Exploring Midwest manufacturing employment from 1990 to 2019

Using data from the Current Employment Statistics program, this article explores manufacturing employment dynamics between 1990 and 2019 in the Midwest region of the United States. The article compares and contrasts employment trends for both the region as a whole and the individual states that comprise it. Additionally, the article presents an examination of selected detailed industries. For context, the article uses periods within historical business cycles to frame analysis of manufacturing employment trends.

Since the peak of 19.4 million jobs in June 1979, manufacturing employment has declined throughout the United States, as both a relative share of total employment and in absolute terms. This article is one in a four-part series that uses Current Employment Statistics program data to examine long-term trends in regional manufacturing employment. In this article, we explore data trends in the Midwest region of the United States. The data span three decades, from 1990—the earliest available date of the state-level manufacturing employment data under the North American Industry Classification System (NAICS)—through 2019, just before the recession that was ushered in by the coronavirus disease 2019 pandemic.

For this article, we define the Midwest region using the U.S. Census Bureau designation of 12 states: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. This region has a history as the backbone of manufacturing in the United States, accounting for roughly one-third of all manufacturing jobs in the country. Factory employment trends in the Midwest have been similar to the nation as a whole. However, the region has a unique mix of industries within the manufacturing sector. Within the industries and subindustries across the region, the employment dynamics over time show an evolving manufacturing landscape.

Regional trends
The recent history of Midwest manufacturing can be broken down by decade, with distinct trends during business cycle expansions, as shown in chart 1. The 1990s began with a brief recession, resulting in a modest dip. Throughout the rest of the decade, manufacturing employment in the Midwest remained relatively flat with moderate growth. In January 1990, there were 5.2 million manufacturing jobs in the Midwest region of the United States. Through the end of 2000, the region added roughly 278,000 additional manufacturing jobs (growing the industry by 5.4 percent). During the same period, total nonfarm employment in the region grew by 5.1 million jobs (18.9 percent). This modest growth in the manufacturing sector during a period of economic expansion reveals a major shift in the industrial composition of the region and nation. From the end of 2000 and over the next decade, manufacturing jobs would decline greatly, despite the region experiencing periods of economic expansion.


The 2000s were a period of near continuous manufacturing job loss in the Midwest. The decade began with a sharp decline before and during the 2001 recession, with 561,000 jobs lost from an employment peak in January 2000 to the end of the recession in November 2001. As the economy as a whole was expanding from November 2001 to December 2007 (the business cycle peak before the Great Recession), the decline in Midwest manufacturing employment slowed. In this period, the manufacturing industry shed roughly 604,000 jobs, 12.3 percent of its November 2001 level. Although factory job loss in the early 2000s has no single explanation, the decade saw a major change in international competition after China was granted permanent normal trade relations with the United States in 2000. This change in trade relations has often been cited as a key factor in the manufacturing employment decline of the 2000s. After the expansion of the 2000s ended, the ensuing Great Recession resulted in the single largest drop in manufacturing jobs for the region. From the business cycle peak of December 2007 to the trough of June 2009, the Midwest region lost 761,000 manufacturing jobs. Employment for the industry contracted by over 17 percent in less than 2 years.

Postrecession manufacturing employment bottomed out in February 2010 at 3.5 million. Since that low, employment in the manufacturing sector has experienced sustained growth, adding 554,000 jobs through the end
of 2019. As of December 2019, jobs in manufacturing had grown to 4.1 million, a 17.1-percent increase since the trough of the recession in February 2010.

Although manufacturing employment declined in the Midwest and elsewhere, output did not decline in the same way, because a corresponding increase occurred in labor productivity.[3] That is, companies needed fewer workers to produce the same level of output. Labor productivity in manufacturing increased by 101.8 percent from 1990 to 2019, although it fell slightly after 2013.[4] Total measured output grew substantially in the 1990s but showed little net growth in the 2000s and 2010s, with variation around the business cycle.[5] Manufacturing also saw an increase in capital intensity, becoming more dependent on capital and less reliant on labor.[6] The division between durable and nondurable goods provides context for those employment declines and the industry concentrations of Midwestern states.

Despite the large decline in manufacturing jobs in recent decades, the region maintained its share of national manufacturing employment. In 1990, manufacturing employment in the Midwest region accounted for 29.1 percent of the national employment in the manufacturing sector. While the industry shrank both nationally and regionally, the Midwest’s share grew by 2.8 percentage points to 31.9 percent in 2019, since national employment in manufacturing declined at a greater rate than in the Midwest region. Between 1990 and 2019, the number of jobs in the manufacturing sector in the Midwest shrank by 1.1 million, 21.2 percent. Over that same period, nationally, 5.0 million manufacturing jobs were lost, 28.0 percent of the 1990 level. In addition, the manufacturing industries on which the region depended most, such as transportation equipment manufacturing and fabricated metals manufacturing, saw the greatest declines as the global economy took shape in the late 20th century.[7]

**State manufacturing dynamics**

As shown in chart 2, while the Midwest region has experienced a substantial decline in manufacturing since 1990, the relative employment by state has remained somewhat stable. In 1990, Ohio accounted for 20.3 percent of all manufacturing employment in the region, followed by Illinois with 17.6 percent. By 2019, both states experienced the largest declines in share of regional manufacturing employment: –3.2 percentage points and –3.3 percentage points, respectively. Between 1990 and 2019, two other states saw their share of regional employment decline, Missouri (–0.8 percentage points) and Michigan (–0.7 percentage points), which by 2019 had more factory jobs than Illinois. Each of the remaining eight states—North Dakota, Indiana, Minnesota, Iowa, South Dakota, Kansas, Nebraska, and Wisconsin—represented a modestly greater proportion of regional manufacturing employment in 2019 than in 1990.
We use location quotients to examine the change in industrial concentration of manufacturing employment in the states of the Midwest region.[8] We calculate the location quotients by taking the manufacturing industry’s share of total nonfarm employment for that state and dividing it by the share of manufacturing employment at the national level. A location quotient greater than 1.0 indicates that a state’s concentration of manufacturing employment is greater than the national proportion. Location quotients for all Midwestern states and the region as a whole are displayed for each state for 1990 and 2019 in chart 3. The increase in the concentration of manufacturing employment in the Midwest region since 1990 is due to the combination of slower regional nonfarm employment growth as well as the slower rate of decline in manufacturing jobs in the region relative to the rest of the nation. Between 1990 and 2019, the location quotients for all states in the Midwest region increased, indicating that manufacturing employment has become more concentrated in the region. Indiana, Iowa, and Wisconsin experienced the greatest growth in concentration of manufacturing employment relative to the national average. Indiana has the highest location quotient in the region at roughly 2.02, indicating that in 2019, manufacturing employment accounted for twice the share of employment in the state as it did nationally. Of the 12 states in the region, 8 were more concentrated than the national average in 1990. In 2019, the four states with the highest manufacturing concentration were in the Midwest—Indiana, Iowa, Michigan, and Wisconsin—and all states in the region except North Dakota had a quotient greater than 1.
While manufacturing grew more concentrated in the Midwest than the nation as a whole, manufacturing employment still fell as a share of payroll jobs in most Midwestern states. Chart 4 displays manufacturing employment as a proportion of total nonfarm employment for each state in the Midwest region for 1990 and 2019. Examining the changes of employment in manufacturing with respect to total nonfarm employment reveals how much the industrial landscape has changed. Over these three decades, the total number of manufacturing jobs has increased in four of the smallest states in the region: Iowa (+4,300), Nebraska (+4,100), North Dakota (+11,900) and South Dakota (+12,000). However, North Dakota was the only state where employment in the manufacturing industry increased as a percentage of total nonfarm employment, up 0.2 percentage points. The remaining eight states in the region—Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, Ohio, and Wisconsin—witnessed a decline in both the number of manufacturing jobs and their proportion relative to total nonfarm. The greatest decline in manufacturing employment as a percentage of total nonfarm employment occurred in Ohio. In 1990, manufacturing accounted for roughly 21.7 percent of all employment in the state. In 2019, manufacturing accounted for 12.5 percent of all jobs in Ohio, after the industry shed roughly 359,000 jobs. Other states in the region where the concentration of employment in manufacturing declined notably include Illinois (–7.7 percentage points), Indiana (–6.9 percentage points), Michigan (–6.9 percentage points), Missouri (–7.2 percentage points), and Wisconsin (–6.7 percentage points).
To better show the manufacturing trends of the Midwest, the next section explores what happened in more detailed industries. A breakdown between employment in durable and nondurable goods is available for all 12 Midwestern states. (See chart 5.)
Durable goods

Of the 1.1 million jobs lost in manufacturing between January 1990 and December 2019, 78.0 percent were in durable goods, with 880,000 jobs vanishing over this period. Between December 2007 and June 2009, 634,000 jobs were lost. Between June 2009 and December 2019, durable goods manufacturing saw modest gains in employment, adding 414,200 jobs, but failed to reach prerecession levels.

Transportation equipment

Ten Midwestern states account for almost two-fifths of nationwide transportation equipment employment, and transportation equipment (NAICS 336) is a core part of Midwest manufacturing, with nearly a fourth of the region’s durable goods manufacturing employment.[9] Transportation equipment in the region includes a large share of the domestic automotive industry—centered in Detroit and extending into Indiana, Ohio, and other states—as well as other industrial hubs. Wichita, Kansas, has been dubbed the “Air Capital of the World,” and anchors the aerospace industry in that state, while Elkhart, Indiana, is known as the “RV Capital of the World.” Of recreational vehicles sold in the United States, 80 percent are manufactured in Indiana, with Elkhart County making up 65 percent of that production.[10] Transportation equipment is also important since much of the output of other industries serves as intermediate goods in producing cars, trucks, and airplanes. Nationwide, transportation equipment uses 27 percent of the commodity output of primary metals (NAICS 331), 17 percent of fabricated metal products (NAICS 332), 13 percent of plastics and rubber products (NAICS 326), and 15 percent of computer and electronic products (NAICS 334).[11]

Michigan, Ohio, and Missouri are home to a substantial concentration of U.S. employment in motor vehicle manufacturing—which is engaged in the final assembly of light vehicles and chassis. These three states had 146,100 jobs in motor vehicle manufacturing in 1990, 54 percent of the national total. In 2019, this number dropped to 72,000, just 30 percent of the national total. The drop of approximately 74,000 jobs in these three
states more than accounts for the 34,000 jobs lost nationwide. As of 2019, motor vehicle manufacturing employment in Michigan reached just 42 percent of its 1990 level, while Missouri and Ohio reached 70 percent and 58 percent of their 1990 levels, respectively.

From 1990 to 2019, motor vehicle manufacturing grew more geographically diverse, with the South accounting for a growing proportion of this industry’s employment. For example, between 1990 and 2019, Alabama’s share of motor vehicle employment rose from 0.1 percent to 5.2 percent, Kentucky’s share rose from 3.9 percent to 8.1 percent, and Texas’ share rose from 1.6 percent to 4.5 percent.

**Machinery**

In the 11 Midwestern states where data are available (all except South Dakota), employment in machinery (NAICS 333) fell by 136,000 (−22.3 percent) from 1990 to 2019, representing almost half the nationwide decline of 283,200 jobs (−20 percent). Nearly half the Midwest losses were in Illinois, which saw its employment drop by 61,600 jobs (−46 percent). Other states with large losses include Michigan (−23 percent), Ohio (−32 percent), and Wisconsin (−12 percent). Employment in North Dakota’s machinery industry remains small, even after it nearly doubled from 1990 (3,100) to 2019 (6,000). Since 2009, these 11 Midwestern states have gained 12.9-percent employment on average. Indiana, Iowa, Kansas, Michigan, Minnesota, Ohio, and Wisconsin have all seen double-digit percentage gains since 2009, while Illinois lost 6.4 percent over the same period.

**Computer and electronic products**

Another industry that has seen notable losses across the Midwest is computer and electronic products (NAICS 334). Six states have data available back to 1990. These states lost a collective 127,200 jobs between 1990 and 2019, a 50-percent aggregate decline.[12] Of these states, Minnesota experienced the smallest percentage decline (−31.2 percent), whereas Indiana had the largest percentage decline (−62.4). Ohio, Michigan, and Missouri have seen employment gains since 2009. Ohio’s employment has risen by 3 percent, Michigan’s by 16 percent, and Missouri’s by 72 percent.

In Minnesota, computer and electronic products lost 20,700 jobs (−31.2 percent) from 1990 to 2019, but electronic instruments (NAICS 3345) gained 7,500 jobs (38.5 percent). Minnesota has shown a trend counter to the industry nationwide, which has lost 212,800 jobs (−33.5 percent) in electronic instruments employment since 1990.

**Furniture**

Furniture (NAICS 337) has also seen steep declines across the Midwest since 1990, particularly in Michigan, where employment in the industry has declined by 16,100 (−41 percent). Furniture manufacturing in Michigan saw a substantial decline in employment between 2000 and 2003, when 12,100 jobs were lost. Michigan’s decline in furniture manufacturing is highlighted because its city of Grand Rapids is known as “Furniture City,” as it had been home to major furniture manufacturers since the mid-1800s. Since 2009, the industry has recovered 3,500 jobs in Michigan, but employment continued to decline, however, in Ohio and Illinois. Combined job losses in Illinois and Ohio totaled 15,700 (−36 percent) between 1990 and 2019.

**Nondurable goods**

Between January 1990 and December 2019, nondurable goods employment in the Midwest fell by 247,300 jobs (−14.5 percent). Nationally, employment in nondurable goods manufacturing declined by 2.2 million jobs (−31.7 percent) over the same period. The Midwest lost relatively fewer jobs in this industry than the rest of the country, with other regions accounting for 88.9 percent of the job losses in nondurable goods. Nationally, 61 percent of the decline in nondurable goods employment was in textiles, textile product mills, and apparel. Midwestern states lack major employment in these industries, explaining, at least partially, the divergence between the Midwest and national trends. Midwest nondurable goods manufacturers lost 134,700 jobs between December 2007 and June 2009 but recovered 125,000 between June 2009 and December 2019. This 9.3-percent growth rate was higher than the national rate of 5.5-percent growth over the same period.

