Beyond BLS

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

September 2023

Shipping prices, import price inflation, and the COVID-19 pandemic

Summary written by: Douglas Himes

Just as everyone observed COVID-19's effects on other economic statistics, they also noticed the large price increases that occurred during and following the pandemic (2021). Prices of imports into the United States rose especially steeply over this period, increasing at rates not seen in decades, while the cost of international shipping by sea rose to levels almost 7 times higher than they had been before the start of the pandemic. These price increases were accompanied by delivery delays and congestion at ports the world over. Manufacturers and wholesalers reported shortages of parts and materials, and the term "supply chain" entered the lexicon of ordinary citizens. Many wondered, what effects do shipping costs have on import price inflation rates?

In "Shipping prices and import price inflation" (Federal Reserve Bank of St. Louis *Review*, second quarter 2023), authors Maggie Isaacson and Hannah Rubinton examine the relationship between shipping costs and import price inflation during the pandemic, specifically the extent to which increases in shipping costs were responsible for the rise in U.S. import price inflation. They use data from various sources, including import price data from the U.S. Bureau of Labor Statistics, to construct measures of the pass-through of shipping costs to import prices for different commodities at various times.

Isaacson and Rubinton find that modest, some might say small, amounts of shipping costs are passed through to import prices. They estimate approximately a 0.07-percentage-point increase in import price inflation for each 1.0-percent increase in shipping costs. However, because of the extreme rise in shipping costs during the pandemic, shipping costs accounted for between roughly 3.6 and 5.9 percentage points of the increase in import price inflation each year.

The amount of the pass-through varied among different types of commodities. More of the shipping costs were passed through to the purchaser for products more likely to be transported by sea and for those products that have a higher ratio of shipping costs to the price of the good (that is, relatively low-cost goods with high shipping costs). They also find more pass-through in imports of foods, machines, electronics, and parts. They suggest that perishable and intermediate goods are more likely to have higher pass-through values compared with final goods and consumer goods.

In addition, the authors find that in 2021, the pass-through was larger than in the period from 2010 to 2019, again with differing pass-through amounts for different types of goods. The authors also note that other factors, such as demand shocks, fiscal stimulus, and other supply shocks also affect the extreme rise in domestic prices. Thus, they conclude that the extreme increases in import prices observed during the pandemic can be partially, but not entirely, be attributed to the increased shipping costs during that time.

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September 2023

How hard is it to replace a minimum-wage job?

Summary written by: Nicholas A. Schaffer

The job market in the United States fluctuates greatly. Each month, millions of workers separate from their jobs. These job separations occur disproportionately among low-wage workers. A widespread view among economists is that the labor market for low-wage workers is nearly frictionless, meaning a worker earning near minimum wage should have little trouble finding an identical replacement position. But is this assumption true?

In studying job displacement, researchers have mostly explored its effect on tenured workers earning higher wages. Little research has been done on the effects of job displacement on workers earning near minimum wage, whose hourly pay cannot fall far. Instead of experiencing a large cut in hourly pay, these workers may experience reduced work hours and employment. Several factors may make finding a new job difficult for a worker earning near minimum wage. These factors include skill degradation while workers are unemployed, technologies that prioritize part-time availability, and job rationing, which arises when market wage is below the minimum wage.

In their paper, “How replaceable is a low-wage job?” (National Bureau of Economic Research, Working Paper 31447, July 2023), Evan K. Rose and Yotam Shem-Tov, using household surveys and administrative records, study the results of job loss for low-wage workers. Rose and Shem-Tov find that low-wage earners are more likely to experience long-term earnings losses and employment reductions.

The authors use household responses from the U.S. Census Bureau’s American Community Survey (ACS) and unemployment insurance earnings data from the U.S. Census Bureau’s Longitudinal Employer Household Dynamics (LEHD) program. The ACS collects information on employment status, usual hours, weeks worked, and earnings over the year. The LEHD program produces quarterly unemployment insurance earnings data collected from each state and the District of Columbia. These data cover 96 percent of private sector jobs and state and local government workers. Rose and Shem-Tov create their sample by linking ACS data on low-wage workers employed full time with LEHD program data on unemployment insurance.

The authors’ empirical strategy isolates changes in labor demand by using coworkers’ separation rates and then compares the changes in labor demand by using traditional methods for analyzing the effects of job loss. Their approach allows them to include workers of all tenures while still accounting for job separations. This empirical strategy shows that reduced work hours and employment contribute greatly to earnings loss for low-wage workers in the long term. Rose and Shem-Tov then analyze the effects of job loss on workers earning between $15 and $30 an hour. This analysis tests the effectiveness of their empirical strategy and allows them to compare the impacts of job loss on low-wage and higher wage workers. The authors then assess if the drivers of long-run job loss costs are different for each group.

Rose and Shem-Tov ultimately find that workers earning less than $15 an hour who experience job loss later face reduced employment, labor force participation, and earnings. So, why are earnings from low-wage jobs difficult to replace? Low-wage jobs are largely difficult to replace because workers cannot easily find full-time work again. Other frictions such as job rationing may also contribute to the difficulties of replacing a low-wage job. The authors suggest that determining the importance of these frictions is a topic for future research.

Article

September 2023

The NAICS 2022 update and its effect on BLS employment estimates in the retail trade sector

The 2022 update to the North American Industry Classification System (NAICS) had a large impact on the retail trade industry, resulting in substantial reclassifications within the industry sector. The U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) program uses NAICS to classify its published estimates of employment, hours, and earnings by detailed industry. Beginning with the release of the January 2023 data, the CES–National program implemented changes to reflect the update to NAICS 2022. This article examines how the update affected CES–National employment estimates in the retail trade sector and its component industries.

The retail trade sector plays an important role in the U.S. labor market, and its evolving landscape caught the attention of policymakers during their most recent review of the North American Industry Classification System (NAICS). NAICS is a standard industry classification system that classifies establishments into industry groups on the basis of their primary activity. NAICS is updated every 5 years to reflect emerging trends and changes in the economy, with the most recent update being NAICS 2022.[1]

According to the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES)–National program, which produces the payroll employment data in the closely watched monthly *Employment Situation* news release (commonly referred to in the media as the "monthly jobs report"), retail trade accounts for approximately 10 percent of total nonfarm employment.[2] The retail trade sector comprises establishments that sell merchandise in small quantities to the general public, such as food and beverage retailers, general merchandise retailers, and gasoline stations.[3]

With the rise of e-commerce over the past several decades, the retail trade landscape has shifted away from establishments offering products and services either in physical stores (store retailers) or through other channels (nonstore retailers) to establishments offering products and services through a wide variety of channels. For example, a single establishment classified as a general merchandise retailer may now sell merchandise both in physical stores and online. This shift in the economic activity of retailers raised concerns about the industry structure of retail trade under NAICS. During the most recent review and update, NAICS removed the distinction between store and nonstore retailers.[4]

The CES program uses NAICS in its published detailed industry estimates of employment, hours, and earnings, so updates to the NAICS structure can subsequently impact CES estimates. With the release of the January 2023 data on February 3, 2023, the CES–National program implemented publication changes and updated the national nonfarm payroll employment series to reflect the transition from NAICS 2017 to NAICS 2022.[5] This article discusses the retail trade structure under NAICS 2017, examines the effects the NAICS 2022 update had on the retail trade structure, and explains how the NAICS 2022 update affected retail trade employment.[6]

The structure of retail trade under NAICS 2017

NAICS uses industry codes to classify establishments by their primary economic activity. NAICS industry codes range from two to six digits, with the broadest industry classification occurring at the two-digit level, known as "sectors."[7] The NAICS codes for the retail trade sector are 44 and 45.

With each additional digit in the NAICS code, the classification becomes more detailed. The third digit represents the subsector; the fourth represents the industry group; the fifth represents the NAICS industry; and the sixth digit represents the national industry (i.e., the United States, Mexico, or Canada). Although the CES program bases its published industries on NAICS, the CES industries are not identical to the NAICS industries.[8]

This article refers to three-digit NAICS codes as "industries" and four- to six-digit NAICS codes as "components" (of those industries).

Under the NAICS 2017 structure, retail trade comprised 12 industries with three-digit NAICS codes. (See table 1.) The first 11 of those 12 industries included establishments engaged in retailing through physical stores and were grouped across broad product lines.

Table 1. Retail trade industries, NAICS 2017

NAICS 2017 CES industry title	NAICS 2017 code
Motor vehicle and parts dealers	441
Furniture and home furnishings stores	442
Electronics and appliance stores	443
Building material and garden supply stores	444
Food and beverage stores	445
Health and personal care stores	446
Gasoline stations	447
Clothing and clothing accessories stores	448
Sporting goods, hobby, book, and music stores	451
General merchandise stores	452
Miscellaneous store retailers	453
Nonstore retailers	454

Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

The 12th industry, nonstore retailers, aimed to capture all economic activity in retail trade occurring outside the in-person store setting. The industry included five components: electronic shopping and mail-order houses, vending machine operators, direct selling establishments, fuel dealers, and other direct selling establishments. (See table 2.)

Table 2. Components of nonstore retailers, NAICS 2017

NAICS 2017 CES industry title	NAICS 2017 code
Electronic shopping and mail-order houses	4541
Vending machine operators	4542
Direct selling establishments	4543
Fuel dealers	45431
Other direct selling establishments	45439

Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

The purpose of the electronic shopping and mail-order houses component was to capture retail activity made primarily through nonstore means, such as web retailers, catalogs, toll-free telephone numbers, television infomercials, and other mail-order houses or electronic media.[9] Vending machine operators included establishments primarily engaged in retailing merchandise through vending machines they service.[10] Direct selling establishments aimed to capture the remaining nonstore retail economic activity, including establishments that typically go to the customers' location, rather than the customer coming to them.[11] Within this component, fuel dealers comprised establishments engaged in retailing fuel through direct sales to consumers; examples include bottled gas dealers, coal dealers, and firewood dealers.[12] In addition, other direct selling establishments included those that retail merchandise (other than food for immediate consumption and fuel) through direct sales to customers. Examples include frozen food and freezer meal plan providers, party plan merchandisers, and coffee-break supplies providers.[13] Although the components of nonstore retailers varied in terms of their primary economic activity, the purpose of classifying establishments within the industry was to capture only nonstore retail activity.

Economic Classification Policy Committee review of NAICS 2017

During its review of NAICS 2017, the U.S. Office of Management and Budget (OMB) Economic Classification Policy Committee (ECPC), which is responsible for maintaining and reviewing NAICS, raised concerns about the growing prevalence of e-commerce and how the pervasive nature of electronic shopping created confusion in classifying certain industries.[14] As mentioned previously, an establishment classified within the general merchandise stores industry might offer products through channels other than its storefront, such as online ordering, either with home delivery, in-store pickup, or delivery to temporary storage lockers. Because the NAICS 2017 structure classified such establishments as store retailers within the broader category general merchandise stores, all sales were registered to the storefront. As in this case, the ECPC suggested that the NAICS 2017 industry structure did not always result in the retail trade industries accurately capturing the intended retail economic activity.

To reflect the many changes in retail trade over the past decade, the ECPC recommended eliminating the distinction between store and nonstore retailers and reclassifying the components of nonstore retailers.[15] Ultimately, the OMB accepted this proposal, and the NAICS 2022 structure removed the distinction between store and nonstore retailers in retail trade.[16]

In addition to eliminating the distinction between store and nonstore retailers, 4 three-digit NAICS 2017 industries combined into 2 new NAICS 2022 industries, reducing the number of three-digit industries within retail trade from 12 to 9.

CES structure of retail trade under NAICS 2022

Following the final decision from the OMB on the recommendations put forth by the ECPC, the CES–National program updated the national nonfarm payroll employment series from NAICS 2017 to NAICS 2022.[17] As displayed in table 3, the NAICS 2022 structure of retail trade contains several changes to CES industry titles and NAICS codes, combines several NAICS 2017 industries into new NAICS 2022 industries, and removes the distinction between store and nonstore retailers.

Table 3. Retail trade industries, NAICS 2017 and NAICS 2022

NAICS 2017 CES industry title	NAICS 2017 code	NAICS 2022 CES industry title	NAICS 2022 code
Motor vehicle and parts dealers	441	**Motor vehicle and parts dealers**	441
Furniture and home furnishings stores	442	**Building material and garden equipment and supplies dealers**	444
Electronics and appliance stores	443	**Food and beverage retailers**	445
Building material and garden supply stores	444	**Furniture, home furnishings, electronics, and appliance retailers**	449
Food and beverage stores	445	**General merchandise retailers**	455
Health and personal care stores	446	**Health and personal care retailers**	456
Gasoline stations	447	**Gasoline stations and fuel dealers**	457
Clothing and clothing accessories stores	448	**Clothing, clothing accessories, shoe, and jewelry retailers**	458
Sporting goods, hobby, book, and music stores	451	**Sporting goods, hobby, musical instrument, book, and miscellaneous retailers**	459
General merchandise stores	452	[1]	[1]
Miscellaneous store retailers	453	[1]	[1]
Nonstore retailers	454	[1]	[1]

[1] Not applicable.

Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.

Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

CES industry titles and NAICS codes updates

In addition to the update to NAICS 2022, the CES–National program also broadly updated its industry titles to align more closely with the corresponding NAICS industry titles.[18] Within retail trade, several industries received new titles. As shown in table 3, the update removed the distinction between store and nonstore retailers by referring to establishments as “retailers” instead of “stores.” For example, the NAICS 2017 industry title food and beverage stores was updated to food and beverage retailers. The only two industries that contain a reference to a “store” are department stores and gasoline stations with convenience stores. In these two industries, the use of the word “stores” more accurately reflects the industry’s economic activity. This update further reflects how the NAICS 2022 structure of retail trade classifies industries by broad category line, including both store and nonstore activities.

In addition, the broad content and scope changes within retail trade resulted in several NAICS code changes, with six of the nine NAICS 2022 industries in table 3 receiving new codes. The “Update to NAICS 2022” section of the CES–NAICS page provides further detail on the several ways the conversion from NAICS 2017 to NAICS 2022 affected the CES industry codes.[19]

Combining NAICS 2017 industries into NAICS 2022 industries

The NAICS 2022 update combined the NAICS 2017 industries furniture and home furnishing stores (NAICS code 442) and electronics and appliance stores (NAICS code 443) into the new NAICS 2022 industry furniture, home furnishings, electronics, and appliance retailers (NAICS code 449). In addition, the update combined sporting goods, hobby, book, and music stores (NAICS code 451) and miscellaneous store retailers (NAICS code 453) into the new NAICS 2022 industry sporting goods, hobby, musical instrument, book, and miscellaneous retailers (NAICS code 459). (See table 4.)

Table 4. NAICS 2017 industries combined into NAICS 2022 industries

NAICS 2017 CES industry title	NAICS 2017 code	NAICS 2022 CES industry title	NAICS 2022 code
Furniture and home furnishings stores	442	**Furniture, home furnishings, electronics, and appliance retailers**	449
Electronics and appliance stores	443		
Sporting goods, hobby, book, and music stores	451	**Sporting goods, hobby, musical instrument, book, and miscellaneous retailers**	459
Miscellaneous store retailers	453		

Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

Under the NAICS 2022 structure, most of the combined NAICS 2017 industries are still available under more detailed industry codes. (See table 5.) For example, the three-digit NAICS 2017 industry furniture and home furnishing stores (NAICS code 442) is available as a four-digit NAICS 2022 industry, with a new title and NAICS code: furniture and home furnishings retailers (NAICS code 4491). The three-digit NAICS 2017 industry electronics and appliance stores (NAICS code 443) is also available as a four-digit NAICS 2022 industry, with a new title and code: electronics and appliance retailers (NAICS code 4492).

Table 5. Components of furniture and home furnishing stores and furniture, home furnishings, electronics, and appliance retailers, NAICS 2017 and NAICS 2022

NAICS 2017 CES industry title	NAICS 2017 code	NAICS 2022 CES industry title	NAICS 2022 code
Furniture and home furnishings stores	442	Furniture, home furnishings, electronics, and appliance retailers	449
Furniture stores	4421	Furniture and home furnishings retailers	4491
Home furnishings stores	4422	Furniture retailers	44911
Floor covering stores	44221	Home furnishings retailers	44912
Other home furnishings stores	44229	Floor covering retailers	449121
Electronics and appliance stores	443	Window treatment and all other home furnishings retailers	449122,9
Household appliance stores	443141	Electronics and appliance retailers	4492
Electronics stores	443142	[1]	[1]

[1] Not applicable.
Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

Similarly, the three-digit industry sporting goods, hobby, book, and music stores (NAICS code 451) now exists at the four-digit level under the NAICS 2022 structure, with an updated title and NAICS code: sporting goods, hobby, and musical instrument retailers (NAICS code 4591). (See table 6.) With this update, the five-digit NAICS 2017 components still exist, but the industries received new titles and NAICS codes. For example, the NAICS 2017 component sporting goods stores (NAICS code 45111) is now sporting goods retailers (NAICS code 45911) under the NAICS 2022 structure.

Table 6. Sporting goods, hobby, musical instrument, book, and miscellaneous retailers, three-, four-, and five-digit NAICS codes, NAICS 2017 and NAICS 2022

NAICS 2017 CES industry title	NAICS 2017 code	NAICS 2022 CES industry title	NAICS 2022 code
Sporting goods, hobby, book, and music stores	451	Sporting goods, hobby, musical instrument, book, and miscellaneous retailers	459
Sporting goods and musical instrument stores	4511	Sporting goods, hobby, and musical instrument retailers	4591
Sporting goods stores	45111	Sporting goods retailers	45911
Hobby, toy, and game stores	45112	Hobby, toy, and game retailers	45912
Sewing, needlework, and piece goods stores	45113	Sewing, needlework, and piece goods retailers	45913
Musical instrument and supplies stores	45114	Musical instrument and supplies retailers	45914
Book stores and news dealers	4512	Book retailers and news dealers	4592
Miscellaneous store retailers	453	Florists	4593
Florists	4531	Office supplies, stationery, and gift retailers	4594
Office supplies, stationery, and gift stores	4532	Used merchandise retailers	4595
Used merchandise stores	4533	Other miscellaneous retailers	4599
Other miscellaneous store retailers	4539	[1]	[1]

[1] Not applicable.
Note: NAICS = North American Industry Classification System. CES = Current Employment Statistics.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

In some instances, the NAICS 2017 industry no longer exists under the NAICS 2022 structure. For example, the NAICS 2017 industry miscellaneous store retailers (NAICS code 453) does not exist under the NAICS 2022 structure. However, all four of its components exist under the new structure, with new titles and codes: florists (NAICS code 4593); office supplies, stationery, and gift retailers (NAICS code 4594); used merchandise retailers (NAICS code 4595); and other miscellaneous retailers (NAICS code 4599).

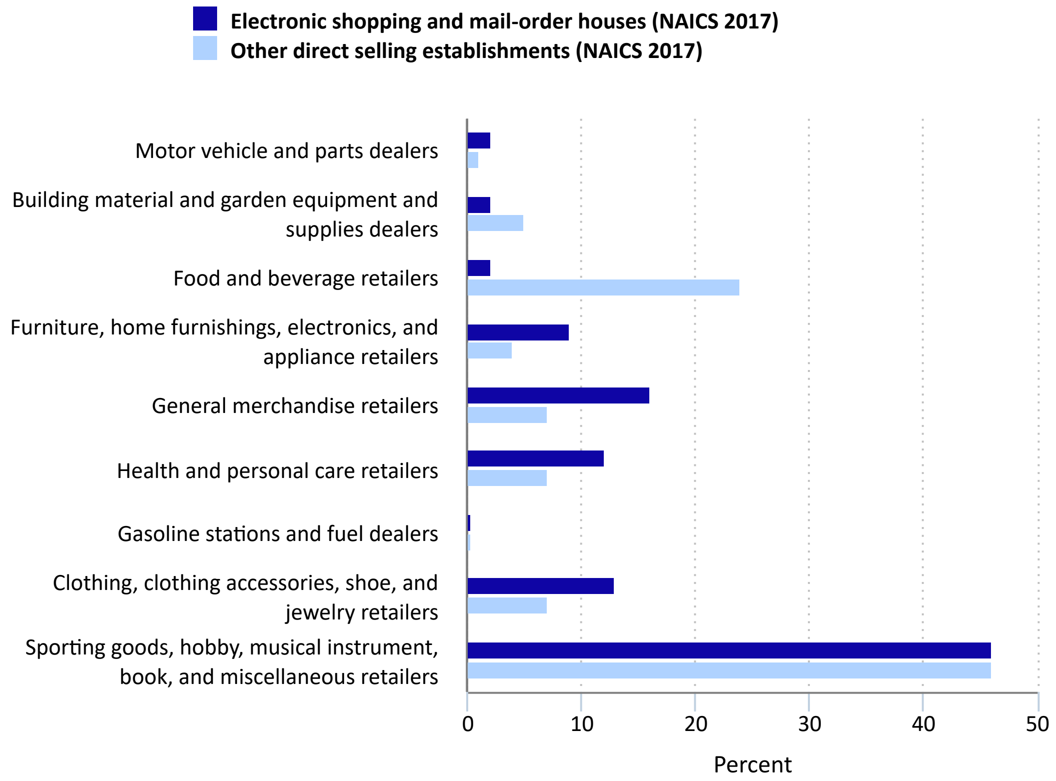
Eliminating nonstore retailers

To remove the distinction between store and nonstore retailers, the NAICS 2022 update removed the NAICS 2017 industry nonstore retailers, and the CES–National program reclassified the employment from its components within the appropriate NAICS 2022 industries.

During the conversion from NAICS 2017 to NAICS 2022, the CES–National program reclassified employment from electronic shopping and mail-order houses, vending machine operators, other direct selling establishments, and fuel dealers. As described in the 2022 benchmark article, about 15 percent of employment (68,000 jobs) in electronic shopping and mail-order houses (NAICS 2017 code 4541) moved into corporate, subsidiary, and regional managing offices (NAICS 2022 code 551114), which is part of the professional and business services sector.[20] The remaining employment from electronic shopping and mail-order houses and 100 percent of employment from the other three components were reclassified within retail trade.

Employment from two of the four components of nonstore retailers was reclassified broadly across retail trade; employment from electronic shopping and mail-order houses (NAICS code 4541) and from other direct selling establishments (NAICS code 45439) was reclassified within eight of the nine NAICS 2022 industries by broad product line. Chart 1 displays the ratio of employment reclassified from these two NAICS 2017 industries within NAICS 2022 retail trade industries. The ratios in chart 1 do not include the 15 percent of employment in electronic shopping and mail-order houses reclassified into the professional and business services sector. As outlined in an official BLS–CES notification, “industries that move directly and completely from a NAICS 2017 CES industry to a NAICS 2022 CES industry have a ratio of 100. NAICS 2017 CES industries that moved only a portion of their employment from the old NAICS 2017 CES industry to a new NAICS 2022 CES industry have ratios of less than 100.”[21]

Chart 1. Ratio of employment reclassified from NAICS 2017 industries into new NAICS 2022 retail trade industries



Click legend items to change data display. Hover over chart to view data.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

View Chart Data

Sporting goods, hobby, musical instrument, book, and miscellaneous retailers received the largest share of employment from the reclassification of electronic shopping and mail-order houses (46 percent). The remaining reclassified employment was widespread, led by general merchandise retailers (16 percent); clothing, clothing accessories, shoe, and jewelry retailers (13 percent); health and personal care retailers (12 percent); and furniture, home furnishings, electronics, and appliance retailers (9 percent).

Similarly, sporting goods, hobby, musical instrument, book, and miscellaneous retailers received the largest share of reclassified employment (46 percent) from other direct selling establishments. Food and beverage retailers also received a notable portion of employment (24 percent) from other direct selling establishments, with the remaining reclassified employment being widespread.

In contrast to electronic shopping and mail-order houses and other direct selling establishments, the other two components of nonstore retailers reclassified 100 percent of the component's employment into one three-digit NAICS 2022 industry. Employment from vending machine operators was reclassified completely within food and beverage retailers (NAICS code 445) at the six-digit level as vending machine operators (NAICS code 445132). In addition, employment from fuel dealers was reclassified completely within gasoline stations and fuel dealers (NAICS code 457) at the four-digit level as fuel dealers (NAICS code 4572). (See table 7.)

Table 7. Reclassified employment from vending machine operators and fuel dealers from NAICS 2017 industries to NAICS 2022 industries

NAICS 2017 industry	NAICS 2017 code	Reclassification to NAICS 2022 industry	NAICS 2022 code	Ratio (in percent)
Vending machine operators	4542	**Vending machine operators**	445132	100
Fuel dealers	45431	**Fuel dealers**	4572	100

Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics, Current Employment Statistics survey.

Total impact on CES employment in retail trade

Although the NAICS 2022 update notably affected the structure of retail trade, and the CES reclassifications changed the employment composition of the three-digit NAICS 2022 industries, the impact on employment at the two-digit level of retail trade was less prominent; all employment from nonstore retailers was reclassified within the retail trade sector, except for about 15 percent of electronic shopping and mail-order houses.

Conclusion

The NAICS 2022 update and the subsequent changes made by the CES–National program substantially affected the structure of the retail trade sector. These updates included several changes to retail trade NAICS codes and CES industry titles; a decrease of three-digit industries from 12 to 9; and the elimination of the distinction between store and nonstore retailers. As part of the NAICS 2022 conversion, the CES–National program reclassified employment to fit the NAICS 2022 classifications. Most of the employment from nonstore retailers was reclassified within retail trade, except for 68,000 jobs that were reclassified within the professional and business services sector. The new classifications within retail trade resulted in substantial employment reclassifications, affecting every three-digit industry. However, the impact at the sector level of retail trade was less salient.

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Notes

[1] For more information on the structure, review, and update process of the North American Industry Classification System (NAICS), see *North American Industry Classification System: United States, 2022* (U.S. Office of Management and Budget, 2022), https://www.census.gov/naics/reference_files_tools/2022_NAICS_Manual.pdf.

[2] Major industry sector data from the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey can be accessed at https://www.bls.gov/webapps/legacy/cesbtab1.htm. The latest edition of *The Employment Situation* news release can be found at https://www.bls.gov/news.release/empsit.htm.

[3] For a full description of the retail trade sector, see the 2022 NAICS definition in "North American Industry Classification System" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=44&year=2022&details=44.

[4] See "2017 North American Industry Classification System (NAICS)—Updates for 2022; Update of Statistical Policy Directive No. 8, Standard Industrial Classification of Establishments; and Elimination of Statistical Policy Directive No. 9, Standard Industrial Classification of Enterprises," *Federal Register*, vol. 85, no. 38, February 26, 2020, pp. 11120–11124, https://www.federalregister.gov/documents/2020/02/26/2020-03797/2017-north-american-industry-classification-system-naics-updates-for-2022-update-of-statistical.

[5] For information on the CES publication changes resulting from the NAICS 2022 update, see "Current Employment Statistics–CES (National): The North American Industry Classification System in the Current Employment Statistics Program" (U.S. Bureau of Labor Statistics, last modified February 3, 2023), https://www.bls.gov/ces/naics/naics-2022.htm.

[6] This article examines national data from the CES survey. For information on the effect that the NAICS 2022 update had on data from the CES–State and Metro Area program, see "State and Metro Area Employment, Hours, and Earnings: Update to the 2022 North American Industry Classification System on March 13, 2023" (U.S. Bureau of Labor Statistics, accessed August 28, 2023), https://www.bls.gov/sae/notices/2022/update-to-the-2022-north-american-industry-classification-system-on-march-13-2023.htm. For more information on NAICS 2017, see *North American Industry Classification System: United States, 2017* (U.S. Office of Management and Budget, 2017), https://www.census.gov/naics/reference_files_tools/2017_NAICS_Manual.pdf.

[7] For more information on the structure of NAICS codes, see the sector definitions in "Economic Census: NAICS Codes & Understanding Industry Classification Systems" (U.S. Census Bureau, last modified August 19, 2022), https://www.census.gov/programs-surveys/economic-census/year/2022/guidance/understanding-naics.html#par_textimage_1.

[8] For more information on how CES industry codes are derived from the NAICS codes, see "Current Employment Statistics–CES (National): Industry Classification Overview" (U.S. Bureau of Labor Statistics, last modified June 2, 2023), https://www.bls.gov/ces/naics/.

[9] For a detailed description of the 2017 NAICS definition of electronic shopping and mail-order houses, see the entry for the industry in "North American Industry Classification System: 2017 NAICS Definition" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=4541&year=2017&details=454110.

[10] For a detailed description of the 2017 NAICS definition of vending machine operators, see the entry for the industry in "North American Industry Classification System: 2017 NAICS Definition" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=4542&year=2017&details=454210.

[11] For a detailed description of the 2017 NAICS definition of direct selling establishments, see the entry for the industry in "North American Industry Classification System: 2017 NAICS Definition" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=4543&year=2017&details=4543.

[12] For a detailed description of the 2017 NAICS definition of fuel dealers, see the entry for the industry in "North American Industry Classification System: 2017 NAICS Definition" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=4543&year=2017&details=454310.

[13] For a detailed description of the 2017 NAICS definition of other direct selling establishments, see the entry for the industry in "North American Industry Classification System: 2017 NAICS Definition" (U.S. Census Bureau, last revised September 6, 2023), https://www.census.gov/naics/?input=4543&year=2017&details=454390.

[14] An explanation of the interest in updating the classification of retail establishments was outlined in "2017 North American Industry Classification System (NAICS)—Updates for 2022," *Federal Register*, February 26, 2020. (See note 4.)

[15] The U.S. Office of Management and Budget (OMB) Economic Classification Policy Committee's recommendations for updating industry classification in retail trade can be found in "North American Industry Classification System (NAICS) Updates for 2022; Update of Statistical Policy Directive No. 8, Standard Industrial Classification of Establishments; and Elimination of Statistical Policy Directive No. 9, Standard Industrial Classification of Enterprises," *Federal Register*, vol. 86, no. 125, July 2, 2021, pp. 35350–35365, https://www.federalregister.gov/documents/2021/07/02/2021-14249/north-american-industry-classification-system-naics-updates-for-2022-update-of-statistical-policy.

[16] Final OMB decisions on revisions to the NAICS 2022 update can be found in "North American Industry Classification System—Revision for 2022; Update of Statistical Policy Directive No. 8, North American Industry Classification System: Classification of Establishments; and Elimination of Statistical Policy Directive No. 9, Standard Industrial Classification of Enterprises," *Federal Register*, vol. 86, no. 242, December 21, 2021, pp. 72277–72279, https://www.federalregister.gov/documents/2021/12/21/2021-27536/north-american-industry-classification-system-revision-for-2022-update-of-statistical-policy.

[17] For more information on the CES-National update to NAICS 2022, see "Current Employment Statistics–CES (National): The North American Industry Classification System in the Current Employment Statistics Program." (See note 5.)

[18] For more information on the industry title updates for published CES–National data, see the downloadable Excel file titled "CES industry title updates with the March 2022 benchmark" (U.S. Bureau of Labor Statistics, accessed August 28, 2023), https://www.bls.gov/ces/naics/title-updates-naics-2022.xlsx.

[19] For a detailed description of the scope and impact of the NAICS 2022 conversion on CES–National data, see "Current Employment Statistics–CES (National): The North American Industry Classification System in the Current Employment Statistics Program; Update to NAICS 2022" (U.S. Bureau of Labor Statistics, last modified February 3, 2023), https://www.bls.gov/ces/naics/naics-2022.htm#NAICSconversion.

[20] For more information on the historical reconstruction of CES employment in electronic shopping and mail-order houses, see "CES National Benchmark Article: BLS Establishment Survey National Estimates Revised to Incorporate March 2022 Benchmarks" (U.S. Bureau of Labor Statistics, accessed August 28, 2023), https://www.bls.gov/ces/publications/benchmark/ces-benchmark-revision-2022.pdf.

[21] For a full listing of the ratios of employment moved from NAICS 2017 industries to NAICS 2022 industries, see "Current Employment Statistics–CES (National): the North American Industry Classification System in the Current Employment Statistics Program," table 4, "NAICS 2017 to NAICS 2022 AE ratios," https://www.bls.gov/ces/naics/naics-2022.htm#Rat_AE_NAICS.

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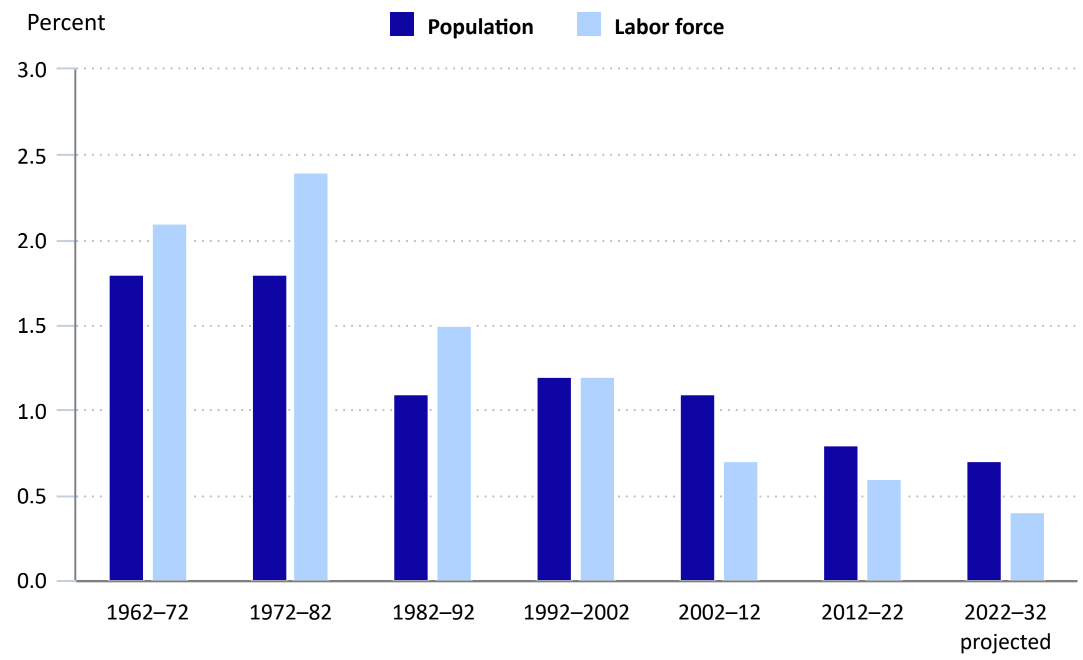
Labor force and macroeconomic projections overview and highlights, 2022–32

The U.S. Bureau of Labor Statistics projects subdued labor force and employment growth over the next decade. This growth is expected to affect gross domestic product (GDP), which is projected to grow at a modest annual rate of 1.9 percent. Labor force, employment, and GDP growth have rebounded substantially since the 2020 recession induced by the COVID-19 pandemic. This rebound leaves less room for growth as the economy appears to be at or near full employment. Additionally, demographic trends continue to lower population and labor force growth rates.

Each year, the U.S. Bureau of Labor Statistics (BLS) publishes the U.S. job outlook for the next 10 years. Underlying this job outlook are projections for the labor force and the aggregate economy. The present set of projections covers the period from 2022 through 2032.[1] These projections support the *Occupational Outlook Handbook*,[2] a resource widely used by students, career counselors, job changers, and others to inform their career choices and related educational decisions. This article details the outlook for the labor force and the aggregate economy.[3]

Changes in the labor force have an outsized effect on economic growth. Slower labor force growth over the last few decades has contributed to slower gross domestic product (GDP) growth. The slowdown in labor force growth has been driven by two demographic trends: lower population growth and an aging of the U.S. population. The labor force grew 0.6 percent annually from 2012 to 2022, much slower than in the 1980s and 1990s, when growth exceeded 1 percent, and in the 1960s and 1970s, when growth exceeded 2 percent.[4] (See chart 1.) Through 2032, BLS projects the labor force to grow 0.4 percent annually as the aging of the population accelerates.

Chart 1. Population and labor force growth, 10-year compound average annual rates, for selected periods and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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Several underlying trends are occurring in the labor force. For instance, many people are moving from the 65-to-74 age group into the 75-and-older age group, in which they are highly unlikely to work. Although the participation rate of people ages 75 and older is projected to rise by about 2 percentage points from 2022 to 2032 (from about 8 percent to nearly 10 percent), this increase does not change the expectation that many individuals will retire and exit the labor force. The gap between men's and women's participation rates is expected to continue to narrow. This is especially true for prime-working-age (hereafter, prime-age) people (those ages 25 to 54), among whom the women's participation rate has been increasing while that for men has been decreasing. The recent increase in labor force participation for women ages 25 to 34 coincides with a decreasing fertility rate, which is holding down population growth. The participation rate of young people (those ages 16 to 24) is projected to continue its downward trend.

Decreasing rates of labor force and employment growth will limit GDP growth over the next decade. From 2022 to 2032, GDP is projected to grow 1.9 percent annually, with that growth stemming mostly from annual productivity gains of 1.9 percent over the same period.[5] (See publication table 4.1 under source data.) Although this productivity growth is faster than that recorded in the past decade, it is in line with growth recorded in the 2000s. (See publication table 4.1 under source data.)

Because the business cycle is unpredictable over a 10-year horizon, BLS projections assume that the unemployment rate in the target year (the final year of the projection period) will be equivalent to the nonaccelerating inflation rate of unemployment (NAIRU) for that year.[6] In 2022, the unemployment rate was 3.6 percent, below NAIRU, implying that this low of unemployment is unsustainable in the long run. By 2032, the unemployment rate is expected to recover to 4.3 percent, the NAIRU estimate. Slow projected labor force growth and an increase in the unemployment rate are expected to result in employment growth of 0.3 percent annually over the 2022–32 decade.

Methodology

The labor force projections serve as an input to the aggregate economy model. These projections consist of three components: population, labor force participation rates, and the resulting labor force. Each component is modeled at the detailed level by age, sex, and race or ethnicity. The resulting detailed levels can then be aggregated to larger categories (e.g., by race or sex) and, ultimately, to the total.

The projections for labor force participation rates are modeled by using historical trends.[7] Population projections are derived from 2017 U.S. Census Bureau population projections, the most recent available. However, Census projections are for the resident population, whereas BLS publishes estimates for the civilian noninstitutional population.[8] BLS benchmarks Census resident population projections to the most recent (2022) annual population estimates available from the Current Population Survey (CPS). Labor force projections are obtained by multiplying each detailed demographic group's population by its participation rate.

Once labor force projections are developed, they are supplied to the aggregate economy (macroeconomic) model. BLS develops macroeconomic projections with a model licensed from Macroeconomic Advisers (MA) by IHS Markit.[9] The MA model assumes full employment in the target year, 2032. Data for energy prices come from the U.S. Energy Information Administration, and BLS determines other critical variables—most notably the labor force—and supplies them to the MA model exogenously.[10] The MA model then projects economic aggregates, including total employment, output, productivity, prices, interest rates, and many other variables for the U.S. economy. These variables—most importantly nonfarm payroll employment, labor productivity, and GDP—serve as constraints for the industry output and employment projections.

