expected to nearly double, for a total loss of 511,000 jobs over the 10-year projections period, a decline of 14.2 percent. Meanwhile, in the strong impact scenario, more permanent changes to consumer behavior are projected to lead to an even greater decline in cashier positions, resulting in a total loss of 714,500 jobs, a decrease of 19.8 percent. (See figure 9.)

Similarly, the increasing adoption of automation and productivity-enhancing technology in clerical and administrative work is likely to accelerate the use of online appointment booking systems and automated check-in kiosks. A potential strengthening of these trends underlies the projected decline in demand for receptionists and information clerks. In the moderate impact scenario, the occupation is projected to lose about 24,300 jobs over the
10-year projections period. In the strong impact scenario, the occupation is expected to shed as many as 114,900 jobs. This greater drop partly results from an expected decline in demand for receptionists in healthcare—a decline due to an assumed rise in the use of telehealth in the strong impact scenario.

Accelerated automation and reduced human interaction also account for substantial changes in the projections for several occupations related to travel and accommodation. Online and mobile phone booking systems are expected to reduce the number of available jobs for reservation and transportation ticket agents and travel clerks, while automated self-check-in stands and mobile phone room keys are expected to dampen demand for hotel, motel, and resort desk clerks.

In the moderate impact scenario, employment of reservation and transportation ticket agents and travel clerks is projected to fall from 126,300 in 2019 to 112,200 in 2029. In the strong impact scenario, the employment level falls further, down to 102,200 by the end of the projections period. Meanwhile, in the moderate impact scenario, the number of hotel, motel, and resort desk clerks is projected to shrink by 30,100, dropping to a level of 246,500 by 2029. In the strong impact scenario, the occupation is expected to lose as many as 60,700 jobs because of a sharper reduction in business travel, weaker demand for tourism, and stronger consumer preferences for reduced human interaction.

In the food services and drinking places industries, the occupations projected to have the largest changes in employment relative to the baseline projections are waiters and waitresses, hosts and hostesses, bartenders, and cooks at institutions and cafeterias. Many restaurants will likely continue to seek ways to reduce contact between employees and customers, including through the use of contactless ordering on mobile phone applications or online. Potential long-term trends of increased delivery, takeout, and curbside pickup services, coupled with adapted restaurant floor plans to limit capacity, prevent congestion, and help consumers feel safe while dining out, are expected to constrain employment of restaurant staff. Increased telework will likely reduce the number or size of office cafeterias, decreasing demand for cooks at institutions and cafeterias.

Employment for waiters and waitresses is projected to fall 5.6 percent between 2019 and 2029 in the moderate impact scenario, compared with a 3.7-percent increase in the baseline projections. (See figure 10.) Likewise, employment of hosts and hostesses is expected to fall 10.8 percent in the moderate impact scenario, a sharp reversal from the baseline’s 8.2-percent surge in employment. The number of bartenders is projected to shrink by 2.1 percent in the moderate impact scenario, compared with a 5.9-percent expansion in the baseline projections.
In the strong impact scenario, increased telework and a greater likelihood that consumers will prefer to avoid crowded places are expected to result in a 12.9-percent contraction in employment of waiters and waitresses. In the same scenario, employment of hosts and hostesses is expected to decrease by 18.0 percent, while employment of bartenders is projected to drop by 13.8 percent.

**Additional occupational employment losses in the strong impact scenario**

As noted previously, altered social behaviors are likely to involve reduced attendance of entertainment offerings such as live performances. As a result, in the strong impact scenario, employment of musicians and singers is projected to decline 1.7 percent from 2019 to 2029, compared with a 0.9-percent increase in the baseline projections. Meanwhile, accelerated automation and reduced human interaction are projected to weigh on demand for ushers, lobby attendants, and ticket takers. Employment in this occupation is expected to contract 7.2 percent over the 10-year projections period, losing 10,000 jobs.

**Stronger occupational employment growth in the alternate scenarios**

Employment in several occupations is poised to strengthen because of the effects of the pandemic. As noted earlier, a key assumption underlying the alternate scenarios is an acceleration in job growth both in medical research and development and in several IT and computer-related occupations.

Given the unprecedented impact of the COVID-19 pandemic on daily life, as well as the heightened uncertainty surrounding the mechanisms of disease spread and the best policies for mitigating contagion, both the public and private sectors will likely pay greater attention to pandemic preparedness going forward. This development should fuel demand for epidemiologists, medical scientists, biochemists and biophysicists, and biological technicians.
Gains for these occupations are expected to be broadly similar between the two alternate scenarios under the assumption that the increased need for future pandemic preparation and medical research will be paramount in either scenario.

Epidemiologists are a relatively small occupation, with an employment level of 8,000 in 2019. The occupation’s employment is expected to grow about 31 percent over the projections period in both alternate scenarios—a significant increase from the 4.6-percent growth in the baseline scenario. (See figure 11.) However, this acceleration will account for only about 2,500 new jobs over the next decade. Medical scientists, biochemists and biophysicists, and biological technicians are projected to experience similarly marked accelerations in employment growth. As the largest medical research occupation considered here, medical scientists are projected to add roughly 40,000 new jobs in both alternate scenarios, compared with only 8,400 new jobs in the baseline projections.