**Printing and related support activities**
Illinois and Ohio have seen substantial losses in printing and related support activities (NAICS 323) losing over 68,000 jobs between 1990 and 2019. These losses represent 26.9 percent of the overall decline in Midwest nondurable goods manufacturing during this period. Printing has not recovered in Illinois or Ohio since the end of the Great Recession, shedding 11,900 jobs (−20 percent) from 2009 to 2019. Illinois and Ohio largely reflect national industry trends, which had a loss of an additional 96.8 thousand jobs (−18.5 percent) in the same period.

**Paper and paper products**

A related industry experiencing a similar national decline is paper and paper products (NAICS 322). Establishments in this industry lost 281,900 jobs (−43.5 percent) nationally between 1990 and 2019, 12.9 percent of total nondurable job losses. Illinois alone lost 14,500 jobs (−43.9 percent) over the same period, mirroring the national trend. These losses represent 16 percent of the nondurable job losses for the state and followed a steady downward trend after a peak in 1995.

**Plastics and rubber products manufacturing**

Ohio employment in plastics and rubber products (NAICS 326) fell by over 20,000 jobs (−25.9 percent) from 1990 to 2019. Rubber products employment in Ohio saw a decline of over 52 percent in employment, highlighting the struggles for cities like Akron. Akron once hosted corporate offices for four of the “Big Five” tire companies and 68.4 percent of total wage earners in the industry, hence the title “Rubber Capital of the World.”[13] Other states in the Midwest bucked the downward trend in plastics and rubber manufacturing: Wisconsin and Michigan added a combined 12,100 jobs from 1990 to 2019, representing 23.5-percent and 15.7-percent increases, respectively. Illinois saw similar but smaller declines in this industry. Employment in the industry steadily increased from 47,500 in 1990 to a high of 59,300 jobs in 1998, before declining to 39,700 in 2009. From 2009 through 2019, the industry regained 3,600 jobs, reaching a level of 43,300 in 2019, 1,400 jobs short of the 2007 level. Between 1990 and 2019, Illinois saw a cumulative decline of 8.8 percent in plastics and rubber products manufacturing employment.

**Food manufacturing**

One industry, in particular, has grown steadily since 1990: food manufacturing (NAICS 311). Midwestern states for which data go back to 1990 have seen an average increase of 14.3 percent in employment through 2019.[14] Kansas has seen the largest percentage growth, expanding employment by just over 40.7 percent. Indiana has grown by 23.2 percent since January 2002. Illinois and Michigan are the only states that have lost employment, with Michigan declining by 8.4 percent and Illinois losing 1.0 percent.

**Conclusion**

Midwest manufacturing underwent significant changes from 1990 to 2019. While manufacturing employment declined across the nation, including most of the Midwestern states, the reallocation in the share of employment from manufacturing to other industries was not as rapid in the region. That is, the location quotient for manufacturing increased in every Midwestern state from 1990 to 2019, and by 2019, manufacturing represented a larger share of payroll employment than the national average for every state in the region except North Dakota. The net declines in Midwest manufacturing employment are evident across NAICS industries, with food manufacturing being an outlier in this respect. These employment changes occurred against a backdrop of a more competitive global manufacturing marketplace and increasing capital intensity and labor productivity in U.S. manufacturing.

SUGGESTED CITATION

Seasonally adjusted monthly data are used for overall manufacturing employment as well as durable and nondurable goods manufacturing. Seasonally adjusted data are not available at a more detailed level for some industries, so annual averages of not seasonally adjusted data are presented.


The general formula for location quotients is represented as

\[
\text{Location Quotient} = \frac{\text{local concentration of specific industry’s employment}}{\text{national concentration of specific industry’s employment}} \\
\times \frac{\text{national total nonfarm employment}}{\text{local total nonfarm employment}}.
\]

States with available transportation equipment manufacturing data include Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, and Wisconsin.


Transportation equipment’s share of industry commodity output was calculated based on 2019 industry use of various commodities by industries after redefinitions (producers’ prices) data from the U.S. Bureau of Economic Analysis, [https://www.bea.gov/data/industries/input-output-accounts-data](https://www.bea.gov/data/industries/input-output-accounts-data).

Employment in computer and electronic products is available starting in 1990 for Illinois, Indiana, Michigan, Minnesota, Missouri, Nebraska, and Ohio. The time series for this industry in Michigan begins in 2001.

The U.S. Bureau of Labor Statistics publishes food manufacturing employment beginning in 1990 for all Midwestern states except Indiana and South Dakota. Indiana data are available beginning in 2002, while employment data for this industry are not available for South Dakota.

Related Articles

- Manufacturing employment in the Southeast: examining the last 30 years, Monthly Labor Review, July 2021.

Related Subjects

- Manufacturing
- Midwest
- Employment
- Economic development and growth
- Recession
Alternative measurements of Indian Country: understanding their implications for economic, statistical, and policy analysis

The term “Indian Country” is often used to mean either the demographic group of Native Americans in the United States or the geographic, tribal communities in which many Native Americans live. This double meaning has led to various treatments of the socioeconomic measures describing Indian Country. Unfortunately, some of these treatments can potentially lead to inaccurate or misleading analyses of Indian Country, for two reasons. First, because socioeconomic data on Indian Country are sparse, analysts frequently do not have the ideal data for their studies, and they have to make do with the only information they can obtain that is close to the concept being analyzed. Second, some previous studies have already mistakenly “mixed apples and oranges” with regard to Indian Country data (as suggested above) and, in so doing, have set a precedent for others to follow. This article addresses this problem by offering a reality check on the alternative definitions of Indian Country and on how different they truly are. The article then provides a taxonomy of these definitions, offering guidance on when they should be applied in efforts to promote the most accurate and reliable findings possible.

The term “Indian Country” has often referred to the totality of tribal communities in which many American Indians and Alaska Natives (AIANs) reside. However, other definitions have existed for Indian Country, causing ambiguity that has created substantial uncertainty and confusion whenever socioeconomic statistics on Indian Country (or on “Native Americans in the United States,” etc.) are presented and used in economic and policy analyses.

The definition of Indian Country has two extremes, with a wide gray area between them. At one extreme is a precise, legal definition used by any federal agency, such as the Bureau of Indian Affairs (BIA), that commonly analyzes Indian Country and reports findings about it. At the other extreme is a vague operational definition that refers to any commonly used demographic classification of Native Americans in the United States. The choice of definition by analysts is often arbitrary, as is the case when they conveniently adopt the definition used in their data sources. However, because the choice of definition can affect the analytical results obtained by researchers, it should not be arbitrary, adopted out of convenience,
but reasoned and deliberate in order to deliver the most meaningful and relevant results. This is the topic of this article.

In strict legal terms (the first definitional extreme mentioned above), Indian Country is defined in 18 U.S.C. § 1151 and 40 CFR § 171.3 as “(a) all land within the limits of any Indian reservation under the jurisdiction of the United States Government, notwithstanding the issuance of any patent, and, including rights-of-way running through the reservation, (b) all dependent Indian communities within the borders of the United States whether within the original or subsequently acquired territory thereof, and whether within or without the limits of a state, and (c) all Indian allotments, the Indian titles to which have not been extinguished, including rights-of-way running through the same.”¹ This definition has been accepted into practice by federal agencies.²

The other definitional extreme contains several open-ended options for what might be called Indian Country. These include the U.S. Census Bureau’s “self-identified” AIAN population, for which that agency develops statistics through its American Community Survey (ACS). A similar set of socioeconomic statistics are provided by the U.S. Bureau of Labor Statistics (BLS) Current Population Survey (CPS). One of the notable differences between the U.S. Census Bureau’s measurement of Indian Country and the federal legal definition is that the latter applies only to federally recognized tribes, whereas the former includes state-recognized tribes as well.³ (See appendix.)

Because the U.S. Census Bureau, unlike the BIA, includes state-designated tribal service areas in its measurement of Indian Country, it could be argued that Indian Country is effectively larger for the U.S. Census Bureau than it is for the BIA. Of the 695 tribal areas identified in the U.S. Census Bureau’s “My Tribal Area” database,⁴ only 582 could be matched to federally recognized tribes; the remaining 113 could not be matched, because they were associated with tribal entities that were not federally recognized. For example, 75 of the 113 tribal areas that could not be matched are in Hawaii, which has no federally recognized tribes. However, other ways of defining Indian Country would indicate that tribal areas represent far less than half of all Indian Country, in the sense that most AIANs in the United States do not live in tribal areas. This fact is common knowledge among those who study the AIAN population, but it often appears to be unknown to many members of the public, including, perhaps, individuals who may be associated with media coverage or policy analysis of Indian Country.

Using data for the self-identified AIAN population from the CPS, Mary Dorinda Allard and Vernon Brundage Jr. recently published a Monthly Labor Review (MLR) article titled “American Indians and Alaska Natives in the U.S. labor force.”⁵ Some of the most revealing estimates presented in that article are those for employment differences between AIANs who live in tribal areas and AIANs who live outside tribal areas. (See table 1.)

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**Table 1. Selected labor force measures for AIANs (alone or in combination with other races), averages for the combined years 2016–18**

<table>
<thead>
<tr>
<th>Measure</th>
<th>Total</th>
<th>Residing in AIAN area</th>
<th>Not residing in AIAN area</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Number (thousands)</td>
<td>Percent of total</td>
</tr>
</tbody>
</table>

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<tbody>
<tr>
<td></td>
<td></td>
<td>Number (thousands)</td>
<td>Percent of total</td>
</tr>
<tr>
<td>Total population</td>
<td>5,086</td>
<td>939</td>
<td>18.5</td>
</tr>
<tr>
<td>In labor force</td>
<td>3,117</td>
<td>494</td>
<td>15.8</td>
</tr>
<tr>
<td>Not in labor force</td>
<td>1,969</td>
<td>445</td>
<td>22.6</td>
</tr>
<tr>
<td>Unemployed</td>
<td>226</td>
<td>54</td>
<td>23.9</td>
</tr>
<tr>
<td>Unemployment rate (percent)</td>
<td>[1]</td>
<td>10.9</td>
<td></td>
</tr>
</tbody>
</table>

[1] Not applicable.

Note: AIAN = American Indian and Alaska Native.


Although the 2020 recession caused by the coronavirus disease 2019 (COVID-19) pandemic led to increases in unemployment rates, table 1 reveals statistics generally applicable to the prepandemic period. On the basis of Allard and Brundage’s findings, one can estimate that only 18.5 percent of the roughly 5 million people who self-identify as AIAN-AOIC (alone or in combination [with other races]) reside in the tribal areas identified in BLS data. However, this estimation may be misleading, because many other AIAN-AOIC households may live in the vicinity of these tribal areas, that is, in extended “tribal service areas” as described below. Even more revealing is the difference in AIAN-AOIC unemployment between tribal areas and localities outside those areas. Unemployment is much higher in tribal areas (10.9 percent) than outside of them (6.6 percent). This difference reflects a common understanding about Indian Country, namely, that moving out of a tribal area often increases the odds of finding employment. These findings reveal that, in discussing employment in Indian Country, one should clearly differentiate between the situations facing Native Americans living in tribal areas and the situations facing Native Americans in the United States in general.

Another approach that researchers can use to measure Indian Country from an economic perspective is to analyze listings of organizations that are either headed by Native Americans or located in tribal areas. One example of this approach is a recent study, titled “Reservation nonemployer and employer establishments: data from U.S. Census longitudinal business databases,” by the Center for Indian Country Development (CICD) at the Federal Reserve Bank of Minneapolis. In general, however, such studies rightly do not claim to be capturing all of Indian Country per se; instead, they focus on specific aspects of Indian Country. For example, the identification of businesses that are physically located in tribal areas would include many businesses that are not owned by Native Americans and would exclude many (and probably most) Native-owned businesses that are not physically located in tribal areas (but that may easily be in the vicinity of tribal areas, in a “border town”). Likewise, as discussed in greater detail in the sections that follow, the employment level of businesses inside tribal areas may not reflect the employment of the residents of those areas. Finally, when using data sources based on the ownership or location of businesses, analysts should be careful in interpreting the findings of studies that were never intended to
cover Indian Country at an aggregate, or comprehensive, level. For instance, the aforementioned CICD study does not include any tribes in Alaska. In addition, it does not include the Navajo Nation (which, alone, represents about 10 percent of the tribal-area AIAN population), because, according to the study, the Navajo Nation’s “exceptionally large area and population make it an extreme outlier for our purposes.”

8 How findings can be highly dependent on the definition of Indian Country

Given the various definitions of Indian Country that exist, one’s analytical findings about Indian Country would depend on the precise definition one uses. As a quick example, suppose one were to ask the question, “Is home ownership (the proportion of households who own their dwellings) greater in Indian Country than in the United States overall?” The answer could be yes or no, depending on how one defines Indian Country. If the analyst is studying the living conditions in the tribal areas of the United States, the answer would be affirmative, indicating that home ownership is greater in Indian Country than in the United States, on average. Households in tribal areas tend to own their dwellings at higher rates than the national average, simply because, in tribal areas, far fewer households rent out apartments (especially because tribal areas are generally rural). As a statistic, however, a “yes” answer could be misleading, because, in general, the rate of home ownership for any demographic group is seen as a reflection of greater household wealth. In this broad sense, home ownership can be an indicator of a demographic group’s relative economic well-being. In tribal areas, however, the homes that households generally own often have a lower value, on average, than other homes in the United States and, in terms of living conditions, are often much worse than typical rented apartments. Higher-than-average home ownership in tribal areas can thus be a rather misleading statistic, because it may suggest a level of wealth that is nonexistent.