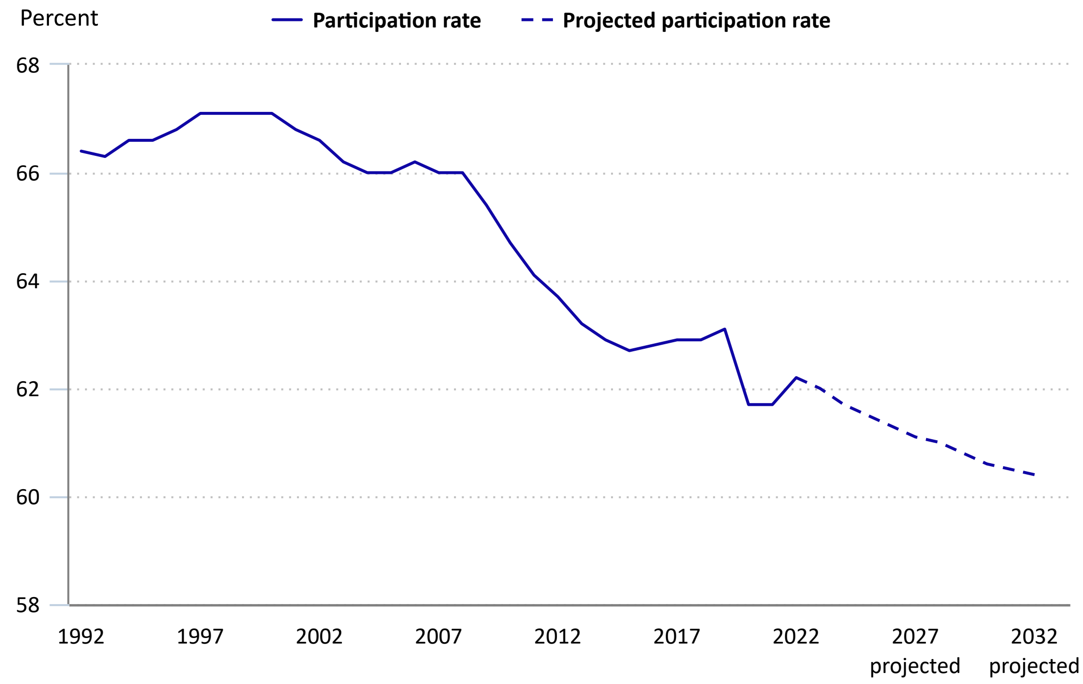
Overview of labor force projections

The impacts of lower population growth and an aging labor force are projected to accelerate over the coming decade. BLS projects that the annual rate of labor force growth will decelerate to 0.4 percent over the projection period, down from 0.6 percent in the preceding decade. This deceleration equates to a labor force of 170.7 million in 2032, up from 164.3 million in 2022. Population growth also slowed over the last few decades, although not as steeply as labor force growth. In the previous decade, population growth slowed to 0.8 percent annually, compared with just above 1 percent in the 1980s, 1990s, and 2000s. (See chart 1.) BLS projects slightly slower population growth over the upcoming decade, at 0.7 percent annually. These lower rates of population growth primarily result from fertility rates rarely breaking above the replacement rate of 2.1 births per woman since the early 1970s. Slowing immigration also plays a role in the slowdown.

Although the rate of labor force growth is now lower than that of population growth, this has not always been the case. During the 1960s, 1970s, and 1980s, the labor force was growing faster than the population, with the bulk of those gains being driven by baby boomers moving into the prime-age segment of the population and with women's participation rates rapidly increasing. Conversely, in more recent decades, labor force growth has been slowing more steeply than population growth, a change due to baby boomers entering retirement age. By 2032, all baby boomers will be ages 68 and older; thus, most population gains will be in older age groups.

This aging of the population is associated with a declining labor force participation rate. The overall participation rate has been trending down since 2000 and is projected to continue to do so. The participation rate declined from 67.0 percent in 2000 to 62.2 percent in 2022, for an average annual decline of 0.3 percent. The rate is projected to decline further over the next decade, to 60.4 percent in 2032, for an average annual decline of 0.3 percent. (See chart 2.)

Chart 2. Overall labor force participation rate, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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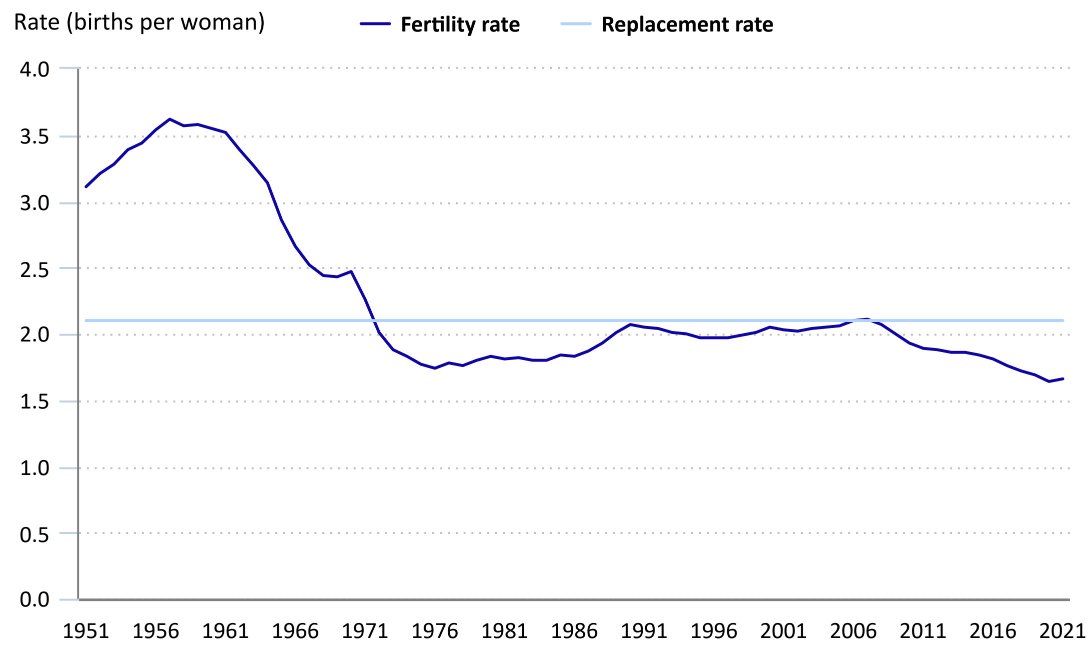
Although the overall participation rate has declined, the rates of some demographic groups have increased. BLS develops detailed demographic projections for 14 age groups (by sex, race, and ethnicity) for participation rates, the labor force, and the population. Changes in key demographic trends drive changes in the labor force outlook. This article focuses on some of the more noteworthy trends and their influence on the overall participation rate, population, and labor force.

Fertility-rate influence on the population and the labor force

Lower fertility rates since the 1970s act as a drag on population growth—and, therefore, labor force growth—over the projection period. The fertility rate—the total number of children born to each woman—is the primary driver of population and labor force growth. (Because the labor force is a subset of the population, it is constrained by population growth.) Additionally, the age at which a mother gives birth plays a role in population growth, particularly over shorter timespans. Over the past few decades, a shift has occurred whereby women are having children later in life.[11] Moreover, in a given year, the "base," or the level of women at reproductive age (roughly 15 to 44), can also be a factor in population growth. Because fertility rates have been relatively consistent over time, staying below the replacement level of 2.1 births per woman since the early 1970s, the base has been growing relatively consistently as well. (See chart 3.) An exception to this consistency is a carryover from the baby boom, commonly referred to as the "echo boom." Although the fertility rate was not especially high in the 1980s and early 1990s, the base was high as a result of the post-World War II baby boom. As a result, births increased despite a lackluster fertility rate over much of this period.[12]

Chart 3. Historical fertility rates in the United States, 1951–2021



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Source: United Nations, World Population Prospects 2022.

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The youngest age covered in BLS labor force and population measures is 16.[13] Therefore, fertility rates will have no impacts on the population and the labor force for 16 years. Chart 3 plots historical fertility rates over time and can be useful in considering how these rates affect the various age groups. The youngest age group is affected by fertility rates 16 to 19 years after they occurred, and the oldest age group is affected by fertility rates 75-plus years after they occurred. Relative to the target year of 2032, these rates occurred in, respectively, 2013–17 and 1957 and prior. Although the fertility rate is not the only factor affecting population growth, seeing its changes associated with different age groups in 2032 can be informative.

One of the few age groups with negative projected labor force growth is that of people ages 20 to 24. (See publication table 3.2 under source data.) This group has been influenced by a declining fertility rate (see the rate's decline between 2008 and 2013 in chart 3) and by women putting off having children until later in life.[14] A declining population, along with other factors at play (detailed later in the article, in the section on youth's participation rates), is another reason for this group's projected labor force decline.

In 2032, all baby boomers will be in the 65-to-74 and 75-and-older age groups. People in these age groups were born prior to 1968, when the fertility rate was mostly above 3 births per woman, and are projected to have the fastest population and labor force growth over the next decade. In the proceeding years after the baby boomers were born, the fertility rate fell substantially (to 1.7 births per woman in the mid-1970s), at a time when those ages 55 to 64 were born. This latter group is one of the few with projected population and labor force declines, and these declines (0.8 and 0.4 percent, respectively) are consistent with the falling fertility rate in the 1970s.

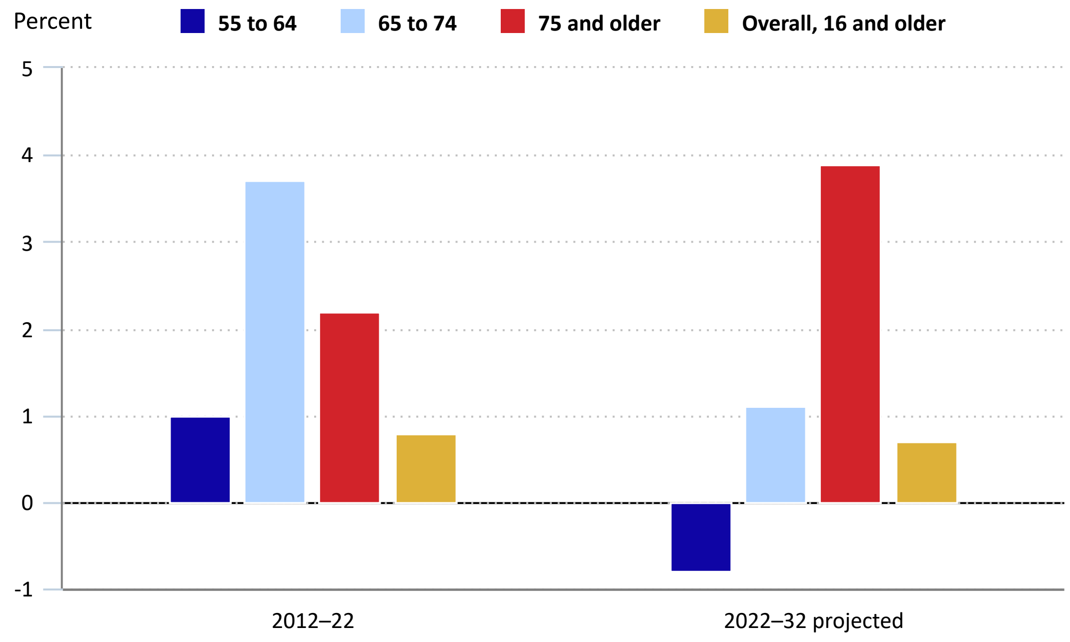
The trend for baby boomers and the projected declines for the 55-to-64 age group are mirrored, albeit to a lesser degree, a generation later, among those born in the wake of the echo boom. The echo boomers are those born between 1982 and 1995.[15] These individuals will be in the 35-to-44 and 45-to-54 age groups in 2032. The population of the 25-to-34 age group that has been vacated by echo boomers is projected to decline 0.1 percent annually over the next decade.

Baby boomers, aging, and changes in the population mix

High fertility rates resulted in 76 million births during the baby-boom years of 1946 through 1964. In contrast, Generation X (those born between 1965 and 1980) recorded only 55 million births, and millennials (those born between 1981 and 1996) recorded 62 million.[16] The large number of baby boomers and their tendency to work later into life have played pivotal roles in labor force trends and, therefore, economic growth.

Most baby boomers entered the 65-to-74 age group during the 2012–22 decade. Over this period, this age group grew the fastest, 3.7 percent annually, much faster than the overall population, which grew 0.8 percent annually. (See chart 4.) In 2032, baby boomers will be between 68 and 86 years old. Many of them will move out of the 65-to-74 age group and into the 75-and-older age group, which will result in rapid growth, 3.9 percent annually, of the 75-and-older population. As baby boomers move out of the 55-to-64 age group over the next decade, the population of this group is projected to decrease much faster than that of any other age group, at an annual rate of 0.8 percent.

Chart 4. Population growth by age group, 10-year compound average annual rates, 2012–22 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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The 65-and-older age group is expected to account for more than three-fourths of the overall projected population growth from 2022 to 2032.[17] This development will affect labor force participation rates. The overall participation rate is a weighted average of the participation rates of all individual age groups. The older age groups have lower participation rates than the prime-age group. (See publication table 3.3 under source data.) The participation rate of the 75-and-older age group, 8.2 percent, is considerably lower than the 82.4-percent rate of the prime-age group. As the 65-to-74 and 75-and-older age groups grow faster than the rest of the population, their lower participation rates are weighted more heavily in the overall participation rate. The result has been a declining overall participation rate since 2000, as many baby boomers have retired. (See chart 2.)

This dynamic also affects the 55-and-older age group. As the 65-to-74 and 75-and-older age groups grow and the 55-to-64 age group shrinks, the oldest groups are weighted more heavily in the participation rate of the 55-and-older age group. The result is somewhat counterintuitive because the participation rate of people ages 55 and older is projected to decline by 1.4 percent annually, although the rates of all three age subgroups within that group are projected to increase. This result occurs for a combination of reasons, including a declining population of people ages 55 to 64 and substantial growth (more than 10 million) of the 75-and-older population. The 55-to-64 age group is projected to have a participation rate of nearly 70 percent in 2032, whereas the 75-and-older age group is expected to have a rate closer to 10 percent in that year. (See table 1.)

Table 1. Changes in population and labor force participation rates of people ages 55 and older, 2022–32 projected

Age group	Change in labor force participation rate, 2022–32 (percent)	Population change, 2022–32 (thousands)	Participation rate, 2032 (percent)
55 and older	-1.4	10,941	37.4
55 to 64	3.2	-3,419	68.4
65 to 74	3.3	3,779	29.9
75 and older	1.7	10,580	9.9

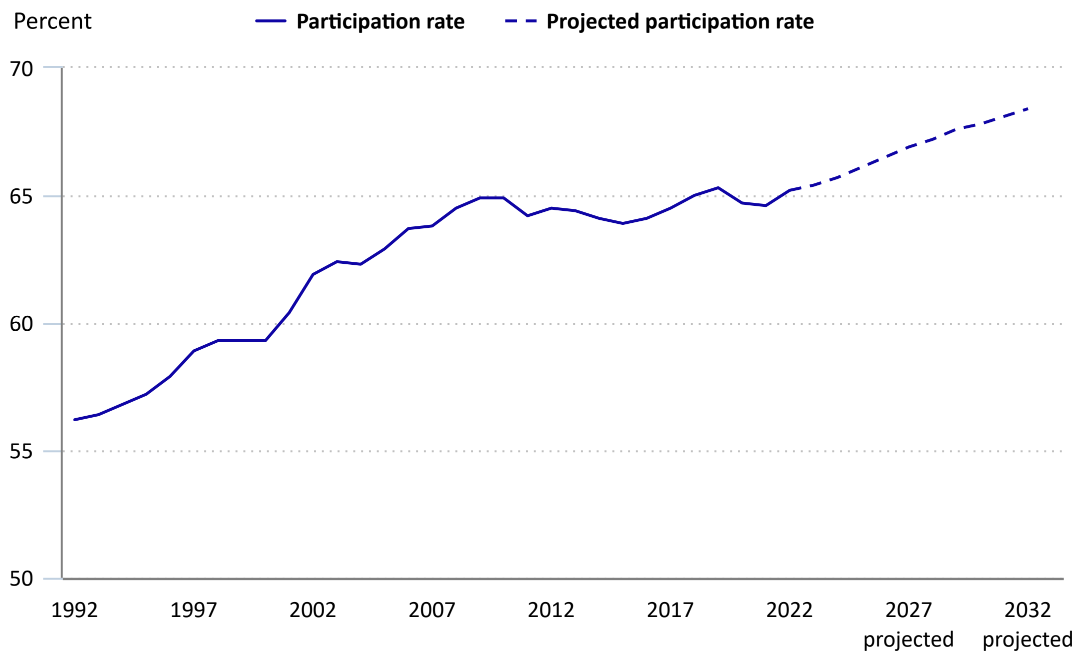
Source: U.S. Bureau of Labor Statistics.

Working later into life

A trend offsetting some of the baby boomers' downward pressure on labor force growth is their propensity to work later into life. The primary reasons for this group's increasing participation rate are Social Security reforms and employers moving away from defined benefit pension plans.[18] Surveys indicate that most older workers who continue to work do so out of financial necessity.[19] Additionally, there has been a shift in the economy to less physically demanding jobs. Workers in these jobs are generally able to work longer than their counterparts in more physically demanding jobs.[20]

Despite dipping in 2020 and 2021 because of the COVID-19 pandemic, the participation rates of all older age groups (those 55 and older) have been trending up over the past few decades and are projected to continue to do so. (See charts 5 through 7.) Although the rates of the 55-to-64 and 65-to-74 age groups have not yet returned to their prepandemic levels, they did increase in 2022, suggesting a return to the prepandemic upward trend.

Chart 5. Labor force participation rates of people ages 55 to 64, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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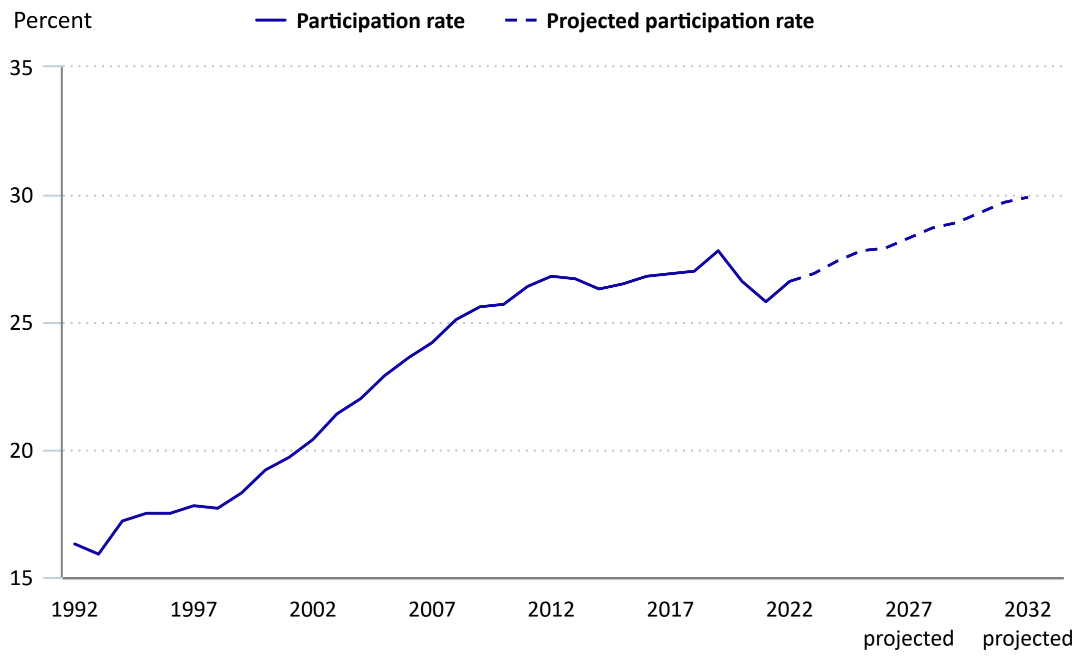
Chart 6. Labor force participation rates of people ages 65 to 74, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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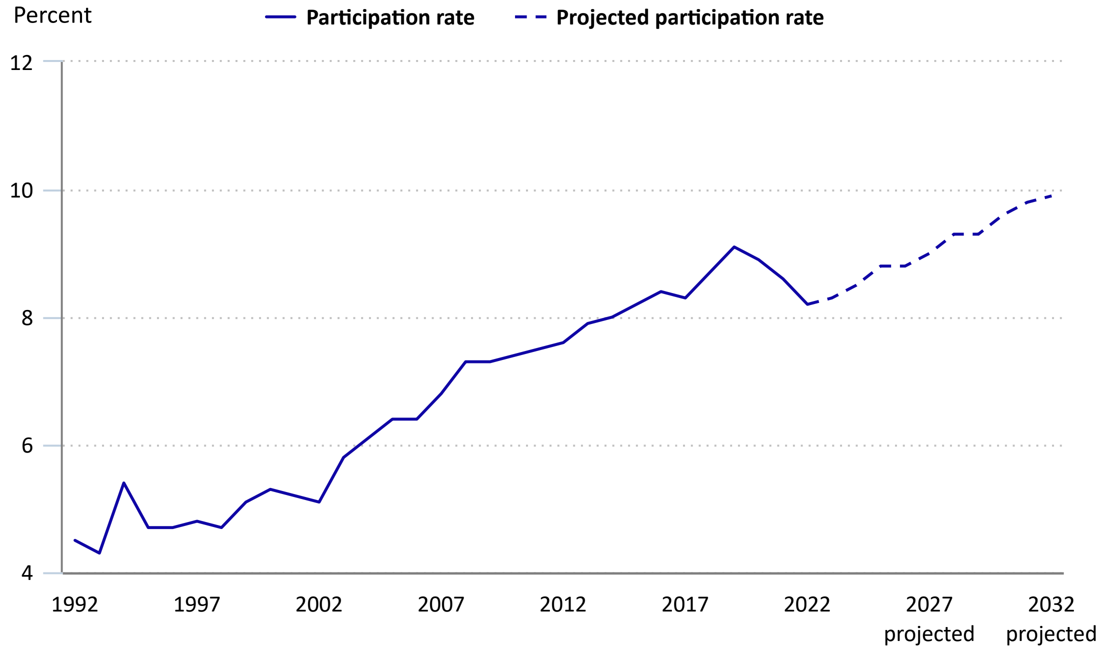
Chart 7. Labor force participation rates of people ages 75 and older, 1992–2022 and 2022–32 projected



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

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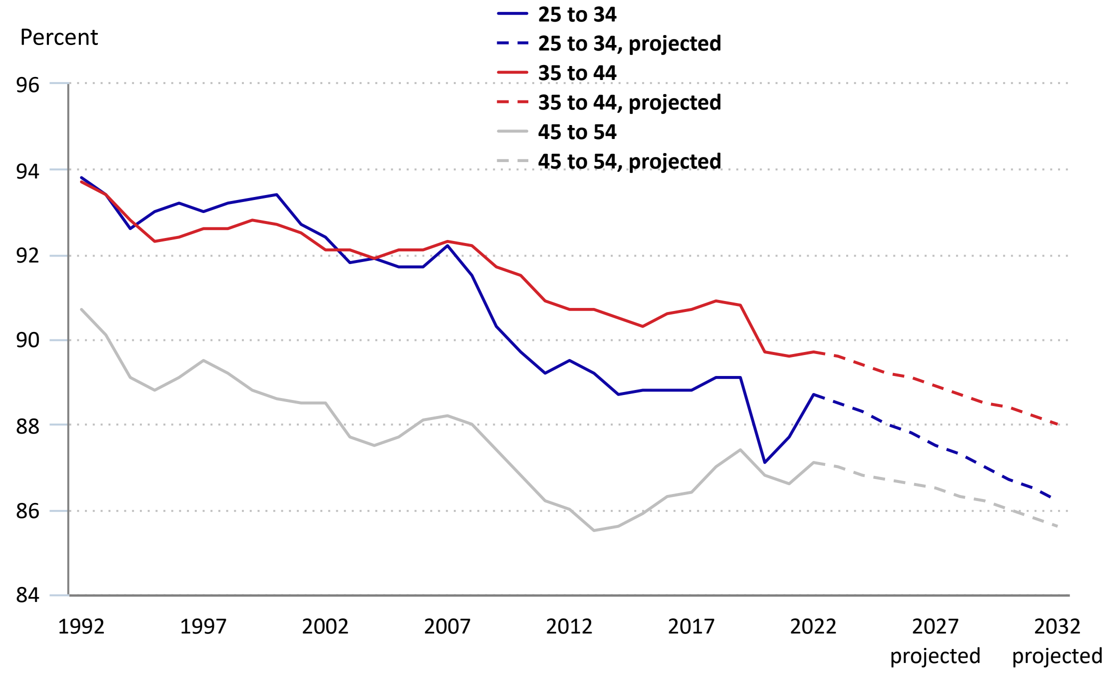
Over the past 30 years, the participation rates of the 55-to-64 and 65-to-74 age groups have increased by 8.9 and 10.3 percentage points, respectively. Although the rate of people ages 75 and older has risen as well, it is up by only 3.8 percentage points. Over the projection period, the participation rate of the 55-to-64 age group is projected to grow from 65.2 to 68.4 percent, and the rate of the 65-to-74 age group is projected to grow from 26.6 to 29.9 percent. The participation rate of the 75-and-older age group is projected to grow to 9.9 percent in 2032; people in this group will be twice as likely to work as they were 40 years earlier (in 1992).

Diverging participation rates of prime-age men and women

Although population aging drives most of the decline in the overall participation rate, it is not the only driver. Some demographic groups' participation rates have been trending down. The rate of prime-age men has experienced one of the more notable declines. For prime-age women, the participation rate has been more dynamic, decreasing throughout the 2000s and early 2010s and then increasing to present.

After declining slightly throughout the 1970s and 1980s, the men's participation rate declined more sharply from the 1990s onward. This trend could be due to a substantial decline in middle-skill jobs. This decline has resulted from technological advancements automating away "routine" occupations and from offshoring jobs to other countries where wages are lower.[21] The participation rates of men in prime-age groups are expected to continue edging down. Over the projection period, the participation rate of men ages 25 to 34 is projected to decline from 88.7 to 86.2 percent, while the rates of men in the 35-to-44 and 45-to-54 age groups are projected to decline from 89.7 to 88.0 percent and from 87.1 to 85.6 percent, respectively. (See chart 8.)

Chart 8. Labor force participation rates of men in prime-age groups, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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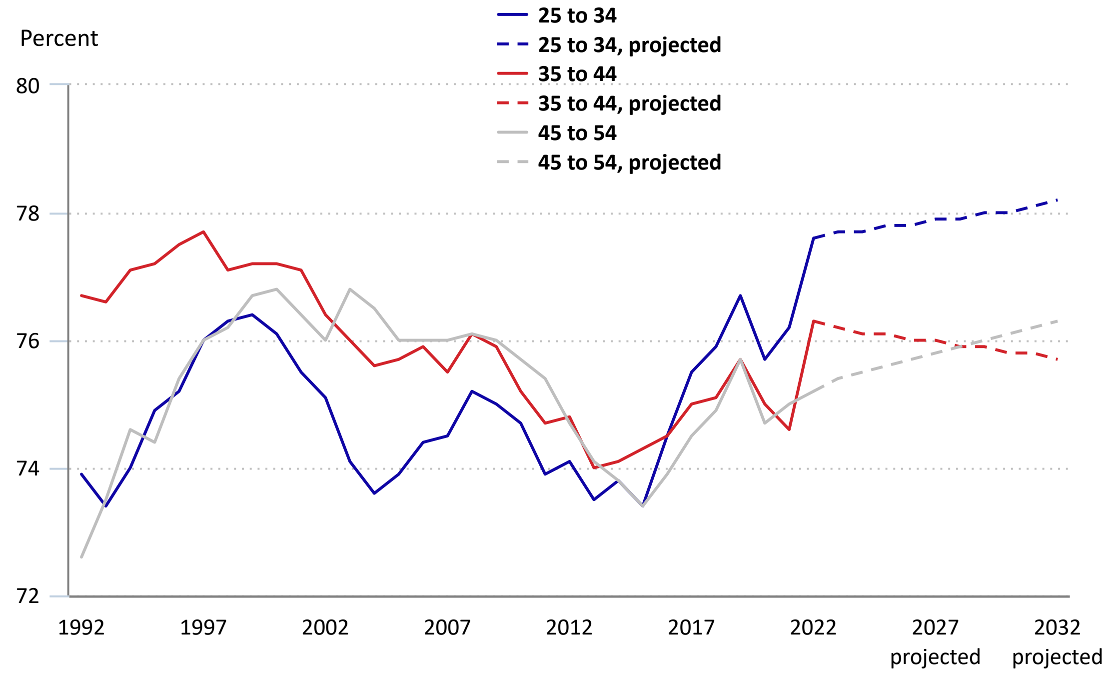
The participation rates of women in prime-age groups were peaking around the turn of the 20th century. Although these rates declined similarly to those of men for a decade and a half, they have been trending up since around 2015. (See chart 9.) Having children reduces women's participation rate, an effect that is strongest when women are younger.[22] Therefore, reduced fertility rates may partly explain why the participation rate of women ages 25 to 34 posted the most substantial gains among prime-age women since the 2015 lows. (See chart 3.)

Chart 9. Labor force participation rates of women in prime-age groups, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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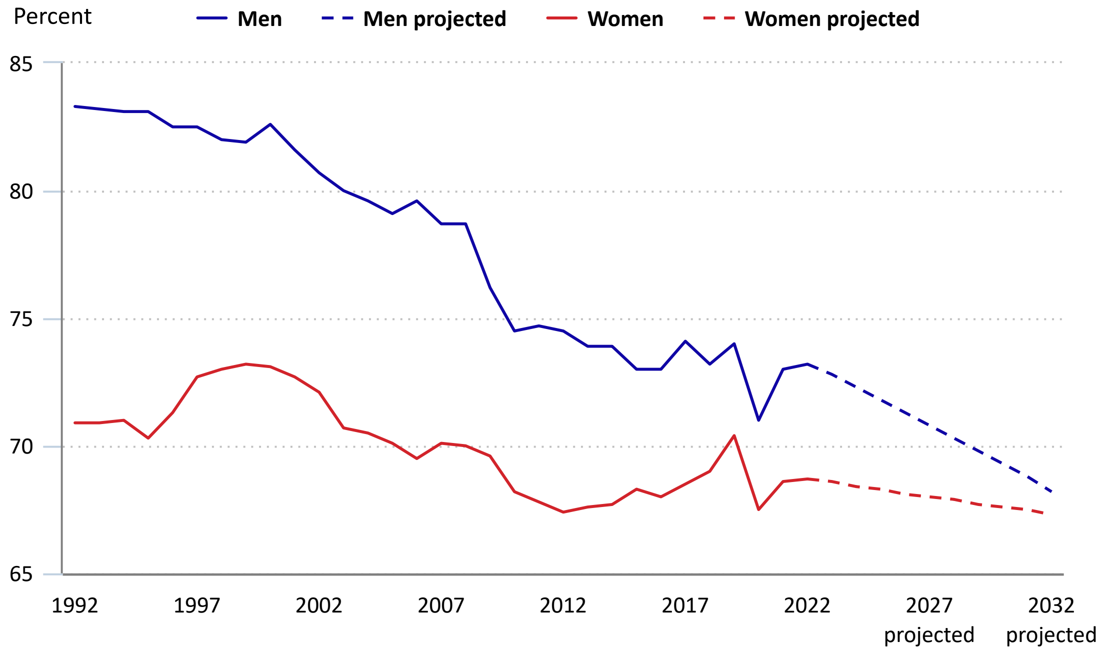
Additionally, a trend affecting women of all ages is the growth of employment in certain female-dominated service sectors of the economy, such as healthcare and education.[23] Projections are somewhat mixed for different prime-age groups of women as their participation-rate increases over the past 5–7 years are weighed against the longer duration decline since 2000. From 2022 to 2032, the participation rate of women ages 25 to 34 is projected to increase from 77.6 to 78.2 percent, the rate of women ages 35 to 44 is projected to decrease from 76.3 to 75.7 percent, and the rate of women ages 45 to 54 is projected to increase from 75.2 to 76.3 percent. Although the participation rates of prime-age men have declined in recent decades and are projected to continue to do so, they are still expected to remain higher than those of prime-age women. However, the gap between men's and women's participation rates in prime-age groups is expected to shrink.

Youth's declining participation rate

The 20-to-24 age group shows different trends in participation rates by sex. This group's labor force participation has been affected by increased higher education and delayed entry into the labor force. College enrollment peaked in 2010.[24] Although it declined slightly through 2020, it has remained high, at 19.0 million, relative to its levels in the 1970s, 1980s, and 1990s.[25] Men's college enrollment fell about 8 percent between 2010 and 2020, compared with about 3 percent for women.

The participation rate of women ages 20 to 24 grew steadily throughout the second half of the 20th century, peaking at 73.2 percent in 1999. Since then, the rate has declined, hitting a low of 67.4 percent in 2012 before rebounding slightly. This trend is consistent with higher education trends over this period, suggesting that women delay entry into the labor force as they attend college. The peak in female college enrollment occurred 2 years before the participation rate hit its 2012 low. The rate then rose slightly as enrollment fell between 2010 and 2022. BLS projects the participation rate of women ages 20 to 24 to continue to edge down, from 68.7 percent in 2022 to 67.3 percent in 2032. (See chart 10.)

Chart 10. Labor force participation rates of men and women ages 20 to 24, 1992–2022 and 2022–32 projected



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Source: U.S. Bureau of Labor Statistics.

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The participation rate of men ages 20 to 24 has declined more dramatically than that of women in this age group, despite college enrollment falling more sharply for men. Hovering around 85 percent throughout the 1970s and 1980s, the men's participation rate declined slightly throughout the 1990s, rapidly throughout the 2000s, and again more slowly in the 2010s. (See chart 10.) After falling from 82.6 percent in 2000 to 74.5 percent in 2010, the rate declined more slowly. In 2022, it stood at 73.2 percent, only slightly lower than its 2010 level.

The participation rates of men and women ages 20 to 24 have been converging as the men's participation rate continued to decline from 2010 to 2022. This declining trend also occurred among prime-age men, suggesting that many of the structural factors affecting prime-age men are also likely affecting men ages 20 to 24. These factors, detailed earlier in the article, can be summarized as automation and globalization. BLS projects the participation rate of men ages 20 to 24 to decline from 73.2 percent in 2022 to 68.2 percent in 2032.

Immigration

BLS population projections are derived from 2017 Census projections that include estimates of immigration flows.[26] Although the impacts of fertility rates on 10-year projections are known (because births have already been counted), those of immigration are tentative because immigration is highly uncertain over the long term. Policy decisions and economic conditions in both sending and receiving countries can have abrupt impacts on net migration. For example, the COVID-19 pandemic and the emergency policies adopted in response to it abruptly slashed immigration. U.S net immigration exceeded 1 million annually between 2014 and 2017. Immigration trended down before the onset of the pandemic and then fell considerably in 2020 and 2021. In 2021, immigration was 376,000, less than a third of its 2017 total. Immigration rebounded in 2022, with Census estimating slightly over 1 million immigrants in that year.[27] It remains to be seen whether this rebound will begin a new trend similar to that of 2014–17 or whether the 2022 level was high because of an influx of a large number of immigrants who would otherwise have immigrated in 2021.

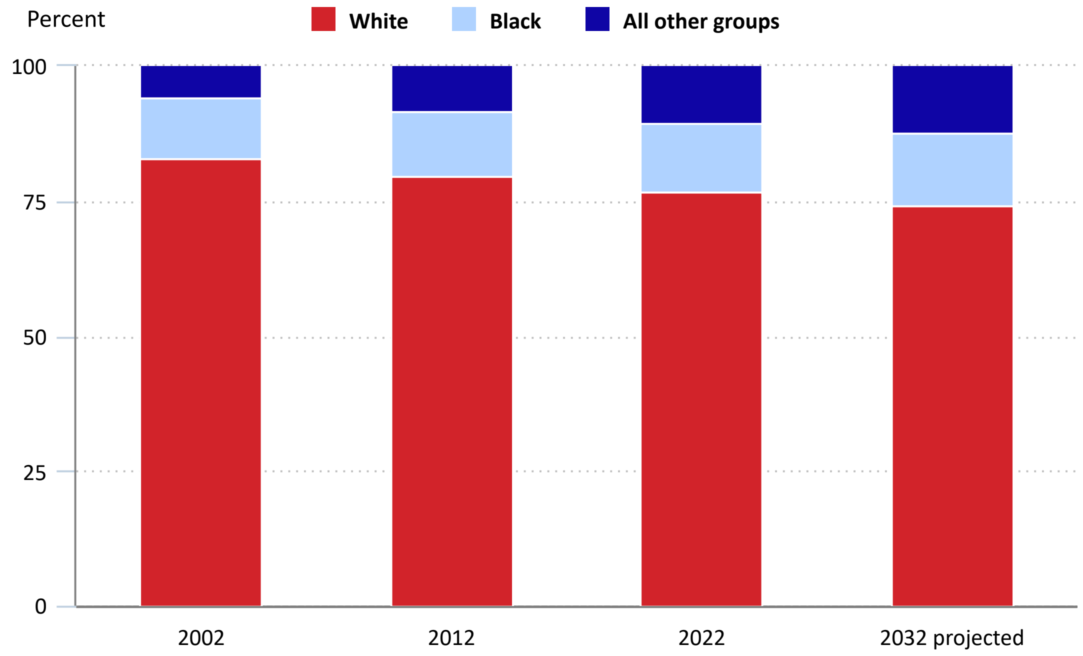
Labor force composition by race and ethnicity

BLS projections include data for three racial categories: White, Black, and "all other groups."[28] The latter category consists of individuals of multiple racial origins, including Asians, American Indians and Alaska Natives, and Native Hawaiians and Other Pacific Islanders. Projections are available for population and labor force growth. For all races, labor force and population trends are similar.

The labor force for the "all other groups" category grew faster than that for Whites and Blacks over the last few decades and is projected to continue to do so. Growth in the Black labor force has been moderate and is projected to continue, while that for Whites has lagged behind.

BLS projects that, from 2022 to 2032, the "all other groups" labor force will grow 2.1 percent annually, the Black labor force will grow 0.7 percent annually, and the White labor force will grow 0.1 percent annually. By the end of the projection period, the percentage of Whites in the overall labor force is expected to drop below 75 percent, to 74.3 percent. In 2032, Blacks are projected to account for 13.4 percent of the overall labor force, with the "all other groups" category accounting for the remaining 12.3 percent. (See chart 11.)