Given that telework will likely persist in American worklife moving forward, another occupational group that is expected to experience stronger growth in the alternate scenarios includes IT and computer-related occupations. A rise in telework, particularly for companies that did not offer telecommuting before the pandemic, should boost demand for software, IT infrastructure, and cybersecurity. As was the case with the medical-related occupational group, employment growth in IT and computer-related occupations is projected to be only slightly faster in the strong impact scenario than in the moderate impact scenario. This expectation is based on the assumption that, after an initial investment in a telework infrastructure, the same software can serve a larger audience with marginal cost of production.
In the baseline projections, information security analysts were among the top 10 fastest growing occupations. The increase in telework and robust demand for work-related digital security are expected to make these analysts the fourth-fastest-growing occupation in either alternate scenario. Software developers and software quality assurance analysts and testers are also expected to experience much-faster-than-average growth, because increased telecommuting is likely to boost demand for new web applications and platforms. Likewise, greatly expanded telework should drive increased employment for computer and information research scientists. (See figure 12.)

Figure 12. Projected percent change in employment, by selected IT and computer-related occupations, 2019–29

Figure 13 shows the differences in percent changes in employment between the baseline projections and the alternate scenarios for all occupational groups covered in the employment projections.
Conclusion

The COVID-19 pandemic has caused a substantial shock to the U.S. labor market and significantly altered consumer and business behavior. For this article, the BLS Employment Projections program designed two alternate scenarios to estimate some of the long-term structural labor market changes that could result from the pandemic. By altering final demand for selected industries and occupational staffing patterns in the baseline 2019–
29 projections, the program has provided an estimate of how the potential shifts in consumer spending behavior and workplace structural changes can affect employment levels over the next decade.

The 2020–30 projections, scheduled to be released in September 2021, will include full revisions to the labor force and macroeconomic projections, as well as a more thorough assessment of the ramifications of the pandemic for the detailed industry and occupational projections. As the pandemic situation and the public response to it continue to evolve, uncertainty about the trajectory of the economic recovery is likely to remain elevated in 2021. However, additional information on the extent of the economic effects of the pandemic, as well as data on which of these effects may prove to be long-term trends, will be used to inform the research that underlies the 2020–30 projections. As a result, the next projections cycle may see revisions to the significance of the factors identified in the present alternate scenarios or the degree to which the 2020–30 industry and occupational employment projections deviate from the 2019–29 projections.


NOTES


4 For detailed information on these projections and how they were developed, see “Employment projections,” Handbook of Methods (U.S. Bureau of Labor Statistics), https://www.bls.gov/opub/hom/emp/pdf/emp.pdf.

5 Final-demand category 10, information processing equipment, is distributed to commodity sectors 65 (commercial and service industry machinery manufacturing, including digital camera manufacturing), 70 (computer and peripheral equipment manufacturing, excluding digital camera manufacturing), 73 (semiconductor and other electronic component manufacturing), 91 (other miscellaneous manufacturing), 107 (software publishers), 114 (data processing, hosting, and related services), and 204 (used and secondhand goods).

6 The industry sectoring plan is documented on the Employment Projections program webpage (https://www.bls.gov/emp/documentation/crosswalks.htm). Industries and commodities use the same sectoring plan.

7 For simplicity of analysis, the section of final demand involving imports of goods and services has been left unchanged.


15 See recreation services category in table 2.4.6U, “Real personal consumption expenditures by type of product, chained dollars” (U.S. Bureau of Economic Analysis), https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2&isuri=1&1921=underlying#reqid=19&step=2&isuri=1&1921=underlying.

16 Dubina et al., “Projections overview and highlights, 2019–29.”

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Lockdowns and innovation: evidence from the 1918 influenza pandemic

Arthak Adhikari

To measure local invention, Berkes et al. use monthly patenting rates as a proxy. These data are retrieved from the Comprehensive Universe of U.S. Patents (CUSP), which describes “the city of each inventor, filing and award dates, technology class, and ownership status for the near-universe of U.S. patents since 1836.” The authors’ data for NPI length comes from an updated version of a database constructed by Markel et al. (“Nonpharmaceutical interventions implemented by US cities during the 1918–1919 influenza pandemic,” JAMA Network, 2007). From these sources, Berkes et al. build a sample of 50 large U.S cities, which accounted for 21 percent of the population and 39 percent of all patent filings in 1910, and estimate the effect of NPIs, during the 1918 pandemic, on the local patenting rates of these cities.

To estimate the effect of NPIs on patenting rates, the authors use a difference-in-differences (DD) framework. This framework contains a control group and treatment group. The control group, or “short-NPI cities,” includes cities with a cumulative length of NPIs of less than 90 days, and the treatment group, or “long-NPI cities,” comprises cities with the cumulative length of NPIs of more than 90 days. In their sample, the share of cities classified in the treatment group is 0.36. A key assumption of the DD framework is that the control group and the treatment group are homogenous, and their key difference is the application of the “treatment.” The authors find that their model satisfies the homogenous assumption and cite evidence that both groups (control and treatment) had similar trends in monthly patenting rates before the 1918 pandemic and had sharp rebounds in patenting rates following the pandemic.

In their standard DD model, the authors find that cities in the treatment group, those with longer NPIs, had higher patenting rates then cities in the control group. The authors also find that the effect of longer NPIs was substantially stronger for patents with multiple inventors—they report a higher patenting rate for multiple inventor patents overall in the treatment group, compared with single inventor patents.

Berkes et al. paper contributes greatly to COVID-19 research. Their research examines the long-run economic effects of a similar pandemic from our history and serves as a resource for future research on the long-run economic effects of the current pandemic. The authors, however, warn against directly comparing the two pandemics. They point out that modern communications technologies may substitute for social interaction during the current pandemic. In addition, the NPIs of 1918 were shorter and less extensive than the social-distancing restrictions of today. The authors conclude by stating their research shows that policies restricting social interactions affect invention rates through a variety of channels. Thus, the net effect of these policies will be determined by the behavioral, economic, and public policy forces that shape the relative strength of those channels.