From a different perspective, one should note that the majority of people who would consider themselves to be AIAN in the United States—and who would also be considered by others to belong to this racial group—do not live in tribal areas (as was shown in table 1). Most AIANs who live outside tribal areas have a lower-than-average rate of home ownership, which is most likely explained simply by their relatively low household income. Therefore, if this more general AIAN population is what is meant by Indian Country, one would find the rate of homeownership in Indian Country to be below average. Indeed, by this indicator alone, this population may appear to be worse off, on average, than the population of people who live in tribal areas, although, in reality, the national AIAN population is better off, on average, in terms of income and living conditions.

In the analytical literature on Indian Country, it is not uncommon for very different definitions of Indian Country to enter into and out of the same discussion, sometimes even within the same paragraph of text. For example, one might find a study that presents statistics on the relatively low income levels and high unemployment rates of people living in tribal areas and, then, within the same thread, mentions the relatively low homeownership rate of all AIAN households in the United States (as if the former explains the latter). Some studies of Indian Country do, indeed, mix measurements in a manner that is inconsistent with scientific methods of analysis.

This methodological problem may be exacerbated by there being a continuum, in the discourse on Indian Country, between rigorous statistical analysis, at one extreme, and qualitative generalizations, at the other.
All else being equal, the more removed the discussion is from a mathematical or objective measurement approach—and the closer it is to an approach involving public relations and advocacy—the more likely it is for this statistical “mixture” of sorts to take place. Nevertheless, the problem can still be found even within what would otherwise appear to be purely scientific approaches. In technical terms, this problem may be described as a failure of the analysis to establish and uphold, at the outset, a consistent analytical “domain,” which defines exactly what it is that is being studied. Analyses cannot waver back and forth over what that domain is—doing so would not be analytically valid and would discredit the legitimacy of the study and its findings.

It is also worth noting that there is no single “correct” definition of Indian Country. In fact, each definition is important in its own right, depending on what questions need to be asked and answered. Moreover, there is no absolute requirement that only one definition be used throughout any study—only that, whatever definition is used in a given argument, it should be transparent and not confused with any other definition. For example, there is nothing wrong with a study stating the following: “Most tribal-area residents own their dwellings, while most members of the AIAN population in the United States do not.” If each domain is unambiguously identified, any statement about that specific domain may be valid and informative. Moreover, the researcher’s choice of domain often requires a compromise, or balance, among what is most appropriate conceptually, what can feasibly be measured, and what has already been measured (and for which there already exists a useful body of available data). These issues are explored in the sections that follow.

A taxonomy of alternative definitions

Table 2 presents a taxonomy of alternative definitions of Indian Country as they may be used in economic and statistical analyses. There is a total of nine alternative definitions, or domains, for the socioeconomic analysis of Indian Country. In theory, additional domains could be identified in various ways; however, the nine identified here are the most common in studies of Indian Country, primarily because they are the ones for which data are available.

<table>
<thead>
<tr>
<th>Conceptual basis</th>
<th>Variations</th>
<th>Code</th>
<th>Socioeconomic characteristics of people</th>
<th>Characteristics of employers</th>
<th>When the measure is most relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geography (where people and businesses are located)</td>
<td>Designated tribal land areas</td>
<td>GL</td>
<td>Population lower than for GS and GC</td>
<td>Many employers of workers who live in these areas are not Native, and many of their establishments</td>
<td>Alleviating poverty, meeting trust responsibilities</td>
</tr>
<tr>
<td>Population</td>
<td>Economic well-being</td>
<td>High poverty/low income/high unemployment (especially among AIAN-AOIC)</td>
<td>Many employers of workers who live in these areas are not Native, and many of their establishments</td>
<td>Alleviating poverty, meeting trust responsibilities</td>
<td></td>
</tr>
</tbody>
</table>

Note: AIAN = American Indian and Alaska Native; AOIC = alone or in combination (with another race)
<table>
<thead>
<tr>
<th>Conceptual basis</th>
<th>Variations</th>
<th>Code</th>
<th>Socioeconomic characteristics of people</th>
<th>Characteristics of employers</th>
<th>When the measure is most relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tribal service areas (in vicinity of GL)</td>
<td>GS</td>
<td>Population</td>
<td>Ranges from about 1 million (for AIAN), to 2 million for AIAN-AOIC, to about 5 million for everyone living in the area</td>
<td>are outside the tribal area.</td>
<td></td>
</tr>
<tr>
<td>Census-based tribal statistical areas</td>
<td>GC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment in tribal statistical areas</td>
<td>PW</td>
<td></td>
<td>Mostly AIAN-AOIC; less than populations for GS or GC</td>
<td></td>
<td>Many are likely to be Native.</td>
</tr>
<tr>
<td>Population (anywhere in the world)</td>
<td>Tribal membership roles</td>
<td>PT</td>
<td>Expected to be similar to PA</td>
<td>Expected to be similar to PA</td>
<td>Very few are Native.</td>
</tr>
<tr>
<td></td>
<td>Self-identified AIAN—alone</td>
<td>PA</td>
<td>About 3 million; most not in tribal area</td>
<td>Lower than national average but higher than GL, GS, and GC</td>
<td>Comparing the experience of Native Americans with that of other races in the United States</td>
</tr>
<tr>
<td></td>
<td>AIAN-AOIC</td>
<td>PC</td>
<td>About 5 million; vast majority outside tribal area</td>
<td>Lower than national average but higher than PA</td>
<td></td>
</tr>
<tr>
<td>Institutions (who owns them)</td>
<td>Tribal government enterprises</td>
<td>LT</td>
<td>Population of employees depends on which organizations are recognized. Many employees may not be Native.</td>
<td>Data do not exist on the economic well-being of the employees of these institutions. It is likely that they are similar to national averages.</td>
<td>Assessing the fiscal viability of tribes</td>
</tr>
<tr>
<td></td>
<td>Native-run business or nonprofit</td>
<td>LM</td>
<td></td>
<td>These employers are Native, by definition.</td>
<td>Native-run businesses are the subject of analysis.</td>
</tr>
</tbody>
</table>

Note: AIAN = American Indian and Alaska Native; AOIC = alone or in combination (with another race)
Geographic approaches to measuring Indian Country

The first three of the four domains under the geographic conceptual basis (see table 2) reflect the geographic areas in which households reside. The first domain listed is defined as the tribal area designated as legal, tribal land (although there are finer categories within this designation). The second domain is generally an expansion of the first, to include a wider geographic area in which households may be located and receive services from the tribe (thus the name “tribal service area”). A similar geographic area is what the U.S. Census Bureau has defined, in consultation with the tribes, as a tribal statistical area. These areas are particularly important in terms of data availability, because the households living in them are the ones for which the U.S. Census Bureau collects and maintains data.

Using the data collected through the ACS, the U.S. Census Bureau has developed an elaborate database—the aforementioned “My Tribal Area” database—that provides socioeconomic data on each tribal area.10 Tribal areas in the database are rigorously defined, especially geographically, which makes them comparable (although not identical) to those conforming to the legal definition provided previously. Still another geographically based definition of Indian Country involves the “service area” of tribes.

Already mentioned briefly, the service areas of tribes, and the service populations that reside in those areas, have historically been defined in a periodic report to Congress titled the American Indian Population and Labor Force Report, also known as the “Labor Force Report” (LFR).11 The most recently published LFR provided the following background information:

Information has been collected since 1982 on the population and employment conditions of American Indians and Alaska Natives in federally recognized tribes. This information has been published in the American Indian Population and Labor Force Report. Since 1992, the collection and reporting of this information has been performed pursuant to Public Law 102-477—the Indian Employment, Training, and Related Services Demonstration Act of 1992, as amended. 25 U.S.C. § 3416(a). The Act provides for: [A] report on the population, by gender, eligible for the services which the Secretary provides to Indian people. The report shall include, but is not limited to, information at the national level by State, Bureau of Indian Affairs Service Area, and tribal level for the—(1) total service population; (2) the service population under age 16 and over 64; (3) the population available for work, including those not considered to be actively seeking work; (4) the employed population, including those employed with annual earnings below the poverty line; and (5) the numbers employed in private sector positions and in public sector positions.12

As just stated, Congress required information on the service populations of BIA geographic service areas that is consistent with U.S. Department of the Interior programs designed to provide services to tribal members living in those areas. The LFR defined the term “service population” as follows:
The tribe’s estimate of all American Indians and Alaska Natives who are living on or near the tribe’s reservation (or tribal area) during the 2010 calendar year and who are eligible to receive services funded by Indian Affairs. This definition is consistent with previous American Indian Population and Labor Force Reports. The service population of a tribe is not the same as the members (or “enrollment”) of the tribe. For example, members of one federally recognized tribe, whose tribal area is not nearby, may be living nearby the tribal area of another federally recognized tribe and they may be eligible to receive services from that nearby tribe. In this case they will be recognized as belonging to the service population of the nearby tribe.\textsuperscript{13}

It is important to note that, originally (in 1992), 25 U.S.C. § 3416 (section 17) required the Secretary of the U.S. Department of the Interior to develop and publish the LFR “in consultation with the Secretary of Labor.”\textsuperscript{14} This requirement was changed by amendment on April 6, 2017, and the LFR now must be prepared by the Secretary of Labor “in consultation with the Secretary, Indian tribes, and the Director of the Bureau of the Census.”\textsuperscript{15}

Although the service-area population measure of Indian Country was mandated as the measure to be used in the LFR—and despite its intuitive appeal as a “practical measure”—in practice its use was fraught with difficulties. Among these was the obvious problem of where to draw the line in the continuum of distance implied by “nearby” in the definition of service area. For instance, suppose “nearby” is first defined as one’s residence being within a 1-hour drive from a geographical tribal area, although this definition is difficult to apply in practice. If that definition is then revised by increasing the driving time to, say, 2 hours, the measured service-area population of a tribe may more than double.

Another problem is that, even if narrowly defined, the service areas of nearby tribes will often overlap. This possibility implies that, to avoid population double counting, other information about tribal membership would be needed. However, as indicated in the definition of service population, if two tribes are near each other, a member of one tribe may still receive services from the other tribe. This implies that the only way one might accurately estimate the service population of each tribe is neither by geography nor by membership; rather, it is by the observed receipt of services. Because such estimation requires detailed data that are not readily available, the best an analyst of Indian Country might be able to accomplish is to develop socioeconomic statistics for groups of tribes in the same geographic areas, rather than for individual tribes, especially if the tribes are close together or share the same area.

For these and other reasons, measuring service populations in Indian Country appears to be conducted only for the LFR. The populations in the U.S. Census Bureau’s tribal areas could be regarded as lower bounds on such service-area populations, because any tribal members living in those areas are most certainly within the bounds of the service area.

The fourth domain under the geographic conceptual basis in table 2 involves establishments physically located in tribal statistical areas. The relevant population associated with this domain consists of the employees of these establishments and the households to which these employees belong. Establishments in tribal statistical areas need not be Native-owned, but they are much more likely to be Native-owned than establishments outside tribal statistical areas. Likewise, the employees who work for an establishment in a tribal statistical area need not be residents of that area, nor do they need to be Native,
although they are much more likely to be Native than employees of establishments outside the tribal statistical area.

Generally, an asymmetry exists between employment inside and outside tribal areas. It is much more common for someone who lives inside a tribal area to work outside the tribal area (e.g., in a “border town”) than it is for someone who lives outside a tribal area to work inside the tribal area. For this reason, the population of households living in a tribal statistical area is likely to have a rate of employment that is much higher than that which would be obtained by measuring how many people are employed by establishments that are physically located in the tribal area. As a simple example, suppose that 1,000 tribal members live in a tribal statistical area, are in the labor force, and are the only labor force participants living in the area. However, suppose further that there are only 500 full-time employment opportunities available in the tribal area, all filled by tribal members. Under this situation, a household survey would be unlikely to yield an unemployment rate of 50 percent for the tribe. This is because some tribal members of the original 1,000 may be fully employed in a border town right outside the tribal area. If the number of these members is, say, 450 (for a total of 950 working tribal members), a household survey would yield an unemployment rate of 5 percent for households living in the tribal area. As the use of telework increases, it will become more common for workers who live in tribal areas to work for organizations that are physically located (in terms of their headquarters) outside those areas.

For this reason, surveys collecting employment information from establishments (sometimes called “tribal enterprises”) located inside tribal areas may tell us little about the employment of tribal members who live in those areas. Because many people can live in a tribal area and work right outside of it, the best way for an analyst to acquire information about employment status is to ask individuals known to live in the area whether they are working (wherever that may be). Furthermore, because many of the worst cases of poverty and unemployment among Native Americans in the United States exist within geographical tribal areas, it is this domain that is arguably the most relevant to the study of poverty alleviation. Another important consideration in this type of analysis is that many people—and, in some cases, most people—who live in a tribal area are not AIAN or AIAN-AOIC.