Chart 11. Labor force shares, by race, 2002, 2012, 2022, and 2032 projected



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

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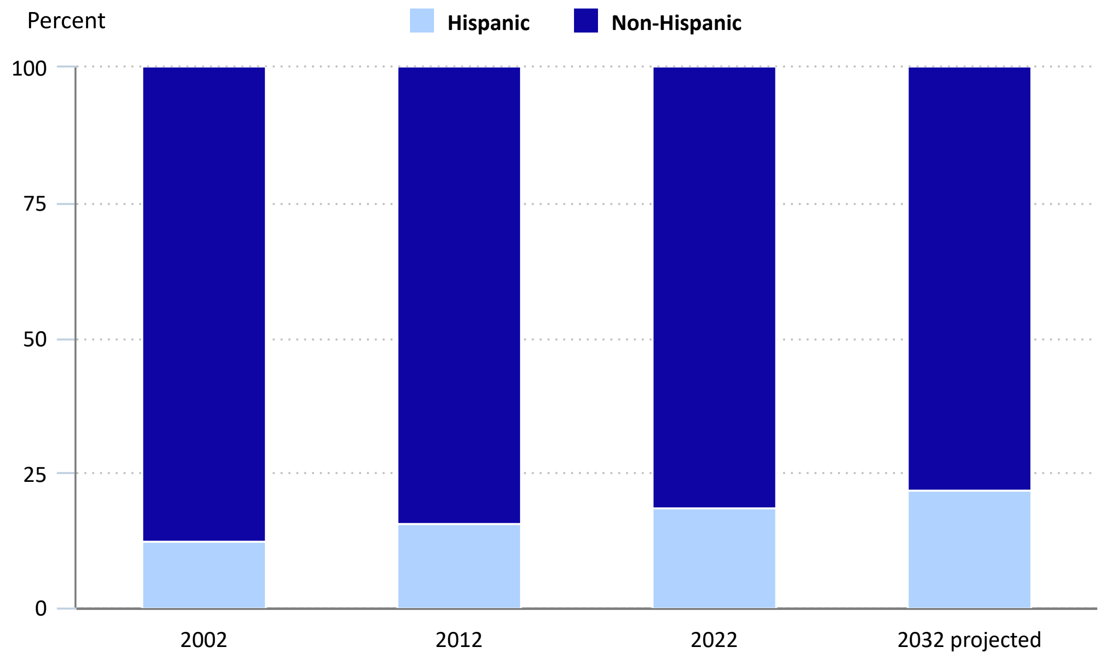
Besides projecting data by race, BLS projects data by ethnicity. Ethnicity, which is independent of race, is split between Hispanic and non-Hispanic categories. People of Hispanic ethnicity can be of any race. Over the last few decades, the Hispanic labor force has been growing faster than the non-Hispanic labor force, a trend that is projected to continue. From 2022 to 2032, the Hispanic labor force is projected to grow 2.0 percent annually, whereas the non-Hispanic labor force is projected to see no growth. (See publication table 3.1 under source data.) As a result, Hispanics are expected to make up 21.9 percent of the overall labor force in 2032, up from 18.6 percent in 2022. (See chart 12.)

Chart 12. Labor force shares, by ethnicity, 2002, 2012, 2022, and 2032 projected



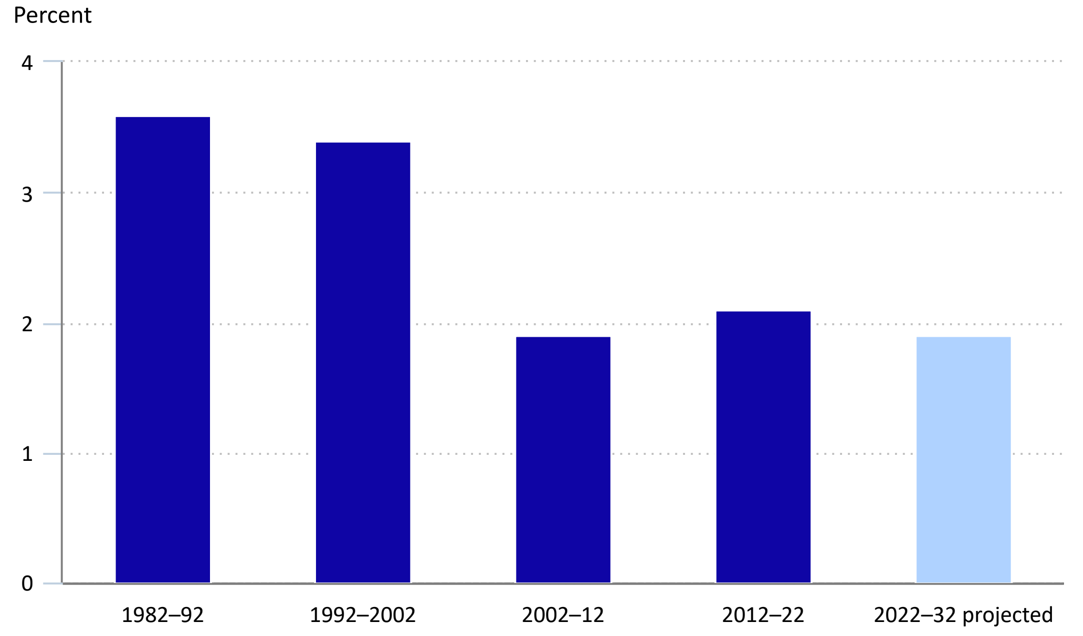
Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Overview of macroeconomic and aggregate economy projections

The slow labor force growth projected for the 2022–32 decade will act as a drag on the economy. Although recent years have seen faster economic growth because of the recovery from the 2020 pandemic recession, the economy appears to be at full employment.[29] Therefore, future growth will stem from labor force and productivity growth. BLS projects that output, expressed as GDP, will grow 1.9 percent annually over the next decade. This growth is in line with that recorded in the 2000s and 2010s, although it is low relative to growth in the 1980s and 1990s, when the labor force was growing notably faster.[30] (See chart 13.)

Chart 13. Growth in real gross domestic product, 10-year compound average annual rates, for selected periods and 2022–32 projected



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

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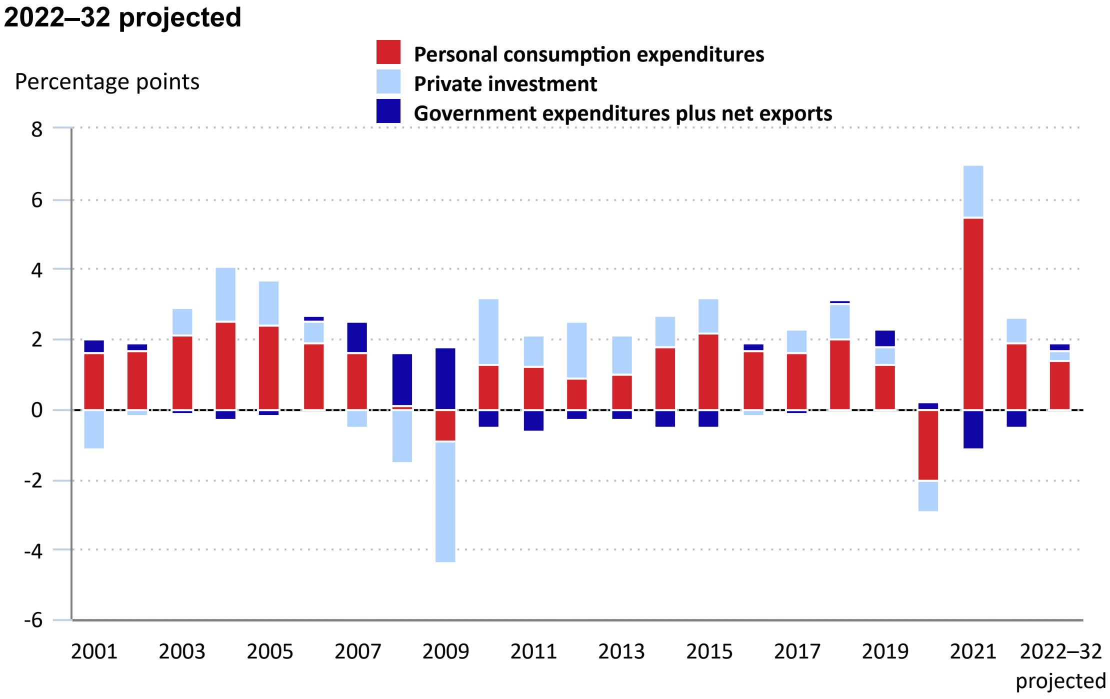
GDP consists of personal consumption expenditures (PCE), investment, government expenditures, and net exports. PCE, while tending to contract during recessions, typically accounts for the majority of GDP growth, with the next highest contribution coming from investment. Over the 2022–32 decade, BLS projects PCE to contribute 1.4 percentage points annually to GDP growth, and investment to contribute 0.3 percentage point. (See chart 14.)

Chart 14. Contributions to growth in real gross domestic product, 2001–22 and 2022–32 projected



Click legend items to change data display. Hover over chart to view data.
Source: Historical data are from the U.S. Bureau of Economic Analysis. Projected data are from the U.S. Bureau of Labor Statistics.

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Net exports and government expenditures do not account for much of GDP growth in ordinary times, although government expenditures can contribute heavily to growth during recessions (as the government spends more to stimulate the economy). Collectively, over the next 10 years, these two components of output are projected to contribute 0.2 percentage point annually to GDP growth, with each component contributing 0.1 percentage point.

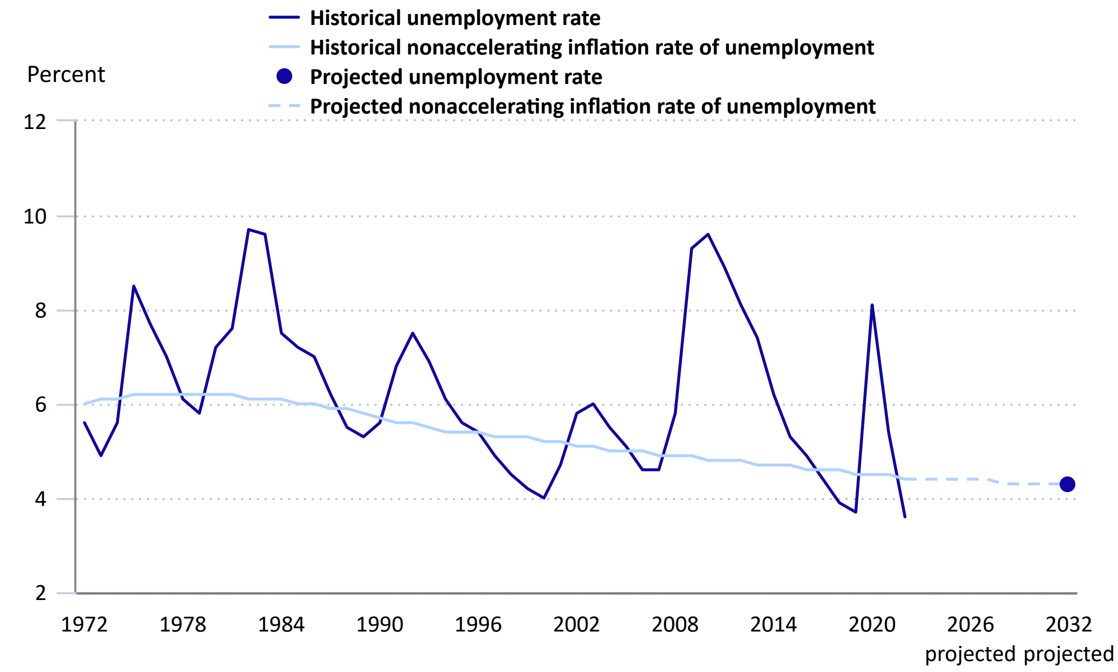
Nonaccelerating inflation rate of unemployment

The labor force includes both the employed and the unemployed. Unemployment typically increases during recessions, whereas employment increases during expansions. Recessions and expansions are parts of the business cycle. Growth rates for upcoming years depend on where in the business cycle the economy is at present. The bottom of a recession is referred to as a "trough," and the top of an expansion is referred to as a "peak."

When the economy is at or close to a peak, it is said to be at full employment.[31] Because BLS projections assume full employment in the target year, when the economy is already at or close to a peak, its potential growth is constrained by labor force growth.

A peak is associated with the unemployment rate being at, or even below, NAIRU. The current unemployment rate is below NAIRU (see chart 15), suggesting that the economy is at full employment and the employment (and output) growth rate is constrained accordingly.

Chart 15. Unemployment rate and estimated nonaccelerating inflation rate of unemployment, 1972–2022 and 2032 projected



Click legend items to change data display. Hover over chart to view data.
Source: Historical and projected data for the unemployment rate are from the U.S. Bureau of Labor Statistics. Historical and projected data for the nonaccelerating inflation rate of unemployment are from the Congressional Budget Office.

View Chart Data

BLS uses the CBO estimate of the noncyclical unemployment rate to estimate NAIRU.[32] This value is estimated to be 4.3 percent in 2032. Because the 3.6-percent unemployment rate in 2022 is below the 2032 estimate, there is less room for employment to grow. The unemployment rate is projected to reach the NAIRU value of 4.3 percent by 2032. Consequently, employment is expected to grow by a meager 0.3 percent annually over the next decade. The fact that employment is projected to grow simultaneously with unemployment is attributable to increases in the labor force.

Employment

There are various employment concepts. The two most common are household employment and establishment (or payroll) employment. The names of these concepts are based on how the concepts are measured. Household employment, used by the CPS at BLS, is estimated by directly asking households about how many individuals in them are working. Payroll employment, used by the Current Employment Statistics survey at BLS, is estimated by asking employers how many employees are on their payrolls. Estimates from these two surveys are not expected to match because a single individual with multiple employers will be counted twice in the establishment survey but only once in the household survey. Additionally, the two estimates are based on distinct survey and estimation methods.[33]

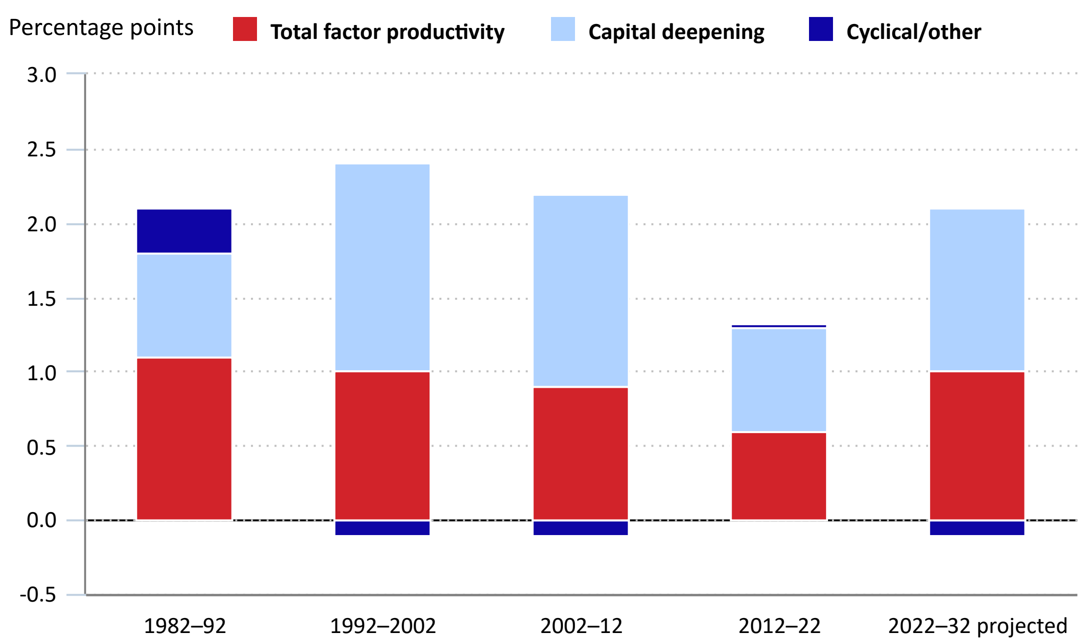
Household and payroll employment are both projected to grow 0.3 percent annually over the next decade. (See publication table 4.1 under source data.) This slow rate is due to the low (although slightly higher, at 0.4 percent) rate of labor force growth, as well as the projected rise in the unemployment rate back to NAIRU. (See chart 15.)

Productivity

Employment and productivity growth drive output. Productivity is influenced by capital deepening and total factor productivity (TFP).[34] Capital consists of durable goods that, after being produced, are used as inputs to further production.[35] These inputs include computers, equipment, intellectual property, buildings, and the like. Capital deepening refers to an increase in the ratio of capital to labor. Greater investment increases this ratio, although capital naturally depreciates over time. TFP can increase because of technological improvements, increases in the education or quality of the workforce, improvements in management practices, and economies of scale.

From 2012 to 2022, productivity grew 1.2 percent annually, more slowly than in prior decades, when growth surpassed 2 percent annually. (See chart 16.) Over the 2022–32 period, BLS projects productivity growth to be 1.9 percent annually, similar to, although slightly slower than, growth recorded before 2012. Historically, capital deepening has been responsible for slightly more than half of productivity growth, and this dynamic is projected to continue over the next decade. Capital deepening will account for 1.1 percentage points of productivity growth, while TFP will account for 1.0 percentage point. (Cyclicality also plays a role in productivity growth, so the sum of these components does not equal overall productivity growth.)

Chart 16. Growth in labor productivity and its components, 10-year compound average annual rates, for selected periods and 2022–32 projected



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

View Chart Data

Monetary policy and inflation

Since March 2022, monetary policy has changed significantly in response to inflation, with the Federal Reserve (hereafter, the Fed) raising the federal funds rate (the rate underpinning most loans made in the United States) to levels not seen since 2007.[36] Depending on how it is measured, inflation increased between 6.2 and 8.0 percent in 2022.[37] This range is substantially higher than the Fed's target inflation rate of 2.0 percent, indicating that the economy is above full employment. Consequently, the Fed increased the federal funds rate from a range of 0.00–0.25 percent in January 2022 to a range of 5.00–5.25 percent in May 2023.

At the time of this publication, inflation has subsided. BLS projects inflation to decrease notably over the next 10 years, down to levels consistent with the Fed's target inflation rate and with rates recorded in much of the past decade. The Consumer Price Index is projected to increase 2.2 percent annually, and the GDP price index is projected to increase 2.3 percent annually. (See publication table 4.4 under source data.) BLS expects the Fed to lower its federal funds rate to 2.8 percent in 2032.

Conclusion

Over the next decade, demographic changes are expected to reverberate throughout the U.S. economy and affect GDP growth.[38] The aging of the baby-boom generation has already lowered the overall labor force participation rate, a trend that is projected to continue as many baby boomers enter the 75-and-older age group by 2032. Lower fertility rates will reduce population and labor force growth throughout the projection span. Over the past two decades, these trends have contributed to lower GDP growth relative to growth seen in much of the 20th century. As the trends continue into 2032, GDP is projected to grow at an annual rate of 1.9 percent, similar to growth rates in the 2000s and 2010s.

SUGGESTED CITATION:

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Notes

1 Labor force projections are the only U.S. Bureau of Labor Statistics (BLS) projections that include intrayear and target-year projections. Aggregate economy projections are available only for the target year, 2032.

2 See https://www.bls.gov/ooh/.

3 The detailed industry output and employment projections are not covered in this *Monthly Labor Review (MLR)* article. A separate *MLR* article outlining the 2022–32 industry and occupational employment projections is forthcoming.

4 In this article, annual growth rates are calculated as compound average annual growth rates.

5 Productivity reflects private nonfarm business output per hour worked, chained.

6 The nonaccelerating inflation rate of unemployment is a theoretical level of unemployment below which inflation would be expected to rise.

7 For a more detailed methodological discussion, see Kevin S. Dubina, "Full employment: an assumption within BLS projections," *Monthly Labor Review*, November 17, https://doi.org/10.21916/mlr.2017.30.

8 For a more detailed discussion, see the Current Population Survey (CPS) concept "civilian noninstitutional population" at https://www.bls.gov/cps/definitions.htm#population and the U.S. Census Bureau concept "resident population" at https://www.census.gov/programs-surveys/popest/about/glossary/national.html.

9 BLS develops macroeconomic projections with the Macroeconomic Advisers (MA) model, a structural econometric model of the U.S. economy. The model, licensed from MA by IHS Markit, comprises more than 1,000 variables, behavioral equations, and identities. Central characteristics of the MA model are a life-cycle model of consumption, a neoclassical view of investment, and a vector autoregression for the monetary policy sector of the economy. The full-employment foundation of the model is the most critical characteristic for the BLS outlook. Within MA, a submodel calculates an estimate of potential output from the nonfarm business sector. The calculation is based on full-employment estimates of the sector's hours worked and output per hour. The structure of the model, exogenous assumptions, and MA's view of the Federal Reserve's long-term policy objective largely determine the characteristics of the model's long-term outlook for the economy. For more information, see http://www.macroadvisers.com/.

10 Energy Information Administration estimates include prices for West Texas Intermediate crude oil, Brent crude oil, and natural gas and assume that current energy regulations will remain unchanged. For more information, see *Annual Energy Outlook 2022* (U.S. Energy Information Administration, March 3, 2022, released annually), https://www.eia.gov/outlooks/aeo/.

11 See "Age-specific fertility rates by five-year age group, region, subregion and country, annually for 1950–2100 (births per 1,000 women)," columns L through T, in *World Population Prospects 2022* (United Nations, July 2022), https://population.un.org/wpp/Download/Files/1_Indicators%20(Standard)/EXCEL_FILES/3_Fertility/WPP2022_FERT_F02_FERTILITY_RATES_BY_5-YEAR_AGE_GROUPS_OF_MOTHER.xlsx.

12 Michelle J. K. Osterman, Brady E. Hamilton, Joyce A. Martin, Anne K. Driscoll, and Claudia P. Valenzuela, "Births: final data for 2021," *National Vital Statistics Report*, vol. 72, no. 1, January 31, 2023, https://www.cdc.gov/nchs/data/nvsr/nvsr72/nvsr72-01.pdf.

13 BLS population projections are for the civilian noninstitutional population. For a thorough explanation, see CPS concepts and definitions at https://www.bls.gov/cps/definitions.htm#:~:text=The%20labor%20force%20includes%20all,or%20actively%20looking%20for%20work.

14 See "Age-specific fertility rates by five-year age group," columns L through T.

15 Rebecca Lueung, "The echo boomers," *CBS News*, October 1, 2004, https://www.cbsnews.com/news/the-echo-boomers-01-10-2004/.

16 See births underlying each generational chart in Richard Fry, "Millennials overtake baby boomers as America's largest generation" (Washington, DC: Pew Research Center, April 28, 2020), https://www.pewresearch.org/short-reads/2020/04/28/millennials-overtake-baby-boomers-as-americas-largest-generation/.

17 The overall population is projected to grow by 18.7 million, while the 75-and-older age group is projected to grow by 10.6 million, accounting for 57 percent of overall growth.

18 C. S., "Why people are working longer," *The Economist*, June 11, 2018, https://www.economist.com/the-economist-explains/2018/06/11/why-people-are-working-longer.

19 Elissa Chudwin, "Survey: older adults planning to work in retirement for financial reasons" (Washington, DC: American Association for Retired Persons, July 21, 2022), https://blog.aarp.org/fighting-for-you/working-while-retired-survey.

[20] David H. Montgomery, "Who's not working? Understanding the U.S.'s aging workforce" (Federal Reserve Bank of Minneapolis, February 27, 2023), https://www.minneapolisfed.org/article/2023/whos-not-working-understanding-the-uss-aging-workforce.

[21] Didem Tüzemen, "Why are prime-age men vanishing from the labor force?," *Economic Review* (Federal Reserve Bank of Kansas City, first quarter 2018), https://www.kansascityfed.org/Economic%20Review/documents/653/2018-Why%20Are%20Prime-Age%20Men%20Vanishing%20from%20the%20Labor%20Force%3F.pdf.

[22] Joan R. Kahn, Javier García-Manglano, and Suzanne M. Bianchi, "The motherhood penalty at midlife: long-term effects of children on women's careers," *Journal of Marriage and Family*, vol. 76, no. 1, February 2014, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4041155/.

[23] L. Rachel Ngai and Barbara Petrongolo, "Gender gaps and the rise of the service economy," *American Economic Journal: Macroeconomics*, vol. 9, no. 4, October 2017, https://pubs.aeaweb.org/doi/pdfplus/10.1257/mac.20150253.

[24] Melanie Hanson, "College enrollment & student demographic statistics" (Education Data Initiative, July 26, 2022), https://educationdata.org/college-enrollment-statistics.

[25] Richard V. Reeves and Ember Smith, "The male college crisis is not just in enrollment, but completion" (Washington, DC: The Brookings Institution, October 8, 2021), https://www.brookings.edu/blog/up-front/2021/10/08/the-male-college-crisis-is-not-just-in-enrollment-but-completion/.

[26] See "Projected population size and births, deaths, and migration: main projections series for the United States, 2017–2060" (U.S. Census Bureau, September 2018), https://www2.census.gov/programs-surveys/popproj/tables/2017/2017-summary-tables/np2017-t1.xlsx.

[27] Anthony Knapp and Tiangeng Lu, "Net migration between the United States and abroad in 2022 reaches highest level since 2017" (U.S. Census Bureau, December 22, 2022), https://www.census.gov/library/stories/2022/12/net-international-migration-returns-to-pre-pandemic-levels.html.

[28] For overall and detailed demographic labor force data by race or ethnicity, as well as by age group, see publication tables 3.1 through 3.4 under source data. For the most detailed data, see the "Data for researchers" section of the Employment Projections program's website (https://www.bls.gov/emp/data/labor-force.htm). Besides being supplied with data from published labor force data tables, the BLS aggregate economy model is supplied with overall labor force and population data, as well as some demographic data.

[29] For a detailed discussion on full employment and how the concept is incorporated into BLS projections, see Dubina, "Full employment: an assumption within BLS projections."

[30] Throughout this article, all references to growth rates for gross domestic product (GDP) or GDP components reflect real rather than nominal growth rates.

[31] See endnote 29.

[32] The Congressional Budget Office (CBO) downplays the link between the unemployment rate and wage or inflation growth. Consequently, CBO refers to the structural unemployment rate as the noncyclical unemployment rate rather than the nonaccelerating inflation rate of unemployment. See "History and projections for key economic variables," data supplement to *The Budget and Economic Outlook: 2023 to 2033*, Report 58848 (Congressional Budget Office, February 2023), https://www.cbo.gov/system/files/2023-02/55022-2023-02-Historical-Economic-Data.zip.

[33] See "Comparing employment from the BLS household and payroll surveys," *Labor Force Statistics from the Current Population Survey* (U.S. Bureau of Labor Statistics), https://www.bls.gov/web/empsit/ces_cps_trends.htm.

[34] Productivity is calculated as total output divided by total hours worked. Total hours worked are equivalent to employment multiplied by average hours worked. Employment is noted as it changes from year to year, whereas average hours worked tend to remain consistent.

[35] Paul A. Samuelson and William D. Nordhaus, *Economics*, 17th edition (New York: McGraw-Hill, 2001), p. 270.

[36] See "Federal funds effective rate" (FRED, Federal Reserve Bank of St. Louis), https://fred.stlouisfed.org/series/FEDFUNDS.

[37] In 2022, the gross domestic product chain price index increased 7.0 percent, the Consumer Price Index increased 8.0 percent, and the Personal Consumption Expenditures index increased 6.2 percent.

[38] These trends also affect BLS occupational and employment projections, which will be detailed in a forthcoming *MLR* article.

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Article

September 2023

Global labor market debates in the ILO publications in the COVID-19 era

The COVID-19 pandemic, which began in 2020, significantly changed the dynamics of working life. To help capture these changing dynamics, we examined publications that the International Labour Organization published during this period. This article aims to determine what kind of discussions are made within the framework of these publications in the context of COVID-19 by period and region. Thus, we researched the most intense discussion themes and tried to discover the global agendas of the labor markets. Within the scope of this article, we downloaded, classified, and examined a total of 1,062 publications (reports, webinars, and bulletins) published between January 2020 and April 2021. As a result of the analysis, we saw that the themes of working hours, informal workers, vulnerable workers, decent work, social protection, remote working, skills development, social dialogue, and labor standards were dominant.

Discussions of remote work and the digitalization of the workspace have gained momentum since the early 2000s. Following the onset of the pandemic in 2020, we have seen a shift in the production process toward remote work. With the prevalence of digital business platforms in many countries of the world, work has become more independent of space and distance.

The International Labor Organization (ILO) produces reports and documents for all subjects related to work. The ILO has produced a substantial number of publications in the context of COVID-19 and the transformation in working life it has caused. This article aims to find, using an exploratory analysis, themes that stand out in each period and region in ILO publications. Labor standards are not fixed, and the forms of work and its conditions will continue to evolve. This article also aims to evaluate the possible changes in working life after the pandemic period, such as changed expectations or potential policies. By analyzing the text of previous ILO publications, we seek to read the future from the past and shed light on previous research that has been overlooked despite describing the current dynamics of working life. The ILO has produced rich discussions and an enormous amount of literature about what the future of work might look like. Labor markets in developing and developed countries will likely undergo significant transformations in the following years and decades.[1] What the future of work looks like, then, depends heavily on how those transformations play out. Popular scenarios include ones with technological revolution, ecological conversion, decent work, and the dismantling of labor laws.[2] ILO is a crucial organization in global economic policymaking.[3] The ILO reports can serve as indicators of future trends in the labor market and can follow the global market agenda ahead of time.[4] For example, technological unemployment was at the center of policy debates about automation processes in the 1960s, and the ILO archives show that many of today's policy recommendations were first put forward in the ILO at that time.[5] Also, ILO first introduced the concept of decent work at the 87th session of the International Labour Conference in 1999.[6] After that, decent work became, and continues to be, one of the central concepts of working life.[7] For this reason, we believe that the results we obtain from the ILO documents we have analyzed can help forecast the future of the labor market.

For this article, we downloaded 1,062 publications (reports, webinars, and bulletins) from the ILO. We divided the publication into 5 quarters, from January 2020 to April 2021. First, we created word frequencies and clouds with the NVivo software, then we created thematic topics by evaluating words together with their word-tree components. We looked for themes in the publications with an eye toward how we would separate them via our coding, and we cross-checked the results of the automated classification to confirm that the classifications were accurate. With the data classified, we then analyzed by period and by region.

This article consists of four parts. The first part is devoted to theoretical explanations of the thematic components that emerged within our qualitative research. In the second part, we explain our method. The third part is about our findings. In that part, we see which of the most frequently used words, sentences, and themes are associated, and we reveal the level of discussions within the topics presented. That part also compares the intensities of discussion on the themes over the ILO regions and selected 5 quarters. The last part is devoted to our discussion and conclusion. In that section, we combine and evaluate all thematic components.

Theoretical background

Since the beginning of the COVID-19 pandemic, the ILO has closely followed the effects of the pandemic on working life and the business world. The global economic crisis that emerged because of the pandemic has increased the importance of public interventions and regulations for workers and employers. To shield their vulnerable populations from the direst effects of the crisis, governments have responded with an unprecedented expansion of economic assistance and social protection. These expansions have included job retention measures, support to enterprises in severely impacted sectors, expansion of unemployment benefits, and social assistance aimed at the poorest and most vulnerable.[8] All these practices have had a place in the publications of the ILO, in the form of actual practices as well as recommendations to member countries. In the COVID-19 and Enterprises briefing notes, the ILO states that the COVID-19 pandemic has been affecting enterprises of all sizes and types. In this context, the importance of business and jobs sustainability is emphasized in the fight against increasing global unemployment and working poverty. The briefing notes also emphasize supporting small and medium enterprises in their effort to develop contingency plans to protect their workers and businesses from the consequences of sudden disasters.[9] Besides tax policy and tax administration measures, governments could also consider social security benefits, direct labor subsidies, wage subsidies, leave and self-isolation support, business cash flow, short-time work support, and unemployment payment.[10] In addition, the ILO briefing notes also examined the effectiveness of government interventions such as direct grants, selective tax advantages (and advance payments), state guarantees for loans taken by companies from banks, subsidized public loans to companies, safeguards for banks that channel state aid to the real economy, and short-term export credit insurance.[11]

Remote work and digital labor platforms (like gig work), which became widespread during the COVID-19 pandemic, radically changed working conditions, working hours, and working arrangements and increased the importance of decent work. In times of crisis, International Labor Standards provide a strong foundation for critical policy responses that focus on the crucial role of decent work in achieving a sustained and equitable recovery. These standards, adopted by representatives of governments, workers and employers, provide a human-centered approach to recovery, including triggering policy levers that both stimulate demand and protect workers and enterprises.[12] There are 10 indicators of decent work:

- Employment opportunities
- Adequate earnings and productive work
- Decent working time
- Combining work, family and personal life
- Work that should be abolished
- Stability and security of work
- Equal opportunity and treatment in employment
- Safe work environment
- Social security
- Social dialogue, workers' and employers' representation.[13]

During the COVID-19 pandemic, ILO gave special attention to vulnerable population groups, especially migrant workers, women workers, workers with disabilities, elderly workers, and informal workers.[14] For millions of workers around the globe (especially manual laborers), working from home is not an option. This group of workers, at various points during the COVID-19 pandemic, was forced to stay home or was under (temporary) unemployment.[15]

The lockdown and confinement phase of the pandemic has provided an excellent opportunity to invest in retraining staff to develop new skills or become certified in the skills they already have. One of the impacts of COVID-19 has been the proliferation of free online courses. The ILO has taken advantage of digital technology and social media to encourage people to access online courses and on-the-job tutorials. The ILO already uses digital communication channels to raise awareness of occupational safety and health in the context of COVID-19 in some countries.[16]

Method and background process

We collected the 2020 data within the scope of the research from the official website of the ILO between March 22, 2021 and April 6, 2021.[17] We carried out this search by typing the keyword "COVID-19" in the search bar on the site. At the time of writing, according to the search result, there were 2,373 results in 2020 that were displayed on 238 pages in total. There were 10 documents per page (with 3 documents displayed on the last page, number 238).

After the search result for the keyword "COVID-19," we preserved the way the official site presented the data, and we then prepared an Excel file and began to record the data.[18] We collected the data in the order the site presented them (nonchronologically) and wrote them on each line separately in our database. We then put them in chronological order for 2020. After we reordered the results, we labeled them with the relevant quarter. The quarters for 2020 are determined as follows: quarter one with January–February–March data, quarter 2 with April–May–June data, quarter 3 with July–August–September data, and quarter 4 with October–November–December data.

We collected the data for 2021 through the same process. A total of 815 documents for 2021 on the official site of the ILO were displayed on 82 pages. We started the data collection process for the 2021 data on April 14, 2021 and finished on April 16, 2021.

The total number of data recorded for 2020 and 2021 is 3,188. After we removed files that were not capable of being textually analysed (such as those in video or photo formats) as well as duplicate items, we had 1,062 files from the ILO site remaining. We performed no other filtering on the documents except to ensure that the word COVID-19 was present and the publication date was within the sample period.

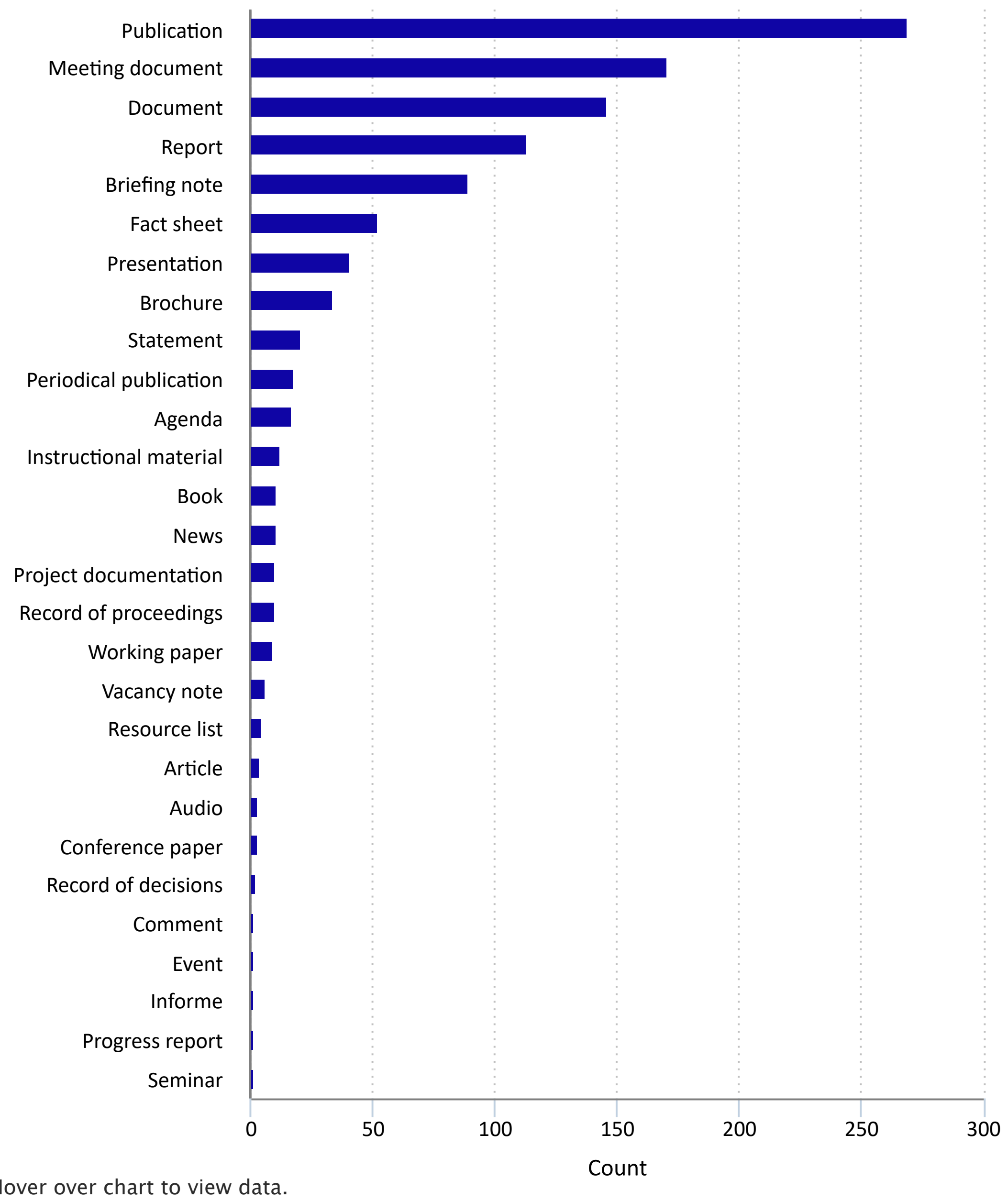
In this article, we do not test a previous hypothesis, and instead let the features of the data guide us. Because of this nature, it is an inductive analysis.[19] Since our aim is to examine the relationships between the data in detail from a holistic perspective and to make inferences, we decided that "qualitative research" was the most appropriate method.[20] To reach high-level themes from low-level concepts, we decided to use the grounded theory methodology.[21] The labor market experiences of the research team over the years, their readings, and academic studies have significant value in thematic classification. In addition, if the dataset is developed in the future, we have already made an infrastructure for future studies on the subject because of the convenient structure of embedded theory analysis.

We chose qualitative data analysis as the research method, and we preferred the content analysis method because it would be the first detailed analysis of the data. In order to reduce human error in the research method and to facilitate many processes, we decided to use NVivo, a computer-aided qualitative data analysis software (CAQDAS).[22] CAQDAS is not a program that allows all operations to be performed automatically by loading the data into the program, but it is rather a tool that automates the processes of a research design.[23] The introduction of these codes is called *manual coding*, and this forms the basic infrastructure (code structure) of the rest of the research.

The manual coding section resulted in the creation of four main titles (with various subtitles) and defined the most fundamental topics in the data. For the thematic analysis of the publications, we manually coded with the help of NVivo. NVivo assigned the ILO-term data to the categories we created, and to ensure that all the data were properly assigned by NVivo, we manually checked each assignment to confirm it was accurate (and if not, we reassigned the term to the proper category).

In this article, we carry out our analyses at various levels with the help of manual and automatic coding. First, we perform a single-level analysis to determine document type. (See chart 1).