**Indian Country based on population surveys**

The next conceptual basis for defining Indian Country is the population basis, which identifies people as either enrolled tribal members or individuals who self-identify (in a U.S. Census Bureau survey) as AIAN or AIAN-AOIC. On the one hand, focusing only on AIAN or AIAN-AOIC individuals who live in tribal areas would have the advantage of homing in on the most severe cases (on average) of poverty among Native Americans. On the other hand, such a focus may underestimate, in a variety of ways, the economic opportunities offered to Native Americans. For example, in partly meeting its trust responsibilities, the federal government may offer educational grants to tribal youth, enabling them to acquire selective secondary and tertiary education that is offered outside the tribal area where the youth originated. Other tribal members who originally lived in a tribal area may similarly follow employment opportunities elsewhere, including those with the federal government (such as enrolling in the military, in which Native Americans are overrepresented in proportion to their population). The economic circumstances of individuals who remain in the tribal area may then reflect a biased sample of the actual economic circumstances faced by an earlier generation. Here, again, there is an analytical ambiguity associated with alternative definitions of Indian Country.
As an example, suppose a tribe initially has 1,000 individuals in the labor force, all living in the tribal area, of which only 900 are employed. These figures suggest that the tribe has 100 unemployed people, and its unemployment rate is 10 percent. Now, suppose that 50 of those 100 unemployed people move out of the tribal area, becoming residents in a new location, where they also get a job over the next year, while 50 new, young, unemployed people enter the labor force in the tribal area by simply becoming old enough to work. If we define the analytical domain in terms of the tribal members living in the tribal area at any point in time, we would conclude that the tribe has always experienced an unemployment rate of 10 percent (with 100 out of 1,000 people always out of work). On the other hand, if we restrict the domain to the original cohort of 1,000 people in the labor force, we would find that as many as 950 individuals were able to find jobs, which would imply that the unemployment rate of the original tribal cohort is 5 percent rather than 10 percent. It could be argued that this latter analytical approach is more informative for understanding the economic prospects of tribal members, because it holds the original domain constant. However, adopting this approach requires the ability to analyze what happens to AIAN-AOIC populations when they are not living in tribal areas. As indicated in table 2, a focus on self-identified AIAN-AOIC populations has the additional advantage of capturing the specific experiences of Native Americans and comparing them with the experiences of individuals of all races who also live in the tribal area.

One disadvantage of focusing on AIAN-AOIC populations regardless of geography, however, is that the geographic areas in which these populations live (especially tribal areas) may have special importance to some agencies. One such agency is the BIA, whose mission generally focuses on economic development and social assistance within tribal communities located on, or near, tribal land. The greater the focus is on geographically defined, Native communities, the more relevant it becomes for statistics on Indian Country to be based on geography rather than population.

It follows that there are both advantages and disadvantages to using geographically based or population-based domains in socioeconomic analyses of Indian Country. The task of the analyst is not to find the "perfect domain," which is never possible (and certainly not possible here), but to report accurately whatever he or she might conclude from the use of any particular domain. As indicated in table 2, geographically based domains are more relevant to policy issues involving poverty alleviation. Population-based domains, on the other hand, are more useful for comparing the experience of Native Americans in the United States with the experience of other ethnic and racial groups.

**Indian Country based on the ownership of organizations**

One other frequently used conceptual basis for defining Indian Country is that of institutional ownership. Here, the focus is on those institutions that are either tribal government enterprises or businesses and nonprofit organizations owned by a tribal member. As shown in table 2, using tribal government enterprises as the domain is most appropriate for assessing the fiscal viability of tribes. This is because tribes generally rely on the success of their government enterprises to raise revenue for tribal governments and for the provision of services by tribal governments to tribal members. For a variety of reasons, some of which may be obvious, tribes cannot rely on income taxes levied on their members for such funds. Some tribes with particularly profitable government enterprises, especially in the gaming and mining industries, generally translate this success into “per cap” distributions to their members, thereby increasing their community’s economic well-being, infrastructure and government services, and economic opportunities.
At the same time, however, too much should not be read into the progress (or lack thereof) of tribal enterprises in creating jobs for Native Americans. Most tribal enterprises may be seen as hiring primarily Native workers, but these enterprises are typically fairly small. The largest of these enterprises, especially in the gaming industry, hire mostly non-Native workers, so their success may not be as closely tied to the creation of jobs for AIAN-AOIC populations as might be thought by some analysts.

The same may also be said of Native-owned businesses. In many cases, these businesses do employ Native Americans, but in other cases, their owners may be the only Native Americans affiliated with the business. Nevertheless, the success of Native-owned businesses may warrant study in its own right, in two general respects. Although this success may have a limited connection to AIAN-AOIC employment in many cases, it speaks strongly to the economic development of Indian Country, where entrepreneurship may be key to the economic advancement of many tribal communities. Even when Native-owned businesses are not headquartered in tribal areas, their success is often tied to the economic well-being of AIAN-AOIC households, and successful Native business leaders may serve as role models to Native youth. Along similar lines, many successful Native-owned businesses have also been philanthropic toward tribal communities, creating networks that have supported new generations of Native entrepreneurs.

**Meeting standards of data quality**

Because accurate socioeconomic data on Indian Country are often scarce, some analysts tend to accept and use whatever data may become publicly available, paying little attention to the quality of those data. This problem can be especially pronounced when data from certain sources are not reliable. Such unreliable data may result from three major causes, or any combination of them:

1. The organization collecting the data may not possess the adequate level of expertise in survey and statistical methodology that would ensure the collection and processing of high-quality, reliable data.

2. The definitions or categories used in collecting the data are inconsistent with more established standards regarding such definitions or categories.

3. The surveyed entities, or the organization processing the data, may have a vested interest in the data having higher or lower values, depending on the variable.

The last of these possible causes may not necessarily reflect any deliberate deception on the part of the entities that provide or process the data. For example, in cases involving an estimation that can be arrived at through equally defensible, alternative methods, the method yielding the most favorable result might be employed without there being any deception. However, the chosen method may still cast a shadow over objectivity.

As an example of what can occur to prevent data quality problems, consider a 2010 Indian Affairs labor force survey of federally recognized tribes. Data from the survey were to be used in the production of the *American Indian Population and Labor Force Report*, which, as mentioned previously, was eventually submitted to Congress in January 2014. As also mentioned, one of the main statistics being sought by the survey—and which became a prominent feature of the report—was the *tribal service-area population* of individual tribes. This population measure was meant to estimate the number of tribal members both in the tribal area and in the vicinity of the tribal area (close enough for tribal members to receive services...
from the tribe). This measure was not meant to include entire tribal enrollments, which often counted people who lived far away from the tribal area (and in some cases even outside the United States). In response to the survey, many tribes provided what appeared to be reasonably accurate estimates of their service-area populations. Some other tribes, however, did not have such estimates readily available and simply reported their enrollment numbers as their service-area populations. (Because the survey also asked for enrollment numbers, this practice was easy to detect when both numbers were observed to be identical.) Some of the claimed service-area populations far exceeded the U.S. Census Bureau population estimates for all AIAN-AOIC populations in that broad geographic area. Given this inconsistency, the Office of Management and Budget advised the U.S. Department of the Interior to revise some of the tribal service-area estimates for the report on the basis of the U.S. Census Bureau data. This advice was then carried out in the production of the report, after consultations with tribes.

As providers of service-area data on Indian Country, the U.S. Census Bureau and BLS generally have certain advantages over other data providers (such as trade associations or individual tribal entities) in ensuring data quality. Among these advantages (which other organizations may possess as well) are having well-developed vetting and peer review of survey methodologies and statistical analyses and operating under mandates that ensure scientific objectivity. In this regard, Susan Offutt, former Chief Economist at the Government Accountability Office and Administrator of the U.S. Department of Agriculture Economic Research Service, has written the following about federal statistical agencies:

> Federal statistical agencies subscribe to guidelines that establish the primary importance of their work of policy relevance, credibility, trust, and independence. Now in its fourth edition, *Principles and Practices for a Federal Statistical Agency* (known as the “purple book”) is a product of the National Academies’ [of Science] Committee on National Statistics…. While intended explicitly for the 12 largest, or principal, statistical agencies, the logic of principles and practices applies to any unit of government that performs statistical analysis.

The Office of Management and Budget (OMB) coordinates the federal statistical system and promotes fidelity to the guidance in the purple book. In addition, OMB issues statistical policy directives that govern the release and dissemination of statistical products. These products include census and survey data, economic indicators, and analysis of these data. Published in 2008, Directive No. 4 is aimed at ensuring that “statistical data releases adhere to data quality standards through equitable, policy-neutral, transparent, and timely release of information to the general public.”

### Examples of cases in which federal statistics should be carefully examined

One example of how Indian Country statistics could be analyzed more carefully involves the methods employed in a U.S. Social Security Administration study titled “Measures of health and economic well-being among American Indians and Alaska Natives aged 62 or older in 2030.” In this study, which is based on data collected from the U.S. Census Bureau Survey of Income and Program Participation (SIPP), Amy Dunaway-Knight et al. present socioeconomic statistics, such as population and median per capita income, for a population they call the “AIAN population.” The authors explain that “individuals described as AIAN in our analysis are those who listed their race as ‘American Indian, Eskimo or Aleut’ in the SIPP.”
Attached to this explanation is the following endnote: “For the SIPP panels…respondents could select only a single race. However, readers should be aware that the AIAN population is heterogeneous and includes individuals with single- or multi-race ancestry.” The endnote basically describes the survey results as being limited by excluding those members of the AIAN-AOIC population who would consider themselves AIAN-AOIC if given the opportunity to provide this information in a survey response, but who would not self-identify in the single-race AIAN category. To the extent that this limitation may be seen as a sampling error (as implied by the endnote itself), it may also reflect a biased sampling error. That is, among all AIAN-AOIC individuals, those who self-identify as AIAN (as being of a single race) are more likely to live in a tribal area, more likely to be unemployed, and more likely to have lower income (as discussed earlier in this article in the context of Allard and Brundage’s findings). Overall, one might see the AIAN population sample from the SIPP as a hybrid between the AIAN (alone) population and the AIAN-AOIC population. More precisely, by asking respondents to select a single race, the SIPP is expected to capture all of the AIAN (alone) population and only some of the “in-combination” AIAN-AOIC population. This means that the socioeconomic statistics acquired from the SIPP data, described as “AIAN statistics,” might differ from the AIAN and AIAN-AOIC statistics that come from any other surveys (such as the ACS) that provide respondents with the option to report more than one race.

The results here will depend, arbitrarily, on the specific domain used in the analysis. This is precisely the type of problem that federal statistical standards are designed to avoid and that can create confusion regarding the public’s consumption of these statistics. For example, suppose that, because of the difference in sampling just described, the SIPP systematically yielded a higher AIAN median household income than the ACS. If some researchers or members of the media were then to compare the SIPP statistic in year $X$ with the ACS statistic in year $X + 10$, the change in median income would be much lower than if they were to compare the ACS statistic in year $X$ with the SIPP statistic in year $X + 10$. Of course, in theory, researchers should only perform time-series analyses on the same, unchanging statistical sources. Unfortunately, statistics on Indian Country are too rare for this ideal to be consistently upheld, making the consistency of the domain (across different data sources) essential for accurate comparisons of Indian Country over time.

Another example of how statistics from different sources can vary involves a marked difference between the employment estimates for tribal gaming enterprises provided in Allard and Brundage’s MLR article and those provided by an independent consulting group—Meister Economic Consulting, LLC. Meister Economic Consulting, which consists of eight team members led by Alan Meister, specializes in the Indian gaming industry and publishes an annual Indian Gaming Industry Report. It describes its organization as follows:

Meister Economic Consulting is an economic consulting firm that specializes in the application of economic research and analysis to litigation, regulatory, public policy, business development and operations, and economic development matters…. Despite the complexity of our work, we convey data, analyses, and results in straightforward, simplified terms so that they can be easily understood. For these reasons, we are routinely called upon to analyze complex issues and assist clients in high-stakes and controversial matters, and their work is widely accepted and well respected by governments, regulators, courts, the media, and the public.
Table 3 shows Allard and Brundage’s estimates, based on data from the Quarterly Census of Employment and Wages (QCEW), for employment in tribal establishments. According to these estimates, total employment in tribal establishments (for all employees, regardless of ethnicity) was about 334,500 in 2017, of which about 50 percent (168,000) was in the industry “casinos and casino hotels.” It should be noted that these estimates are neither official BLS estimates nor federal statistics in general; they are the reported findings in a research article and, thus, may be considered preliminary.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Establishments, fourth quarter 2017</th>
<th>Employment, December 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total (thousands)</td>
<td>Percent of total establishments</td>
</tr>
<tr>
<td>Total</td>
<td>2.3</td>
<td>100.0</td>
</tr>
<tr>
<td>Private industry</td>
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<td>Trade, transportation, and utilities</td>
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<td>10.1</td>
</tr>
<tr>
<td>Financial activities</td>
<td>0.1</td>
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</tr>
<tr>
<td>Professional and business services</td>
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<td>Education and health services</td>
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<tr>
<td>Casinos and casino hotels</td>
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<tr>
<td>Other private industry</td>
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<tr>
<td>Tribal government</td>
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</tr>
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</table>

Notes: Includes workers covered by unemployment insurance and Unemployment Compensation for Federal Employees programs. Tribal establishments are establishments owned and operated by American Indian tribes or Alaska Native villages. The "other private industry" category includes natural resources and mining, construction, manufacturing, information, and other services.


On a webpage discussing the effects of COVID-19, Meister Economic Consulting reports the following: “The one-month closure impacts directly at tribal casinos alone are estimated as follows:…296,000 people out of work.” This implies that employment in tribal casinos (and presumably casino hotels) is at least 296,000. (Here, the term “at least” is used because one might expect that a skeleton crew of guards would still be working to protect the facility.) This estimate of tribal casino employment in 2020 is 76.2 percent higher than Allard and Brundage’s estimate for 2017.

This difference in estimates cannot be explained easily by the 3-year difference in their timing, and it could be due, in part, to differences in how the estimates were derived, such as when, within the year, the
data were collected. Thus, instead of being actual, the difference may result from different estimation methodologies. However, as Allard and Brundage point out in their *MLR* article, there are several other possible reasons for the difference:

The QCEW data presented in this article should not be regarded as a complete count of establishments owned and operated by... Indian tribes.... First, not all establishments owned and operated by Indian tribes or Alaska Native entities are required to file Unemployment Insurance (UI) tax and may not appear in administrative UI records.... Second, [these] establishments....can be difficult to identify.... Also, an Indian tribe... may have jurisdiction over land in more than one state and may operate establishments outside of the state in which it is primarily located.... Third, the QCEW identifies....only those establishments that are owned and operated by federally recognized tribes; establishments owned and operated by state-recognized tribes... are not identified. Finally,... sometimes reporting establishments do not break out all of their individual worksites.... In this case, the record would be coded to the dominant industry.... and would not identify all... their correct industry codes.26

With regard to the limitations of the statistics reported in Allard and Brundage’s *MLR* article—in particular their reliance on entities with UI tax records—it is important to note that tribal casinos are not required to participate in federal unemployment compensation programs.27 Therefore, the employment levels shown in table 3—especially for Indian gaming—would tend to be lower for this reason alone, all else being equal. (During the 2020 recession caused by the COVID-19 pandemic, the eligibility of Indian casino workers for federal unemployment compensation of some kind may have been in flux.) For these reasons, the employment levels in table 3 may be regarded as lower bound estimates, whereas the Meister Economic Consulting employment estimate of 296,000 for tribal casinos should be seen as representing a more comprehensive account of all possible workers in Indian-run casinos (whether they can receive UI or not). As mentioned earlier, however, it is likely that most of the 296,000 laid-off employees in the Meister Economic Consulting estimate are not AIAN.

**Conclusion**

The choice of domain in performing any socioeconomic study of Indian Country requires careful thought. In addition, it often requires a reasoned balance between theoretical and practical considerations, because a domain that might be ideal from a theoretical perspective may not offer an adequate amount of data from which one can draw meaningful conclusions. In choosing a domain, and in interpreting research results, analysts must be especially careful not to assume relationships that do not truly exist, such as assuming a high correlation between, on the one hand, investment in Native-owned businesses that are located anywhere and, on the other, poverty alleviation in tribal areas. In this regard, Indian Country researchers must also be careful in drawing conclusions from previous studies without first investigating whether those studies exhibit this kind of error themselves. Although this article has focused on economic variables (especially employment), researchers in other fields have encountered the same issues with regard to health measures of Indian Country.28

Given the analytical challenges described in this article, even studies that have been peer reviewed and published by reputable institutions have not been completely immune to potential misinterpretations resulting from inconsistencies in the definition of Indian Country. Of course, it remains a widely accepted
principle that researchers should not have overconfidence in particular studies only because these studies have been published in peer-reviewed journals. Along these lines, federal agencies that generate and analyze socioeconomic statistics on Indian Country may wish to consider establishing an interagency working group to objectively and scientifically peer review those statistics and analyses.

Appendix: U.S. Census Bureau definitions of tribal areas

The U.S. Census Bureau defines tribal areas as follows:

- **American Indian reservations-federal (federal AIRs)** are areas that have been set aside by the United States for the use of tribes, the exterior boundaries of which are more particularly defined in the final tribal treaties, agreements, executive orders, federal statutes, secretarial orders, or judicial determinations. The Bureau of Indian Affairs maintains a list of all federally recognized tribal governments and makes final determination of the inventory of federal AIRs. The Census Bureau recognizes federal reservations (and associated off-reservation trust lands) as territory over which American Indian tribes have primary governmental authority. American Indian reservations can be legally described as colonies, communities, Indian colonies, Indian communities, Indian rancherias, Indian reservations, Indian villages, pueblos, rancherias, ranches, reservations, reserves, settlements, or villages. The Census Bureau contacts representatives of American Indian tribal governments to identify the boundaries for federal reservations through its annual Boundary and Annexation Survey. Federal reservations may cross state and all other area boundaries.

- **American Indian reservations-state (state AIRs)** are reservations established by some state governments for tribes recognized by the state. A governor-appointed state liaison provides the names and boundaries for state-recognized American Indian reservations to the Census Bureau. State reservations must be defined within a single state but may cross county and other types of boundaries.

- **American Indian tribal subdivisions**, described as additions, administrative areas, areas, chapters, county districts, communities, districts, or segments, are legal administrative subdivisions of federally recognized American Indian reservations and off-reservation trust lands or are statistical subdivisions of Oklahoma tribal statistical areas (OTSAs). These entities are internal units of self-government or administration that serve social, cultural, and/or economic purposes for the American Indians on the reservations, off-reservation trust lands, or OTSAs. The Census Bureau obtains the boundary and name information for tribal subdivisions from tribal governments.

- **Alaska Native Regional Corporations (ANRCs)** are corporate entities organized to conduct both for-profit and nonprofit affairs of Alaska Natives pursuant to the Alaska Native Claims Settlement Act. ANRCs have legally defined boundaries that subdivide all of Alaska into twelve regions (except for the area within the Annette Island Reserve). The nonprofit officials of ANRCs review their legal boundary and may, in the absence of participation by the Alaska Native village official, act as proxy in the delineation of ANVSAs in their regions.

- **Alaska Native Village Statistical Areas (ANVSAs)** are statistical geographic entities representing permanent and/or seasonal residences of Alaska Natives who are members of, or receive governmental services from, the defining Alaska Native village (ANV). ANVSAs are intended to include only an area where Alaska Natives, especially members of the defining ANV, represent a substantial proportion of the population during at least one season of the year.
Off-reservation trust lands are areas for which the United States holds title in trust for the benefit of a tribe (tribal trust land) or for an individual American Indian (individual trust land). Trust lands can be alienated or encumbered only by the owner with the approval of the Secretary of the Interior or his/her authorized representative. Trust lands may be located on or off a reservation; however, the Census Bureau tabulates data only for off-reservation trust lands with the off-reservation trust lands always associated with a specific federally recognized reservation and/or tribal government. As for federally recognized reservations, the Census Bureau obtains the boundaries of off-reservation trust lands from American Indian tribal governments through its annual Boundary and Annexation Survey. The Census Bureau recognizes and tabulates data for reservations and off-reservation trust lands because American Indian tribes have primary governmental authority over these lands. The Census Bureau does not identify fee land (or land in fee simple status) or restricted fee lands as specific geographic areas.

Oklahoma Tribal Statistical Areas (OTSA) are statistical areas that were identified and delineated by the Census Bureau in consultation with federally recognized American Indian tribes based in Oklahoma. An OTSA is intended to represent the former American Indian reservation that existed in Indian and Oklahoma territories prior to Oklahoma statehood in 1907. OTSAs are intended to provide geographic entities comparable to the former Oklahoma reservations so that statistical data can be viewed over time. OTSAs were referred to as Tribal Jurisdiction Statistical Areas (TJSAs) in the 1990 Census data products.

State Designated Tribal Statistical Areas (SDTSA) are statistical geographic areas identified and delineated for state recognized tribes that are not federally recognized and do not have an American Indian reservation or off-reservation trust land. The Census Bureau works with a governor appointed state liaison to delineate statistical areas for state-recognized tribes. SDTSA do not cross state lines and are limited to the state in which the respective tribe is officially recognized. SDTSA provide state recognized tribes without reservations statistical data for a geographic area that encompasses a substantial concentration of tribal members. SDTSA were called State Designated American Indian Statistical Areas (SDAISA) for Census 2000.

Tribal Designated Statistical Areas (TDSA) are statistical geographic entities identified and delineated for the Census Bureau by federally recognized American Indian tribes that do not currently have an American Indian reservation and/or off-reservation trust land. A TDSA is intended to encompass a compact and contiguous area that contains a concentration of individuals who identify with the delineating federally recognized American Indian tribe. TDSAs are also intended to be comparable to American Indian reservations within the same state or region and provide a means for reporting statistical data for the area.

SUGGESTED CITATION:

Notes
See, for example, “Definition of Indian Country” (Environmental Protection Agency), https://www.epa.gov/pesticide-applicator-certification-indian-country/definition-indian-country.


“My Tribal Area” (U.S. Census Bureau), https://www.census.gov/tribal/.


Ibid.


“My Tribal Area” (U.S. Census Bureau), https://www.census.gov/tribal/.


Ibid., p. 12.

Ibid., pp. 6–7.


20 Ibid.

21 Ibid.

22 Allard and Brundage, “American Indians and Alaska Natives in the U.S. labor force”; and “Coronavirus impact on tribal gaming; as of April 21, 2020” (Mester Economic Consulting, 2020).

23 For more information about Meister Economic Consulting, see http://www.meistereconomics.com/.


25 “Coronavirus impact on tribal gaming; as of April 21, 2020” (Meister Economic Consulting, 2020).


29 See, for example, Steven Payson, “Cite this economics paper! It is time for the house of cards to fall down,” *Open Economics*, De Gruyter, vol. 2, no. 1, January 2019, pp. 1–18; and Sascha Schweitzer and Jan Brendel, “A burden of knowledge creation in academic research: evidence from publication data,” *Industry and Innovation*, vol. 28, no. 3, February 2020, pp. 283–306.

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COVID-19 causes a spike in spending on durable goods

Demetrio Scopelliti

During times of economic uncertainty, consumers typically postpone purchasing durable goods, such as kitchen appliances, motor vehicles, sports equipment, and furniture. In fact, at the onset of the coronavirus disease 2019 (COVID-19), household spending on durable goods contracted substantially. However, as time passed, spending on durable goods rose sharply. What caused this to happen?

In “Why has durable goods spending been so strong during the COVID-19 pandemic?,” authors Kristen Tauber and William Van Zandweghe (Economic Commentary, Federal Reserve Bank of Cleveland, July 2021) use an econometric model to support their assertion that increased spending on durable goods was caused by a shift in consumer demand from services to durable goods and by increased disposable income from fiscal stimulus. The authors indicate that these two conditions account for approximately half of the rise in durable goods spending in 2020.

Tauber and Zandweghe argue that the lockdown and social-distancing safeguards implemented by government, businesses, and consumers during COVID-19 caused a shift in consumer demand from services to durable goods. By spending more time at home, consumers reduced travel, cut back on eating at restaurants, and exercised at home instead of the gym. These actions may have led consumers to substitute services with durable goods by upgrading their kitchen appliances and electronics and purchasing sports equipment.

The authors indicate that unlike the gradual increase in disposable income typically seen after peaks in previous business cycles, disposable income during COVID-19 rose sharply and indirectly caused a boom in durable-goods spending as a result. The authors cite data from U.S. national accounts showing that disposable income increased by $1.18 trillion in 2020 and that about 81 percent of that increase, or $957 billion, resulted from fiscal stimulus. Tauber and Zandweghe show that increased consumer spending on motor vehicles, recreational goods, and furniture and appliances coincided with three rounds of fiscal stimulus that were paid out between April 2020 and April 2021.
The authors acknowledge that the change in consumer behavior brought on by COVID-19 will not be permanent as public health concerns subside and the economy reopens, enabling consumption to emulate a more traditional combination of spending on durable goods, nondurable goods, and services. Reducing fiscal stimulus will cause disposable income to return to its normal long-term trajectory, thus slowing consumer spending on durable goods.
Why do labor standards in global supply chains fail to improve?


In 2013, the collapse of the Rana Plaza garment factory in Bangladesh’s Dhaka District killed 1,134 workers. As global outcry over the incident condemned the harsh conditions faced by Bangladeshi workers, corporations began to reevaluate the private regulation of labor standards in their supply chains. In 2015, a segment of the comedy TV show Last Week Tonight with John Oliver exposed deficiencies in this type of regulation, eventually motivating Sarosh Kuruvilla’s new book, Private Regulation of Labor Standards in Global Supply Chains: Problems, Progress, and Prospects. In the book, Kuruvilla examines questions such as the following: How is private regulation of labor standards carried out? How effective is it? What can be done to improve labor conditions for workers in global supply chains? Using new quantitative and qualitative data, the author offers a thoughtful analysis of private regulation systems and presents a path forward for these systems.

Kuruvilla’s book takes the reader through every aspect of private regulation of labor standards. It starts by explaining how a private regulation system is implemented. Global buyers, who source their goods from privately owned suppliers, establish codes of conduct for labor standards that suppliers must implement. These codes of conduct cover areas such as wages, worker health and safety, and collective bargaining rights. The global buyers then perform audits to ensure that their suppliers adhere to the set rules. Suppliers often provide goods to multiple global buyers and thus must follow multiple codes of conduct. The main incentive for compliance with these codes is the threat that a global buyer would stop sourcing goods from a supplier if that supplier has many code violations. In addition, by incorporating themselves as benefit corporations or by seeking certifications as B Corps, global buyers attempt to show to the public that strict enforcement of labor standards is important to them. Kuruvilla tests and challenges certain assumptions of private regulation. Among these are the belief that the existing system of incentives will compel suppliers to comply with the codes of conduct imposed on them, and the belief that such compliance will improve labor outcomes.
Instead of revolving around one central argument, the book exposes various deficiencies of private regulation systems. The theory of behavioral invisibility, which posits that global buyers are not able to accurately measure supplier compliance, points to one such deficiency. Using data from a trusted company, Kuruvilla shows that audits of suppliers are often unreliable or falsified, finding that audits in certain countries are unreliable over 50 percent of the time. In one of the most compelling sections of the book, readers are presented with an analysis of the audit consulting industry in China. That case involves instances of audit coaches working with supplier factories to help them pass audits, even when working conditions at those factories do not meet established codes of conduct.

Kuruvilla also discusses the theories of practice multiplicity and causal complexity, which point to another problem with private regulation of labor standards—the ambiguity that exists in determining how to achieve effective labor outcomes. Because suppliers must adhere to different codes of conduct and because laws and cultures differ across countries (practice multiplicity), a cause-and-effect relationship that could inform a strategy for improving working conditions is difficult to determine (causal complexity). This section of the book also analyzes the variables that purportedly lead to greater supplier compliance with codes of conduct. This analysis finds that variables expected to increase compliance, such as audit scores and length of buyer–supplier relationships, do not predict how well a supplier complies with established rules. I think this finding is intriguing and partly explains why problems with labor standards persist and are not easily remedied.