Chart 1. Count of document types published by the ILO, 2020–21



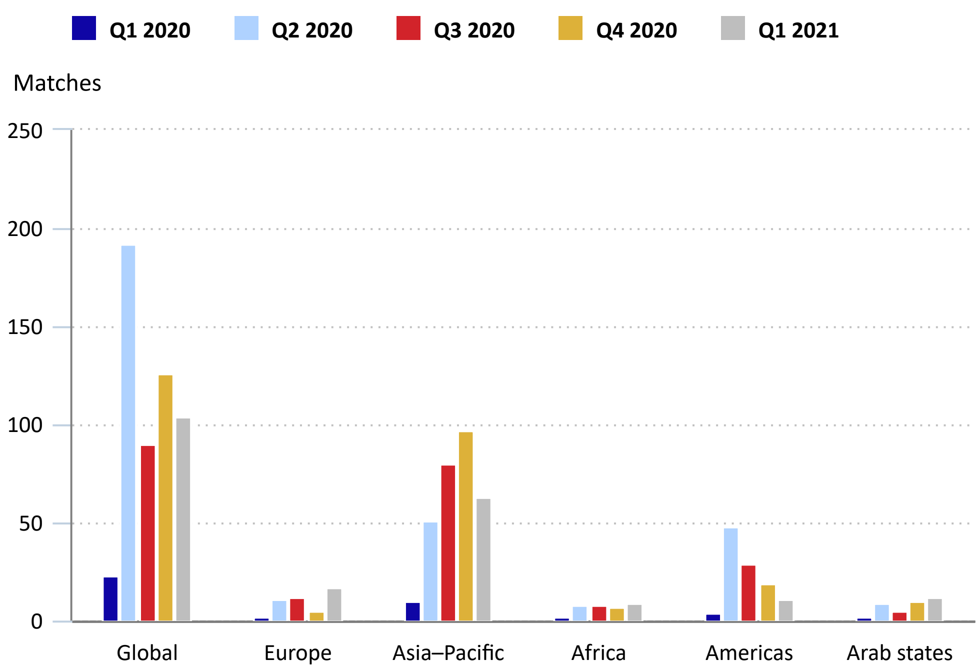
Hover over chart to view data.
Note: ILO = International Labour Organization.
Source: Authors' calculations from International Labour Organization publications.

View Chart Data

According to our classification of the 1,062 documents, there are 269 general publications, 171 meeting documents, 146 featured documents, 113 reports, 89 briefing notes, 52 fact sheets, 41 presentations, 34 brochures, 21 statements, 18 periodical publications, 17 agenda documents, 12 instructional materials, 11 news items, 11 books, 10 project documentations, and 10 records of proceedings. Twelve categories, with fewer than 10 counts each, contain the remaining 37 items.

We then perform a dual-level analysis to determine the period and region relationship of the documents. (See chart 2.)

Chart 2. Matching ILO terms by region and quarter, 2020–21



Click legend items to change data display. Hover over chart to view data.
Note: ILO = International Labour Organization; Q = quarter. Regions are as defined by the ILO.
Source: Authors' calculations from ILO publications

View Chart Data

The majority of the documents in the analyzed dataset are global and 192 of the 534 documents classified as global were published in the second quarter of 2020. Out of 301 documents associated with the Asia–Pacific region, 97 were published in the fourth quarter of 2020. Finally, 111 documents are related to the Americas, 47 are related to Europe and Central Asia, 37 to the Arab States, and 32 to the African region.[24]

In the second stage, we counted word frequencies for all categories. Our aim here was to find the most common words in every category and create a study guide. When we ordered the meaningful words according to their frequency of use, it started to explain the central theme discussed in the relevant period in 1,062 publications.

Word cloud analysis is the visual expression of the most mentioned words in a dataset. In word cloud analysis, the words that are mentioned the most are in the middle of the cloud and in large fonts while less frequently mentioned words are toward the edges of the cloud shape and in smaller fonts. Word clouds are used to visually reveal the words and values that may be overlooked in a frequency table, and they contribute to making the research results understandable for the reader.

NVivo software automatically analyzed all documents and determined the 1,000 most commonly used words in the documents.

Figure 1. ILO word cloud analysis, 2020–21

Note: ILO = International Labour Organization.
Source: Authors' calculations from ILO publications.

In word cloud analysis, the most used words in the articles are “workers,” “work,” “labor,” “ILO,” “social,” “covid,” “employment,” “women,” “health,” “support government,” “sector,” “skills,” and “policy.” We took a subset of the top 1,000 words to be a subject for our more detailed analysis. The frequencies of the words that are used the most and of the words that we decided to remove from our analysis are given in table 1.

Table 1. Frequency of examined ILO terms, 2020–21

Word	Count	Selected for word cloud
Workers	39,925	Yes
Work	39,765	No
Labor	35,231	Yes
ILO	34,845	Yes
Social	30,712	Yes
Employment	25,447	Yes
COVID	25,148	Yes
Per	22,793	No
Cent	19,562	No
Women	18,794	No
Countries	16,216	No
Development	14,960	No
Health	14,732	No
Support	14,279	No
Working	13,449	No
Government	12,960	Yes
Skills	12,790	No
Training	12,596	Yes
Economic	12,511	No
Sector	12,502	Yes
Policy	12,448	No
Protection	12,197	No
Measures	12,078	No
May	12,058	No
National	11,996	No
Including	11,270	No
Crisis	11,120	No
Pandemic	10,545	No
Services	10,481	No
Enterprises	10,308	Yes
Business	10,225	No
Market	9,823	No
Based	9,754	No
Gender	9,673	Yes
Data	9,509	No
Global	9,267	No
Time	9,254	No
World	9,216	No
New	9,076	No
Income	9,028	Yes
Jobs	8,894	Yes
Trade	8,893	Yes
Country	8,720	No
People	8,478	No
One	8,354	No
Public	8,205	No
Impact	8,110	No
Report	8,086	No
Economy	8,075	No
Information	7,850	No
Level	7,807	No
Decent	7,770	Yes
Interventions	7,594	Yes
Access	7,534	No
Migrant	7,501	No
Well	7,425	No

Note: ILO = International Labour Organization; OHS = occupational health and safety.
Source: Authors' calculations from International Labour Organization publications.

Word	Count	Selected for word cloud
Wage	7,411	No
Job	7,173	No
Education	6,924	Yes
Rights	6,814	No
Provide	6,759	No
Sectors	6,753	No
Informal	6,752	No
Activities	6,747	No
Policies	6,721	No
Many	6,671	No
Employers	6,665	No
Office	6,625	No
High	6,500	No
Key	6,422	No
Response	6,344	No
Group	6,339	No
Number	6,300	No
Available	6,298	No
Youth	6,258	Yes
Use	6,232	No
Programme	6,205	No
Management	6,092	No
Poverty	6,072	Yes
Ensure	6,038	No
Financial	6,013	No
Figure	5,977	No
Security	5,961	No
Dialogue	5,914	No
Org	5,901	No
Union	5,878	No
Organizations	5,857	No
Related	5,721	No
Risk	5,684	No
Safety	5,634	No
Among	5,617	No
System	5,590	No
Total	5,535	No
Survey	5,530	No
See	5,385	No
OHS	5,372	Yes
Conditions	5,331	No
Entrepreneurship	5,297	Yes
Home	5,252	No
Digital	5,246	Yes

Note: ILO = International Labour Organization; OHS = occupational health and safety.
Source: Authors' calculations from International Labour Organization publications.

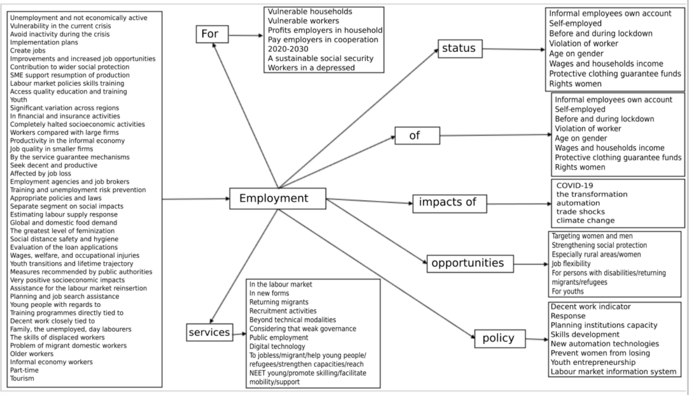
On the basis of the most used words in the dataset, we decided to perform a word tree analysis of 22 words.[25] We chose these 22 words because of our readings and field experiences. Word tree analysis is a qualitative data analysis tool that reveals the words used before and after a selected word or phrase and helps to obtain general information about the articles. After the word tree analysis (and discussions with experts), we classified the articles by topic and subtopic.

We prioritized the words obtained from the word tree analysis according to our experience and the objectives of the study. We then examined the three words before and after the selected words to look for patterns and associations.[26] When all the documents were scanned, the word tree analyses began to provide us with more detailed information about general trends. To better understand word tree analysis, in figure 2, we give examples for the word "employment."

During the word tree analyses, other concepts and commonly paired words in the documents emerged. For example, the use of the words "unemployment" and "arrangements" before the word "work" reveals that the concepts of unemployment and labor market regulations are mentioned together frequently in the documents.

Some of the analyzed words, such as "employment," have multiple-level expressions associated with them, while for other words the analysis is single level. We grouped themes under main headings. (See figure 3). With the manual coding, the points in the documents that we consider essential and the points that we want to emphasize are revealed. When the words identified during the manual coding phase are associated with close components from the covered ILO publications, all of the identified words can be grouped under four main headings: "regulations/interventions," "labor relations," "vulnerabilities," and "education/training."[27]

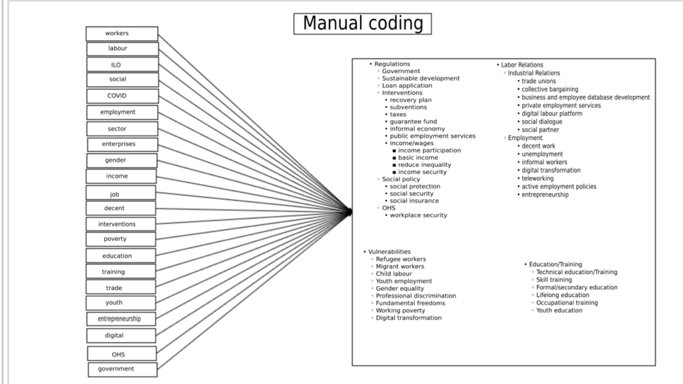
Figure 2. Word tree analysis of “employment”



Note: ILO = International Labour Organization; NEET = not in employment, education, or training; SME = small and medium enterprises.
Source: Authors’ calculations from ILO publications.

The four main headings, which we determined from the word trees we formed by manual coding, express the macro topics that the 1,062 publications focus on. After we completed the regional and periodical thematic discoveries, we classified the identified themes under these four main headings.

Figure 3. Manual coding example for ILO publicatons



Note: ILO = International Labour Organization; OHS = occupational safety and health.
Source: Authors’ calculations from ILO publications.

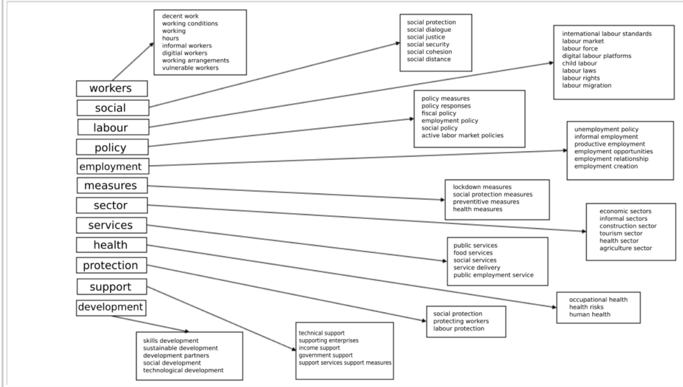
After the manual coding process, we determined the repeated focal points in ILO documents within the themes that emerged as a result of manual coding. The recurring focal points in the ILO documents were revealed by the word cloud and word tree analysis as well as our own experience, and we classified the topics that emerged. Thus, it was possible to separate the most popular issues under the main headings. Topics resulting from automatic coding associated with manual coding are given in figure 4.

After we examined the themes from automatic coding, we narrowed our word list from 22 to 12. The remaining words are those that we found to be most closely related to the point of our study. With the automatic coding done after manual coding inferences, we could see which subjects were emphasized within the scope of the ILO during the COVID-19 pandemic period. Thus, we were able to conduct a detailed content analysis for each thematic component. The discovery process and content at the end of automatic coding are presented in figure 5.

The topics that stand out on a global scale within the scope of 12 main themes that emerged from the dataset we examined follow.

Social protection and support frequently appear in every theme.[28] From the articles, we see that mentions of public aid became much more common and that social policies and new labor law regulations became more prevalent. In the articles that are under the employment and unemployment headings, we see warnings about the destruction of decent work. We find that decreasing employment opportunities, worsening working conditions, uncertain working hours, and increasing unregistered employment were all being discussed more and more. The reports state that the social dialogue mechanism, occupational health and safety, and general health conditions have all deteriorated. Some articles draw attention to the increase in digital labor platforms and comment that there was a weakening in social security rights and an increase in the number of vulnerable workers. A number of publications mention the adverse effects of the COVID-19 pandemic on the construction, tourism, and agriculture sectors. The ILO publications also mention the difficulties encountered in public services, food services, and a deterioration in service delivery. Migrant labor and child labor issues also have a prominent place among the documents we examined.

Figure 5. Automatic themes and thematic components



Note: ILO = International Labour Organization.
Source: Authors’ calculations from ILO publications.

Findings

From our results, it was possible to separate regional and periodical themes. When we analyzed by region, we were able to decompose the prominent issues according to each region.

By region

According to the thematic intensities disaggregated in the ILO five-region classification, the most discussed issue in the Americas region was “working hours.” The ILO articles emphasized that unregistered employment had increased, labor rights had weakened, and labor laws had been inadequate in keeping up in a changing environment. The articles also noted that the region had quite a number of public policies for business development as well as for income support for its denizens. The articles from the region also emphasized the health system and the problems encountered in health services. There are also determinations regarding real minimum wage discussions and new union organizing movements.

The topic of “local workers” was frequently discussed in the articles from the Europe and Central Asia region. Because of a decrease in the working-age population, the issue of migrant labor and unregistered employment was at the forefront of the ILO articles. The publications emphasized that remote work was gaining momentum, working conditions were deteriorating, and vulnerable labor was increasing. Some reports focused on temporary government measures, the need to reduce informality, and the damage that the COVID-19 pandemic created in the services, tourism, and food sectors. The region’s articles also expressed the importance of support for workers and employers and gives recommendations for restructuring social security and insurance services. There were statements about the need to review the minimum wage policy, the increase in wage differences, and wage support. Some articles also suggested reviewing social assistance payments’ structure, introduced new human health-oriented approaches to social policies, and stressed the importance of institutional labor market practices and occupational health and safety.

“Migrant workers and vulnerable workers” were the most frequently reported issue in the Asia and Pacific region. Forced labor, child labor, and the inadequacy of labor laws were heavily discussed. The ILO articles emphasized labor force participation difficulties and the need for improvements to labor market information systems. Articles also discussed the forms of informal employment and flexible work as well as what policies governments should take toward immigrants. The destruction of the supply chain of food services and the disruptions in social services were also a focus. The articles for the region stated that the social protection system should be improved and that wages should be protected, and overall they emphasized the importance of supports for both employers and workers. There were also discussions on providing more technical and institutional support for talent and capacity building.

In the African region, the most intense debate within the ILO was the “informal economy.” Skill development and obtaining valid work permits were among the critical issues. The publications highlighted migrant labor, employment contracts, and the inadequacy of labor demand. Many reports stressed the necessity of increasing the efficiency of private employment agencies in this regard. They stated that socioeconomic development is destroyed because of the inadequacy of labor market institutions and information systems. The areas of discussion included the desire to introduce effective vocational training and on-the-job training programs to address the lack of skilled labor; poverty and poverty reduction policies; the need for the establishment of social protection systems, national qualification systems, and job security systems; and the establishment of electronic tax payment systems to prevent tax losses.

The most intensely debated issue in the Arab States region was “working conditions and the fragility (vulnerability) of local and migrant workers.” Syrian and Lebanese workers and working conditions were among the critical issues. The publications emphasized that participation in the labor force and the skills demanded by the labor market are low. They stated that labor costs and inputs are expensive, so the informal sector could not be regulated. Export-oriented sectors stood out because of oil revenue, but other sectors lagged behind. Psychosocial support service providers have been increasing in recent years. The ILO articles emphasized that agrochemical products were concentrated in the region, that production costs and greenhouse production were increasing. They also emphasized the importance of health insurance and that the government provides many supports such as technical support, business support packages, childcare supports, and financial support. Looking toward the future, the articles said that labor market capabilities should be developed through on-the-job learning in line with digital capabilities even though informality has increased because of home-based work.

After we completed the regional analysis, we made another analysis using the same data, this time looking individually at the 5 quarters covering January 2020 to April 2021.

By period

In the first of the 5 quarters covering the selected COVID-19 pandemic period, the ILO publications extensively discussed the issue of informal labor on a global scale. “Decent work, vulnerable workers, and social dialogue” were the hot topics of discussion. Health institutions and the activities of social protection, assistance, and security were among the priority issues, and the discussion of measures taken for the protection of workers intensified over this period. This quarter’s publications emphasized that for the continuation of labor demand, government-based income supports and measures to increase the workforce’s productivity should be taken.

Discussions on “working conditions and social protection measures” gained momentum in the second quarter. The health sector and occupational diseases came to the forefront again within the framework of international labor standards. The publications suggested that social protection systems should be combined with labor laws and new structures should be formed. They emphasized financial measures, including wage protection, and the need to strengthen public employment services. The need to strengthen technical and income support was also among the priorities discussed. Measures against destruction, especially in the tourism sector, were also among the reports of the period.

“Working conditions and intensified informal labor” were the prominent themes of the third quarter. Unlike the previous quarters, child labor was also on the agenda. Labor rights, active labor market policies, and social protection measures maintained their importance. Discussions around the problems of the supply chain in food services began during this quarter. In addition, the articles emphasized that digital capabilities should be strengthened in order to continue the business process. While the concept of decent work kept its agenda in this quarter, job losses and wage protection began to gain importance.

“The destruction of international labor standards in the context of decent work” stood out in the fourth quarter. Many articles mentioned that for a country to have a sustainable development process it must create national polices to target unregistered employment. The publications stated that social protection systems should be combined with active labor market policies, and the workforce should be protected. While the articles generally emphasized the need to create new jobs at the national level, they also mentioned minimum wages and generally low wage levels.

In the fifth quarter, the ILO’s use of the phrase “decent work and working conditions” increased, especially within the scope of remote work. The articles stated that national employment policies were gradually deteriorating in the face of international labor standards and that employee productivity had decreased while unregistered employment had increased. Some articles addressed social protection systems and their implications for sustainable growth, as well as how data collection and analysis has increased with the growth of social security systems. There were also many reports that business continuity was a prominent problem in this quarter in particular.

Discussion and conclusion

This article aims to reveal the most intensely discussed themes in the publications originating from the ILO’s regions during the COVID-19 pandemic period.

Discussion

We gathered themes under four main headings within the scope of the ILO regional separation and the limitation of the 5-quarter period (January 2020–April 2021). (Additional figures are available under "source data.") These themes are “regulations/interventions,” “labor relations,” “vulnerabilities,” and “education/training.”

The intensities of the regional discussion themes were as follows:

- Americas: working hours, labor rights, labor laws
- Europe and Central Asia: local workers, working-age population, migrant and working conditions
- Asia and Pacific: migrant workers, vulnerable workers, forced labor
- Africa: informal economy, skills development, work permits
- Arab States: working conditions, local/migrant workers, vulnerable workers.

The periodic theme intensities were as follows:

- First quarter: informal workers, decent work, vulnerable workers
- Second quarter: working conditions, lockdown measures, social protection measures
- Third quarter: working conditions, informal economy workers, vulnerable workers
- Fourth quarter: decent work, international labor standards, national policy
- Fifth quarter: decent work, working conditions, remote work.

We mostly see supports and interventions under the heading of “regulations/interventions.” Many articles in this heading deemed it necessary to build a set of rules, especially to address the unique dynamics of digital labor markets. The articles also expressed that the prevalence of remote work necessitates a total restructuring of institutional arrangements. They suggested that there is a need for specially structured recommendations, contracts, and laws regarding a new working order, even though a great deal has been made in the global context since the industrial era on issues such as fundamental rights, working hours, and occupational health and safety. New tax policies seem to be discussed alongside social security systems. Many reports stated that there is a need for a new structure regarding tax collection systems and tools. In summary, regulations are commonly discussed in this theme title.

Under the classification of “labor relations,” we find that statements to strengthen employment relations within the scope of social dialogue are predominant. Social dialogue includes healthy relations between the parties and reveals a new area of negotiation within the scope of decent work. The documents reported that there is a need for new forms of organization to protect and develop the rights of the workforce formed by the new working styles. Unions could compensate for the worsening situation, especially in the case of enchroachment on the fundamental rights and benefits of workers who use digital labor platforms. However, the rapid evolution of the traditional structure of trade union organizations is not easy. That is not to say that unions are unprepared, as the publications stress that unions are aware of the transformation dynamics accelerated by the pandemic. In the country reports examined, we see that there was an effort to develop job and worker databases. Although the reports stated that the databases were primarily structured to create new employment opportunities or to keep the social security system under control, the databases could also help establish an infrastructure for new trade union organizing. Many reports emphasized that there may be significant problems in today’s traditional structure, especially in the organization of gig workers and contractors. Inside the ILO publications, there were statements that the loss of rights resulting from digital and remote work significantly damages the concept of decent work that the ILO has emphasized for years, statements that new measures should be taken to protect the scope of decent work, and statements that indicate that decent work standards are rapidly deteriorating in many countries. In summary, the main theme of the classification of “labor relations” is the concepts of social dialogue, employment relationships, and decent work.

Under the “vulnerabilities” classification, we interprete themes for disadvantaged groups and those who lost their jobs during the pandemic and had difficulty finding new jobs. The ILO articles touched on the subjects of refugees, youth, children, the elderly, and the disabled, especially women. The reports stated that the invisible labor burden of women (for example, responsibilities such as housework and the care of children, elderly, and disabled people) has increased even more. The publications also emphasized that with the increase in the invisible labor burden of women, women’s employment is in danger of shrinking, a situation that would negatively affect gender equality in working life. In the documents examined, we see that the subjects were mainly informal employment, lack of income, working hours, and unemployment. There were also determinations that the number of vulnerable people was increasing as a result of the employment gradually turning into underemployment.[29] Unemployment, which occurs at different levels with the deterioration of the balance of labor markets, has came to the fore as an area that all countries focus on for a solution. Because of the support of governments, informal employment can decrease, however this decrease did not seem to apply to refugees in informal employment. From the widespread mentions of informality, we see that the problem of informality has now become a worldwide problem. Informal employment risks were higher in developing countries because of their relatively low capacity to provide substantial financial support to the labor market. The works we classified under “vulnerabilites” also pointed out that the millions of workers who have shifted to digital platforms have become more vulnerable generally.

To increase accuracy, we separate informality into different dimensions of the workforce. Although the general global statistical trend shows that the working poverty rates have decreased, we understand from the examined publications that working poverty has become more prominent because of the pandemic and the sudden shift to remote work. From the sheer amount of mentions of working poverty we see in the documents we analyzed, we would not be surprised if the global poverty rates stopped decreasing and started to increase. The publications saw a rise in investigations of working poverty at the same time as they saw a rise in the investigations of the remote and gig work. There were statements that members of the labor force, especially those working remotely, were at risk of becoming the working poor. In summary, the “vulnerabilities” classification comprises the concepts of disadvantaged groups (women, refugees, youth, children, the elderly, and the disabled), migrant workers, informal employment, unemployment, and working poverty.

In the “education/training” classification, articles emphasize the importance of training, and most reports contain statements about distance education. The publications noted that some trainings, such as occupational health and safety training, technical training, or new-employee training, could be provided more cost effectively and efficiently online than in person. The analyzed reports stated that it will be possible for the scope of lifelong learning to be more effective thanks to distance education and that many measures have been taken in this regard. Many articles posited that new training programs should be created to replace traditional vocational education institutions. These reports show that throughout the pandemic businesses are rethinking how to deliver training to employees. We see that the publications gave special attention to the on-the-job and vocational training of young people who often face higher levels of unemployment. There were also recommendations for the national qualification system establishment. Since physical distance matters less now because of digitalization, the determinations that the workforce should be equipped with global skills were also noteworthy. In summary, the main theme of the education/training classification is the concepts of talent, business development, skills and vocational training in particular and also lifelong learning and online education in general.

Conclusion

To summarize, the main theme “regulations/interventions” includes interventions such as government measures, social services, supporting income/enterprises/wages/technical, public employment services, active labor market policies, labor market institutions, labor protection, social security, social dialog, and social policy. The “labor relations” theme comprises decent work, labor standards, employment relationships, employment contracts, labor force participation, remote work, and unemployment. “Vulnerabilities” covers topics such as refugee/migrant child, youth, gender discrimination, informal workers, working conditions, and working hours. Finally, the “education/training” theme contains topics such as technical, skill and vocational training, skills development, capacity development, digital skills, and national qualification system.

We find in these articles and reports that vulnerable populations, working conditions, wages, trade unions' rights, working poor, occupational health and safety, social security and dialogue have shaped the bulk of the research surrounding the COVID-19 pandemic. More research will be needed to see if these themes continue in the postpandemic environment.

SUGGESTED CITATION:

M. Çağlar Özdemir, Hakan Mete, Cihan Selek Öz, and V. Çağrı Arik, "Global labor market debates in the ILO publications in the COVID-19 era," *Monthly Labor Review,* U.S. Bureau of Labor Statistics, September 2023, https://doi.org/10.21916/mlr.2023.20

Notes

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[21] Grounded theory is a qualitative approach with dynamics. This method was introduced in the 1960s as part of a sociological research program on death in hospitals. See Barney G. Glaser and Anselm L. Strauss, *The Discovery of Grounded Theory: Strategies for Qualitative Research* (Chicago: Aldine Transaction, 1967). Grounded theory emerged in an effort to discover the root causes of an event beyond the apparent empirical evidence. For example, see Juliet M. Corbin and Anselm Strauss, “Grounded theory research: procedures, canons, and evaluative criteria,” *Qualitative Sociology* vol. 13, no. 1, 1990, pp. 3–21, https://doi.org/10.1007/BF00988593. Although grounded theory is a qualitative method, it effectively reveals the truth by blending the strengths of quantitative methods with qualitative approaches. See Kathy Charmaz, “Grounded theory: objectivist and constructivist methods” in *Handbook of Qualitative Research*, eds. Norman K. Denzin and Yvonna S. Lincoln, 2nd ed. (Thousand Oaks, California: Sage, 2000). In this context, it can be defined as the whole of the systematic analysis process inherent in quantitative survey research, with combined logic, rigour, and the depth and richness of qualitative interpretative traditions. See Barbara Keddy, Sharon L. Sims, and Phyllis Noerager Stern, “Grounded theory as feminist research methodology,” *Journal of Advanced Nursing* vol. 23, no. 3, March 1996, pp. 448–453, https://doi.org/10.1111/j.1365-2648.1996.tb00005.x. See also Linda C. Robrecht, “Grounded theory: evolving methods,” *Qualitative Health Research* vol. 5, no. 2, May 1995, pp. 169–177, https://doi.org/10.1177/104973239500500203.

Grounded theory is a methodology that starts with data collection and then derives insight from the systematically collected data. See Ian Dey, *Grounding Grounded Theory: Guidelines for Qualitative Inquiry* (Emerald Group Publishing Limited, 1999). In grounded theory, first researchers identify an area they would like to research. Next, they determine the scope of data about the theme, and then they find, code, and systematically analyze the data. Once the data are examined, the researchers then develop and test a hypothesis. In the first stage of coding and analysis, called "manual coding", analysts code independently from each other and create a theoretical infrastructure for the data. Next, researchers segment, compare, and categorize the data. At this stage, researchers use inductive and reductive thematic analytical processes to determine similarities and differences between items, and new categories are created. (In this context, inductive means reaching from data to facts and then from facts to theme and main idea. Reductive means taking a large dataset and streamlining it to its core components. For more information, see Corbin and Strauss, “Grounded theory research.”) Then the generated structure can be subjected to a more advanced analysis tool, and automatic coding can be used. Thanks to the chains of relationships structured within the data, it is possible to reveal the embedded theory about the researched subject as a result of the analysis. This inference also helps to compare scattered data in context. See Diane Walker and Florence Myrick, “Grounded theory: an exploration of the process and procedure,” *Qualitative Health Research,* vol. 16, no. 4, April 2006, pp. 547–559, https://doi.org/10.1177/1049732305285972.

[22] For an account of the history of computer-aided qualitative data analysis software and a reflection on its role in science, see FC Zamawe “The implication of using NVivo software in qualitative data analysis: evidence-based reflections,” *Malawi Medical Journal,* vol. 27, no. 1, March 2015, pp. 13–15, https://doi.org/10.4314%2Fmmj.v27i1.4.

[23] For more information, see Christina Silver and Ann Lewins, *Using Software in Qualitative Research: A Step-by-Step Guide* (Sage, 2014), https://doi.org/10.4135/9781473906907.

[24] The regions correspond with the regions defined by the ILO. A complete list of which countries appear in which region can be found at https://ilostat.ilo.org/resources/concepts-and-definitions/classification-country-groupings/.

[25] The 22 words are as follows: workers, labour, ILO, social, COVID, employment, sector, enterprises, gender, income, job, decent, interventions, poverty, education, training, trade, youth, entrepreneurship, digital, OHS (occupational health and safety), and government.

[26] This technique is called "word tree analysis ±3."

[27] A “close component” is any of the words, related phrases, sentences, and paragraphs that are the subject of the analysis.

[28] We emphasize that measures for social protection are not only for workers but also for employers.

[29] Underemployed workers are those who are not working to their full potential at a full-time job (for example, a worker with a PhD working at a job that does not require one) or who would like to work full time but have to work part time only.

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Announcement

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Book Review

September 2023

Recontextualizing the relationship between statistics and economics

Exploring the History of Statistical Inference in Economics. Edited by Jeff Biddle and Marcel Boumans. Durham and London: Duke University Press, 2021, 332 pp., $18.00 paperback.

Anyone who has taken an econometrics course knows that statistical inference and probability theory are inexorably linked. But is that the whole story? How much do we know about the tools we use to explain economic phenomena? *Exploring the History of Statistical Inference in Economics*, a volume edited by Jeff Biddle and Marcel Boumans, helps us answer these questions. The volume outlines the history of statistical inference and traces how the economics profession has both molded the field and been molded by it. This is accomplished by focusing on work in statistical inference that falls outside the field's long-calcified standards.

The volume consists of 10 papers divided into three themed sections: "Inference in the field," "Inference in time," and "Inference without a cause." This review briefly covers each section, discussing the papers in the order in which they are presented.

The first section highlights that, over time, statistical inference has varied in both complexity and adherence to theory, with the latter being conditional on data availability and inputs from many, often biased, actors. The section refers both to work done outside of academia and to work involving agriculture, a sector covered in two of the section's three papers.

In the first paper, Paul Burnett details agricultural economist Theodore Schultz's use of "statistical parables" to subvert the prevailing assumptions of development economics in the 1950s and 1960s. According to Burnett, these parables employed limited analysis and relevant examples to disprove these assumptions by counterexample.

In the next paper, Jeff Biddle relays the work of a team of economists at the U.S. Bureau of Agricultural Economics in the 1920s and 1930s. The team employed advanced techniques to forecast livestock and crop harvests, placing more emphasis on methodological rigor than on economic theory. For example, the team revised survey questions to account for recall bias and extensively used alternative data sources ("check data") to improve its forecasts. Biddle argues that the team's work exemplified inference as it existed at the time—using data to generalize about a statistical universe outside a sample, without employing probability-based inference.

In the section's last paper, Boris Samuel discusses statistical misreporting of macroeconomic indicators to the International Monetary Fund (IMF) by the government of Mauritania in the early 2000s. Samuel argues that IMF's sanitized peer-review process and bureaucracy favored legibility, simplicity, and consistency over methodological rigor. As a result, IMF staff stuck to outdated economic models, allowing what the author calls a "statistical lie" to persist.

The volume's second section, also composed of three papers, focuses on the chronological development of statistical techniques, previewing research into economic trends and business cycles as a touchstone. Here, reexamining the past does more than simply providing useful historical parallels and examples; it gets to the core of the economics profession—understanding and explaining economic phenomena—by highlighting the mutability of the profession's tools.

In the section's first paper, Mary S. Morgan uses the work of Thomas Malthus (late 1700s to early 1800s) and Nikolai Kondratiev (early 20th century) to introduce and highlight the act of "narrative making." Morgan argues that, because of the rise of mechanized statistical inference from the 1970s onward, we have forgotten crucial components of the inferential process, namely, the deciphering of statistical phenomena and their placement in a larger context. The author recenters narrative making in the scientific process, showing how the scientist weaves together elements of a phenomenon to explain the whole.

Next, Laetitia Lenel discusses economist Warren Persons' work and the development of the Harvard Index of General Business Conditions (an index for forecasting the business cycle on the basis of probability-based inference) in the early 20th century. Although Persons espoused probability-based inference well before it became dominant, he would renounce it as inadequate when the index would not accurately forecast future economic conditions. Crucially, Lenel argues that the index's eventual failure triggered a paradigmatic shift in the economics profession, whereby ideas of individual expectations and uncertainty—as opposed to natural, mechanistic laws—guided the business cycle and the greater economy. On top of confounding the "linear history" view of statistical inference in economics and putting into question the clean shift from nonprobabilistic to probabilistic inference, this development reframes the forecaster's ever-changing toolkit as reflective of shifting economic worldviews and helps contextualize the work of economists at the time, and even today.

Closing the second section, a paper by Thomas A. Stapleford further muddies history by bending it into a circle, comparing statistical inferential techniques actualized by economists of the "data revolution" (circa 2014) with those predicted by economist Wesley Mitchell 90 years prior. In this comparison, Stapleford highlights four shared traits: a deemphasis on probability-based inference, a shift from theoretical modeling to model building based on observational data, an adoption of a common data analysis technique to encourage interdisciplinary work, and a global shift toward promoting data collection and analysis.

The volume's last section, composed of four papers, details how several parties used or developed statistical methods to advance biased argumentation, with varying results. The section highlights the interplay among economic research, the environment in which researchers collect and disseminate data, and the researchers themselves. The main takeaway from this discussion is that how we identify and navigate situations of potential bias has reverberating effects on our field of study, the larger community of applied research, and the broader society.

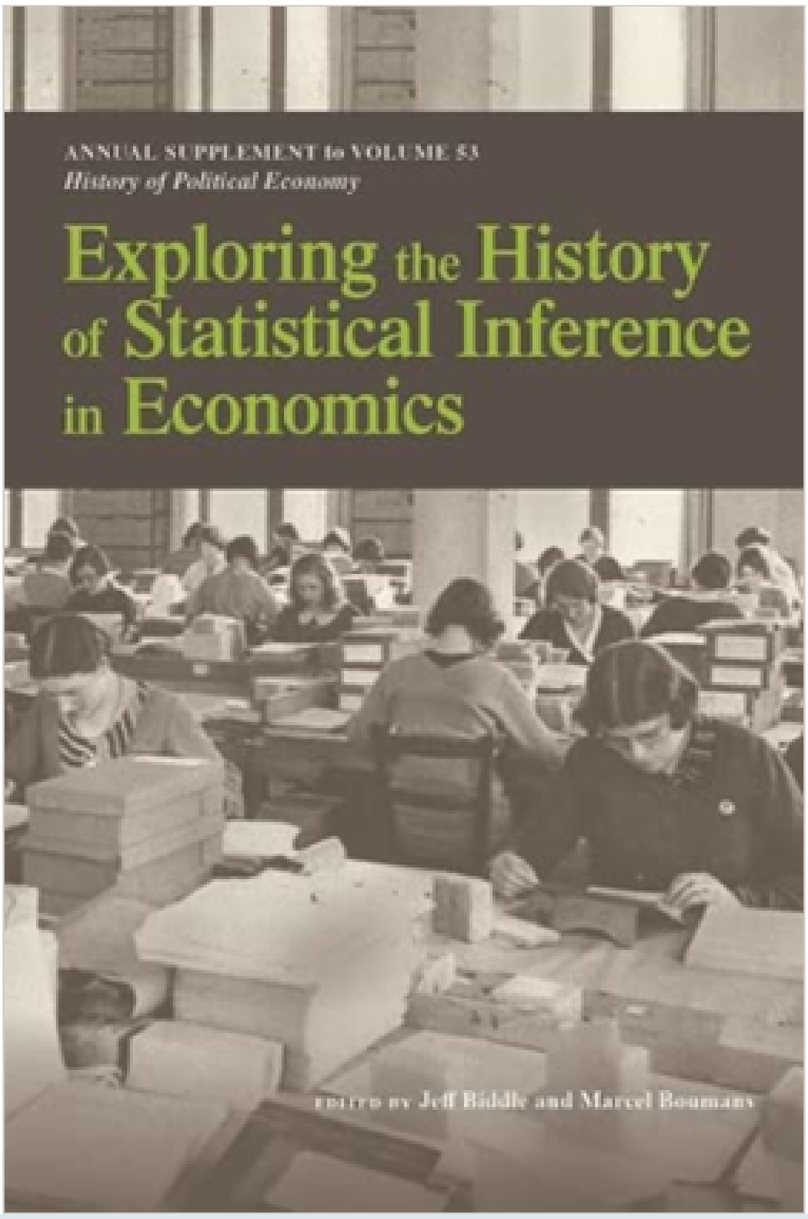
In the section's opening paper, Marcel Boumans discusses Francis Galton's (late 19th century) composite photography experiment. Galton, a eugenicist, used "pictorial statistics" to objectively prove the inferiority of certain groups. Yet, instead of showing inferiority, his composite photographs revealed "beautiful" archetypes, undermining his beliefs. Boumans also shows the bias in Galton's procedure: it was the act of grouping photographs, not the taking of their composite, that constituted inference, and that act could not avoid bias.

Next, Aashish Velkar uses examples from Great Britain to highlight how economists involved in the production of price-index statistics contended with inferential gaps in the creation and presentation of information. Inferential gaps are chasms between a given phenomenon and what the scientist measures; they can arise at any point of the scientific process. However, these gaps may involve not just dynamics between people and phenomena but also interactions among people with differing aims. For example, Velkar discusses a cost-of-living index created in Great Britain in the early 1900s, showing that, despite the index's use in inferential statistics at the government level, political factions ignored it and favored cherry-picked data designed to mislead the public and slander political opponents.

In the section's third paper, Amanar Akhabbar details Nobel laureate Wassily Leontief's (1941) early work in interindustry studies, documenting the formation of what Leontief coined "direct inference" (which he considered superior to probability-based "indirect inference"). Specifically, Akhabbar shows how Leontief used sample data to infer the structural parameters of a model that applied to the entire economy. Crucially, Leontief derived these parameters directly from his mathematical model's structural equations, not from a reduced-form equation. Akhabbar's paper contributes to the early history of alternative statistical inference by demystifying Leontief's key contribution: the field of input–output analysis.

In the section's last paper, Harro Maas closes the volume with a history of contingent valuation, a survey-based inferential technique intended to ascribe value to nonmarket goods such as the environment. The author details a long-running disagreement between resource and environmental economists over the technique's merits. Although a guiding framework for the technique was established from the 1970s to the 2000s, a series of court battles would politicize the technique and crush its reputation.

The aim of statistical inference in economics is to draw generalizations and conclusions about a population from limited data. *Exploring the History of Statistical Inference in Economics* contributes to this common goal by presenting nonstandard statistical techniques and important contributions to the field. It is equal parts history and apophatic inquiry. By highlighting nonstandard statistical inference, the volume deepens our understanding of both our profession's tools and our place in their evolving applications.