To provide insight into how labor standards have changed over time, Kuruvilla examines developments in wages, freedom of association (FOA), and collective bargaining (CB). In most codes of conduct, global buyers require that suppliers pay their workers a livable wage. However, after observing considerable variation in wages (by country and industry) and in the way the term livable wage is defined, the author concludes that while wages in each country have risen over time and are consistently higher than the minimum wage, they fall short of what is considered a livable wage. This conclusion left me wondering whether the goal of a livable wage is achievable given the various ways in which the concept can be defined. Kuruvilla’s analysis of FOA and CB is more persuasive. The author asserts that FOA and CB are some of the most effective vehicles through which labor standards can be improved, but he finds that global buyers continue to source goods from suppliers in countries that do not support such vehicles. Additionally, the audits of global buyers fail to effectively seek out FOA and CB violations, preventing improvements to labor practices.

Kuruvilla suggests that one way to improve labor outcomes is to give more resources to global buyers’ compliance departments, which tend to be underfunded. These departments also face the problem of being kept separate from sourcing departments and of having little influence on sourcing decisions. Kuruvilla proposes that, by integrating these organizational structures, global buyers can better align their sourcing and compliance practices. The author also suggests a range of other approaches for improving outcomes, including the creation of predictive models for compliance (a data-driven approach), increased process transparency (necessitated by behavioral invisibility, practice multiplicity, and causal complexity), and large structural changes. In my view, it has become apparent that it will take more than the work of individual actors to achieve better labor outcomes, and the entire industry will have to shift its current practices. I am skeptical that these changes are possible, especially without proper incentives for global buyers.
Private Regulation of Labor Standards in Global Supply Chains is an important read that reveals the need for change in private regulation of labor standards. The data used by Kuruvilla draw a sobering picture of just how deep these problems go, and how little has been done to remedy them. However, the insightful analysis provided in the book shows that private regulation systems can be improved. The book is well written and will appeal to audiences ranging from policymakers to inquisitive laypeople. After reading it, readers may consider their own purchasing practices and whether they should pay more attention to the origins of their goods. Hopefully, Kuruvilla’s book will motivate further research into private regulation of labor standards in global supply chains, as there is still much to be added to this topic.

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ABOUT THE REVIEWER

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Assessing Consumer Expenditure Surveys data quality through the lens of data use

This article describes the uses of BLS Consumer Expenditure Surveys (CE) data at the federal level, discusses the CE program’s approach to assessing data quality, and reviews the data’s fitness for use from the perspective of the data users.

The Consumer Expenditure Surveys (CE) program of the U.S. Bureau of Labor Statistics (BLS) sponsors nationwide household weekly diary and monthly interview surveys each year for the purpose of producing nationally representative estimates of expenditures, income, and demographics. The surveys’ main objective is to measure the spending patterns of consumers living in the United States. The surveys are the only federal government data collection efforts that provide information on the complete range of consumers’ expenditures, as well as their income and demographic characteristics. Similar to other large scale federal survey programs, the BLS CE program aggregates the survey data for a primary purpose, which is to provide estimates critical to the Consumer Price Index (CPI), a Principal Federal Economic Indicator.

BLS also uses the CE data to report on the economic well-being of consumers in the United States. In particular, BLS produces a regular series of economic analyses based on CE data. In addition, many other federal agencies rely on CE data, with each individual use increasing both the value of the time that respondents give in answering questions from field interviewers and the return on investment to U.S. taxpayers. Individual organizations also have their own unique set of objectives for data use, sometimes with distinct considerations regarding data quality. In particular, factors such as response rates, measurement error, aggregation, data level, and timeliness differ in importance for each data-user constituent according to their analytic objectives.

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Daniel Dorfman
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This article summarizes the various uses of BLS expenditure data at the federal level, discusses the CE program’s approach to defining and assessing data quality, and reviews fitness for use from the data-user perspective.

One survey with many uses

Although one of the primary purposes of CE data is to update the relative importance of goods and services in the CPI market basket (in addition to other uses within BLS), CE data are also used by many other federal government, nonprofit, and private-sector organizations, as well as individual users, such as policy analysts and other researchers. Government and private agencies use the data to assess spending patterns for specific groups of people, such as those over age 65 or part of low-income households, as well as to make decisions about issues affecting these groups. Policymakers use CE data to gauge the impact of policy changes on different socioeconomic groups. Academic researchers use CE data to assess the spending behavior of different types of families across various products (including newly introduced goods and services) and to examine people’s gift-giving behavior. Market researchers use CE data to analyze consumers and businesses and their interest in various goods and services.2

In this article, we focus on the use of CE data by eight federal government departments or agencies: BLS, the Census Bureau, the U.S. Department of Agriculture, the U.S. Department of Defense, the U.S. Department of State, the U.S. Department of Health and Human Services, the U.S. Bureau of Economic Analysis, and the Internal Revenue Service. (See table 1.) The descriptions of CE data uses that follow are based on discussions with agency subject-matter experts and on documentation presented in department and agency materials, including official reports, methodology papers, and websites.

Table 1. Use of Consumer Expenditure Surveys data by department or agency, topic, and format

<table>
<thead>
<tr>
<th>Department or agency</th>
<th>Topic</th>
<th>Format</th>
<th>Use and frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. Department of Agriculture</td>
<td>Children</td>
<td>Published tables</td>
<td>Determine the cost of raising a child (periodic)</td>
</tr>
<tr>
<td>U.S. Bureau of Economic Analysis</td>
<td>Housing</td>
<td>Custom tables</td>
<td>Input for several key components of BEA’s economic statistics, including the national income and product accounts, the input–output accounts, the travel and tourism satellite accounts, and the new outdoor recreation satellite account (annual)</td>
</tr>
<tr>
<td>U.S. Bureau of Labor Statistics (BLS)</td>
<td>Consumer Price Index</td>
<td>Internal microdata</td>
<td>Estimate lower level spending weights for the Chained Consumer Price Index for All Urban Consumers (C-CPI-U, monthly), the CPI-U, and the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W, annualized from biennial data), as well as spending weights for lower-level index calculations. Select item sampling probabilities (annual). Derive outlet sample frame and selection probabilities for the CPI Commodities and Services Survey (semiannual)</td>
</tr>
<tr>
<td>U.S. Census Bureau</td>
<td>Construction</td>
<td>Unprocessed microdata</td>
<td>Estimate residential construction spending (monthly)</td>
</tr>
<tr>
<td>U.S. Census Bureau</td>
<td>Poverty</td>
<td>Custom tables</td>
<td>Use BLS-produced thresholds to produce estimates of poverty based on the Supplemental Poverty Measure methodology (annual)</td>
</tr>
<tr>
<td>U.S. Department of Defense</td>
<td>Military</td>
<td>Custom tables</td>
<td>Determine cost-of-living allowances for military personnel living off base (annual)</td>
</tr>
</tbody>
</table>

See footnotes at end of table.
The U.S. Bureau of Labor Statistics

The U.S. Bureau of Labor Statistics (BLS), an agency within the U.S. Department of Labor, is responsible for measuring labor market activity, working conditions, price changes and productivity in the U.S. economy. BLS serves as one of the principal agencies of the U.S. Federal Statistical System. The BLS CPI program is responsible for measuring the average change over time in the prices paid by urban consumers for a market basket of goods and services. The CPI is among the most widely used measures of inflation and serves as an indicator of the effectiveness of government efforts to control inflation through its fiscal and monetary policy. In addition, business executives, labor leaders, and other private individuals use the index as a guide in making economic decisions. The CPI is used to make cost-of-living adjustments to salaries and pensions paid to millions of American workers and retirees; it is also used to adjust the federal income tax structure to prevent inflation-induced increases in taxes and to adjust income eligibility levels for government programs and assistance.

The CPI program uses CE data to (1) calculate expenditure weights for CPI calculation, (2) determine item sampling probabilities, and (3) collect data on outlet point of purchase. The CPI program produces three official indexes: the Consumer Price Index for All Urban Consumers (CPI-U); the Chained Consumer Price Index for All Urban Consumers (C-CPI-U); and the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W). Numerous research indexes are also produced, including the Consumer Price Index for Americans 62 years of age and older (R-CPI-E). The CPI-U, which is often referred to as the “headline index,” measures the average monthly change in the price of goods and services paid by urban consumers living in the United States. The CPI-U is based on expenditures of urban wage earners and clerical workers; professional, managerial, and technical workers; the self-employed; short-term workers; and the unemployed, retirees, and others who are not in the labor force. The C-CPI-U is similar, except that it is designed to be a closer approximation to a cost-of-living index in that, in its final form, it accounts for any substitution that consumers make across item categories in response to changes in relative prices. Similarly, the CPI-W differs from the CPI-U in that it is based only on expenditures made by those in wage-earning or clerical occupations. The CPI-E is designed to represent the inflation experience of consumers aged 62 years and older currently living in the United States, with expenditure weights derived from the spending behavior of consumer units with reference to people aged 62 years or older.

Table 1. Use of Consumer Expenditure Surveys data by department or agency, topic, and format

<table>
<thead>
<tr>
<th>Department or agency</th>
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<th>Format</th>
<th>Use and frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. Department of Health and Human Services</td>
<td>Health</td>
<td>Custom tables</td>
<td>Estimate health expenditures for National Health Expenditure Accounts (annual)</td>
</tr>
<tr>
<td>Internal Revenue Service</td>
<td>Taxes</td>
<td>Custom tables</td>
<td>Calculate alternate sales tax standard deduction tables (annual)</td>
</tr>
<tr>
<td>U.S. Department of State</td>
<td>Foreign Service cost-of-living allowances</td>
<td>Published tables</td>
<td>Determine cost-of-living allowances for diplomats living overseas (annual)</td>
</tr>
</tbody>
</table>

Expenditure weights for CPI index calculation

The CPI uses CE data to update the expenditure weights across CPI products and processes. This includes (1) determining lower-level weights used to calculate basic-level indexes from underlying prices collected, (2) updating monthly weights for aggregating basic-level index components into the final estimate of the C-CPI-U, and (3) providing biennial weights for aggregating basic-level index components to calculate the CPI-U, the CPI-W, and the CPI-E.

- **Lower-level weights for basic indexes.** All CPI products are calculated in two stages. In the first stage, basic indexes are calculated for each of the 7,776 item-area combinations. For instance, a basic index is calculated for bananas in Boston as a weighted average of the change in the price of bananas at sampled stores across the Boston area. The weights for the first stage are usually derived from the sampling frame for the category in the area.\(^9\) Prior to 2018, the CE was only used to calculate lower-level weights for item categories whose outlet samples were derived from sources other than the Telephone Point of Purchase Survey (TPOPS).\(^10\) TPOPS data collection ended in September 2019 and the last TPOPS-sourced sample initiated in the commodities and services survey occurred in August 2020. The first CE-sourced sample initiation in the commodities and services survey began in August 2021. Beginning with this sample, CE data are used to estimate all of the lower-level weights in the basic-level indexes. The first CE-sourced sample initiation in the commodities and services survey began in August 2021. Beginning with this sample, CE data are used to estimate all of the lower-level weights in the basic-level indexes.

- **Monthly weights for C-CPI-U.** The C-CPI-U differs from the CPI-U in the formula and weights used to combine basic indexes. The formula used in the C-CPI-U accounts for consumers’ ability to achieve the same standard of living from alternative sets of consumer goods and services.\(^11\) This formula requires consumer spending data that are not immediately available. Consequently, the C-CPI-U, unlike the other two official CPI data series, is published first in preliminary form and is subject to scheduled revisions using updated expenditure data.\(^12\) In publishing the final C-CPI-U, the CPI program uses monthly expenditure estimates from each elementary item-area combination to create aggregation weights. The monthly expenditure estimates for an item are summed across 32 areas to obtain a U.S. monthly item expenditure and then allocated across these areas according to each area’s relative expenditure share for the prior 12 months. The CE program delivers microdata on a quarterly basis for the monthly weights in the C-CPI-U.\(^13\)

- **Aggregation weights for published indexes.** In calculating the CPI-U, the CPI-W and the R-CPI-E, CE data are used to derive the reference period aggregation weights at the second stage of index calculation. Aggregate indexes are produced by averaging across two or more of the 7,776 CPI item-area combinations, such as the all-items index for New York, which is the average of its 243 basic indexes. The aggregation weights in the second stage assign each elementary index a relative importance to the aggregate index, corresponding to consumer expenditure choices (from the CE) among the 243 elementary items in the 32 elementary areas in the CPI sample for the reference period.\(^14\) Lastly, these weights are updated biennially and enable the CPI program to keep pace with relatively current spending patterns.

**Item-sampling probabilities**
The CPI's classification is composed of approximately 70 expenditure classes divided into 243 item strata. Each item strata consists of entry-level items (ELIs). These ELIs are the first-stage sampling units for consumer goods and services selected within each sample outlet. In other words, ELIs represent the items from which CPI data collectors sample within in each sampled outlet. CE data are used to probabilistically select which ELIs should be priced in each sample. Every year, the CPI program uses the most recent 2 years of CE data to select new item samples because of the changes in the consumer marketplace.15

**Commodities and services outlet sample frame**

Since 2019, the CE program has collected information on retail stores and service providers for CPI program production use for items purchased by consumers living in the United States. This step replaces the TPOPS, which suffered from rising costs, low response rates, and sample frame issues related to mobile phones. Collecting these data forms the basis for the CPI's commodities and services sample frame, which allows the CPI to then select the retail establishments consumers frequent most and monitor the prices of a sample of goods and services.

**Other federal departments and agencies**

**U.S. Department of Agriculture (USDA)**

The USDA is the federal executive department responsible for developing and executing federal laws related to farming, forestry, rural economic development, and food and nutrition programs (distribution, nutrition assistance and school lunch programs, etc.). The USDA Food and Nutrition Service uses CE data to produce its report *Expenditures on Children by Families*, which is also known as "The Cost of Raising a Child."16

**Expenditures on children.** The USDA, which has been tracking the cost of raising a child since 1960, uses CE data to examine child-related expenses by the age of a child or children, household income, budgetary component (e.g., housing, transportation, education, healthcare, clothing, food, etc.), and geographic region.17 This report fulfills the USDA's mission in supporting the financial health and well-being of American families. These estimates give families a greater awareness of the expenses they are likely to face while raising children, and they provide valuable information to people planning to start a family. In particular, this report provides insights regarding how child-rearing expenses can reflect economies of scale.18 Families may also use this information to identify financial-health resolutions by understanding the costs of feeding a child and plan for both anticipated and unexpected life events. Additionally, courts and state governments use these data to inform their decisions about child support guidelines and foster care payments. Lastly, financial planners may use this information to provide advice to their clients for family financial planning.19

**U.S. Bureau of Economic Analysis (BEA)**

BEA is the federal agency responsible for providing official macroeconomic and industry statistics. The cornerstone of BEA's statistics are the national income and product accounts (NIPAs), which feature estimates of gross domestic product (GDP) and related measures. In a letter to BLS management about the Consumer Expenditure Surveys, BEA Chief Economist Dennis J. Fixler wrote, "This important survey is our only data source for several key components of BEA's economic statistics." Fixler continued:
Information from the CE surveys is critical in preparing the national income and product accounts (NIPA’s), the input–output (I–O) accounts, the travel and tourism satellite accounts, and the new outdoor recreation satellite account. Also, beginning with the 2013 Benchmark Revision, BEA uses the CE Surveys’ data to estimate the diesel fuel portion of the personal consumption expenditure (PCE) gasoline and other motor fuel estimate. Data from the CE surveys is also used for comparison purposes [as they were] during the 2012 NIPA/Benchmark I–O reconciliation [when] these data were used as a check on final demand for personal consumption expenditures.20 [See table A-1.]

**U.S. Census Bureau**

The Census Bureau is the principal agency of the U.S. Federal Statistical System responsible for producing data about the American people and economy.21 The Census Bureau relies on CE data for the calculation of residential housing expenditures and the production of Supplemental Poverty Measure thresholds.

**Residential housing expenditures.** The Census Bureau uses CE data collected on homeowners’ alterations and repairs to produce the monthly Value of Construction Put in Place report, which is a principal federal economic indicator. This measure provides monthly estimates of the total dollar value of construction work done in the United States each month on new, private residential and nonresidential construction, public construction, and improvements to existing buildings and infrastructure. CE data are used as a source for estimating the monthly value in place data for residential improvements to owner-occupied housing units.22 In addition, regular revisions to the owner-occupied residential improvements estimates are benchmarked to the annual total using CE data.23

**Supplemental poverty measure (SPM).** The Census Bureau, in cooperation with BLS, produces the SPM.24 The SPM acts as an experimental poverty measure that defines thresholds and resources in a manner different from the official poverty measure. As a result, it is not used to determine eligibility for government programs, but instead is used to evaluate the impact of benefit programs on poverty. In determining the SPM, the CE serves as the source of the expenditure-based poverty thresholds. More specifically, the BLS Division of Price and Index Number Research (DPINR) is responsible for conducting research and producing the SPM thresholds that are based on CE data. The thresholds are experimental and thus not subject to the same review as official BLS projects. The thresholds are posted on the DPINR webpage and sent to the Census Bureau for use in producing experimental poverty estimates.25 Currently, SPM thresholds are based on 5 years of quarterly CE Interview Survey data on out-of-pocket expenditures for food, clothing, shelter, and utilities (FCSU), by consumer units with two children, with values converted to those for a reference unit composed of two adults and two children. A multiplier is applied to FCSU expenditures to account for other basic goods and services (e.g., household supplies, personal care, and nonwork-related transportation) in the thresholds. The Census Bureau applies equivalence scales to the BLS-produced reference-unit poverty thresholds to derive thresholds for consumer units with differing numbers of adults and children. The Census Bureau also adjusts the housing portion of the thresholds for geographic differences in the cost of housing.

**U.S. Department of Defense (DOD)**

The DOD is the federal executive department that coordinates and supervises all agencies and functions related to national security and the U.S. Armed Forces. The DOD uses CE data to calculate cost-of-living allowances for military personnel who live off base. The DOD uses CE Interview Survey data to calculate the Overseas Cost of
Living Allowance (OCOLA), the continental United States (CONUS) Cost of Living Allowance (COLA), and the spendable income table for military personnel.

The DOD regularly uses specially prepared data from BLS on expenditures by military families from the prior 3 years by family size and income bracket to develop the spendable income tables used in the CONUS weights. The OCOLA is a nontaxable allowance paid to U.S. military personnel stationed overseas to partially offset higher overseas prices on nonhousing goods and services. OCOLA helps maintain the purchasing power of overseas U.S. military personnel so they can purchase goods and services comparable to those of their CONUS-based counterparts. The DOD computes an OCOLA index by comparing the cost of a specific market basket of goods and services overseas to the cost of the same market basket of goods and services in the CONUS, on average. Holding all else constant, if market-basket costs rise in an overseas location compared with average CONUS costs, then the DOD will increase the COLA for service members stationed in that overseas location.

To compute the OCOLA Index, the DOD uses a CE Interview Survey data to construct a weighted system that places a greater significance on frequently purchased goods and services, such as car insurance, gasoline, and day care. The Armed Forces extract of the CE Interview Survey details how U.S. military families allocate their spendable income across all OCOLA types of goods and services. This extract is used to determine the market basket items and the appropriate weights for each item based on relative expenditures. The overseas weighted-average cost for each market basket item (determined by using location-specific data from the Living Pattern Survey and the Retail Price Schedule survey) is compared with the CONUS weighted-average cost for the same item to produce an index for each item.

CONUS COLA compensates for nonhousing expenses incurred in areas that exceed average costs in CONUS by more than 8 percent. By statute, the CONUS COLA index must be comparable to the Consumer Price Index. Therefore, the DOD derives a CONUS COLA index by using data on typical expenditures from the CE. OCOLA and CONUS COLA payments are based on the amount of average spendable income that is applicable for each regular military compensation level. Spendable income is determined using the expenditures by income level generated by the CE.

**U.S. Department of Health and Human Services (HHS)**

The HHS is the federal executive department whose mission “is to enhance the health and well-being of all Americans, by providing for effective health and human services and by fostering sound, sustained advances in the sciences underlying medicine, public health, and social services.” The Centers for Medicare & Medicaid Services (CMS), part of HHS, is responsible for publishing the National Health Expenditure Accounts (NHEA), which consists of national health expenditures (historical and projections), state health expenditures, and age and gender estimates. The NHEA provide official estimates of total healthcare spending in the United States by type of good or service delivered (hospital care, physician and clinical services, retail prescription drugs, etc.), as well as the source of funding for those services (private health insurance, Medicare, Medicaid, out-of-pocket spending, etc.) and the sponsors (businesses, households, and governments).

**Measure out-of-pocket healthcare expenditures.** The CMS uses CE data specifically to measure out-of-pocket spending for healthcare goods and services not covered by insurance. This includes the amount of coinsurance payments or deductibles required by private insurance plans, health savings accounts (HSAs), as well as public programs such as Medicare and Medicaid. The CMS uses CE data in conjunction with several other sources of
data (e.g., the Census Bureau’s Service Annual Survey, the Medical Expenditures Panel Survey, and the Medicare Current Beneficiary Survey) that serve as a baseline for comparing the accuracy of the CMS estimates of private health insurance spending and benefits.

In order to publish the NHEA, the CMS requires timely and detailed expenditure data. The CMS utilizes both annual aggregate summaries (using integrated Interview and Diary surveys) and microdata for various income, asset, and healthcare expenditure categories (including the number of policies). In particular, the CMS requires income and asset characteristics at the aggregate level to account for households with older members (who earn less income and hold more assets). The CMS also uses special tabulations of annual data by age prepared by BLS to produce estimates of individually purchased health insurance expenditures.

**Internal Revenue Service (IRS)**

The IRS is tasked with administering the Internal Revenue Code and collecting federal taxes. The IRS uses CE data to (1) calculate optional state and local sales tax deductions tables, and (2) determine typical household expenditures in investigating tax repayment issues.

**State and local sales tax tables.** The IRS uses CE data to develop optional state and local sales tax tables. These tables are based on the Internal Revenue Code, which provides taxpayers with an option to deduct state and local general sales tax instead of state and local income tax. This option is especially important to taxpayers residing in states with no income tax. Taxpayers can either deduct their actual sales tax amounts or estimate the deduction using these optional state and local sales tax tables. In addition, taxpayers can use the tables to deduct sales taxes paid on certain specified items, such as motor vehicles, aircraft, or boats. For this purpose, BLS produces special tabulations on the purchase of taxable items, which the IRS uses to prepare the optional state and local tax tables. The IRS publishes these tax tables in its annual publication, "Instructions for Schedule A." The IRS also provides an online sales tax deduction calculator, which taxpayers can use to estimate their general sales tax deduction.

In creating these tables, the IRS uses BLS-produced custom tabulations of integrated CE Interview and Diary surveys data to estimate state and local general sales tax amounts by family size and income bracket. The IRS provides both state and local taxability data at Universal Classification Code levels to BLS, which in turn uses these taxability files to estimate the average sales tax amounts along with household income, family size, and other variables by state and locality. Upon receiving these data, the IRS estimates state and local general sales tax amounts by family size and income bracket.

**Collection financial standards.** The IRS also uses typical consumer unit expenditures, as reported in the CE, when investigating tax repayment cases. Specifically, the IRS uses CE data to derive its Collection Financial Standards, which help to assess a taxpayer’s ability to pay a delinquent tax liability. These standards measure allowable living expenses for taxpayers regarding healthcare, food, clothing, housing, utilities, and transportation. Taxpayers may use the standard monthly amount, which is determined by family size. The IRS specifically derives the national standards on food, clothing, and other items, as well as local standards on transportation, from the CE data:
• **National standards: food, clothing, and other items.** The IRS breaks down the national standards into five categories of necessary expenses: food, housekeeping supplies, apparel and services, personal care products and services, and miscellaneous items. The IRS requires detailed data on aggregate expenditures by income level and family size to determine the national standards on food, clothing, and other items.  

• **Local standards: transportation.** The local transportation standards for taxpayers include vehicle ownership and public transportation by Census Region and Metropolitan Statistical Area (MSA). The IRS computes standards for vehicle ownership based on monthly loan or lease payments. The public transportation standards include a single nationwide allowance derived from CE expenditure data on mass transit fares for a train, bus, taxi, ferry, etc.
U.S. Department of State (DOS)

The DOS is the federal executive department responsible for carrying out U.S. foreign policy and conducting international relations. The State Department’s Office of Allowances uses data from the CE in determining spendable-income tables, a key measure for revising the post-allowance (COLA) payment tables. The post-allowance tables provide COLAs supporting the entire federal civilian overseas workforce. Post allowances make it possible for the federal civilian overseas workforce to spend the same portion of their basic compensation for living expenses in a foreign country (where they are “posted”) as they would if they lived in Washington, D.C. The post allowances enable employees to avoid a reduction in their standard of living because of higher costs of goods and services in the location where they are posted.

Cost-of-living adjustments for the federal civilian overseas workforce. Data from the CE Interview Survey are used to calculate the post allowance payment tables. The information in the tables represents a percentage increase over the cost of living in Washington, D.C., and it is applied to “spendable income”—that is, the amount of money that households have available for spending after deductions for taxes, gifts and contributions, savings (including insurance and retirement), and U.S. shelter and household utility expenses.

Unlike the DOD allowance, the DOS post allowance for the federal civilian overseas workforce is developed using a slightly different approach. Price data from overseas are collected and compared with those in the Washington, D.C., areas to determine if the federal overseas civilian workforce qualifies for a post (COLA) allowance. The State Department’s Office of Allowances develops a cost index to evaluate expenditure patterns between foreign locations and Washington D.C. The expenditure patterns (index weights) for Washington, D.C., are updated using data from the CE. The State Department compares costs in the foreign location for goods and services in 11 categories—food (whether purchased at grocery stores, restaurants, or other venues), tobacco and alcohol, clothing, personal care items, furnishings, household goods, medical services, recreation, public transportation, vehicle-related expenses, and household help—to the cost for those same goods and services in Washington, D.C. If the overall costs of goods and services at a foreign post—are at least 3 percent above the cost of the same goods and services in Washington, D.C., area, then the State Department establishes a post allowance for that location.

Approach to assessing data quality

In keeping with “Statistical Policy Directive No. 1: Fundamental Responsibilities of Federal Statistical Agencies and Recognized Statistical Units,” BLS is committed to producing data that consistently are of the highest statistical quality; in other words, the agency strives to produce data that are relevant, accurate, coherent, timely, accessible, and interpretable. Monitoring data quality in the CE includes procedures conducted by the Census Bureau during data collection and by BLS during data processing and analysis. “Fitness for use” is an important component of data quality; as such, the CE is also committed to helping data users assess the fitness for use of the CE data for their purposes. BLS has historically provided a variety of metrics for data users to evaluate the overall quality of its products. Official tables provide standard errors, the public-use microdata user documentation provides response rates, and the datasets contained in the public-use microdata provide all the variables and flags necessary for users to create their own quality measures.
The CE program defines data quality in a manner that allows for objective measurement, provides an assessment framework, and addresses the fitness-for-use concerns of individual program stakeholders. Based on the Total Quality Management and Total Survey Error paradigms, the definition includes six dimensions: relevance, accuracy, coherence, timeliness, accessibility, and interpretability.\(^{54}\) (See table 2.)