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Article

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The importance of output choice: implications for productivity measurement

This article presents three alternative concepts of output (gross output, sectoral output, and value-added output) and describes how they are related. In addition, the article discusses the advantages and disadvantages of using different output concepts in productivity measurement. These advantages and disadvantages are illustrated with an empirical comparison focusing on the U.S. manufacturing sector and selected industries within that sector.

Firms produce goods and services by combining inputs of labor, capital, energy, materials, and purchased services. How efficiently these inputs are converted into outputs is captured in measures of productivity. However, output can be measured in different ways, each having advantages and disadvantages for evaluating productivity. There are three commonly used output concepts: gross output, sectoral output, and value-added output. These concepts vary by whether the goods and services counted are limited to those produced for final consumption or whether they include goods and services purchased by firms as inputs to further production. The choice of output concept depends on the analytical question of interest, as well as the availability and timeliness of data.

In this article, we discuss these alternative concepts of output and show how they are related. We then discuss the implications of using the alternative concepts to measure productivity growth. To illustrate these implications, we construct and evaluate productivity measures based on alternative output concepts for the U.S. manufacturing sector and for selected industries within manufacturing. We use a U.S. Bureau of Labor Statistics (BLS) experimental production account for the U.S. manufacturing sector in order to investigate how output choice affects total factor productivity (TFP) in the sector.

Defining productivity and output

Productivity growth relates the growth in output to the growth in the inputs used in the production process. Labor productivity growth compares the growth in output with the growth in labor input and captures gains in output that do not result from additional hours worked. Labor productivity growth can occur because of changes in capital investment, purchased materials and services, economies of scale, worker skills, and production technologies. Labor productivity is often used to evaluate the marginal product of labor and is compared with trends in compensation.[1] Labor productivity growth (LP growth) is commonly expressed as follows:

$$(1) \quad \text{LP growth} = \text{ Output growth} - \text{Labor growth}.$$

Total factor productivity (TFP), also referred to as multifactor productivity, compares output with a combination of multiple inputs used in production. Production inputs can include capital (machinery and equipment, computers, structures, intellectual property products, inventories, and land), labor, energy, materials, and purchased services. Because TFP measures the growth in output that does not result from using additional inputs, it is often considered an indicator of technological progress. TFP measures reflect the effects of technical change, increases in general knowledge (for example, new scientific findings), and improvements to management techniques and organizational structure.[2] TFP growth is commonly expressed as the difference between the growth rate of output and the weighted aggregate of the growth rates of each input to production:

$$(2) \quad \text{TFP growth} = \text{ Output growth} - \sum_i s_i \text{ Input growth}_i \,,$$

where s_i is the cost-share weight for input *i*. This model, developed by Robert Solow in 1957, assumes constant returns to scale, implying that the value of output equals the total cost of all measured inputs and the cost shares sum to 1.[3]

Productivity estimates can be computed by using any of the three output concepts: gross output, sectoral output, or value-added output. The choice of output concept affects which inputs are explicitly included in the calculation of TFP. Given the relationship among outputs, inputs, and productivity, it is clear that how we define output has implications for addressing different analytical questions.

Output definitions

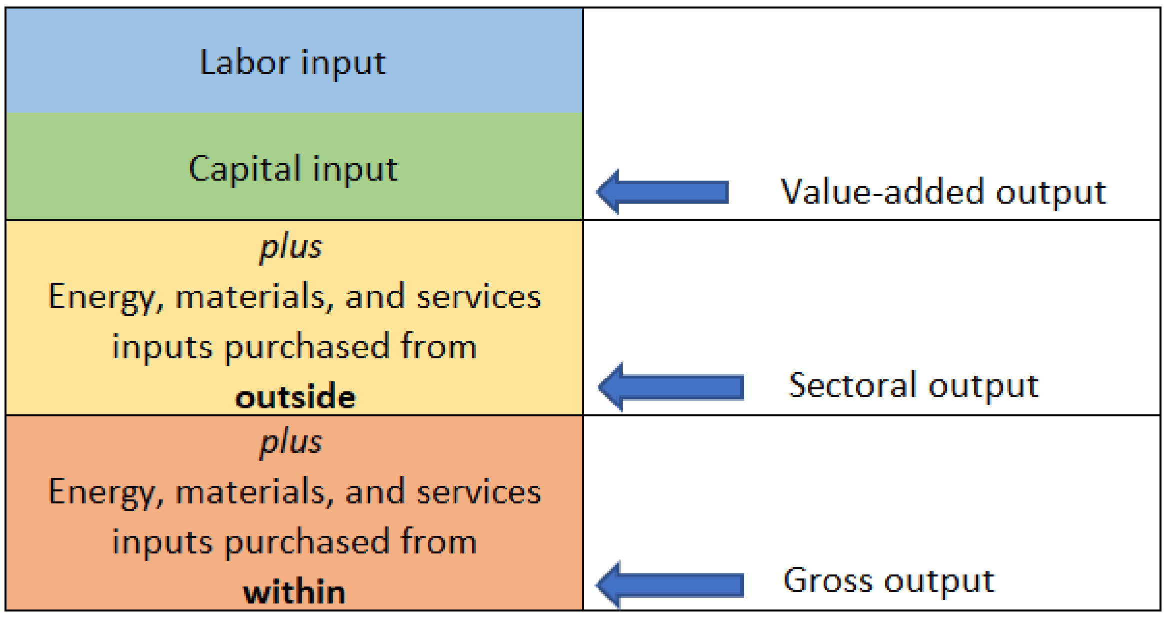
The broadest measure of output is gross output. Gross output is the total value of goods and services produced by all firms in an industry or sector, regardless of whether these goods and services are sold directly to consumers or sold to other firms as inputs to further production. In the case of gross output, an output is counted when it is sold and then counted again in the value of the product it was used to produce. Thus, a measure of gross output for an economy counts the value of an output multiple times if that output is used in the production processes of other firms.

By contrast, value-added output is a more narrowly defined concept that removes the value of all purchased intermediate inputs from the value of gross output. As such, value-added output reflects only the additional value of transforming intermediate inputs into outputs. Value-added output for the aggregate economy equals the sum of the value-added outputs of all firms; it can also be measured as the value of goods and services that are sold to final consumers.

Sectoral output, which lies between gross output and value-added output, equals gross output in an industry or sector less only those intermediate inputs that are produced within that industry or sector (i.e., intrasectoral transactions). Intermediate inputs used in production that are purchased from outside the industry or sector are not removed. Thus, sectoral output represents the value of output leaving the industry or sector.[4] By excluding transactions within an industry or sector, sectoral output measures output as if the industry or sector were vertically integrated.[5]

These three measures of output have a direct mathematical relationship, as illustrated in figure 1. Sectoral output equals value-added output plus the intermediate inputs of energy, materials, and services purchased from *outside* the industry or sector. Gross output equals sectoral output plus the remaining intermediate inputs purchased from *within* the industry or sector. With the use of nominal data, gross output is greater than sectoral output, which is greater than value-added output. However, the relationship between real trends of these three measures depends on trends in intermediate inputs and price changes.

Figure 1. Integrated output measures



Source: U.S. Bureau of Labor Statistics.

When we are measuring the total economy, the number of inputs coming from outside the economy declines and sectoral and value-added output converge. The difference between value-added and sectoral output at the level of the total economy depends mostly on the size of imported intermediate inputs. However, if we are measuring the output of a very detailed industry, we would expect most of the inputs to be coming from outside the industry. Thus, for detailed industries, gross and sectoral output are closely aligned.

Value-added output and productivity

Because value-added output can be measured directly by using data on consumption, it is timelier than measures that require data on purchased inputs. Having less demanding data requirements, value-added output is the most common output measure used for measuring productivity, and it can be produced more frequently than productivity statistics based on other output concepts.[6] Value-added labor productivity ($\mathrm{LP_{VA}}$) growth is calculated as the percent growth in value-added output less the percent growth in hours worked:

$$(3)\quad \mathrm{LP_{VA}}\text{ growth} = \text{Value-added output growth} - \text{Hours-worked growth.}$$

Value-added labor productivity more closely reflects an industry's ability to translate labor hours into final income. Labor productivity (output per hour worked) constructed by using value-added output is often used as an indicator of changes in the standard of living.[7] However, because it omits intermediate inputs, value-added output is sensitive to biases in intermediate-input prices (both import prices and within-industry transaction prices). This simple and easy-to-calculate productivity measure does not tell the whole story. To account for the importance of capital in production, value-added total factor productivity ($\mathrm{TFP_{VA}}$) growth is expressed as the growth in value-added output less the share-weighted sum of growth in labor and capital:[8]

$$(4)\quad \mathrm{TFP_{VA}}\text{ growth} = \text{Value-added output growth} - \left(s_K^{\mathrm{VA}}\dot{K}/K + s_L^{\mathrm{VA}}\dot{L}/L\right),$$

where K is capital input, L is labor input, and s_K^{VA} and s_L^{VA} are cost-share weights for, respectively, capital and labor (the "dot" notation on the inputs denotes growth). Energy, materials, and services are absent from this model because they are not components of value-added output; all intermediate inputs of energy, materials, and services have been removed from the measure of output. Given the assumption of constant returns to scale, the value of output equals the summed costs of capital and labor, and the cost shares sum to 1.

Sectoral output and productivity

Sectoral output equals gross output less intrasectoral transactions (i.e., purchases of intermediate inputs that were produced by other firms in the industry or sector). The concept of sectoral output is particularly useful because it describes output in relation to capital, labor, and intermediate inputs purchased from firms outside an industry, rather than only capital and labor. In addition, by removing the value of intrasectoral transactions, sectoral output avoids the double counting of inputs purchased and used for production within the same industry or sector. Sectoral total factor productivity ($\mathrm{TFP_{SO}}$) growth and sectoral labor productivity ($\mathrm{LP_{SO}}$) growth are expressed as follows:

$$(5)\quad \mathrm{TFP_{SO}}\text{ growth} = \text{Sectoral-output growth} - \left(s_K^{\mathrm{SO}}\dot{K}/K + s_L^{\mathrm{SO}}\dot{L}/L + s_E^{\mathrm{SO}}\dot{E}'/E' + s_M^{\mathrm{SO}}\dot{M}'/M' + s_S^{\mathrm{SO}}\dot{S}'/S'\right).$$

$$(6)\quad \mathrm{LP_{SO}}\text{ growth} = \text{Sectoral-output growth} - \text{Hours-worked growth.}$$

In equation (5), E', M', and S' are, respectively, energy, materials, and purchased services inputs, all adjusted to remove intrasectoral transactions involving energy, materials, and purchased services inputs; s_K^{SO}, s_L^{SO}, s_E^{SO}, s_M^{SO}, and s_S^{SO} are cost-share weights for the growth rates of, respectively, capital, labor, and the adjusted intermediate inputs of energy, materials, and purchased services. The cost-share weights sum to 1, and the weights on capital and labor in the sectoral-output model of TFP are smaller than those in the value-added model.

For both value-added and sectoral output, changes in labor productivity can be due to changes in technology, capital intensity, economies of scale, management techniques, and the skills of the labor force. The key difference between the two concepts is that while sectoral labor productivity includes the effects of substituting other inputs (energy, materials, and services) for labor, value-added labor productivity does not.[9] Therefore, labor productivity based on sectoral output will grow with increased outsourcing of labor and purchases of intermediate inputs because the reduction of labor will not be offset by a reduction in output. In the value-added model, outsourcing of labor has a smaller effect on labor productivity because the substitution of purchased services for labor reduces both output and labor input.[10] This differential effect partly explains why the concepts of value-added and sectoral output are useful for answering different analytical questions.[11] Value-added labor productivity more closely reflects the ability of an industry or sector to translate labor hours into final income, while sectoral labor productivity measures the efficiency with which an industry transforms labor hours into output.[12]

Gross output and productivity

TFP measures based on gross output relate output growth to the growth in all inputs of production, including capital, labor, and all intermediate inputs of energy, materials, and purchased services. These measures provide a way to observe shifts among all inputs to production by presenting a complete accounting of inputs (regardless of where they are produced). Thus, including all intermediate inputs in the production model can shed light on shifts between primary inputs and purchased intermediate inputs (from within and outside the industry) that accompany efficiency gains.[13] Because gross output includes the purchase of output for further production within an industry, both output and input values are increased by the same amount—the value of outputs purchased for use as inputs within the industry. This double counting can obscure the relationship between output and inputs and the resulting measurement of productivity for the aggregate economy.[14]

Gross total factor productivity ($\mathrm{TFP_{GO}}$) growth and gross labor productivity ($\mathrm{LP_{GO}}$) growth are expressed as follows:

$$(7) \quad \mathrm{TFP_{GO}\ growth} = \text{Gross-output growth} - (s_K^{GO}\dot{K}/K + s_L^{GO}\dot{L}/L + s_E^{GO}\dot{E}/E + s_M^{GO}\dot{M}/M + s_S^{GO}\dot{S}/S).$$

$$(8) \quad \mathrm{LP_{GO}\ growth} = \text{Gross-output growth} - \text{Hours-worked growth}.$$

In equation (7), s_K^{GO}, s_L^{GO}, s_E^{GO}, s_M^{GO}, and s_S^{GO} are cost-share weights (summing to 1) for the growth rates of, respectively, capital, labor, energy, materials, and purchased services.[15] Given the assumption of constant returns to scale, the value of gross output equals the summed costs of all inputs—capital, labor, energy, materials, and purchased services.

Relationships among productivity measures

Because the three output measures are directly related, the productivity measures based on them are also directly related. These relationships are well known, but it is useful to briefly summarize them.[16]

Total factor productivity relationships

From our output definitions above, we know that gross output equals value-added output plus intermediate inputs. It follows that the relationship between gross and value-added TFP growth is a function of the ratio of intermediate inputs to gross output. This relationship can be described as follows:[17]

$$(9) \quad \mathrm{TFP_{GO}\ growth} = \left(\frac{\text{Value-added output}}{\text{Gross output}}\right) \times \mathrm{TFP_{VA}\ growth}$$
$$= \left(1 - \frac{\text{Intermediate inputs}}{\text{Gross output}}\right) \times \mathrm{TFP_{VA}\ growth}.$$

Clearly, gross TFP growth will change proportionally less than value-added TFP growth because nominal value-added output is less than nominal gross output. The difference between the TFP growth rates will increase as intermediate inputs increase (for example, because of an increase in outsourcing) relative to gross output.[18]

Similarly, gross TFP growth can also be defined relative to sectoral TFP growth. We know that gross output equals sectoral output plus those intermediate inputs that are purchased from within the industry or sector (i.e., intrasectoral transactions). Thus, the difference between the rate of growth of sectoral TFP and the rate of growth of gross TFP depends on intrasectoral inputs relative to gross output:[19]

$$(10) \quad \mathrm{TFP_{GO}\ growth} = \left(\frac{\text{Sectoral output}}{\text{Gross output}}\right) \times \mathrm{TFP_{SO}\ growth}$$
$$= \left(1 - \frac{\text{Intrasectoral inputs}}{\text{Gross output}}\right) \times \mathrm{TFP_{SO}\ growth}.$$

For narrowly defined industries with most inputs coming from outside the industry and few intrasectoral transactions, sectoral TFP growth will be close to gross TFP growth. As we move from detailed to more aggregate industries or sectors, more inputs will originate inside the industry or sector and the share of intrasectoral inputs in gross output will increase. As a result, gross TFP growth will diverge more from sectoral TFP growth.

Finally, sectoral output can be expressed as value-added output plus intermediate inputs purchased from *outside* the industry or sector. Thus, by combining equations (9) and (10) and rearranging terms, we can express the relationship between value-added and sectoral TFP growth as follows:[20]

$$(11) \quad \mathrm{TFP_{SO}\ growth} = \left(\frac{\text{Value-added output}}{\text{Sectoral output}}\right) \times \mathrm{TFP_{VA}\ growth}$$
$$= \left(\frac{1 - \frac{\text{Intermediate inputs}}{\text{Gross output}}}{1 - \frac{\text{Intrasectoral inputs}}{\text{Gross output}}}\right) \times \mathrm{TFP_{VA}\ growth}.$$

From equation (11), we see that sectoral TFP growth will change proportionally less than value-added TFP growth. This relationship is a function of the relative share of intrasectoral transactions in gross output compared with the share of total intermediate inputs in gross output.

As we move from detailed industries to more aggregate industries or sectors, intrasectoral transactions will increase while purchases of out-of-sector intermediate inputs will fall. For the most aggregate economic sectors, value-added TFP growth will approximate sectoral TFP growth.[21] Conversely, as the share of intermediate inputs from outside an industry or sector grows, the difference between value-added and sectoral TFP growth will increase. When outsourcing increases, for instance, total intermediate inputs increase while intrasectoral transactions do not, and value-added TFP grows faster than sectoral TFP. As a result, value-added TFP is more volatile than sectoral TFP in response to changes in the degree of outsourcing and consumption of intermediate inputs.

In summary, the growth rates of the three related TFP series maintain a predictable ordering. Given the absolute value of each growth rate, this ordering is as follows:

$$|\mathrm{TFP_{GO}\ growth}| < |\mathrm{TFP_{SO}\ growth}| < |\mathrm{TFP_{VA}\ growth}|.$$

Labor productivity relationships

As was the case with TFP growth, the three labor productivity measures directly relate to growth in intermediate inputs:

$$(12) \quad LP_{VA}\text{ growth} = LP_{GO}\text{ growth} - \text{Growth in all intermediate inputs.}$$

$$(13) \quad LP_{SO}\text{ growth} = LP_{GO}\text{ growth} - \text{Growth in intrasectoral inputs.}$$

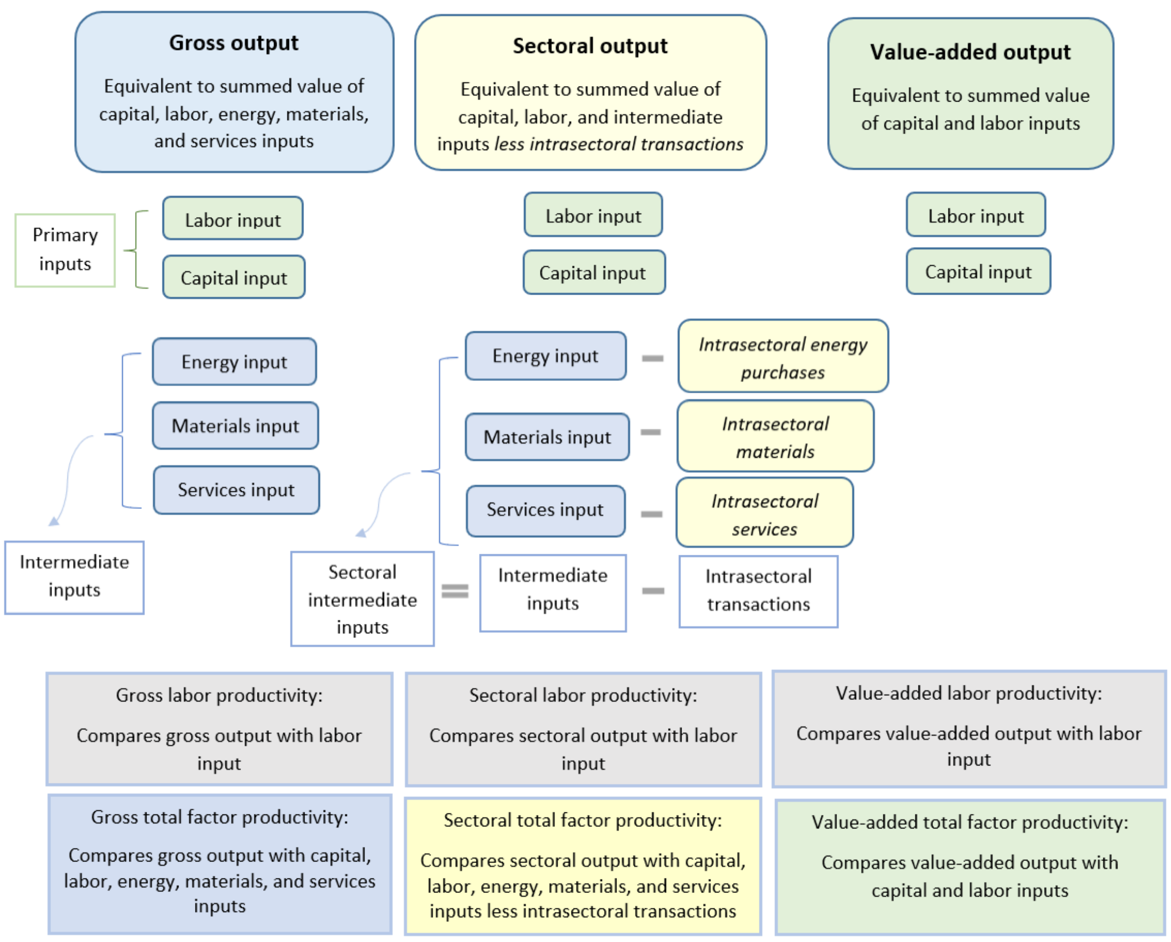
$$(14) \quad LP_{VA}\text{ growth} = LP_{SO}\text{ growth} - \text{Growth in out-of-sector intermediate inputs.}$$

Unlike the TFP measures, however, the three alternative labor productivity measures are not ordered predictably. This can be explained by reviewing the differences in the output measures used to estimate the labor productivity measures. Value-added labor productivity compares growth in real value earned by capital and labor inputs with growth in labor input; sectoral labor productivity compares growth in real value earned by capital, labor, and intermediate inputs purchased from outside a sector with growth in labor input; and gross labor productivity compares growth in capital, labor, and intermediate inputs purchased from both within and outside a sector with growth in labor input.

Therefore, the order of the three alternative labor productivity measures depends on the relative growth rates of capital, labor, and intermediate inputs purchased from both within and outside a sector. A decline in growth in capital and labor inputs that is offset by larger increases in intermediate-input purchases (whether from within or outside a sector) will result in value-added labor productivity growing more slowly than sectoral and gross labor productivity. And, regardless of growth in capital and labor inputs, the relationship between sectoral and gross labor productivity will vary depending on the relative growth rates of within-sector and out-of-sector purchases of intermediate inputs.

Figure 2 summarizes the relationships among the various elements of the integrated productivity growth model.

Figure 2. Elements of the integrated productivity growth model



Source: U.S. Bureau of Labor Statistics.

BLS output and productivity model

To estimate measures of productivity, we need output and input measures that are consistently defined and independently measured. The choice of output measure depends on several factors, including data availability and analytical purpose. The output measure selected from the growth accounting model's integrated system of outputs and inputs must be appropriate both for the level of economic aggregation examined and for the analytical purpose of the application. In this section, we discuss some of the output characteristics BLS considers before selecting the most appropriate output concept for use in developing productivity measures for specific purposes.

Aggregate productivity measures

BLS uses value-added output for its business sector productivity measures, including the quarterly labor productivity measure, which is a Principal Federal Economic Indicator. Value-added output is appropriate for highly aggregated sectors because most inputs are purchased from within the sector.[22] Also, value-added output is measured with the use of data on consumption (final demand of goods and services), and these data are timely and easily obtained. Data on value-added output (gross domestic product) for the United States are available from the U.S. Bureau of Economic Analysis (BEA) shortly after the reference quarter and are used in constructing BLS quarterly labor productivity measures. Having less demanding data requirements, value-added output is the most used output concept and is particularly useful for making international comparisons. BLS also publishes estimates of TFP growth for business sectors by using value-added output.[23] Because labor productivity and TFP measures are based on the same measure of value-added output, it is possible to decompose the labor productivity measures into contributions coming from capital intensity, the composition of the workforce, and TFP.[24]

However, unlike sectoral productivity measures, value-added productivity measures do not provide a way to explain shifts between primary and imported inputs or other purchases from outside a sector. Presenting trends in offshoring, as well as purchases of inputs from the government and nonprofit sectors, can provide useful information about economic trends and bridge the value-added and sectoral productivity series.[25]

Industry productivity measures

For analyses at the industry level, including the manufacturing sector and three- and four-digit North American Industry Classification System (NAICS) manufacturing industries, BLS uses sectoral output to estimate labor productivity and TFP growth.[26] The concept of sectoral output best represents the value of output leaving a particular industry. Compared with value-added TFP, sectoral TFP provides a more complete picture of the sources of growth by showing the contributions of energy, materials, and purchased services inputs, in addition to capital and labor.[27] Moreover, as intermediate inputs become more important in the production process, the productivity measures using sectoral output will reflect the growth that results from the substitution of intermediate inputs for labor.[28] Again, when both productivity measures use the same output concept, it is possible to relate labor productivity to TFP.[29]

The BEA/BLS integrated industry production account uses a gross output concept because it provides a complete accounting of inputs used in production, regardless of where these inputs are produced.[30] Including all intermediate inputs in the production model can shed light on shifts between primary inputs and purchased intermediate inputs from outside and within an industry.

Although measures of gross and sectoral output both include intermediate inputs, sectoral output is comparatively less sensitive to shifts in industry structure due to mergers and split-offs. For example, suppose a single manufacturing plant is restructured into two plants, A and B, such that all the outputs of plant A are consumed by plant B. In this case, industry gross output (and inputs) increases by the output of plant A, whereas sectoral output for the industry (correctly) does not change. This occurs because any outputs produced for consumption within a single plant are not reported to the U.S. Census Bureau as outputs or inputs.[31] However, after the plant restructuring, the outputs produced by one plant are now counted twice, once as the outputs of plant A and again as a component of the outputs of plant B. Because labor productivity measures do not account for purchased materials and services as inputs, this double counting is particularly problematic. Therefore, measuring labor productivity by using gross output is not advisable.

Comparing productivity measures in U.S. manufacturing

BLS publishes measures of labor productivity and TFP for industries and subsectors of the U.S. business sector.[32] We illustrate the impact of using different output measures on related productivity measures by constructing measures of value-added and gross output for the manufacturing sector and 19 manufacturing industries.[33] The method used to construct these measures is consistent with the sectoral-output method used for official BLS productivity measures.[34]

Data

Table 1 illustrates the data sources used in constructing the three productivity measures for the manufacturing sector and its underlying industries. BLS published measures of labor productivity and TFP for the manufacturing sector and manufacturing industries use the concept of sectoral output. In addition, to remove known sources of bias, BLS measures exclude the output of households and nonprofit institutions; thus, our productivity measures based on value-added and gross output also remove these components.[35] All three output measures use value-of-shipments data from the U.S. Census Bureau, as well as BEA data on inputs used in production (energy, materials, and services). Data on intangible outputs are obtained from BEA.

Table 1. Data sources, by output measure

Industry aggregate	Value-added output	Sectoral output	Gross output
Manufacturing sector	**Total factor productivity**: *Output*—U.S. Bureau of Labor Statistics (BLS) estimate of value-added output for the manufacturing sector, constructed by using a chained superlative (Törnqvist) index of three-digit NAICS industry value-added outputs; *Capital and labor*—BLS	**Total factor productivity**: *Output*—BLS estimate of sectoral-output measures for the manufacturing sector, constructed by using a chained superlative (Törnqvist) index of three-digit NAICS industry outputs adjusted to remove manufacturing sector intrasectoral transactions; *Capital and labor*—BLS; *Energy, materials, and services*—BLS	**Total factor productivity**: *Output*—BLS estimate of gross output for the manufacturing sector, constructed by using a chained superlative (Törnqvist) index of three-digit NAICS industry gross outputs; *Capital and labor*—BLS; *Energy, materials, and services*—BLS
	Labor productivity: Value-added output estimate and BLS hours of all persons	**Labor productivity**: BLS sectoral-output estimate and hours of all persons	**Labor productivity**: Gross-output estimate and BLS hours of all persons
NIPA manufacturing industries	**Total factor productivity**: *Output*—BLS estimates of value-added output for detailed manufacturing industries, constructed primarily by using data from the economic censuses and annual surveys of the U.S. Census Bureau and U.S. Bureau of Economic Analysis data on intermediate inputs[1]; *Capital and labor*—BLS	**Total factor productivity**: *Output*—BLS estimates of sectoral output for detailed manufacturing industries, constructed primarily by using data from the economic censuses and annual surveys of the U.S. Census Bureau[1]; *Capital and labor*—BLS; *Energy, materials, and services*—BLS	**Total factor productivity**: *Output*—BLS estimates of gross output for detailed manufacturing industries, constructed primarily by using data from the economic censuses and annual surveys of the U.S. Census Bureau[1]; *Capital and labor*—BLS; *Energy, materials, and services*—BLS
	Labor productivity: Value-added output estimate and BLS hours of all persons	**Labor productivity**: Sectoral-output estimate and BLS hours of all persons	**Labor productivity**: Gross-output estimate and BLS hours of all persons

[1] Output in NAICS 323 (printing and related support activities) is adjusted to remove the output value of households and nonprofit entities, for each type of output measure.
Note: NAICS = North American Industry Classification System; NIPA = National Income and Product Accounts.
Source: U.S. Bureau of Labor Statistics.

All three measures of productivity use the same estimates of labor and capital services. The labor input for our labor productivity measures is hours worked, produced by the BLS productivity program.[36] For our TFP estimates, we use a measure of labor input defined as hours worked adjusted for differences in age, education, and gender and based on the same methodology as that used for BLS published indexes of labor input. Capital input is measured as the flow of capital services from physical capital stock and intellectual property assets.[37] Our measures of capital input for the manufacturing sector and its component industries are consistent with BLS published data but have been adjusted to allow for consistency among the three output estimates.[38]

For the TFP estimates based on gross and sectoral output, we use consistent measures of total intermediate inputs and intrasectoral transactions; there are no intermediate inputs in the calculation of value-added TFP.[39]

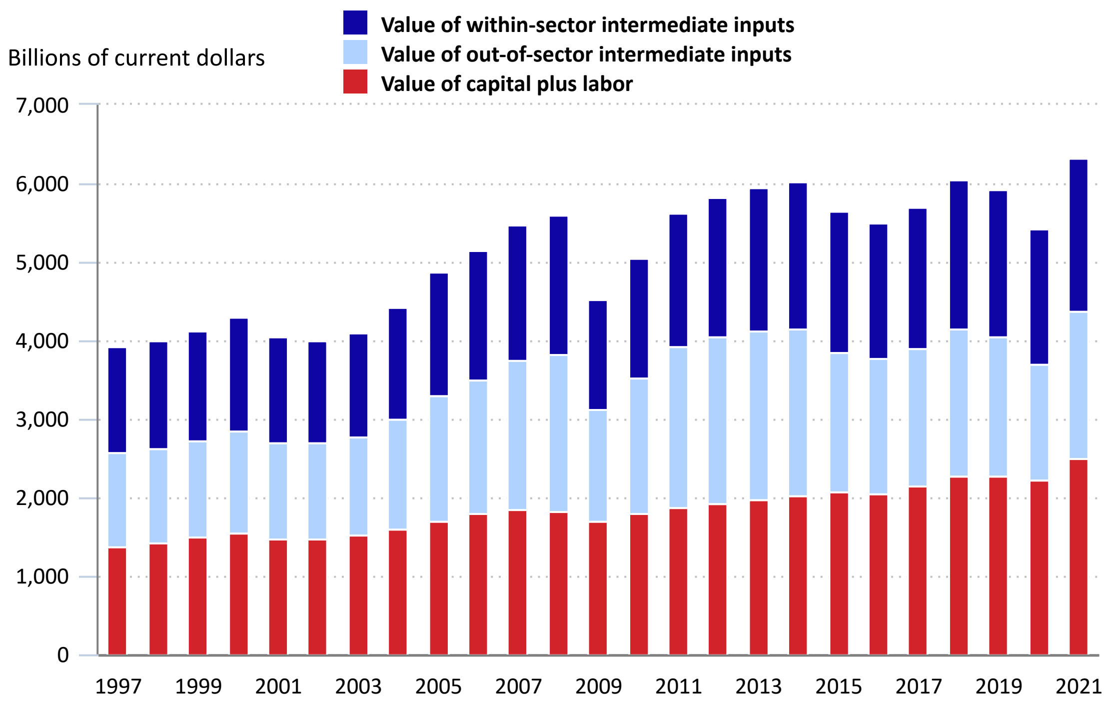
Empirical results

Using the three output measures, we estimate the relationships among output, labor productivity, and TFP for the manufacturing sector and 19 manufacturing industries.

Manufacturing sector: output measures

Chart 1 illustrates the nominal output and input relationships for the manufacturing sector. The height of the bottom bars in the chart depicts the nominal value of capital and labor inputs, or nominal value-added output; the combined height of the lower two bars depicts the nominal value of capital, labor, and out-of-sector intermediate inputs, or sectoral output; and the combined height of all three bars depicts the nominal value of capital, labor, out-of-sector and within-sector intermediate inputs, or nominal gross output. As seen from the chart, the current-dollar data have a predictable relationship: value-added output is less than sectoral output, and sectoral output is less than gross output. However, this is not necessarily the case for the growth rates of the three measures of real output.[40] Differences in the rates of real output growth depend on the growth rates of intermediate inputs and on the price change for output and intermediate inputs.

Chart 1. Output and input relationships for the manufacturing sector, 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: Value-added output = Value of capital plus labor; Sectoral output = (Value of capital plus labor) + (Value of out-of-sector intermediate inputs); Gross output = (Value of capital plus labor) + (Value of out-of-sector intermediate inputs) + (Value of within-sector intermediate inputs).
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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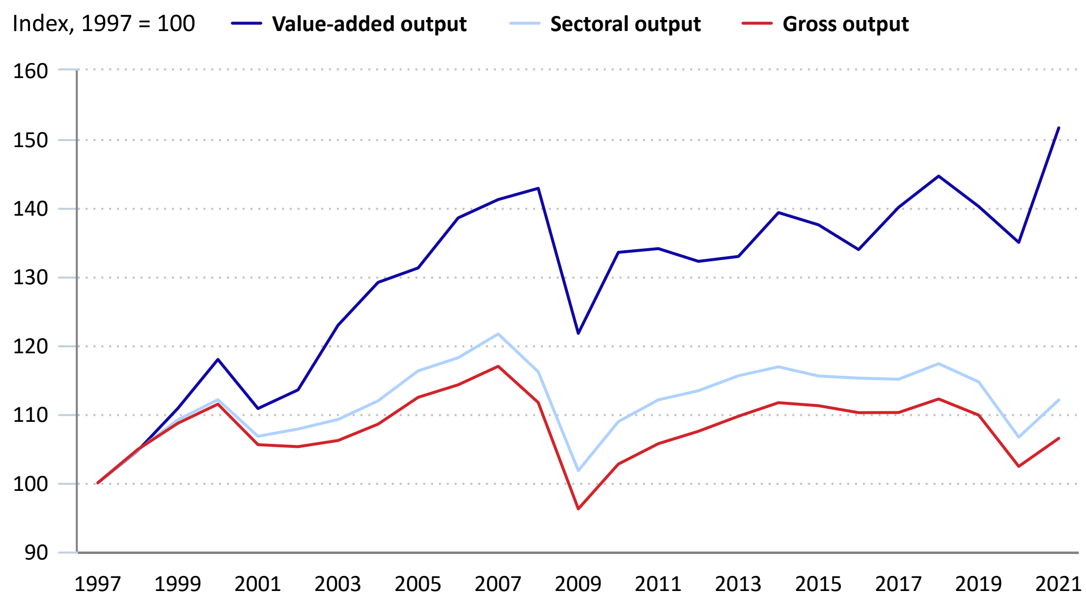
Chart 2 presents trends in the three measures of real output for the manufacturing sector for the 1997–2021 period. The chart shows that real gross output decreased at a 0.22-percent annual rate over the 2000–21 period, compared with a 1.20-percent increase for value-added output and no change for sectoral output. In general, the trends for sectoral and gross output are similar, while the trend for value-added output is very different. (See table 2.) Although current-dollar gross output was larger than sectoral and value-added output over the 2000–21 period, real gross output grew at the slowest rate.

Chart 2. Measures of value-added, sectoral, and gross output for the manufacturing sector, 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

Table 2. Growth in output and intermediate inputs for the manufacturing sector, annual percent change, selected periods

Period	Real value-added output	Real sectoral output	Real gross output	Real within-sector intermediate inputs	Real out-of-sector intermediate inputs
2000–21	1.20	0.00	-0.22	-0.67	-1.48
2000–07	2.60	1.18	0.69	-0.30	-0.33
2007–19	-0.06	-0.49	-0.52	-0.59	-1.30
2019–21[1]	4.00	-1.15	-1.54	-2.41	-6.43

[1] This period is an incomplete business cycle.

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Table 2 highlights how changes in within-sector and out-of-sector intermediate inputs may affect the relative growth trends of the alternative output measures. Our data cover two complete business cycles (2000–07 and 2007–19) and two of the most severe U.S. recessions (2007–09 and 2019–20). Over the 2000–21 period, the long-run growth of real gross output in the manufacturing sector was somewhat slower than that of real sectoral output, reflecting a 0.67-percent annual decrease in the rate of real intermediate-input purchases from within the manufacturing sector.[41]

Chart 2 also shows real value-added output growing faster than sectoral output. This difference is due to a decline in the real value of intermediate inputs purchased from outside the sector, including purchases of imported intermediate inputs and purchases from service industries and the household and government sectors. As shown in table 2, over the 2000–07 period, real imported and out-of-sector purchases of intermediate inputs were falling at an annual rate of 0.33 percent.[42] Thus, from 2000 to 2007, real value-added output grew faster, at a rate of 2.60 percent, than sectoral output, which grew at a rate of 1.18 percent. More recently, from 2007 to 2019, this difference in growth rates narrowed, with real sectoral output declining at a rate of 0.49 percent and value-added output declining at a rate of 0.06 percent. Real imported and out-of-sector purchases of intermediate inputs declined at a rate of 1.30 percent in this period.[43]

In addition, Chart 2 shows that the 2007–09 Great Recession resulted in a decline in all measures of manufacturing output. As shown in table 3, growth in real value-added output fell by 7.15 percent from 2007 to 2009, while growth in real sectoral and gross output fell by 8.54 and 9.30 percent, respectively. The 2007–09 decline in real sectoral output reflects the drop in real value-added output and a 10.19-percent drop in real intermediate inputs purchased from outside the manufacturing sector. The decline in real gross output reflects the drop in real value-added output and a 10.59-percent decline in total real gross intermediate-input purchases.

Table 3. Growth in output and intermediate inputs for the manufacturing sector, annual percent change, recessionary periods

Recessionary period	Real value-added output	Real sectoral output	Real gross output	Real within-sector intermediate inputs	Real out-of-sector intermediate inputs
2007–09	-7.15	-8.54	-9.30	-10.96	-10.19
2019–20	-3.73	-7.02	-6.79	-6.31	-11.49

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

During the 2019–20 recession, which coincided with the COVID-19 pandemic, real value-added output declined more slowly, by 3.73 percent per year. By contrast, real sectoral and gross output declined more rapidly, by 7.02 and 6.79 percent, respectively. The decline in real sectoral output reflects the fall in real value-added output and an 11.49-percent drop in real intermediate-input purchases from outside the manufacturing sector. The decline in real gross output reflects an 8.90-percent decrease in total real gross intermediate-input purchases, as well as an accompanying decline in value-added output. The path to recovery from the shock of the initial pandemic period is yet to be determined.

Manufacturing sector: productivity

In this section, we compare productivity growth across the three output measures for the manufacturing sector. Table 4 presents trends in labor productivity, output, and hours worked under each measurement framework for the 2000–21 period.