**Table 2. Data quality dimensions**

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relevance</td>
<td>The degree to which the survey products meets the user’s specific needs in terms of both content and coverage.</td>
</tr>
<tr>
<td>Accuracy</td>
<td>The degree to which the estimate is similar or dissimilar to the true value of the population parameter. This dimension gives consideration to survey errors stemming from coverage, sampling, nonresponse, construct validity, measurement, and post-collection processing and adjustments.</td>
</tr>
<tr>
<td>Coherence</td>
<td>The degree to which different sources or methods on the same phenomenon are similar.</td>
</tr>
<tr>
<td>Timeliness</td>
<td>The interval between the time data are made available to users and the event or the phenomena the data describe.</td>
</tr>
<tr>
<td>Accessibility</td>
<td>The ease with which statistical information and appropriate documentation describing that information can be obtained from the statistical organization.</td>
</tr>
<tr>
<td>Interpretability</td>
<td>The availability of adequate information to allow users to properly use and interpret the survey products.</td>
</tr>
</tbody>
</table>

Source: U.S Bureau of Labor Statistics

The CE program continuously evaluates these six dimensions of data quality, in part or in whole, through the assessment of internal indicators of data quality, external indicators of data quality, nonresponse bias study results, and measurement-error study results:

- **Internal indicators.** The CE program supports a systematic and integrated approach for monitoring and reporting on internal data quality indicators. Maintaining a consistent, well-defined set of metrics establishes baselines for monitoring trends in the quality of routine survey production activities over time. For external users, this set of metrics serves as an indication of data quality; for internal users, the metrics are actionable and provide a basis for survey improvements. Because the quality of survey estimates is affected by errors that occur anywhere in the survey cycle, it is expected that these internal metrics will evolve over time as the CE continually researches methods to monitor and improve data quality.\(^{55}\) As of 2019, eight internal indicators are being tracked: final disposition rates of eligible units; records use; expenditure edit rates; income imputation rates; respondent burden; information book use; survey mode; and survey time.\(^{56}\)

- **External indicators.** From an external-indicator standpoint, the CE program compares CE data with other data sources that measure the same or similar items. Although every household survey has its own unique set of errors, the monitoring of ratios between sources and any associated change over time can help identify potential underreporting or overreporting of expenditure items. The CE program routinely compares its results to various external sources, including the following: Personal Consumption Expenditures, the Residential Energy Consumption Survey, National Health Expenditure Accounts, the Medical Expenditure Panel Survey, the Current Population Survey, the American Community Survey, the Panel Study of Income Dynamics, the Survey of Consumer Finances, and the American Housing Survey.\(^{57}\)
• **Nonresponse bias.** Nonresponse bias is the systematic error that occurs when results collected from respondents differ in meaningful ways from those that would be collected, but by definition are not collectable, from nonrespondents.\(^{58}\) The Office of Management and Budget (OMB) encourages all federal survey programs to study their nonresponse bias, and OMB requires all federal surveys whose response rates are below 80 percent to conduct such a study.\(^{59}\) Both the CE Interview and Diary surveys have response rates below 80 percent and therefore are subject to the OMB requirement.\(^{60}\) The CE program assesses potential nonresponse bias through the continuous monitoring of response rates (both for collection and estimation rates) and with nonresponse-bias studies. The most recently completed nonresponse-bias study concluded that the data in both the CE Interview survey and Diary survey were not missing completely at random.\(^{61}\) This conclusion is similar to that of other studies, which also find the data are not missing completely at random. However, these other studies find that the amount of nonresponse bias is not substantial.\(^{62}\)

• **Measurement error.** Measurement error is the difference between the reported value of a variable of interest and the true value of that variable.\(^{63}\) Optimally, measurement error is 0 (i.e., the respondent reports the true value), but it is generally not directly observable in survey data, which, by definition, consist of reported values that may or may not be correct. Therefore, in addition to the external data comparisons mentioned previously, the CE program assesses measurement error through (1) comparisons with other administrative data sources,\(^{64}\) (2) comparisons to respondent expenditure records (e.g., bank statements, credit card statements, etc.), and (3) within-survey subgroup comparisons (such as respondents completing the survey in person or on the telephone or using the information booklet or not). As reported by Roger Tourangeau et al., measurement error evaluation results suggest that overestimation is just as common as underestimation in the CE, and that the degree and direction of measurement error varies considerably by expenditure category and respondent characteristics—therefore, analytic objectives play a large role in determining the data’s fitness for use.\(^{65}\)
Fitness for use

Although the regular revision of the CPI remains the primary purpose of the CE, other uses of CE data at the federal level have developed over time. As a result, the CE program continuously endeavors to understand each user’s unique preferences with respect to data quality, as well as the data’s fitness for use. This approach includes addressing concerns of other federal users regarding the six dimensions of data quality mentioned previously: relevance, accuracy, coherence, timeliness, accessibility, and interpretability. It also involves frequently evaluating the survey quality in terms of each federal data user and adjusting production processes as necessary. In recent years, the CE program has also begun an initiative to address specific data quality concerns through the annual release of a data quality profile and more accessible methods research results through an online research library.66

From the CE program perspective, select data quality factors that are critical to major data users include the following:

- **Cost of raising a child (USDA): relevance.** In estimating the cost of raising a child, detailed expenditures by consumer unit are critical to the U.S. Department of Agriculture’s work in estimating the cost of raising a child.

- **CPI (BLS): relevance, accuracy, and timeliness.** Although CE response rates have been declining in recent years, the downward trend does not appear to have affected CPI weights, and the weights for consumer units are quite robust in terms of declining response rates. However, ultimately, the CPI production schedule is highly dependent on receiving CE data on a timely basis.

- **Out-of-pocket healthcare expenditures (CMS): relevance, accuracy, and timeliness.** The Centers for Medicare and Medicaid Services is most concerned with underreporting of healthcare expenditures. Understanding the impact of policies such as the Affordable Care Act on out-of-pocket healthcare spending while also reconciling CE data with other data sources is a major concern of the CMS. Also, because the CMS produces annual estimates, it is imperative that data be available early in the year. The CE program began publishing midyear tables in 2013, and that has helped provide more timely and readily available data. Ultimately, the CE’s level of detail, timeliness, and continuous publication enable the CMS to fulfill its mission of producing national health expenditure estimates.

- **Residential Housing Expenditures (Census): timeliness.** Timely and continuous dissemination of CE data are critical to the Census Bureau’s work in estimating and revising key economic indicators.

- **Supplemental Poverty Measure (Census): coherence, timeliness, interpretability.** For the SPM, data sources that are consistent between threshold and resource definitions, in terms of poverty concepts, are essential. Therefore, priorities include data that are timely, provide simplicity in estimation, stability in the measure over time, and ease of explaining the methodology.

Overall, results from assessments of internal indicators, external indicators, nonresponse bias studies, and measurement error studies show that CE data are generally of high quality for their intended uses.67 However, concerns persist about the impact of declining response rates, measurement error, and a diminishing correspondence to national account aggregates.68 Using observable characteristics, CE samples are designed to
be representative of the population, although there is evidence of underrepresentation at the top of the income distribution as well as underreporting of income and expenditures.  

Conclusion

BLS collects, processes, and disseminates expenditures data for numerous stakeholders, each of whom maintains a particular set of preferences with respect to data quality factors related to their intended use of the estimates. Establishing a framework for continually assessing data quality and viewing results through the lens of fitness for use enables the Consumer Expenditure Surveys program to provide high-quality data. These data present an unbiased statistical picture of consumer expenditures—which are used for the Consumer Price Index, by various government agencies and by other data users—in an effort to improve understanding of consumer economic behavior.

Appendix. Uses of Consumer Expenditure Surveys data by the U.S. Bureau of Economic Analysis (BEA)

Table A-1. BEA use of Consumer Expenditure Surveys data

<table>
<thead>
<tr>
<th>Item</th>
<th>Use</th>
<th>Program area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>Cross-check and comparison with PCE-comparable items</td>
<td>NIPA</td>
</tr>
<tr>
<td>Vehicle renting and leasing</td>
<td>PCE auto and truck leasing; PCE other vehicle leasing</td>
<td>I–O, NIPA, TTSA</td>
</tr>
<tr>
<td>Travel (out-of-town trips)</td>
<td>Travel expenditures</td>
<td>TTSA</td>
</tr>
<tr>
<td>Babysitting or other child care in someone else’s home</td>
<td>PCE child care</td>
<td>NIPA</td>
</tr>
<tr>
<td>Day-care centers, nursery, and preschools</td>
<td>PCE nursery schools</td>
<td>NIPA</td>
</tr>
<tr>
<td>Taxicabs</td>
<td>Total receipts for taxicabs; PCE for taxicabs</td>
<td>I–O, NIPA, TTSA</td>
</tr>
<tr>
<td>All items</td>
<td>Cross-check and comparison with PCE-comparable items</td>
<td>NIPA</td>
</tr>
</tbody>
</table>

BEA use of various Consumer Price Indexes (CPIs) based on Consumer Expenditure Surveys data

| CPI for household fuels                        | PCE housing services for tenant-occupied nonfarm housing and gross housing output | NIPA |
| CPI for owners’ equivalent rent and residential rent | PCE housing services for owner- and tenant-occupied nonfarm housing and gross housing output | NIPA |
| CPI for housekeeping services                  | Real private household compensation                                        | NIPA |
| CPI for ship fare                              | Travel expenditures                                                        | TTSA |
| CPI for intercity train fare                   | Travel expenditures                                                        | TTSA |
| CPI for recreational equipment                 | Consumer expenditures                                                       | ORSA |
| CPI for travel (local trips)                   | Travel expenditures                                                        | ORSA |

Note: CPI = Consumer Price Index; I–O = Input–Output Accounts; NIPA = National Income and Product Accounts; PCE = Personal Consumption Expenditures; TTSA = Travel and Tourism Satellite Account; ORSA = Outdoor Recreation Satellite Account.


NOTES

1 “Sponsors” are federal or state agencies on behalf of whom the Census Bureau manages surveys. The funds for these surveys are appropriated to the sponsoring agency, and the work is conducted on a cost reimbursable basis under the auspices of an interagency agreement.


3 This article looks only at the secondary uses of the Consumer Expenditures Surveys (CE) data by BLS; the analyses and reports that BLS produces on the CE itself are outside the scope of the article.

4 This section discusses the ways that BLS uses the CE data to produce other BLS products and does not include the CE products and publications themselves, which are not discussed at length in this article.


9 Ibid., pp. 4, 18.

10 The Telephone Point of Purchase Survey (TPOPS), conducted by the U.S. Census Bureau, was formerly the source of data on where certain items were purchased by U.S. consumers. Suffering from low response rates and data quality concerns, TPOPS was replaced by the CE in 2018. For more information, see “Telephone Point of Purchase Survey (TPOPS)” (U.S. Census Bureau, last revised October 8, 2021), https://www.census.gov/programs-surveys/tpops.html.

11 The Chained CPI-U uses a superlative index formula designed to reflect consumers’ behavior in response to changes in relative prices. For more information, see “Chapter 17. The Consumer Price Index.”


13 Ibid., p. 32.

14 Ibid., p. 29.

15 Ibid., p. 12.

For access to all of the past reports, see “Expenditures on children by families reports—all years” (U.S. Department of Agriculture, Center for Nutrition Policy and Promotion, March 26, 2019), https://www.fns.usda.gov/resource/expenditures-children-families-reports-all-years.

Economies of scale are achieved when increasing inputs in production by $x$ percent increases average costs by less than $x$ percent. In the present context, consider “inputs” as members of a family, and “costs” as expenditures. A married couple renting a one-bedroom apartment does not spend twice as much for rent on that apartment as a single person would; similarly, their costs for food and other expenses may be less than twice what a single person would spend. If that couple is living in a larger house, and has a child, family size increases by 50 percent. But if there is already a bedroom in the house available for use of the child, the basic housing cost (i.e., rent or mortgage, taxes, and other similar ownership costs) does not change, let alone rise by 50 percent.


For more information, see “What we do” (U.S. Census Bureau, May 2021), https://www.census.gov/about/what.html#par_textimage.

See “Value of construction put in place” (U.S. Census Bureau), https://www.census.gov/econ/overview/co0300.html.


See “Overseas cost of living allowances (COLA) frequently asked questions.”


33 Ibid., p. 16.


38 Schedule A is the tax form on which filers claim deductions for various items, such as state and local income or sales taxes, property taxes, mortgage interest, charitable contributions, etc. For more information, see “2020 Instructions for Schedule A” (U.S. Department of the Treasury, Internal Revenue Service, January 2021), https://www.irs.gov/pub/irs-pdf/i1040sca.pdf.


40 A Universal Classification Code (UCC) is a special code used in the CE program to identify detailed expenditure items or categories. For example, UCC 010110 identifies flour; UCC 010120 identifies prepared flour mixes; UCC 010310 identifies rice; and UCC 020110 identifies white bread. Some items are grouped together in one UCC because sparse data prevent them from being grouped separately. In such cases, data users cannot identify expenditures on the separate items contained in the bundled UCC. See “Consumer Expenditure Surveys public use microdata getting started guide” (U.S. Bureau of Labor Statistics, last modified September 9, 2021), section 7.5, https://www.bls.gov/cex/pumd-getting-started-guide.htm#section7.


45 Ibid.

46 Post allowances, which refer to the place where a State Department employee is “posted” (or stationed) are equivalent to cost-of-living allowances.


48 Ibid.

49 “Office of Allowances: frequently asked questions—post (cost of living) allowance” (U.S. Department of State, effective October 11, 2020), https://aoprals.state.gov/content.asp?content_id=168&menu_id=75#06.


Ibid. See also “Consumer Expenditure Surveys: data quality in the Consumer Expenditure Surveys.”

The bias may result from differences in propensity to respond, as it relates to the outcome, or from differences related to characteristics related to both propensity to respond and the data collected. In the first case, a mail-in survey asking whether respondents agree or disagree with a statement would suffer from nonresponse bias if those who agree are more likely to mail in their surveys than those who disagree; in the second case, people with income above the median may be more or less likely to answer a survey on income than those with income below the median. Similarly, if the survey regards something correlated with income, such as expenditures, and those with income above the median are more or less likely to answer the survey than those with income below the median, nonresponse bias could result.