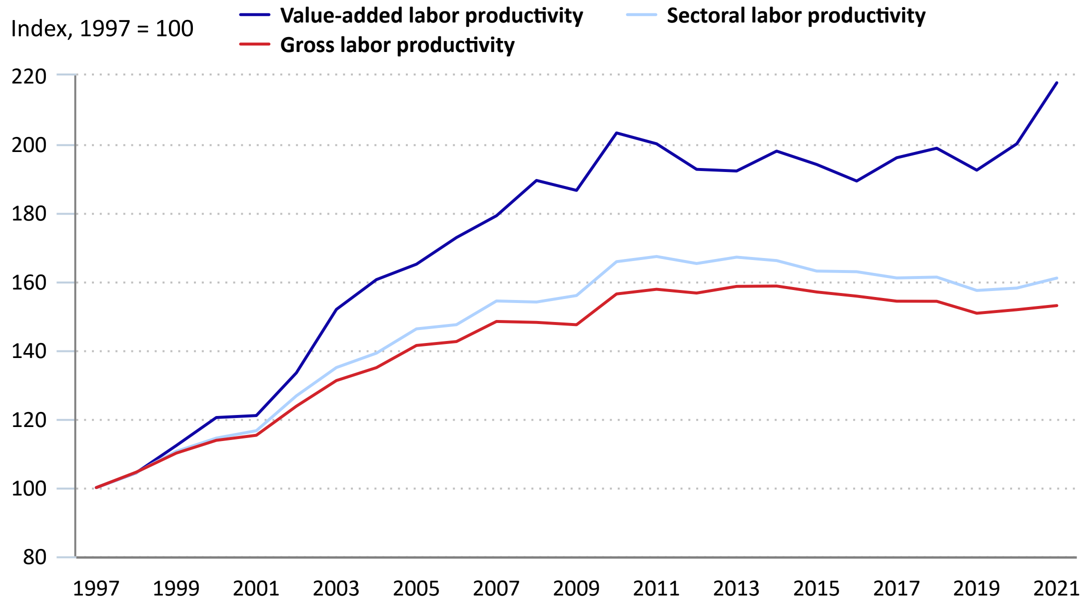
Table 4. Trends in labor productivity for the manufacturing sector, by output measure, annual percent change, 2000–21

Measure	Value-added output	Sectoral output	Gross output
Labor productivity	2.86	1.64	1.42
Output	1.20	0.00	-0.22
Hours worked	-1.61	-1.61	-1.61

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Because we use the same measure of labor input (hours worked) for each of the three labor productivity measures, differences in labor productivity are driven solely by differences in output growth. From 2000 to 2021, hours worked declined at an average annual rate of 1.61 percent, resulting in labor productivity growing faster than output. Like growth for the three output measures, growth in labor productivity was the fastest for the value-added measure and the slowest for the gross-output measure. Chart 3 compares trends in labor productivity by using the three alternative output measures.

Chart 3. Labor productivity in the manufacturing sector, by output measure, 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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Table 5 shows that labor productivity based on value-added output grew at an annual rate of 5.84 percent during the 2000–07 period, increased at a much slower rate of 2.04 percent during the 2007–09 Great Recession, and recovered at a rate of 0.31 percent over the 2009–19 expansionary period. By comparison, sectoral labor productivity grew more slowly in all three periods, at a rate of 4.37 percent during the 2000–07 period, 0.51 percent during the Great Recession, and 0.09 percent during the 2009–19 expansion. Gross labor productivity had the slowest growth prior to the Great Recession, at 3.87 percent per year, and the largest decline during the Great Recession, at 0.32 percent per year. During the 2009–19 recovery period, gross labor productivity grew at an annual rate of 0.23 percent, faster than sectoral labor productivity. Gross labor productivity reflects variation in the value of both within-sector and out-of-sector purchases of intermediate inputs, whereas sectoral labor productivity reflects only variation in out-of-sector purchases of intermediate inputs. In the 2019–20 downturn triggered by the COVID-19 pandemic, value-added labor productivity increased sharply, at a 3.99-percent rate. This reflects a 3.73-percent decline in real value-added output and a 7.42-percent decline in hours worked. Sectoral and gross labor productivity increased slightly—at rates of 0.44 and 0.68 percent, respectively—reflecting declines of 7.02 and 6.79 percent in sectoral and gross output, as well as the decline in hours worked.

Table 5. Labor productivity in the manufacturing sector, by output measure, annual percent change, selected periods

Period	Value-added labor productivity	Sectoral labor productivity	Gross labor productivity
2000–21	2.86	1.64	1.42
Business cycle periods			
2000–07	5.84	4.37	3.87
2007–19	0.60	0.16	0.13
2019–21[1]	6.41	1.14	0.74
Recessionary periods			
2007–09	2.04	0.51	-0.32
2019–20	3.99	0.44	0.68
Expansionary periods			
2009–19	0.31	0.09	0.23
2020–21	8.89	1.84	0.79

[1] The 2019–21 period is an incomplete business cycle.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

For the TFP comparisons, the differences among TFP growth rates are driven both by differences in the growth rates of the alternative output measures and by differences in the change over time in the intermediate inputs of energy, materials, and services; trends in labor and capital are the same for all three TFP measures. Table 6 shows trends in manufacturing TFP, real output, and inputs for the 2000–21 period, by output measure.

Table 6. Trends in total factor productivity (TFP) for the manufacturing sector, by output measure, annual percent change, 2000–21

Measure	Value-added output	Sectoral output	Gross output
TFP	1.03	0.59	0.41
Output	1.20	0.00	-0.22
Combined inputs[1]	0.17	-0.59	-0.62
Input components			
Capital	1.64	1.64	1.64
Labor	-1.01	-1.01	-1.01
Energy, materials, and purchased services	[2]	-1.48[3]	-1.09[4]

[1] Labor input is a combination of hours worked and a labor composition adjustment reflecting the effect of shifts in the age, education, and gender composition of the workforce on the efficiency of the hours worked.

[2] Not applicable.

[3] This trend reflects out-of-sector purchases of intermediate inputs, including imported intermediate inputs. Sectoral energy, materials, and services growth rates for 2000–21 are −5.68, −1.33, and −1.06 percent, respectively.

[4] Gross energy, materials, and services growth rates for 2000–21 are −5.64, −0.92, and −1.09 percent, respectively.

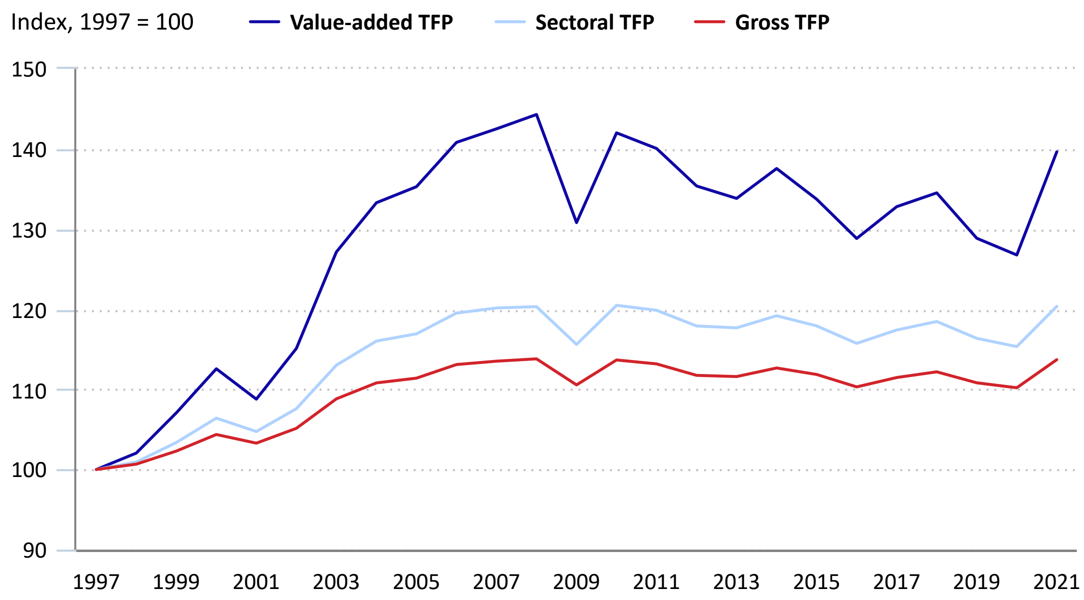
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Over the 2000–21 period, value-added TFP, which relates value-added output to capital and labor inputs only, grew the fastest of the three measures, at a 1.03-percent annual rate. Sectoral TFP grew at a 0.59-percent rate, which reflects a 0.00-percent growth in output and a 0.59-percent decline in combined inputs, with energy, materials, and services purchased from outside the manufacturing sector declining at a 1.48-percent rate. Thus, the slower growth of sectoral output relative to value-added output is primarily responsible for the difference in TFP growth. The out-of-sector intermediate inputs include purchases from all other sectors, including agriculture, mining and oil and gas extraction, utilities, construction, trade, transportation and warehousing, finance, and service sector industries. Also included are purchases of imported intermediate inputs and purchases from the household and government sectors.

Over the 2000–21 period, the TFP measure based on gross output grew at a rate of 0.41 percent, which is slower than the 0.59-percent rate of TFP based on sectoral output. This difference reflects the combination of slower growth in gross output and a similarly decreasing growth of combined capital, labor, and intermediate inputs used to calculate gross TFP. Total energy, materials, and services purchased by the manufacturing sector declined at a slightly slower rate, 1.09 percent, than did intermediate inputs purchased solely from outside the sector. This difference in growth rates for energy, materials, and services inputs was driven by the material inputs produced and consumed within the manufacturing sector (these inputs are included in the gross-output TFP measures and excluded from the sectoral-output measures). The nominal value of intrasectoral intermediate inputs declined slightly, from 53 percent of total intermediate inputs in 2000 to 51 percent in 2021.

Chart 4 compares trends in TFP indexes based on the three output measures, using 1997 as a base year. In this chart, the decline in TFP during business cycle periods is particularly evident. As seen in table 7, value-added TFP declined more steeply than sectoral and gross TFP during both the 2007–09 Great Recession and the 2019–20 pandemic downturn. The faster slowdown in value-added TFP from 2019 to 2020 reflects a steep decline of 3.73 percent in the growth of real value-added output and a lesser decline of 2.15 percent in the growth of combined capital and labor inputs. By comparison, over the same period, larger decreases in the growth of real sectoral and gross output (7.02 and 6.79 percent, respectively) were offset by respective decreases of 6.18 and 6.27 percent in the growth of combined capital, labor, and sectoral or gross intermediate inputs. The decline in combined capital, labor, and gross intermediate inputs reflects the inclusion of within-sector intermediate-input purchases, which fell by 6.31 percent in 2019–20, compared with a decline of 11.49 percent in out-of-sector intermediate-input purchases.

Chart 4. Total factor productivity (TFP) in the manufacturing sector, by output measure, 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

Table 7. Total factor productivity (TFP) in the manufacturing sector, by output measure, annual percent change, selected periods

Period	Value-added TFP	Sectoral TFP	Gross TFP
2000–21	1.03	0.59	0.41
Business cycle periods			
2000–07	3.43	1.75	1.21
2007–19	-0.84	-0.27	-0.20
2019–21[1]	4.10	1.70	1.30
Recessionary periods			
2007–09	-4.19	-1.91	-1.31
2019–20	-1.62	-0.89	-0.56

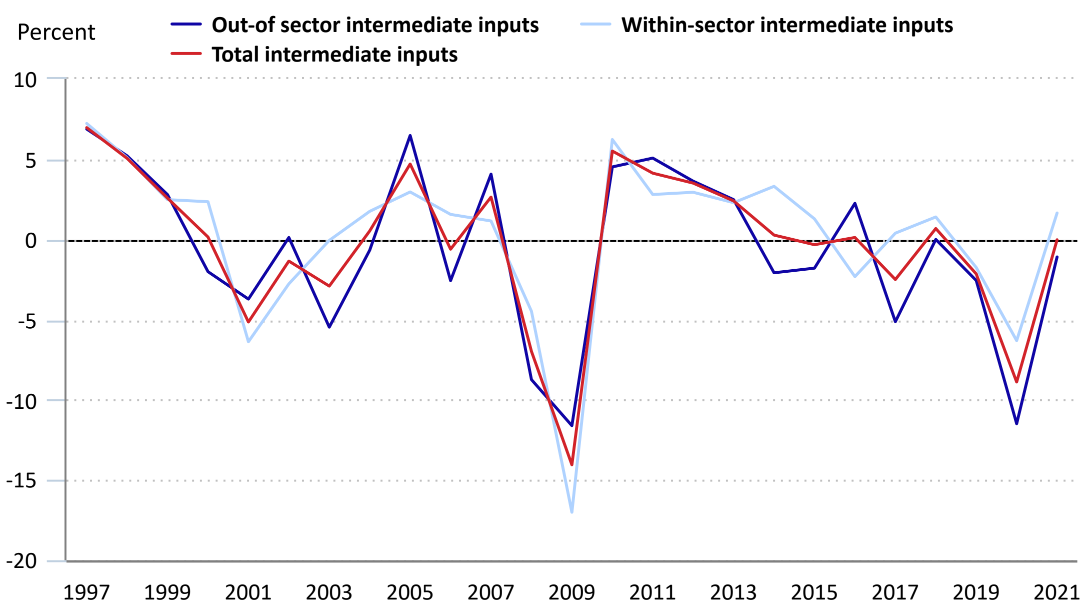
[1] This period is an incomplete business cycle.

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

The annual trends show that movements in gross and sectoral TFP are similar, as is the case for their measures of output. Recall that the difference between gross and sectoral output is represented by the intermediate inputs consumed from within the industry.

Chart 5 presents trends in total, within-sector, and out-of-sector real intermediate inputs for manufacturing from 1997 to 2021. With respect to within-sector intermediate inputs, the chart shows that these inputs exhibited cyclical movements similar to those found in the output measures. The use of intrasectoral intermediate inputs dipped during the 2000–02 period, declined sharply during the 2007–09 Great Recession, experienced a shallow decline from 2015 to 2017, and decreased steeply from 2018 onward. Compared with within-sector intermediate inputs, out-of-sector real intermediate inputs exhibited growth rates with some additional year-to-year variation. In general, however, the trends in growth-rate movements of out-of-sector and within-sector intermediate inputs were similar.

Chart 5. Total, within-sector, and out-of-sector real intermediate inputs for the manufacturing sector, annual percent change, 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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Total intermediate inputs had growth-rate movements that were less pronounced than those of both within-sector and out-of-sector intermediate inputs. The TFP measures using gross output reflect the growth-rate movements of intermediate inputs purchased both within and outside the manufacturing sector. Because movements in the use of within-sector and out-of-sector intermediate inputs were similar, trends in sectoral and gross TFP were also similar.

Manufacturing industries: output

This section explores variations in output, primary inputs (capital and labor), and use of intermediate inputs for 19 manufacturing industries. Table 8 presents the 2021 shares of total, within-industry, and out-of-industry intermediate inputs relative to gross output. The table shows that, in 2021, the share of total intermediate inputs in gross output varied greatly across industries. A low share indicates that production in an industry was more labor or capital intensive, such as in computer and electronic products, where intermediate inputs were only 17 percent of gross output. Generally, manufacturing industries consumed intermediate inputs that were valued at more than 50 percent of the value of gross output. Table 8 shows that petroleum and coal products had the highest share of intermediate inputs in 2021, at 79 percent. Other industries that used large quantities of intermediate inputs were motor vehicles, bodies and trailers, and parts; food and beverage and tobacco products; primary metals; and paper products.

Table 8. Total, within-industry, and out-of-industry intermediate-input purchases relative to gross output, by manufacturing industry, 2000–21

NAICS code	Industry	Share values, 2021 (percent of gross output)			Growth in shares, 2000–21 (annual percent change)		
		Total intermediate inputs relative to gross output	Within-industry intermediate inputs relative to gross output	Out-of-industry intermediate inputs relative to gross output	Total intermediate inputs relative to gross output	Within-industry intermediate inputs relative to gross output	Out-of-industry intermediate inputs relative to gross output
31–33	Manufacturing sector	61	31	30	-0.27	-0.45	-0.08
321	Wood products	59	15	44	-0.87	-0.17	-1.08
327	Nonmetallic mineral products	52	10	42	-0.41	-0.01	-0.50
331	Primary metals	71	18	52	0.04	0.44	-0.09
332	Fabricated metal products	58	8	50	0.25	-0.50	0.39
333	Machinery	58	10	47	-0.33	0.17	-0.44
334	Computer and electronic products	17	7	10	-5.76	-3.83	-6.74
335	Electrical equipment, appliances, and components	53	8	45	-0.89	-0.22	-0.99
3361–3363	Motor vehicles, bodies and trailers, and parts	78	17	61	0.43	-0.69	0.81
3364–3369	Other transportation equipment	49	12	37	-0.65	0.95	-1.06
337	Furniture and related products	60	6	54	0.30	-0.07	0.34
339	Miscellaneous manufacturing	45	12	33	-0.93	1.15	-1.48
311, 312	Food and beverage and tobacco products	71	17	53	-0.12	0.90	-0.41
313, 314	Textile mills and textile product mills	66	16	49	-0.11	-0.74	0.12
315, 316	Apparel and leather and allied products	61	11	50	-0.71	-0.52	-0.75
322	Paper products	68	23	44	0.40	0.68	0.26
323	Printing and related support activities	52	4	48	-0.64	-1.16	-0.59
324	Petroleum and coal products	79	10	68	0.08	2.11	-0.17
325	Chemical products	48	13	35	-0.94	-1.49	-0.72
326	Plastics and rubber products	65	9	57	0.13	1.32	-0.03

Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

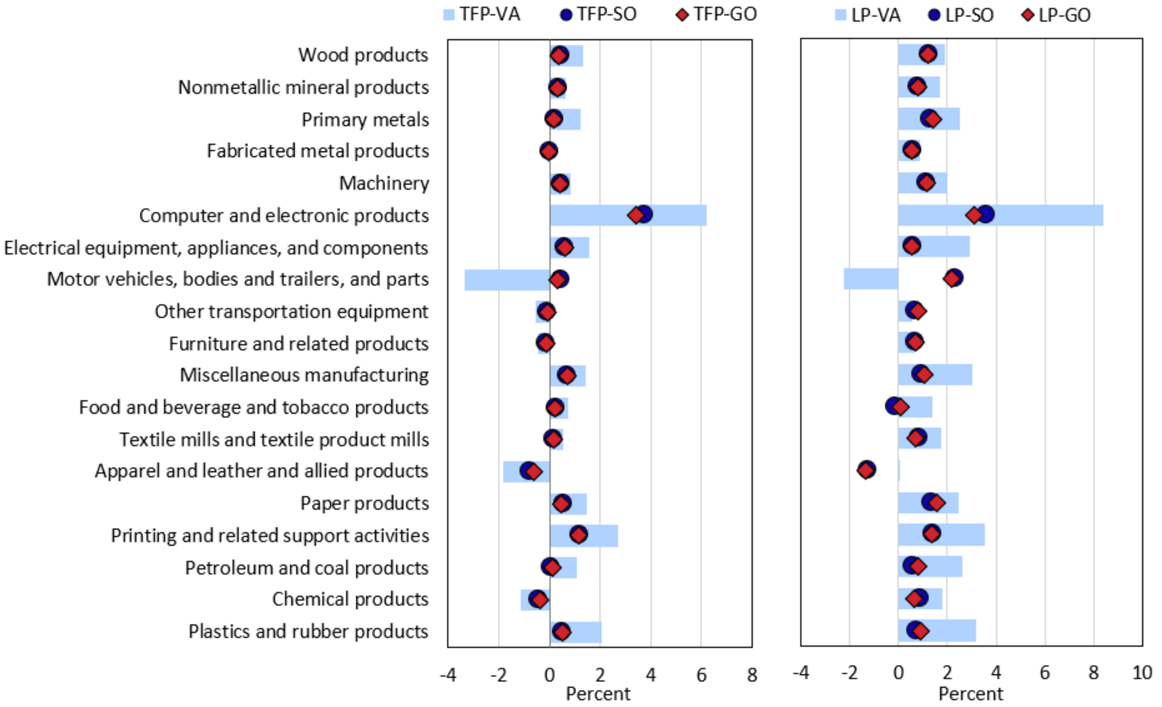
Although the 19 manufacturing industries presented in table 8 used mostly out-of-industry intermediate inputs in 2021, 13 of them used at least 10 percent of intermediate inputs produced by other firms within their industry. The industries with the largest shares of intrasectoral transactions were paper products; food and beverage and tobacco products; and motor vehicles, bodies and trailers, and parts. The industry with the smallest share of within-industry intermediate inputs was printing and related support activities. The relationship between the output share of intermediate inputs and the output share of intrasectoral transactions depends on the level of vertical integration within an industry. By construction, the closer the share of intrasectoral transactions in gross output is to zero, the closer sectoral output is to gross output.

Table 8 also illustrates how these shares have changed over time. The share of total intermediate inputs in gross output for computer and electronic products declined substantially over the 2000–21 period, at an annual rate of 5.76 percent. This industry experienced the largest decline in the share of intermediate-input purchases in the manufacturing sector. From 2000 to 2021, the industry's share of intrasectoral inputs in gross output declined at an average annual rate of 3.83 percent, while its share of out-of-industry inputs declined at an annual rate of 6.74 percent. By comparison, in motor vehicles, bodies and trailers, and parts, the share of total intermediate inputs grew the fastest, at 0.43 percent per year. The share of out-of-industry intermediate inputs for this industry increased by 0.81 percent per year, while the share of intrasectoral inputs decreased by 0.69 percent annually. Petroleum and coal products experienced the largest average annual increase (2.11 percent) in the share of within-industry intermediate inputs from 2000 to 2021, while the share of out-of-industry inputs for this industry declined. In plastics and rubber products, the share of within-industry intermediate inputs grew by 1.32 percent per year, while the share of out-of-industry inputs declined at an annual rate of 0.03 percent.

Manufacturing industries: productivity

Covering the 2000–21 period, chart 6 presents labor productivity and TFP growth rates—constructed by using value-added, sectoral, and gross output—for the 19 manufacturing industries.[44] Because all three approaches are based on the same measure of hours-worked growth, the differences in labor productivity growth across the three output concepts mimic the corresponding differences in output growth. As noted earlier, measuring gross labor productivity is complicated by double counting output but only counting hours worked once, which causes gross labor productivity to be upward biased (hence, the measures must be interpreted with caution). However, intrasectoral intermediate inputs are relatively small in manufacturing, limiting the extent of double counting in gross output. For this reason, chart 6 reveals rather similar growth in gross and sectoral labor productivity in each of the 19 manufacturing industries. In most industries, value-added TFP and labor productivity were growing faster than sectoral and gross TFP and labor productivity. Recall from equation (5) that outsourcing results in a faster increase in TFP based on value-added output than in TFP based on sectoral or gross output.[45] Sectoral and gross TFP are affected by both the decrease in labor input and the increase in intermediate inputs, which results in TFP measures that are less volatile than those measured with value-added output. Finally, chart 6 shows the relative difference in TFP and labor productivity growth over the 2000–21 period for each industry, by output measure.

Chart 6. Productivity measures for selected manufacturing industries, by output measure, annual percent change, 2000–21



Note: NAICS = North American Industry Classification System, TFP-VA = value-added total factor productivity, TFP-SO = sectoral total factor productivity, TFP-GO = gross total factor productivity, LP-VA = value-added labor productivity, LP-SO = sectoral labor productivity, LP-GO = gross labor productivity.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

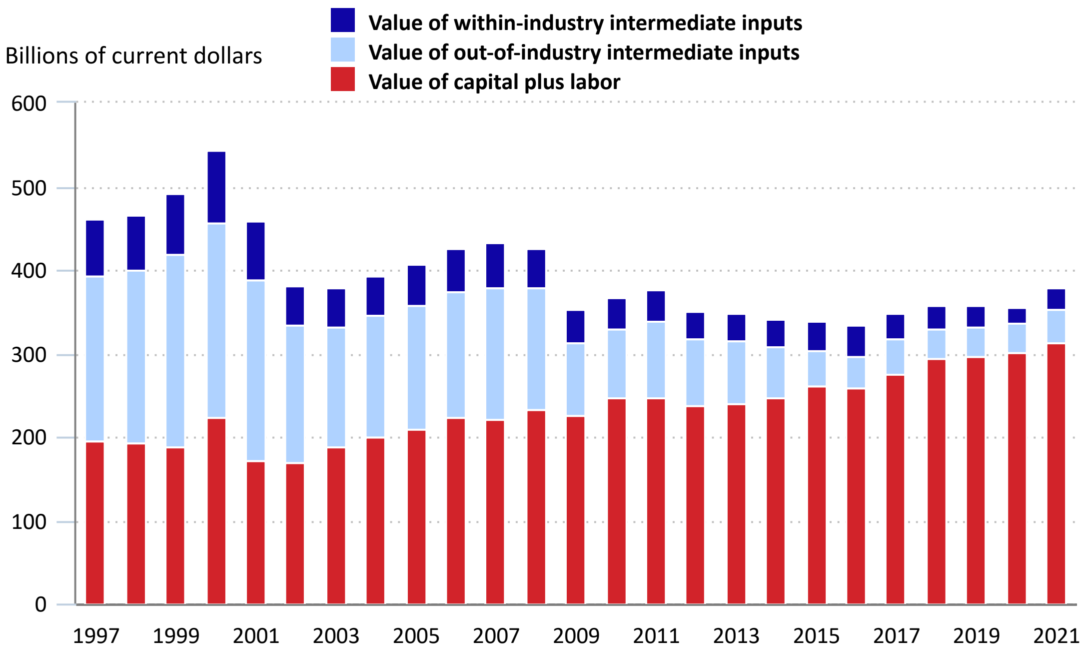
View Chart Data

Manufacturing industries: examples

The charts and tables below illustrate output and input relationships for three selected industries: computer and electronic products (NAICS 334); motor vehicles, bodies and trailers, and parts (NAICS 3361–3363); and plastics and rubber products (NAICS 326). Over the 2000–21 period, computer and electronic products experienced a decline in both within-industry and out-of-industry intermediate-input purchases; motor vehicles, bodies and trailers, and parts experienced substantially faster growth in out-of-industry intermediate-input purchases than in within-industry intermediate-input purchases; and plastics and rubber products experienced faster growth in within-industry intermediate-input purchases than in out-of-industry intermediate-input purchases.

Using the three alternative output concepts, chart 7 presents nominal output in computer and electronic products. In this industry, the nominal values of capital and labor inputs increased over time, whereas the nominal values of *both within-industry and out-of-industry intermediate inputs declined*. These growth patterns are reflected in our three output measures. From 2000 to 2021, nominal value-added output increased at an average annual rate of 1.6 percent, while nominal sectoral and gross output declined at rates of 1.2 and 1.7 percent, respectively. (See table 9.) The current-dollar value of intermediate inputs purchased outside the industry declined steadily from 2000 to 2007, at an average annual rate of 5.6 percent; declined more dramatically from 2007 to 2019, at a rate of 11.5 percent; and then increased from 2019 to 2021, at a rate of 1.8 percent. Nominal purchases of within-industry intermediate inputs also declined from 2000 to 2007, at a rate of 6.7 percent. From 2007 to 2019, these within-industry purchases declined more slowly, at a rate of 6.1 percent, and then increased from 2019 to 2021, at a rate of 3.0 percent.

Chart 7. Nominal output and input relationships for computer and electronic products (NAICS 334), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: Value-added output = Value of capital plus labor; Sectoral output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs); Gross output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs) + (Value of within-industry intermediate inputs). NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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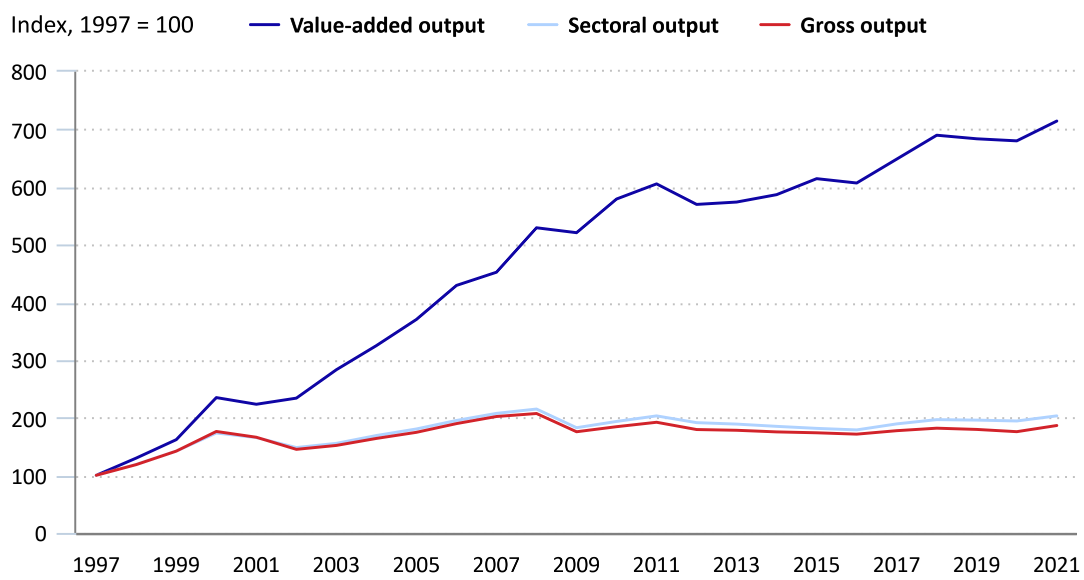
Table 9. Growth in nominal output and intermediate inputs for computer and electronic products (NAICS 334), annual percent change, selected periods

Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	1.6	-1.2	-1.7	-5.5	-8.3
2000–07	-0.1	-2.7	-3.3	-6.7	-5.6
2007–19	2.5	-1.1	-1.6	-6.1	-11.5
2019–21[1]	3.0	2.9	2.9	3.0	1.8

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Chart 8 shows the related measures of real value-added, sectoral, and gross output for computer and electronic products. Over the 2000–21 period, real gross output in the industry increased at an annual rate of 0.3 percent, compared with a 5.4-percent increase for real value-added output and a 0.8-percent increase for real sectoral output. (See table 10.) The comparatively slower growth in real gross output reflects both an annual decline of 3.6 percent in real intermediate inputs purchased from within the industry and a much larger decline of 8.2 percent in real intermediate inputs purchased from outside the industry. The current-dollar value of within-industry intermediate inputs declined at an annual rate of 5.5 percent, while the price of within-industry intermediate inputs declined at a rate of 2.0 percent. The faster growth in real value-added output relative to sectoral output can be explained in the same way, by examining growth in intermediate inputs. Recall that sectoral output differs from value-added output by including intermediate inputs purchased from outside the industry.

Chart 8. Measures of real value-added, sectoral, and gross output for computer and electronic products (NAICS 334), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000–07, 2007–19, and 2019–21. The latter period is an incomplete business cycle. The recession periods are 2007–09 and 2019–20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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Table 10. Growth in real output and intermediate inputs for computer and electronic products (NAICS 334), annual percent change, selected periods

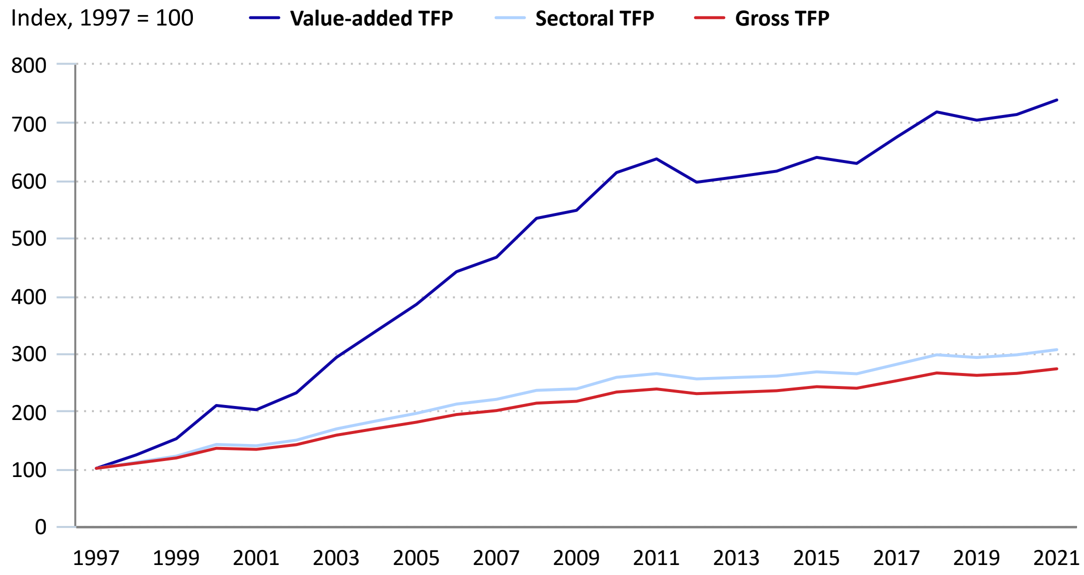
Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	5.4	0.8	0.3	-3.6	-8.2
2000–07	9.8	2.6	2.0	-1.7	-5.0
2007–19	3.5	-0.5	-1.0	-5.6	-10.9
2019–21[1]	2.2	1.9	1.9	2.0	-2.0

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

During the 2000–21 period, real imported and out-of-industry purchases of intermediate inputs declined at a rate of 8.2 percent. This decrease reflects an 8.3-percent decline in the nominal value of out-of-industry intermediate inputs and a 0.2-percent decline in the prices of those inputs. Because real out-of-industry intermediate-input purchases fell substantially from 2000 to 2021, the growth rate of real sectoral output was slower than that of real value-added output. From 2000 to 2007, growth in real value-added output (9.8 percent) was nearly 4 times faster than growth in real sectoral output (2.6 percent). Again, this difference can be explained by examining industry purchases of intermediate inputs by source. Real imported and out-of-industry intermediate-input purchases declined at a rate of 5.0 percent annually. This decrease reflects a 5.6-percent annual rate of decline in nominal purchases of out-of-industry intermediate inputs, whose prices declined at a rate of 0.6 percent annually. From 2007 to 2019, real value-added output increased more slowly, at an annual rate of 3.5 percent, while real sectoral output declined at a rate of 0.5 percent. In this period, real imported and out-of-sector purchases of intermediate inputs declined at an annual rate of 10.9 percent, exhibiting a nominal decline of 11.5 percent and a price decline of 0.6 percent. Over the 2019–21 period, which encompasses the COVID-19 pandemic and related massive federal economic support for industry production, real gross, sectoral, and value-added output saw slow but positive growth of 2.2, 1.9, and 1.9 percent, respectively. Nominal purchases of intermediate inputs also grew, with within-industry purchases increasing at a 3.0-percent rate and out-of-sector purchases increasing at a 1.8-percent rate. Prices of within-industry intermediate inputs increased at a 1.0-percent rate, resulting in positive growth of 2.0 percent for these inputs, while prices of out-of-industry intermediate inputs increased faster, at a 3.9-percent rate, resulting in a decline of 2.0 percent for this category. The larger price increase for out-of-industry intermediate inputs reflects the effects of global production and shipping difficulties that occurred during the initial pandemic years.

Chart 9 displays trends in TFP measures, by alternative output concept, in computer and electronic products for the 1997–21 period. From 2000 to 2021, value-added TFP grew at a rate of 6.2 percent per year, faster than sectoral TFP (3.7 percent) and gross TFP (3.4 percent). (See table 11.) In this period, real value-added output grew at a 5.4-percent rate, an increase offset by a combined decline of 0.7 percent in capital and labor inputs. By comparison, real sectoral and gross output grew at rates of 0.8 and 0.3 percent, respectively, and these increases were offset by respective declines of 2.9 and 3.0 percent in combined capital, labor, and sectoral or gross intermediate inputs. Total input growth was slower for gross TFP than for sectoral TFP, a difference reflecting the inclusion of within-industry intermediate-input purchases, which declined at a rate of 3.6 percent.

Chart 9. Measures of value-added, sectoral, and gross total factor productivity (TFP) for computer and electronic products (NAICS 334), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000–07, 2007–19, and 2019–21. The latter period is an incomplete business cycle. The recession periods are 2007–09 and 2019–20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

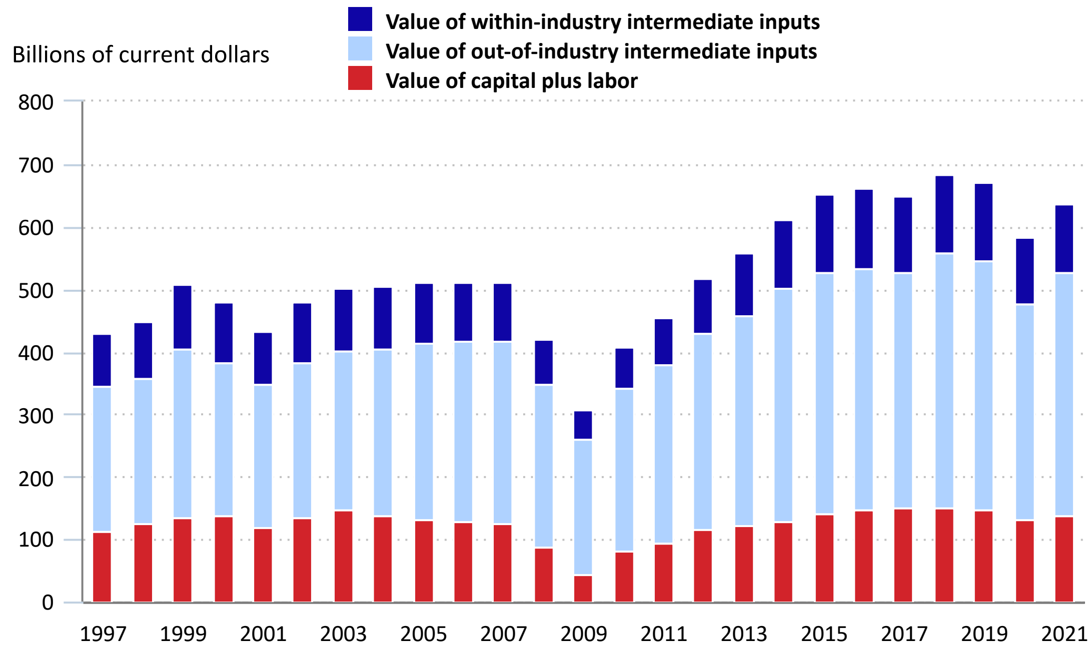
Table 11. Growth in total factor productivity (TFP) for computer and electronic products (NAICS 334), annual percent change, selected periods

Period	Value-added TFP	Sectoral TFP	Gross TFP
2000–21	6.2	3.7	3.4
2000–07	12.1	6.5	5.8
2007–19	3.5	2.4	2.2
2019–21[1]	2.5	2.3	2.2

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

In our second industry example, which focuses on motor vehicles, bodies and trailers, and parts, the pattern of use of capital, labor, and intermediate inputs differed markedly from that observed for computer and electronic products. Here, the nominal value of *purchases of intermediate inputs from outside the industry increased* by 2.2 percent during the 2000–21 period. Chart 10 and table 12 present the relationships between within-industry and out-of-industry intermediate-input growth and output measures for motor vehicles, bodies and trailers, and parts. The share of current-dollar out-of-industry intermediate inputs relative to current-dollar gross output increased steadily in the industry, from 51 percent in 2000 to 61 percent in 2021. By comparison, in computer and electronic products, the share of out-of-industry intermediate inputs relative to gross output declined substantially, from 43 percent in 2000 to 10 percent in 2021. Changes in nominal purchases of within-industry intermediate inputs were more similar between the two industries. In motor vehicles, bodies and trailers, and parts, purchases of within-industry intermediate inputs accounted for 20 percent of gross output in 2000, fell to a low of 15 percent in 2009, and then increased to 17 percent in 2021. In computer and electronic products, purchases of within-industry intermediate inputs initially accounted for 16 percent of gross output, with that share falling to 7 percent by 2021. The share of nominal value-added output in nominal gross output was much smaller in motor vehicles, bodies and trailers, and parts than in computer and electronic products. In the former industry, that share stood at 28 percent in 2000, reached a high of 29 percent in 2003, dropped to a low of 14 percent in 2009 (after the Great Recession), and recovered to 22 percent in 2021. By comparison, in computer and electronic products, the share climbed relatively steadily over time, from 41 percent in 2000 to 83 percent in 2021.

Chart 10. Nominal output and input relationships for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: Value-added output = Value of capital plus labor; Sectoral output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs); Gross output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs) + (Value of within-industry intermediate inputs). NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

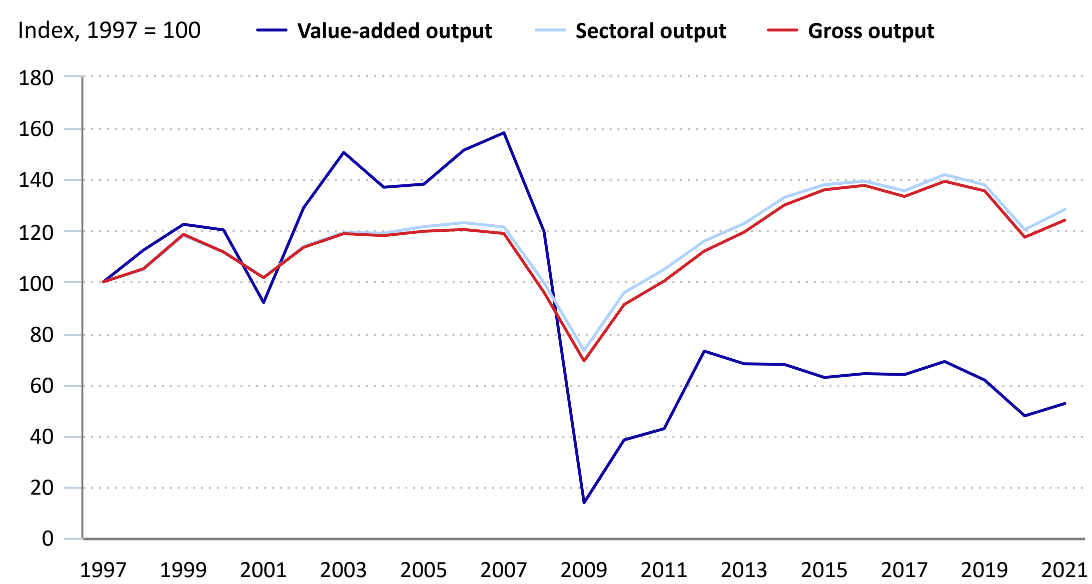
Table 12. Growth in nominal output and intermediate inputs for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), annual percent change, selected periods

Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	0.1	1.5	1.4	0.7	2.2
2000–07	-1.4	1.2	0.9	-0.4	2.5
2007–19	1.4	-1.7	2.3	2.4	2.6
2019–21[1]	-3.1	-1.7	-2.4	-5.8	-1.2

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Chart 11 presents measures of real value-added, sectoral, and gross output for motor vehicles, bodies and trailers, and parts from 1997 to 2021. Over the 2000–21 period, real gross output in the industry increased at an annual rate of 0.5 percent, value-added output decreased at a rate of 3.9 percent, and sectoral output grew at a rate of 0.7 percent. (See table 13.) The faster growth in gross and sectoral output (relative to value-added output) resulted from increased growth in real intermediate inputs purchased from outside the industry. Real within-industry intermediate inputs declined at a rate of 0.2 percent, reflecting a 0.7-percent increase in the current-dollar value of those inputs and a 0.9-percent increase in their prices. At the same time, real out-of-industry intermediate inputs grew at an annual rate of 0.5 percent, reflecting a 2.2-percent increase in the current-dollar value of those inputs and a 1.7-percent increase in their prices.

Chart 11. Measures of real value-added, sectoral, and gross output for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

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Table 13. Growth in real output and intermediate inputs for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), annual percent change, selected periods

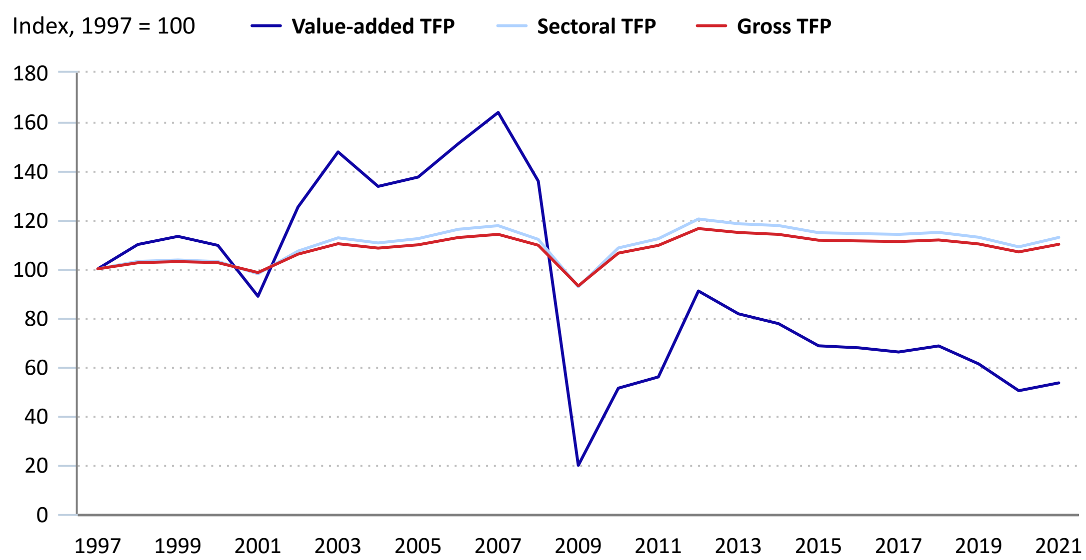
Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	-3.9	0.7	0.5	-0.2	0.5
2000–07	4.0	1.2	0.9	-0.4	-0.1
2007–19	-7.6	1.1	1.1	1.2	1.6
2019–21[1]	-7.7	-3.6	-4.3	-7.7	-4.4

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

However, the output measures and sources of intermediate inputs for business cycle subperiods reveal a different pattern. From 2000 to 2007, purchases of real intermediate inputs from within and outside the industry declined, resulting in value-added output growing faster than both gross and sectoral output. Real imported and out-of-industry purchases of intermediate inputs fell at an annual rate of 0.1 percent, while nominal purchases of those inputs increased at a rate of 2.5 percent and their prices grew at a rate of 2.6 percent. Real sectoral output grew by 1.2 percent, faster than real gross output (0.9 percent). This difference reflects a 0.4-percent decline in nominal purchases of within-industry intermediate inputs and a slight decline of 0.01 percent in the prices of those inputs. In the 2007–19 period, which includes both the Great Recession and the postrecession recovery, purchases of within-industry and out-of-industry intermediate inputs again showed positive growth because of strong growth in nominal purchases of intermediate inputs and somewhat slower growth in input prices. As a result, both sectoral and gross output grew faster than value-added output. The nominal value of out-of-industry intermediate inputs increased at an annual rate of 2.6 percent, while the prices of those inputs increased by 0.9 percent. The nominal value of within-industry intermediate inputs grew at an annual rate of 2.4 percent, while their prices increased more slowly, at a rate of 1.2 percent. During the 2019–21 period, real value-added output declined by 7.7 percent, and nominal purchases of within-industry and out-of-industry intermediate inputs declined by 5.8 and 1.2 percent, respectively. Prices of within-industry intermediate inputs grew at a rate of 2.0 percent, while prices of out-of-industry intermediate inputs increased at a rapid rate of 3.4 percent. As a result, real within-industry and out-of-industry intermediate inputs declined at rates of 7.7 and 4.4 percent, respectively.

Chart 12 displays TFP trends for motor vehicles, bodies and trailers, and parts over the 1997–21 period. Value-added TFP in the industry grew at a steady annual rate of 5.9 percent from 2000 to the beginning of the Great Recession in 2007, when it plummeted as real value-added output declined sharply, reaching a low point in 2009 before beginning to recover. The dramatic decline in value-added TFP during the 2007–09 recessionary period reflects movements in capital and labor inputs only, with capital inputs in that period declining at a 2.3-percent rate and labor inputs falling at a historically rapid 18.6-percent rate. From 2007 to 2019, value-added TFP declined at an annual rate of 7.9 percent, while sectoral and gross TFP each declined by 0.3 percent. (See table 14.) Over the entire 2000–21 period, real value-added output decreased at a 3.9-percent rate, which was offset by a combined decline of 0.5 percent in capital and labor inputs. This resulted in a 3.4-percent decline in value-added TFP. By comparison, from 2000 to 2021, sectoral and gross TFP grew at rates of 0.4 and 0.3 percent, respectively. Real sectoral output grew at a rate of 0.7 percent, which was offset by combined growth of 0.2 percent in capital, labor, and intermediate inputs from outside the industry, while real gross output grew at a rate of 0.5 percent, which was similarly offset by combined input growth of 0.2 percent.

Chart 12. Measures of value-added, sectoral, and gross total factor productivity (TFP) for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

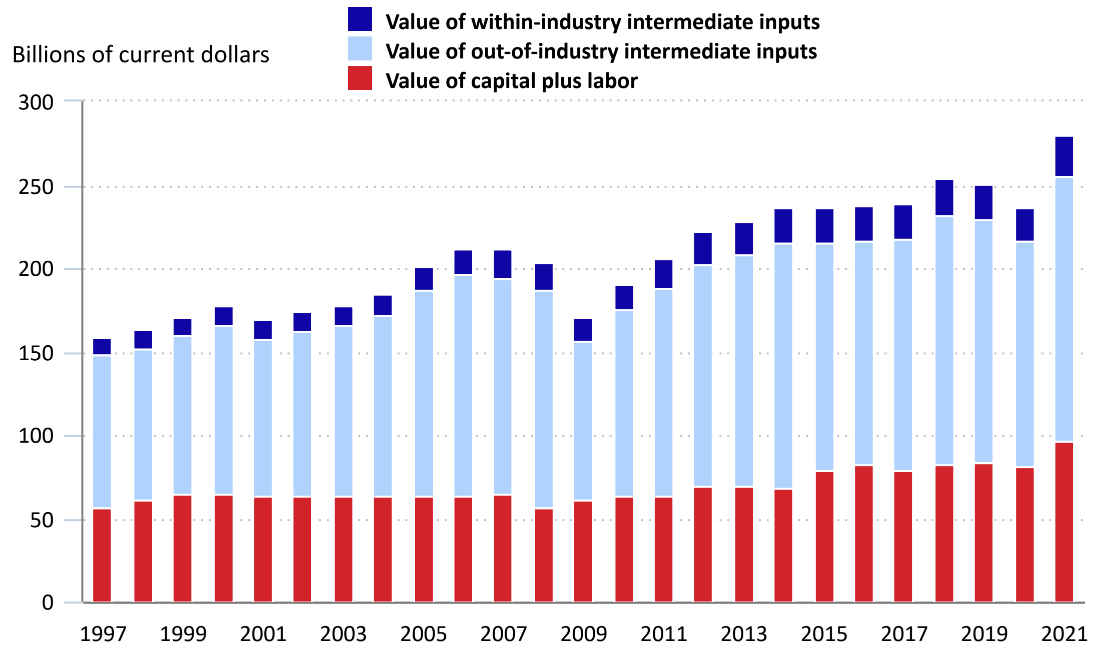
Table 14. Growth in total factor productivity (TFP) for motor vehicles, bodies and trailers, and parts (NAICS 3361–3363), annual percent change, selected periods

Period	Value-added TFP	Sectoral TFP	Gross TFP
2000–21	-3.4	0.4	0.3
2000–07	5.9	1.9	1.5
2007–19	-7.9	-0.3	-0.3
2019–21[1]	-6.5	0.0	-0.1

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

In our final industry example, we focus on plastics and rubber products. In this industry, *purchases of intermediate inputs produced within the industry increased substantially* over time relative to purchases of out-of-industry intermediate inputs. (See chart 13.) During the 2000–21 period, nominal value-added output increased at an average annual rate of 1.9 percent, while nominal sectoral and gross output increased at rates of 2.1 and 2.2 percent, respectively. (See table 15.) Over the same period, the current-dollar value of out-of-industry intermediate inputs grew at a 2.1-percent rate, while the value of within-industry intermediate inputs increased by 3.5 percent per year.

Chart 13. Nominal output and input relationships for plastics and rubber products (NAICS 326), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: Value-added output = Value of capital plus labor; Sectoral output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs); Gross output = (Value of capital plus labor) + (Value of out-of-industry intermediate inputs) + (Value of within-industry intermediate inputs). NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

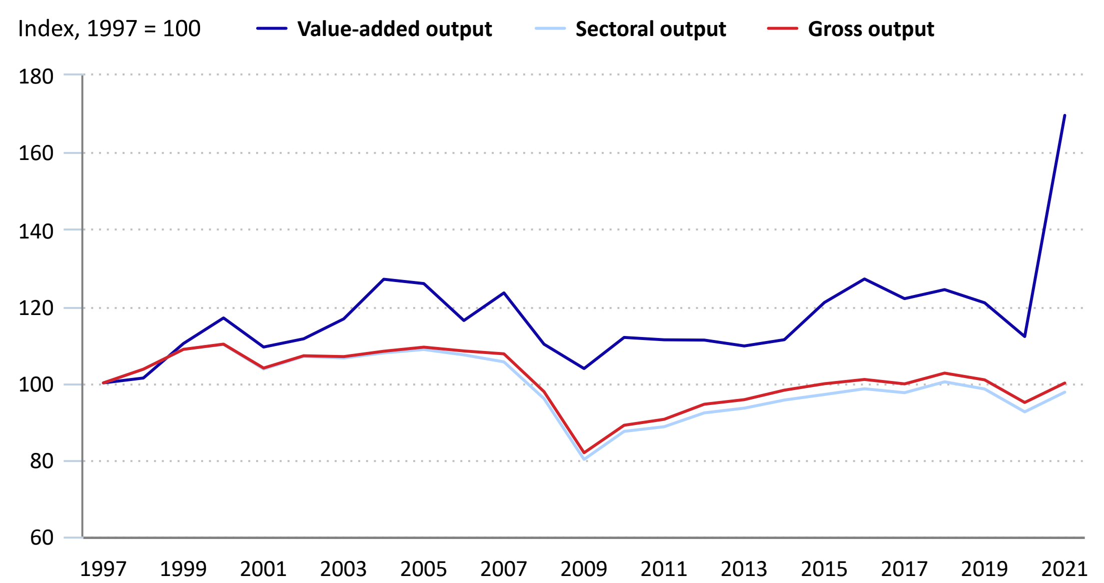
Table 15. Growth in nominal output and intermediate inputs for plastics and rubber products (NAICS 326), annual percent change, selected periods

Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	1.9	2.1	2.2	3.5	2.1
2000–07	-0.1	2.2	2.4	5.8	3.5
2007–19	2.1	1.4	1.4	1.8	1.0
2019–21[1]	8.0	5.6	5.6	5.7	4.1

[1] This period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Chart 14 presents measures of real value-added, sectoral, and gross output for plastics and rubber products. Over the 2000−21 period, real value-added output increased by 1.8 percent per year, while real sectoral and gross output declined by 0.6 and 0.5 percent, respectively. (See table 16.) Because gross output includes the value of within-industry intermediate inputs, real gross output reflects the additional growth of real intrasectoral transactions. From 2000 to 2021, real intermediate inputs purchased from within the industry increased at a 0.9-percent rate, reflecting annual growth of 3.5 percent in nominal purchases of those inputs and a 2.6-percent increase in their prices. Over the same period, real value-added output grew faster than real sectoral output because of a 1.5-percent decline in intermediate inputs purchased from outside the industry. While nominal purchases of out-of-industry intermediate inputs increased by 2.1 percent, prices for those inputs increased faster, by 3.7 percent.

Chart 14. Measures of real value-added, sectoral, and gross output for plastics and rubber products (NAICS 326), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000-07, 2007-19, and 2019-21. The latter period is an incomplete business cycle. The recession periods are 2007-09 and 2019-20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

Table 16. Growth in real output and intermediate inputs for plastics and rubber products (NAICS 326), annual percent change, selected periods

Period	Value-added output	Sectoral output	Gross output	Within-industry intermediate inputs	Out-of-industry intermediate inputs
2000–21	1.8	-0.6	-0.5	0.9	-1.5
2000–07	0.8	-0.6	-0.3	3.0	-1.1
2007–19	-0.2	-0.6	-0.5	-0.2	-0.9
2019–21[1]	18.5	-0.4	-0.4	-0.3	-6.4

[1] This period is an incomplete business cycle.

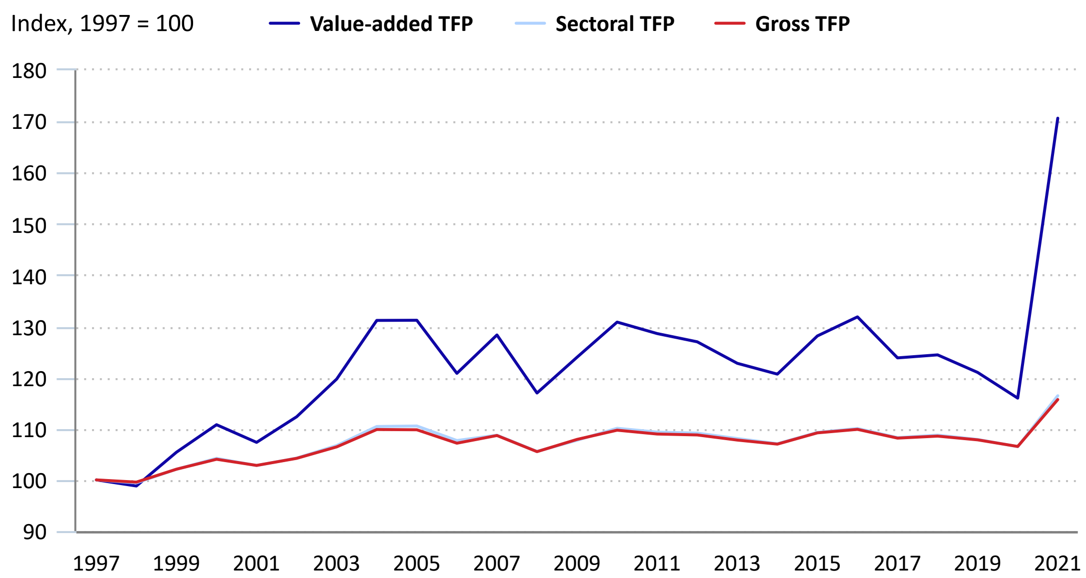
Note: NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Looking at business cycle periods, we see that, from 2000 to 2007, real sectoral output declined at an annual rate of 0.6 percent, while real value-added output grew by 0.8 percent. Over the same period, real imported and out-of-industry purchases of intermediate inputs declined by 1.1 percent, while nominal purchases of those inputs increased at a 3.5-percent rate and their prices increased by 4.6 percent. Real gross output declined by 0.3 percent, reflecting growth of 3.0 percent in real within-industry intermediate inputs. This input growth resulted from a 5.8-percent increase in nominal purchases of intermediate inputs and a 2.8-percent increase in the prices of those inputs. In the latest business cycle period (2007–19), real value-added output decreased at a rate of 0.2 percent, while real gross and sectoral output declined by 0.5 and 0.6 percent, respectively. Real imported and out-of-industry purchases of intermediate inputs declined by 0.9 percent, reflecting an increase of 1.0 percent in nominal purchases of those inputs and an increase of 2.0 percent in their prices. Real within-industry purchases of intermediate inputs declined by 0.2 percent, reflecting an increase of 1.8 percent in nominal purchases of those inputs and an increase of 2.0 percent in their prices. Over the 2019–21 period, real value-added output grew at an accelerated rate of 18.5 percent, while real sectoral and gross output both declined, at a 0.4-percent rate. The decline in sectoral output reflects a large decline of 6.4 percent in purchases of out-of-industry intermediate inputs, which resulted from a 4.1-percent increase in nominal purchases of those inputs and an 11.3-percent increase in their prices. Within-industry intermediate inputs declined slightly, at a 0.3-percent rate, reflecting a 5.7-percent increase in purchases of within-industry intermediate inputs and a slightly faster increase of 6.0 percent in the prices of those inputs.

Chart 15 presents TFP measures, by alternative output concept, for plastics and rubber products. From 2000 to 2021, value-added TFP increased at an annual rate of 2.1 percent, while sectoral and gross TFP grew more slowly, both at a rate of 0.5 percent. (See table 17.) The 0.6-percent decline in real sectoral output was offset by a combined decline of 1.1 percent in capital, labor, and intermediate inputs from outside the industry. Similarly, a 0.5-percent decline in real gross output and a combined decline of 1.0 percent in capital, labor, and gross intermediate inputs resulted in a gross TFP growth of 0.5 percent. The similarity between sectoral and gross TFP results from the offsetting effect of sectoral and gross intermediate inputs relative to trends in real sectoral and gross output. Sectoral intermediate input declined at a 1.5-percent rate, while gross intermediate input declined at a 1.3-percent rate. Because both within-industry and out-of-industry intermediate inputs are included in gross intermediate inputs, and because real within-industry intermediate inputs increased at a 0.9-percent rate while real out-of-industry intermediate inputs declined at a 1.5-percent rate, we see a more moderate decline in gross intermediate inputs and a similar gross TFP value.

Chart 15. Measures of value-added, sectoral, and gross total factor productivity (TFP) for plastics and rubber products (NAICS 326), 1997–2021



Click legend items to change data display. Hover over chart to view data.
Note: The business cycle periods are 2000–07, 2007–19, and 2019–21. The latter period is an incomplete business cycle. The recession periods are 2007–09 and 2019–20. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

Table 17. Growth in total factor productivity (TFP) for plastics and rubber products (NAICS 326), annual percent change, selected periods

Period	Value-added TFP	Sectoral TFP	Gross TFP
2000–21	2.1	0.5	0.5
2000–07	2.1	0.6	0.6
2007–19	-0.5	-0.1	-0.1
2019–21[1]	18.8	3.9	3.6

[1] This period is an incomplete business cycle.

Note: NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Summary

Analyzing productivity growth for an industry or sector requires an understanding of how the choice of output concept will affect measured performance. In this article, we have presented an integrated system of output, input, and productivity measures as characterized by the Solow growth accounting model. We have demonstrated the relationships among the three output concepts of gross output, sectoral output, and value-added output and summarized the strengths and weakness of their related productivity measures. Further, we have empirically compared measures of TFP and labor productivity by using the alternative output concepts for the manufacturing sector and selected manufacturing industries. This analysis highlights the bias that may occur in productivity measurement if one ignores the treatment of within-industry transactions. We have also demonstrated that shifts in outsourcing make the choice of output concept even more important.

BLS productivity measures for the manufacturing sector and its component industries use the concept of sectoral output. This concept captures the output that is leaving an industry or sector but is not affected by changes in firm structures within that industry or sector. In addition, the model based on sectoral output approaches the value-added model for the most aggregated industries and the gross-output model for the most detailed industries. Yet, productivity measures based on value-added and gross output may be useful when they fit the data user's analytical purpose. By constructing an integrated set of productivity measures based on related output measures and by using a consistent framework of outputs and inputs, we hope to provide data users with the broadest and most useful suite of measures for productivity analysis.[46]

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Notes

1 See, for example, Michael Brill, Corey Holman, Chris Morris, Ronjoy Raichoudhary, and Noah Yosif, "Understanding the labor productivity and compensation gap," *Beyond the Numbers*, vol. 6, no. 6, June 2017, https://www.bls.gov/opub/btn/volume-6/pdf/understanding-the-labor-productivity-and-compensation-gap.pdf; and Susan Fleck, John Glaser, and Shawn Sprague, "The compensation–productivity gap: a visual essay," *Monthly Labor Review*, January 2011, https://www.bls.gov/opub/mlr/2011/01/art3full.pdf.

2 "Measuring productivity: measurement of aggregate and industry-level productivity growth" (Paris: Organisation for Economic Co-operation and Development, 2001), p. 11, https://www.oecd.org/sdd/productivity-stats/2352458.pdf.

3 Robert M. Solow, "Technical change and the aggregate production function," *The Review of Economics and Statistics*, vol. 39, no. 3, August 1957, pp. 312–320. Solow's growth model assumes Hicks-neutral technical change and constant returns to scale.

4 For further discussion, see William Gullickson, "Measurement of productivity growth in U.S. manufacturing," *Monthly Labor Review*, July 1995, p. 14, https://www.bls.gov/opub/mlr/1995/07/art2full.pdf.

5 Ibid., p. 18.

6 Internationally, value-added labor productivity is by far the most frequently computed productivity statistic. This measure is easy to calculate and accounts for all factors of production except capital and labor composition. For further discussion, see "Measuring productivity: measurement of aggregate and industry-level productivity growth" (Paris: Organisation for Economic Co-operation and Development, 2001), p.12.

7 See, for example, Lawrence Mishel, Elise Gould, and Josh Bivens, "Wage stagnation in nine charts" (Washington, DC: Economic Policy Institute, January 6, 2015), http://www.epi.org/publication/charting-wage-stagnation/.

8 U.S. Bureau of Labor Statistics (BLS) measures of industry labor productivity compare output with hours worked of all persons, where hours worked of all persons is the total number of hours worked (to produce output) by wage and salary workers, unincorporated self-employed workers, and unpaid family workers. By comparison, BLS measures of industry total factor productivity (TFP) compare output with growth in the combination of capital, labor, energy, materials, and purchased business services, whereby the inputs of materials and, in selected industries, services are adjusted to remove intrasectoral transactions. In addition, labor input is measured as a Törnqvist aggregation of hours worked by all persons, which are classified by education, work experience, and gender with weights determined by their shares of labor compensation in each industry. Using these alternative definitions of labor input allows labor productivity growth to be decomposed into the following components: the contribution of TFP growth, the contribution resulting from capital/labor substitution (capital deepening), and the contribution of labor composition. The measures of labor input used in this article are developed within the manufacturing production model in order to maintain consistency across the three frameworks of value-added, sectoral, and gross output; the methodology is the same as that used to produce the BLS published measures of labor input.

9 This topic is discussed further in Edwin R. Dean, Michael J. Harper, and Mark S. Sherwood, "Productivity measurement with changing weight indices of outputs and inputs," in *Industry Productivity: International Comparison and Measurement* (Paris: Organisation for Economic Co-operation and Development, 1996), pp. 183–215, https://www.oecd.org/sti/ind/1825894.pdf; and Gullickson, "Measurement of productivity growth in U.S. manufacturing," especially footnote 12, p. 27.

10 For additional discussion of this topic, see "Measuring productivity: measurement of aggregate and industry-level productivity growth" (Paris: Organisation for Economic Co-operation and Development, 2001), p. 28. If a technological change within an industry does not affect all factors of production but operates primarily on primary inputs, then a value-added approach is preferable.

11 BLS is conducting research on the feasibility of constructing new productivity measures by using alternative output concepts.

12 For a complete discussion of the advantages and disadvantages of the concepts of gross and value-added output, see "Measuring productivity: measurement of aggregate and industry-level productivity growth" (Paris: Organisation for Economic Co-operation and Development, 2001), pp. 23–33.

13 The U.S. Bureau of Economic Analysis (BEA)/BLS integrated production accounts use a gross-output approach because it provides a complete accounting of inputs used in production regardless of where they are produced. For further information on the Integrated BEA GDP-BLS Productivity Account, see https://www.bea.gov/data/special-topics/integrated-bea-gdp-bls-productivity-account.

14 William Gullickson and Michael J. Harper, "Possible measurement bias in aggregate productivity growth," *Monthly Labor Review*, February 1999, p. 51, https://www.bls.gov/opub/mlr/1999/02/art4full.pdf.

15 Gross output may also be measured as the sum of compensation of employees; taxes on production and imports, less subsidies; gross operating surplus; and the cost of intermediate inputs.

16 For theoretical proofs, see Michael Bruno, “Duality, intermediate inputs and value-added,” in Melvyn Fuss and Daniel L. McFadden, eds., *Production Economics: A Dual Approach to Theory and Applications* (Amsterdam: North Holland, 1978); and Bert M. Balk, “On the relationship between gross-output and value-added based productivity measures: the importance of the Domar factor,” Working Paper 2005/05 (Sydney: Centre for Applied Economic Research, The University of New South Wales, 2003).

17 For a derivation of this relationship, see Lucy P. Eldridge and Susan G. Powers, “Productivity measurement: does output choice matter?,” Working Paper 603 (U.S. Bureau of Labor Statistics, July 21, 2023), footnote 17, p. 67, https://www.bls.gov/osmr/research-papers/2023/pdf/ec230030.pdf.

18 Given gross TFP (TFP_{GO}) growth of 1 percent, an increase (decrease) in intermediate inputs as a result of outsourcing implies an acceleration (deceleration) in the rate of growth of value-added TFP (TFP_{VA}) relative to TFP_{GO}. For further discussion, see Trevor Cobbold, “A comparison of gross output and value-added methods of productivity estimation,” Research Memorandum GA 511 (Canberra: Productivity Commission, November 2003), p. 8, https://www.pc.gov.au/research/supporting/comparison-gross-output-value-added-methods/cgovam.pdf.

19 Eric J. Bartelsman, J. Joseph Beaulieu, Carol Corrado, and Paul Lengermann, “Modeling aggregate productivity at a disaggregate level: a first look at estimating recent MFP growth using a sectoral approach” (working paper for the OECD workshop on productivity measurement, Madrid, Spain, October 17–19, 2005), footnote 5, p. 5, https://www.oecd.org/sdd/productivity-stats/35493055.pdf.

20 For a derivation of this relationship, see Eldridge and Powers, “Productivity measurement,” footnote 20, pp. 67–68.

21 Alternatively, we can show that TFP_{VA} is related to sectoral TFP (TFP_{SO}) as follows: TFP_{VA} = (TFP_{SO} × (1 – Intrasectoral transactions/Gross output) × (1 + Intermediate inputs/Value-added output)).

22 The main exception is imported intermediate inputs.

23 BLS measures of TFP also account for changes in the composition of the labor force by using a measure of labor input defined as hours worked adjusted for differences in worker age, education, and gender (rather than simply hours worked).

24 Using hours worked as a measure of labor input, labor productivity growth (LP growth) can be decomposed into its components, including capital intensity (capital per unit of labor input), the effect of labor composition, and TFP: LP growth = Capital/labor growth + Labor composition growth + TFP growth. For further information on this relationship, see Lucy P. Eldridge, Chris Sparks, and Jay Stewart, “The U.S. Bureau of Labor Statistics productivity program,” in Emilie Grifell-Tatjé, C. A. Knox Lovell, and Robin C. Sickles, eds., *The Oxford Handbook of Productivity Analysis* (New York: Oxford University Press, 2018), pp. 126–127.

25 Lucy P. Eldridge and Michael J. Harper, “Effects of imported intermediate inputs on productivity,” *Monthly Labor Review*, June 2010, pp. 3–15, https://www.bls.gov/opub/mlr/2010/06/art1full.pdf.

26 *Handbook of Methods* (U.S. Bureau of Labor Statistics, September 1983), chapter 11, p. 2.

27 *Trends in Multifactor Productivity, 1948–81*, Bulletin 2178 (U.S. Bureau of Labor Statistics, September 1983), p. 16.

28 “Measuring productivity: measurement of aggregate and industry-level productivity growth” (Paris: Organisation for Economic Co-operation and Development, 2001), p. 14.

29 *Trends in multifactor productivity, 1948–81*, Bulletin 2178 (U.S. Bureau of Labor Statistics, September 1983), pp. 33–34.

30 See endnote 13.

31 Gullickson, “Measurement of productivity growth in U.S. manufacturing,” p. 18.

32 TFP statistics are available for the U.S. business sector, the nonfarm business sector, and the manufacturing sector, as well as for 19 groups of manufacturing industries, 86 detailed manufacturing industries, railroad transportation, air transportation, and utilities. Data on output per hour and unit labor costs are available for the U.S. business sector, the nonfarm business sector, and the manufacturing sector. In addition, data on output per hour and unit labor costs are available for over 400 selected industries in manufacturing, mining, utilities, wholesale and retail trade, and services.

33 The 19 manufacturing industries included in our analysis correspond to industry definitions used in the U.S. National Income and Product Accounts (NIPAs). The NIPA industry definitions, in turn, are based on the North American Industry Classification System (NAICS). Of the 19 industries, 14 are three-digit NAICS industries and 5 are combinations of NAICS industries. These five industries include food and beverage and tobacco products (NAICS 311–312); textile mills and textile product mills (NAICS 313–314); apparel and leather and allied products (NAICS 315–316); motor vehicles, bodies and trailers, and parts (NAICS 3361–3363); and other transportation equipment (NAICS 3364–3369).

34 The sectoral-output and related capital, labor, energy, materials, and services (KLEMS) data used in this article are from an unpublished production account developed for the manufacturing sector. This production account includes measures of gross, value-added, and sectoral output, as well as the congruent KLEMS input measures. Sectoral-output data from this account differ marginally from the published BLS sectoral-output measures for manufacturing. Some minor adjustments to the published BLS sectoral-output and related input data are required to maintain consistency with the related measures of gross and value-added output within the manufacturing production account. Also, these data have been adjusted to remove the output of households and nonprofit entities. For further description of the BLS unpublished manufacturing production account, see Eldridge and Powers, “Productivity measurement,” especially appendix tables A-13 and A-14 comparing published BLS sectoral-output and capital services measures with the research measures developed in the unpublished manufacturing sector production account.

35 BLS TFP measures for manufacturing industries are based on published BLS measures of sectoral output. This article develops TFP measures based on sectoral output by using sectoral-output measures from an unpublished manufacturing production account.

36 By using hours worked as the measure of labor input, we can decompose labor productivity into its component sources of growth, including TFP, capital intensity (capital per unit of labor input), and the effect of labor composition. This decomposition is based on the following relationship: LP growth = TFP growth + Capital/labor growth + Labor composition growth.

37 There are 90 asset types for fixed business equipment, structures, inventories, land, and intellectual property products. The measures of aggregate capital services are obtained by Törnqvist aggregation of the capital stocks for each asset type within each of the 19 NAICS manufacturing industry groupings by using estimated rental prices for each asset type. Each rental price reflects the nominal rate of return to all assets within an industry, as well as rates of economic depreciation and revaluation for the specific asset; rental prices are adjusted for the effects of taxes. Data on investment for fixed assets are obtained from BEA. Data on inventories are estimated by using data from BEA and additional information from Internal Revenue Service (IRS) Corporation Income Returns. Data for land in the farm sector are obtained from the U.S. Department of Agriculture. Nonfarm industry detail for land is based on IRS book-value data. Current-dollar value-added data, obtained from BEA, are used in estimating capital rental prices.

38 The capital services measures for this research are developed by using the model for value-added output and differ very slightly from BLS published capital input measures. For a comparison of the BLS published capital services measure and the research capital services measure, see Eldridge and Powers, “Productivity measurement,” appendix table A-14.

39 For further information on data, methods, and differences, see Eldridge and Powers, “Productivity measurement.”

40 In discussing economic growth and productivity, it is important to evaluate how factors influencing productivity are changing over time. Therefore, output, inputs, and productivity are generally presented as growth rates in order to facilitate the comparison of output and input growth.

41 From 2000 to 2021, the current value of within-sector intermediate inputs grew at a 1.4-percent rate, while the price of within-sector intermediate inputs increased by 2.1 percent.

42 Over the 2000–07 period, nominal out-of-sector intermediate inputs increased at a 5.4-percent rate, and their prices grew by 5.8 percent.

[43] Over the 2007–19 period, nominal out-of-sector intermediate inputs decreased at a 0.54-percent rate, and their prices grew by only 0.77 percent.

[44] Manufacturing TFP growth rates by alternative output measure for the 1997–2021 period are available in Eldridge and Powers, “Productivity measurement,” appendix tables A-4, A-5, and A-6, pp. 79–81.

[45] BLS prioritizes the use of output measures that most accurately reflect movements in output for each specific industry. Measures of manufacturing industry output are derived by using various data sources, including the U.S. Census Bureau Annual Survey of Manufactures, the Energy Information Administration, and industry trade associations. Data on intermediate inputs are obtained from BEA. Because of these differences in data sources for outputs and inputs, empirical measures for a few industries violate this relationship, exhibiting gross TFP slightly larger than value-added TFP.

[46] In our companion *Monthly Labor Review* article, “Industry contributions to productivity growth in U.S. manufacturing: an application of alternative output concepts” (September 2023), we construct and compare industry contributions to aggregate TFP by using alternative output measures. By weighting industry TFP growth with a given industry’s share in aggregate output, we examine the implications of using different output measures and related productivity measures for analysis of industry contributions to productivity growth. We find that the choice of output measure affects the ordering of contribution levels of specific industries.

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September 2023

The Great Resignation in the United States: How long will it last?

Summary written by: Abdulkadir Şenkal

In the last 2 years, the popular press in the United States has covered many stories discussing the "Great Resignation." These news stories have greatly affected society and attracted attention. In particular, because of the COVID-19 pandemic, resignations of millions of workers in the American labor market in 2021 and 2022 have clamored loudly.

In his article "The Great Resignation in the United States: a study of labor market segmentation," published in the *Forum for Social Economics* in January 2023, Thomas E. Lambert analyzes the resignations that occurred in the U.S. labor market after COVID-19 by using data from the U.S. Bureau of Labor Statistics Job Openings and Labor Turnover Survey. In his analysis, Lambert attempts to confirm the Great Resignation phenomenon. After controlling for economic growth, he finds that the levels and rates of turnover during the pandemic (until January 2022) are statistically different from those seen during the Great Recession (2007 to 2009) and the dot-com recession (2001).

The author finds that workers resigned during COVID-19 for many reasons, including the high cost of daycare for working parents, which resulted in many women participating less in the labor force. Other reasons comprise the liberating experience of not working at all or working from home instead of one's usual place of work, low wages that made work less attractive and more stressful, and the feeling of not wanting to work more because of greater job tenure uncertainty and poor working environments.

Lambert shows that these factors not only affected labor force participation but also highlighted problems specific to certain U.S. industries. Some problems are contrary to theoretical expectations. The hypothesized effect of certain industries with more female employees than male, as well as increased childcare and tuition fees, leading to higher resignation rates on average instead shows an inverse correlation. In fact, similar studies identify higher levels of turnover during the pandemic for the whole economy. A regression analysis assessing the impact of the hiring rate, vacancy rate, hourly earnings, and unemployment rate on the quit rate revealed regression coefficients that were statistically significant and theoretically expected.

Given the empirical validity of resignations in Lambert's study, a continued pandemic pressure on the wage-to-profitability ratio could motivate accelerated investments in labor-saving solutions. Likely sensitized to the possibility of another pandemic in the future, public and business leaders could increase their investments in laborsaving technologies that would prevent a repeat of economic impacts similar to those of the COVID-19 pandemic. In particular, higher wages and benefits would persuade firms to automate more so as to minimize rising costs. In this way, improved morale and any increased productivity and lower hiring costs could offset higher labor costs.

Another important finding reported in Lambert's article is that greater pay and benefits not only are likely to reduce turnover rates but also could boost productivity and morale levels in many companies. This method, he claims, can also eliminate management problems and the need for employee supervision. In addition to higher wages, better and more widespread healthcare and childcare benefits would also help address the problem of underuse of labor in competitive, peripheral, and low-wage sectors of the U.S. economy.

However, some jobs are still difficult to replace with automation, according to Lambert. He reports that the corporate culture of many organizations will have to change from one of inadequate guidance and supervision, or "negative" supervision, to one in which employee training and increased productivity are linked to higher pay and retention.

Featured Article

September 2023

Industry contributions to productivity growth in U.S. manufacturing: an application of alternative output concepts

To understand the performance of the U.S. manufacturing sector, in this article, we explore the performance of individual industries. We first use the U.S. Bureau of Labor Statistics published data to look at the influence of industries on sector-level performance and total factor productivity (TFP) growth. The underlying dynamics of production in any given industry determine its influence on the sector as a whole. Both an industry's share of output and its individual TFP growth vary over time, and these changes jointly determine the industry's contribution to performance in the manufacturing sector. Next, we trace the contribution of industries to manufacturing sector TFP by using three alternative output concepts—value-added output, sectoral output, and gross output. We examine the differences in industry contributions that result from the use of the alternative output measures, over 2000–21 and three different business cycles (2000–07, 2007–19, and 2019–21). We show that one must carefully deliberate before selecting a value-added-output, sectoral-output, or gross-output framework for TFP and contribution analysis.

The manufacturing sector is an important part of the U.S. economy. Yet, looking at the manufacturing sector as a whole can mask the varied performance of the many diverse industries that make up this goods-producing sector. An industry's performance along with its relative size will determine how the performance of an individual industry contributes to manufacturing sector performance. Evaluating industry contributions to manufacturing sector performance reveals which industries are dragging down total factor productivity (TFP) growth in the sector and which are enhancing it.

TFP compares growth in the production of goods with changes in the inputs used in production. By capturing the growth in output that is not a result of using more labor, capital, energy, materials, and purchased services, TFP is often used as an indicator of technological progress and performance. In the manufacturing sector, TFP grew at an average compound rate of 0.60 percent per year from 2000 to 2021.[1] Yet, across industries within manufacturing, TFP growth ranged from 3.87 percent in the computer and electronic products industry to a negative 0.47 percent in the chemical products industry.

Looking across the last three business cycles (2000–07, 2007–19, and 2019–21), we present U.S. Bureau of Labor Statistics (BLS) published TFP measures for the manufacturing sector and for 19 industries within manufacturing and estimate the amount contributed by each industry to overall manufacturing sector performance.[2] We discuss changes in industry average shares, or relative size, and industry TFP growth. We also discuss the considerable variation in TFP across industries and in the amount contributed by each industry to manufacturing TFP across business cycles.

Next, we explore whether industry contributions are affected when TFP is measured by using three alternative output concepts (value-added output, sectoral output, and gross output). We use an experimental production account to investigate how output choice affects analysis of industry contributions to manufacturing sector TFP. BLS uses a sectoral-output concept to measure TFP in manufacturing. Sectoral output represents the value of output leaving the sector or industry, by excluding the value of intermediate inputs that are produced and consumed within that same industry or sector (i.e., intrasectoral transactions). By contrast, value-added output excludes all intermediate inputs, while gross output does not exclude any intermediate inputs. As discussed in the companion article, "The importance of output choice: implications for productivity measurement," the choice of output measure (and by extension, the treatment of intermediate inputs in output) has substantive implications for TFP measurement.[3]

Industry TFP growth and contributions to manufacturing sector performance

TFP growth is measured as the percent change in the ratio of output to the weighted sum of inputs used in the production process. Outputs and inputs are measured either in physical quantities or in deflated values, adjusted for price change. Growth in TFP is commonly presented as[4]

$$\text{TFP growth} = \text{Output growth} - \sum_i s_i \text{ Input growth}_i, \qquad (1)$$

where s_i are cost-share weights for each input *i*. This model was developed by Robert Solow in 1957 and assumes constant returns to scale, implying that the value of output equals the total cost of all measured inputs and cost shares sum to 1.[5]

The corresponding output and input trends underlying manufacturing sector and industry TFP growth in the 2000–21 period are presented in table 1. Manufacturing sector TFP growth of 0.60 percent per year is a result of no growth in output and a decline of 0.60 percent in the use of combined inputs during this period. Although capital input increased at a 1.64-percent rate, the use of both labor and intermediate inputs declined by 1.01 percent and 1.50 percent, respectively. Among manufacturing industries, the computer and electronic products industry achieved the highest level of TFP growth because output grew at a rate of 0.76 percent annually and combined inputs declined at a 3.00-percent annual rate. This decline in inputs reflects a large 9.78-percent annual decrease in the growth of intermediate inputs accompanied by a more moderate 2.0-percent decrease in labor input and a 1.62-percent increase in capital input. The printing industry achieved the second-highest TFP growth over this period, with a decrease in output growth of 2.26 percent offset by an even greater 3.39-percent fall in the growth of combined inputs. By contrast, the chemical industry experienced the largest decline in TFP over this period, with the growth in combined inputs (0.72 percent) outpacing the growth in output (0.25 percent). Among inputs in the chemical industry, capital input grew at a rate of 3.47 percent annually, while labor experienced no growth and intermediate inputs of materials, energy, and services declined.

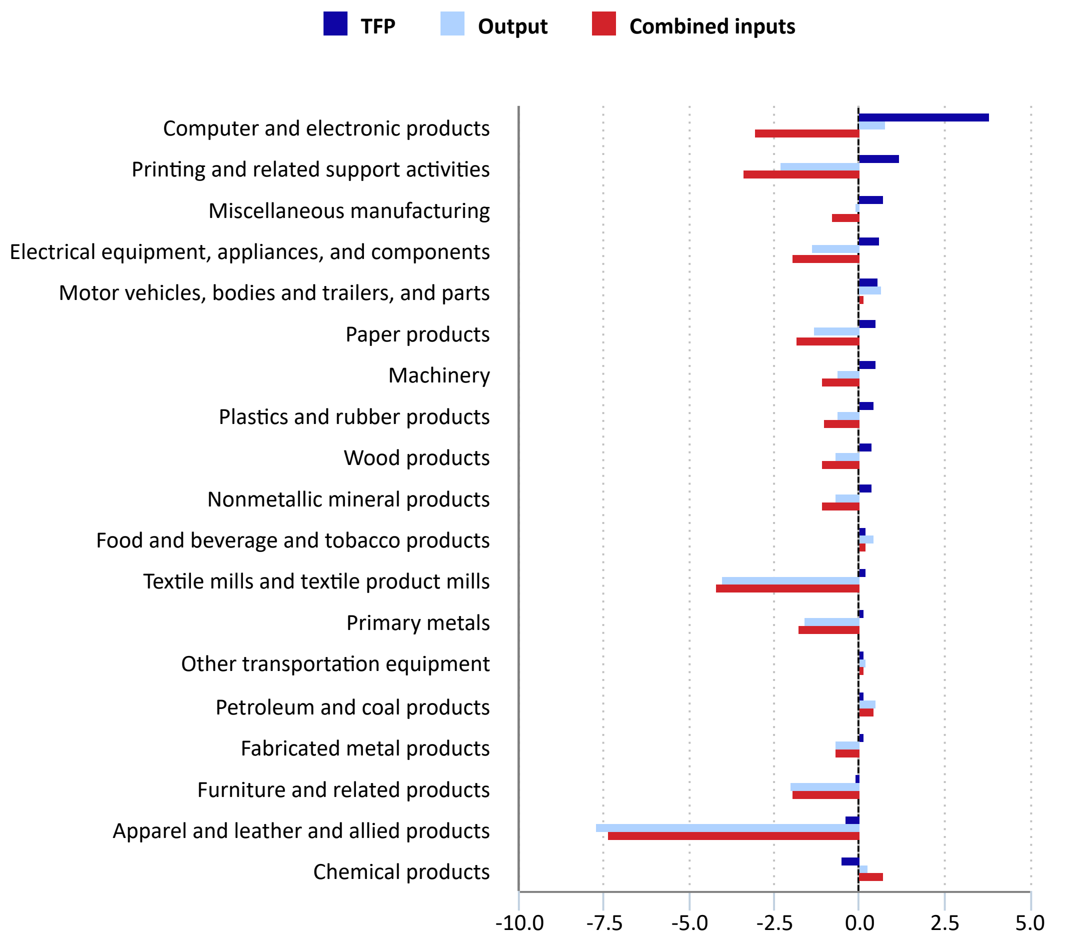
Table 1. TFP growth by manufacturing industry and related components, annual percent change, 2000–21

NAICS codes	NAICS industry	TFP	Output	Combined inputs	Capital input	Labor input	Intermediate inputs
31–33	Manufacturing sector	0.60	0.00	–0.60	1.64	–1.01	–1.50
334	Computer and electronic products	3.87	0.76	–3.00	1.62	–2.02	–9.78
323	Printing and related support activities	1.17	–2.26	–3.39	–0.68	–3.42	–3.91
339	Miscellaneous manufacturing	0.72	–0.04	–0.75	1.99	–0.21	–2.62
335	Electrical equipment, appliances, and components	0.63	–1.32	–1.94	0.54	–1.17	–3.13
3361–3363	Motor vehicles, bodies and trailers, and parts	0.53	0.67	0.13	0.99	–1.21	0.33
322	Paper products	0.52	–1.29	–1.80	–0.91	–2.24	–1.84
333	Machinery	0.48	–0.59	–1.06	0.63	–1.20	–1.45
326	Plastics and rubber products	0.44	–0.57	–1.00	0.90	–0.91	–1.36
321	Wood products	0.39	–0.68	–1.06	0.12	–1.45	–0.84
327	Nonmetallic mineral products	0.37	–0.66	–1.03	0.72	–0.96	–1.53
311, 312	Food and beverage and tobacco products	0.24	0.43	0.19	1.26	1.08	–0.26
313, 314	Textile mills and textile product mills	0.20	–3.98	–4.17	–2.52	–4.01	–4.49
331	Primary metals	0.15	–1.59	–1.74	–0.25	–2.49	–1.76
3364–3369	Other transportation equipment	0.12	0.24	0.12	1.56	0.03	–0.95
324	Petroleum and coal products	0.07	0.49	0.42	1.74	–0.09	0.17
332	Fabricated metal products	0.00	–0.65	–0.65	0.97	–0.78	–0.99
337	Furniture and related products	–0.08	–1.98	–1.91	0.84	–2.29	–2.11
315, 316	Apparel and leather and allied products	–0.37	–7.70	–7.35	–1.84	–5.44	–9.41
325	Chemical products	–0.47	0.25	0.72	3.47	0.00	–0.95

Note: NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

Chart 1 illustrates the relationships among TFP, output, and combined inputs for manufacturing industries. Of the 19 manufacturing industries, 15 experienced positive TFP growth. Among these 15 industries, only 5 had positive output growth that exceeded the growth of combined inputs. The remaining 10 industries experienced decreasing growth in output offset by an even faster decrease in growth of combined inputs. Growth in capital inputs declined in 4 of these 15 industries, while labor input growth decreased in 13 and growth of intermediate inputs slowed in all but 2 of the 15 industries. The four industries with negative TFP growth exhibited varied patterns of output and input use. The chemical industry experienced growth in output accompanied by higher growth in combined inputs. However, the fabricated metal products industry, the furniture industry, and the apparel industry experienced negative growth in combined inputs offset by even faster declines in output growth.

Chart 1. TFP, output, and combined inputs, by manufacturing industry, annual percent change, 2000–21



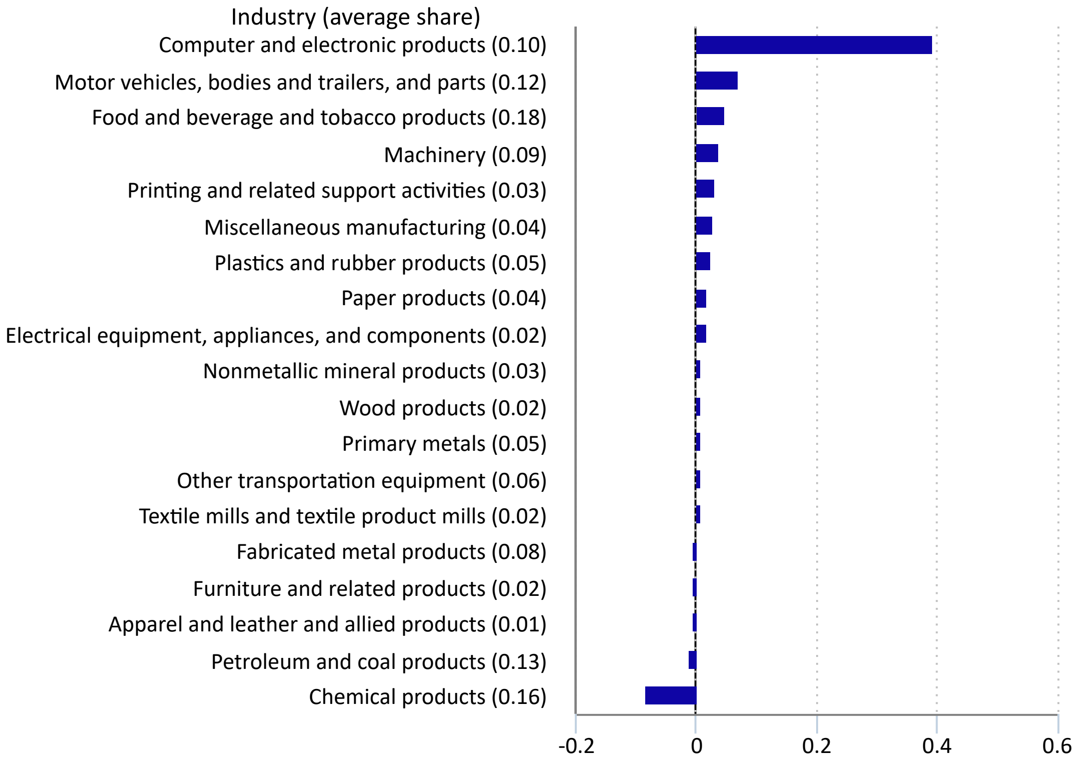
Click legend items to change data display. Hover over chart to view data.
Note: TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

To determine how industries contribute to manufacturing sector productivity, we weight the TFP growth rates for each industry by the value of that specific industry's share of sector output. The weights for each industry are the industry's current-dollar sectoral-output share of the aggregate manufacturing sector's sectoral output.[6] The industry weights reflect not only the contributions of the primary inputs—capital and labor—to production but also the contributions of the intermediate inputs—energy, materials, and purchased services. These industry weights will sum to a value greater than 1 since the numerator—the value of sectoral output in each industry—will include intermediate inputs purchased from outside the industry. The denominator, on the other hand, includes only the value of intermediate inputs purchased outside the aggregate manufacturing sector. TFP growth in any one industry will augment productivity growth in other industries that use other manufactured goods in their production processes.[7]

Chart 2 shows the relative contribution of each industry to manufacturing sector TFP growth from 2000 to 2021 by using BLS published data. For this period, the computer and electronic products industry leads both in TFP growth and in contribution to manufacturing sector TFP. This result reflects not only the highest manufacturing industry TFP growth but also a relatively large average industry share of 0.10 for the 2000–21 period. By contrast, the printing and related support activities industry had a relatively strong TFP growth rate of 1.17 percent per year. Yet, it contributed only 0.03 percentage point to growth in manufacturing sector TFP because of a small 0.03 industry share. While TFP growth rates in the motor vehicles industry and the paper products industry were similar, 0.53 percent and 0.52 percent, respectively, the motor vehicle industry contributed 0.07 percentage point to manufacturing sector TFP growth over the 2000–21 period and the paper products industry contributed 0.02 percentage point. This difference in contribution occurs because the motor vehicles industry's share of sector output (0.12) is 3 times larger than the paper products industry's share (0.04). Combining industry TFP measures with information on the industry's share of manufacturing sector final demand enables those industries driving or detracting from sector-level TFP growth to be identified in any given period.

Chart 2. Contributions to manufacturing sector TFP growth, by manufacturing industry, annual percent change, 2000–21



Hover over chart to view data.
TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Evolution in manufacturing across business cycles

Looking at changes in industry contributions, industry shares, and TFP growth across business cycles provides insights into how the manufacturing sector has evolved over the past 20 years. The 2000–21 period includes three business cycles: 2000–07, 2007–19, and 2019–21. Table 2 presents each industry's contribution to manufacturing sector TFP growth, industry average share, and industry TFP growth, across the last three business cycles.[8]

Table 2. Industry contributions to manufacturing sector TFP growth and related components, selected business cycles

NAICS codes	NAICS industry	Industry contribution to manufacturing TFP growth (annual percent change)			Industry share (average)			Industry TFP (annual percent change)		
		2000–07	2007–19	2019–21	2000–07	2007–19	2019–21	2000–07	2007–19	2019–21
31–33	Manufacturing sector	[1]	[1]	[1]	[1]	[1]	[1]	1.74	–0.18	1.32
321	Wood products	0.024	0.000	0.010	0.03	0.02	0.03	0.90	0.13	0.20
327	Nonmetallic mineral products	0.004	0.006	0.051	0.03	0.03	0.03	0.13	0.30	1.62
331	Primary metals	0.027	0.029	–0.205	0.05	0.05	0.05	0.66	0.54	–3.90
332	Fabricated metal products	0.051	–0.053	0.126	0.08	0.08	0.09	0.64	–0.62	1.46
333	Machinery	0.129	–0.037	0.171	0.09	0.09	0.09	1.53	–0.38	2.00
334	Computer and electronic products	0.738	0.217	0.240	0.13	0.09	0.08	6.59	2.48	2.84
335	Electrical equipment, appliances, and components	0.046	–0.001	0.046	0.03	0.02	0.03	1.60	–0.07	1.43
3361–3363	Motor vehicles, bodies and trailers, and parts	0.253	–0.032	0.037	0.13	0.11	0.13	1.92	–0.24	0.40
3364–3369	Other transportation equipment	0.079	–0.019	–0.110	0.06	0.07	0.06	1.40	–0.29	–1.85
337	Furniture and related products	0.000	–0.001	–0.011	0.02	0.02	0.02	–0.07	–0.01	–0.56
339	Miscellaneous manufacturing	0.061	0.008	0.056	0.04	0.04	0.04	1.48	0.13	1.57
311, 312	Food and beverage and tobacco products	0.118	–0.084	0.607	0.17	0.19	0.20	0.69	–0.45	2.92
313, 314	Textile mills and textile product mills	0.010	–0.001	0.008	0.02	0.01	0.01	0.56	–0.12	0.84
315, 316	Apparel and leather and allied products	–0.011	0.003	–0.014	0.01	0.00	0.00	–1.42	0.84	–3.84
322	Paper products	0.036	0.001	0.078	0.04	0.04	0.04	0.87	0.05	2.15
323	Printing and related support activities	0.078	0.012	–0.004	0.03	0.02	0.02	2.59	0.57	–0.17
324	Petroleum and coal products	–0.111	0.053	–0.020	0.10	0.16	0.12	–0.12	0.21	–0.16
325	Chemical products	0.144	–0.289	0.384	0.15	0.17	0.17	0.89	–1.69	2.22
326	Plastics and rubber products	0.033	–0.001	0.166	0.06	0.05	0.06	0.55	–0.02	2.88

[1] This measure is not applicable to the manufacturing sector.
Note: The 2019–21 period is an incomplete business cycle. NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

TFP in the manufacturing sector grew at a 1.74-percent annual rate from 2000 to 2007. During this period, the growth in industry-level TFP ranged from a positive 6.59 percent per year in computer and electronic products to a negative 1.42 percent in the apparel industry. Output in the computer industry grew considerably, at 2.59 percent, while labor input declined at a 4.01-percent rate and intermediate inputs fell by 5.27 percent annually. (See table 3.) The apparel industry suffered an extreme decrease in output growth of 14.18 along with a decline in use of combined inputs of 12.94, which reflects a 17.64-percent decline in intermediate inputs. Following the Great Recession (2007–09), manufacturing sector productivity declined on average 0.18 percent per year from 2007 to 2019. During this business cycle, computer and electronic products maintained the fastest TFP growth, at 2.48 percent, while the largest negative growth was in chemical products with a decline of 1.69 percent. The growth in TFP in the computer industry resulted from an annual decline in output of 0.48 percent and a faster decline in combined inputs of 2.89 percent annual growth. The fall in combined inputs reflects a 1.17-percen increase in capital input, offset by a 0.99-percent decline in labor input and a 12.15-percent decline in intermediate inputs. With the largest decline in TFP in this period, the chemical industry output growth rate fell 1.51 percent, while growth in combined inputs increased slightly at a 0.18-percent rate. This small increase in combined inputs reflects a large 3.28 growth in capital inputs, accompanied by a small 0.38-percent growth in labor input and offset by a 1.89-percent decline in intermediate inputs.

Table 3. TFP growth and related components by business cycles for selected industries, annual percent change

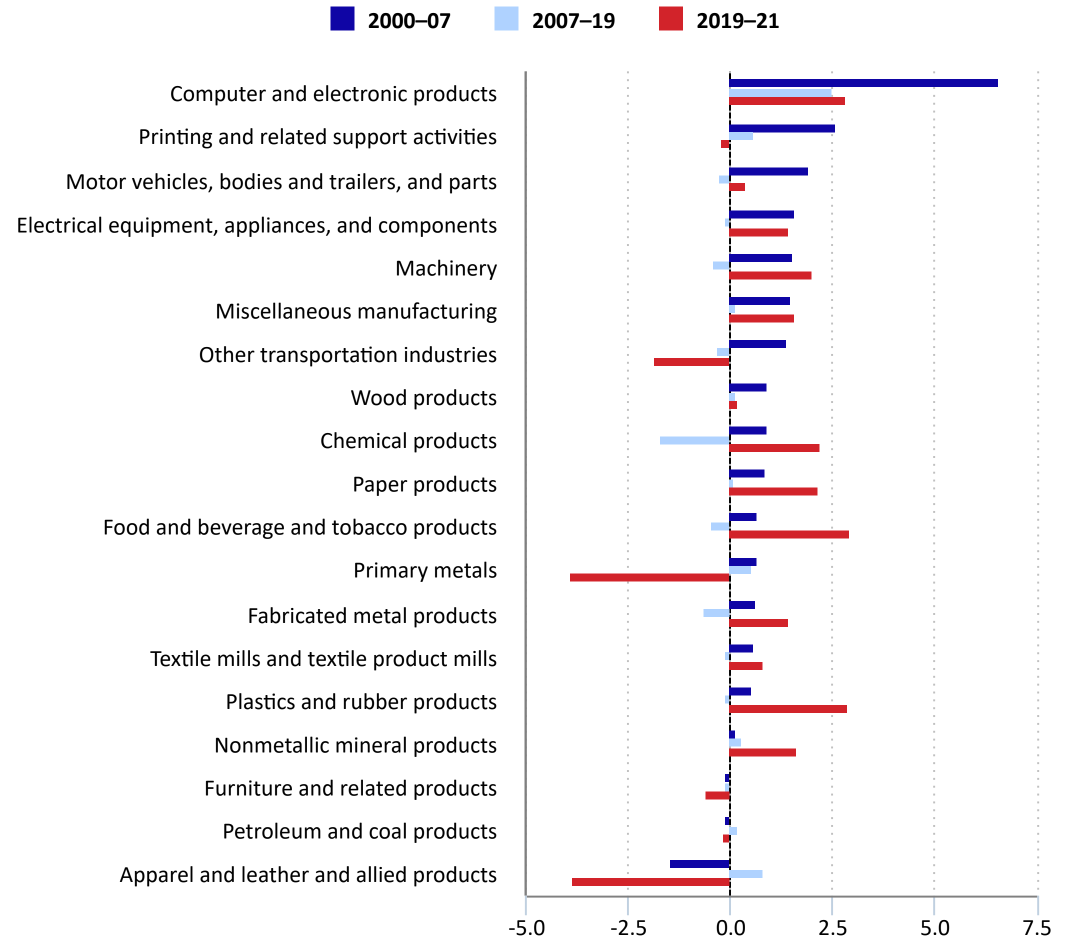
NAICS codes by period	NAICS industry	TFP	Output	Combined inputs	Capital input	Labor input	Intermediate inputs
2000–07							
334	Computer and electronic products	6.59	2.59	–3.75	2.62	–4.01	–5.27
325	Chemical products	0.89	2.99	2.08	3.84	–0.97	2.07
311, 312	Food and beverage and tobacco products	0.69	0.71	0.02	0.85	0.08	–0.18
331	Primary metal products	0.66	–0.30	–0.95	–1.38	–4.38	0.45
315, 316	Apparel and leather and allied products	–1.42	–14.18	–12.94	–2.12	–7.48	–17.64
2007–19							
334	Computer and electronic products	2.48	–0.48	–2.89	1.17	–0.99	–12.15
325	Chemical products	–1.69	–1.51	0.18	3.28	0.38	–1.89
311, 312	Food and beverage and tobacco products	–0.45	0.21	0.67	1.53	1.55	0.30
331	Primary metal products	0.54	–1.19	–1.72	0.37	–0.80	–2.42
315, 316	Apparel and leather and allied products	0.84	–4.67	–5.46	–1.71	–4.32	–7.75
2019–21[1]							
334	Computer and electronic products	2.84	1.87	–0.94	0.81	–1.19	–10.82
325	Chemical products	2.22	1.44	–0.76	3.30	1.19	–5.56
311, 312	Food and beverage and tobacco products	2.92	0.80	–2.06	1.13	1.76	–3.83
331	Primary metal products	–3.90	–8.28	–4.56	0.05	–5.79	–5.35
315, 316	Apparel and leather and allied products	–3.84	–1.88	2.03	–1.66	–4.92	13.40

[1] The 2019–21 period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

In the most recent business cycle, which began at the onset of the COVID-19 pandemic, manufacturing TFP grew at a positive rate of 1.32 percent per year, on average through 2021. From 2019 to 2021, annual industry TFP growth has ranged from 2.92 percent in food and beverage to a negative 3.90 percent in primary metals. Output in the food industry had a small positive increase in growth of 0.80 and a larger decrease of 2.06 in growth of combined inputs in this period. Although both capital and labor inputs increased at 1.13 and 1.76 rates, respectively, intermediate inputs declined at a 3.83-percent rate. The decrease in TFP growth in primary metals reflects large declines in both output and combined inputs. Output declined at an 8.28-percent rate while combined inputs fell at a rate of 4.56. Only capital input increased slightly, at 0.05 percent, during this period, whereas labor input and intermediate inputs both declined sharply, at 5.79 percent and 5.35 percent, respectively.

Chart 3 illustrates the variation in TFP growth in manufacturing industries over the 2000–07, 2007–19, and 2019–21 business cycles, arranged from fastest to slowest industry TFP growth in the 2000–07 period. As just noted, the computer, printing, and motor vehicles industries exhibited the largest TFP growth in the 2000–07 period. From 2007 to 2019, TFP growth was highest in the computer, apparel, and printing industries. During the recent cycle, 2019–21, TFP growth was the strongest in the food, plastics and rubber products, computer, and chemical products industries.

Chart 3. TFP by manufacturing industry, annual percent change, selected business cycles



Click legend items to change data display. Hover over chart to view data.
Note: TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

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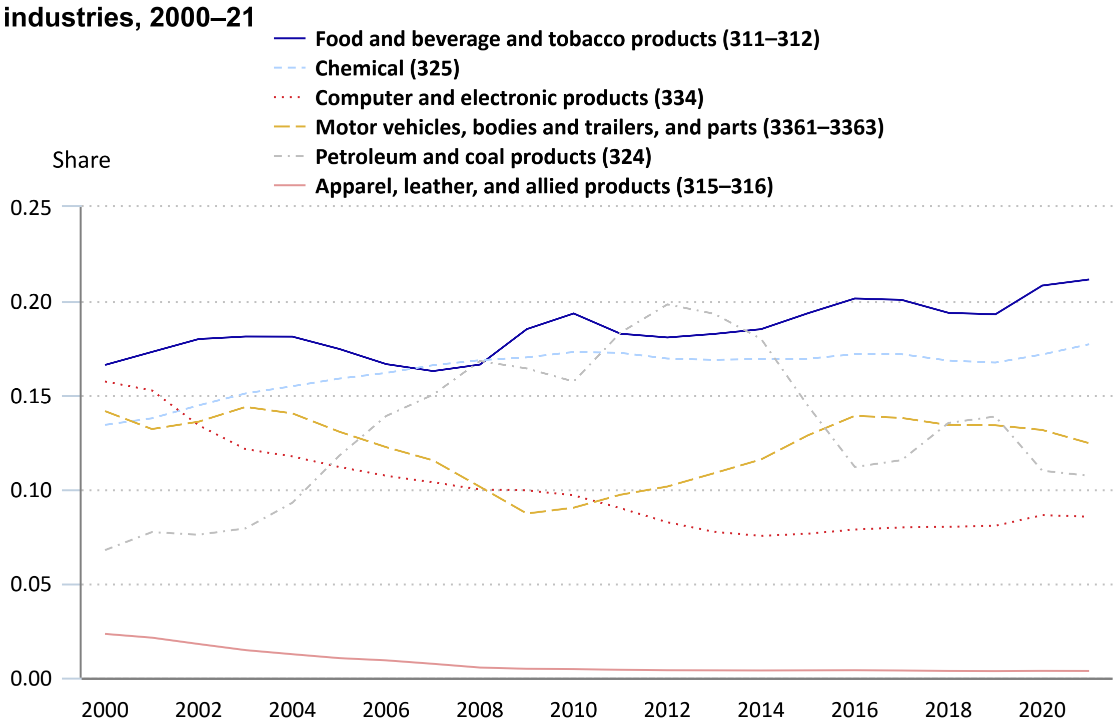
Changes in industry shares

In reviewing industry average shares in table 2, we notice that in 13 industries, the sectoral-output share of manufacturing sector output remained relatively stable over the three business cycles, varying by one or two hundredths of a percentage point or less. The output shares of the remaining six industries varied more widely over time, because the industries' relative importance to the manufacturing sector has increased or diminished. These six industries include the computer, petroleum, chemical, food, motor vehicles, and apparel industries. Of these six industries, the computer industry and the petroleum industry have seen the largest changes in industry shares over the three business cycles.

The computer industry’s output share, at 0.13, placed it as the fourth-highest output share in the 2000–07 business cycle. This output share declined to 0.09 in the next business cycle, from 2007 to 2019, and has fallen to 0.08 in the most recent, still incomplete, 2019–21 business cycle. The computer industry's share of manufacturing output peaked in the late 1990s. From 2001 forward, the industry’s share of manufacturing output began to decline steadily, as shown in chart 4.

Chart 4. Industry shares of manufacturing sector output, selected manufacturing industries, 2000–21



Click legend items to change data display. Hover over chart to view data.
Note: National American Industry Classification System (NAICS) codes are shown in parentheses.
Source: U.S. Bureau of Labor Statistics.

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The petroleum industry’s share of manufacturing sector output jumped from 0.10 in the 2000–07 cycle to 0.16 during the 2007–19 cycle, when U.S. production of petroleum products increased because of the shale oil boom, and then declined to 0.12 in the more recent 2019–21 period.[9] Over the 2000–21 period, the petroleum and coal industry experienced the second-largest gain in industry share of 0.04. The fortunes of the petroleum and coal products industry stemming from the fracking revolution are readily apparent by observing the soaring shares of this industry from 2005 to 2019.

The chemical industry had the largest share gain among manufacturing industries, with a 0.04-percentage-point increase in share of manufacturing output over the 2000–21 period. The average industry share increased from 0.15 in the 2000–07 business cycle to 0.17 during the 2007–19 and 2019–21 business cycles. The annual share peaked in 2011 before declining marginally for several years and then increasing to 0.18 in 2021.

The food industry's share of manufacturing sector output increased 0.05 percentage point from 2000 to 2021. The industry's average share increased from 0.17 in the 2000–07 business cycle to 0.19 from 2007 to 2019 and 0.20 from 2019 to 2021. Shares in the food industry peaked in 2010 before declining through 2014 and increasing slightly thereafter.

Shares in the motor vehicles industry decreased overall by 0.02 over the 2000–21 period. The industry share declined from 2004 to 2009, illustrating a small but steady decrease in industry output relative to manufacturing sector output, beginning in 2004. This slow decline in output share was followed by a rapid drop in the share because of the severe duress that affected U.S. auto production following the Great Recession of 2007–09 and a strong recovery brought about by the subsequent automobile bailout in which funds from the "Troubled Assets Relief Program" or TARP were used.[10] During the Great Recession, the motor vehicle industry's share declined from 0.12 in 2007 to 0.09 in 2009, before recovering to a high of 0.14 in 2016. Industry share declined again during the 2019–21 pandemic business cycle, from 0.13 in 2019 to 0.12 in 2021.

Finally, the apparel industry has been declining for several decades, and this decline continued over the 2000–21 period. As seen in chart 4, the apparel industry's share of manufacturing sector output declined steadily over the 2000–21 period, losing nearly 0.02 percentage point as it declined from a share of 0.023 to less than 0.004. Thus, as chart 4 clearly shows, economic restructuring is important in the evolution of industries' contributions to manufacturing sector TFP growth.

Industry contributions over time

Industry contributions over the three business cycles were more varied and reflect changes in individual industry TFP growth rates and shifts in industry shares. The computer industry was the largest contributor to manufacturing sector growth during the 2000–07 and 2007–19 business cycles, with the highest TFP growth of any manufacturing industry. However, this industry's average share of sector output was only the fourth highest in 2000–07 and sixth highest in 2007–19. During the 2019–21 period, including the COVID-19 pandemic years, the food and chemical industries' contributions to manufacturing final demand exceeded those of the computer industry. These higher contributions were primarily because of large increases in TFP growth in both industries, compared with those of the previous cycle. Previously, the food and chemical industries ranked as the 3rd- and 5th-highest contributors to manufacturing TFP in the 2000–07 cycle and the 18th and 19th highest, respectively, during the 2007–19 cycle. With shares consistently among the top three industries since 2000, this variation in industry contribution by the food and chemical industries was driven by fluctuation in these industries' TFP growth across business cycles.

Table 4 highlights the top five contributing industries for each of the three business cycles. As just noted, the computer and electronic products industry was by far the largest contributor to manufacturing sector TFP growth in the 2000–07 cycle. Its contribution was nearly 3 times as large as the second-highest contributing industry during this period, motor vehicles. Although TFP growth in the computer industry fell by half in the 2007–19 period, this industry continued as the top contributor with a smaller yet still strong industry average share. The petroleum and coal products industry moved from the least contributing industry over the 2000–07 period to the second-highest contributor in the 2007–19 period. This higher contribution reflects an output share that jumped from 0.10 during 2000–07 to 0.16 in the 2007–19 cycle and TFP growth that correspondingly increased from a declining rate of 0.12 percent per year to 0.21 percent. The industry's increased output share and higher TFP growth mirror the historic increase in U.S. oil and gas production from 2010 to 2020, as a result of the "shale boom" and increased fracking.[11]The dynamics of the 2019–21 postpandemic recovery period led to a redistribution of the top contributing industries. In this period, the food and beverage and tobacco products industry became the top contributor, with the strongest industry share of 0.20 and the highest industry TFP growth of 2.92 percent. The chemical products industry moved to the second-highest contributing industry position, with its typically high industry share and rapid TFP growth of 2.22 percent. The computer industry, although still a large contributor to sector-level TFP during the 2019–21 period, fell to the third highest. The plastics and rubber products industry moved to the fifth-highest contributing industry, reflecting its position as the industry with the second-fastest TFP growth in this period.

Table 4. Top five contributors to manufacturing sector TFP growth and related contribution components in selected business cycles

NAICS codes by period	NAICS industry	Industry contribution to manufacturing TFP growth (annual percent change)	Industry share (average)	Industry TFP (annual percent change)
2000–07				
334	Computer and electronic products	0.738	0.13	6.59
3361–3363	Motor vehicles, bodies and trailers, and parts	0.253	0.13	1.92
325	Chemical products	0.144	0.15	0.89
333	Machinery	0.129	0.09	1.53
311, 312	Food and beverage and tobacco products	0.118	0.17	0.69
2007–19				
334	Computer and electronic products	0.217	0.09	2.48
324	Petroleum and coal products	0.053	0.16	0.21
331	Primary metals	0.029	0.05	0.54
323	Printing and related support activities	0.012	0.02	0.57
339	Miscellaneous manufacturing	0.008	0.04	0.13
2019–21[1]				
311, 312	Food and beverage and tobacco products	0.607	0.20	2.92
325	Chemical products	0.384	0.17	2.22
334	Computer and electronic products	0.240	0.08	2.84
333	Machinery	0.171	0.09	2.00
326	Plastics and rubber products	0.166	0.06	2.88

[1] The 2019–21 period is an incomplete business cycle.
Note: NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics.

Different output concepts and industry contributions

The choice of output measure has implications for the measurement and interpretation of productivity.[12] Here, we compare industry contributions constructed using three alternative manufacturing sector TFP measures. These alternative TFP measures are developed by using experimental value-added-, sectoral-, and gross-output measures from our research production account for the manufacturing sector and industries.[13] Recall that the BLS TFP data for manufacturing rely on a sectoral-output definition. We analyze differences among industry contributions on the basis of alternative output concepts and discuss the underlying causes of differences in these measures.

The three most common output concepts used are value-added output, sectoral output, and gross output. The differences among these output concepts are a result of which intermediate inputs, if any, are included in the output measure. Value-added output is a narrowly defined concept of output including only primary inputs of capital and labor and reflects only the additional value of transforming intermediate inputs into outputs. Gross output, on the other hand, is the broadest measure of output and includes capital, labor, and all intermediate inputs (energy, materials, and services). Gross output represents the total value of goods and services produced by all firms in an industry or sector, regardless of whether they are sold directly to consumers or sold to other firms to become an input for further production. As a result, an output is counted when it is sold and counted again in the value of the product it is used to produce. Sectoral output lies between the extremes of value-added output and gross output, by including capital, labor, and intermediate inputs purchased from outside the industry or sector being measured. Sectoral output is greater than value-added output by including the value of intermediate inputs produced outside the industry but is less than gross output by excluding the value of intermediate inputs produced within the industry, intrasectoral transactions.

In the TFP growth accounting model, assuming constant returns to scale ensures that measured nominal output is equal to the sum of the costs of all inputs included in the output concept being measured. Nominal output under all three output concepts (where VA = value-added output, SO = sectoral output, and GO = gross output) will include the costs of capital and labor inputs. However, the nominal value of sectoral and gross output will also include part or all of the costs of intermediate inputs of energy, materials, and services. Because of this commonality, TFP measures constructed with the use of these three different output concepts are mathematically interrelated.[14] These relationships are

$$TFP_{SO} \text{ growth} = \left(\frac{\text{Value-Added Output}}{\text{Sectoral Output}}\right) \times TFP_{VA} \text{ growth}, \qquad \textbf{(2)}$$

$$TFP_{GO} \text{ growth} = \left(\frac{\text{Value-Added Output}}{\text{Gross Output}}\right) \times TFP_{VA} \text{ growth, and} \qquad \textbf{(3)}$$

$$TFP_{GO} \text{ growth} = \left(\frac{\text{Sectoral Output}}{\text{Gross Output}}\right) \times TFP_{SO} \text{ growth.} \qquad \textbf{(4)}$$

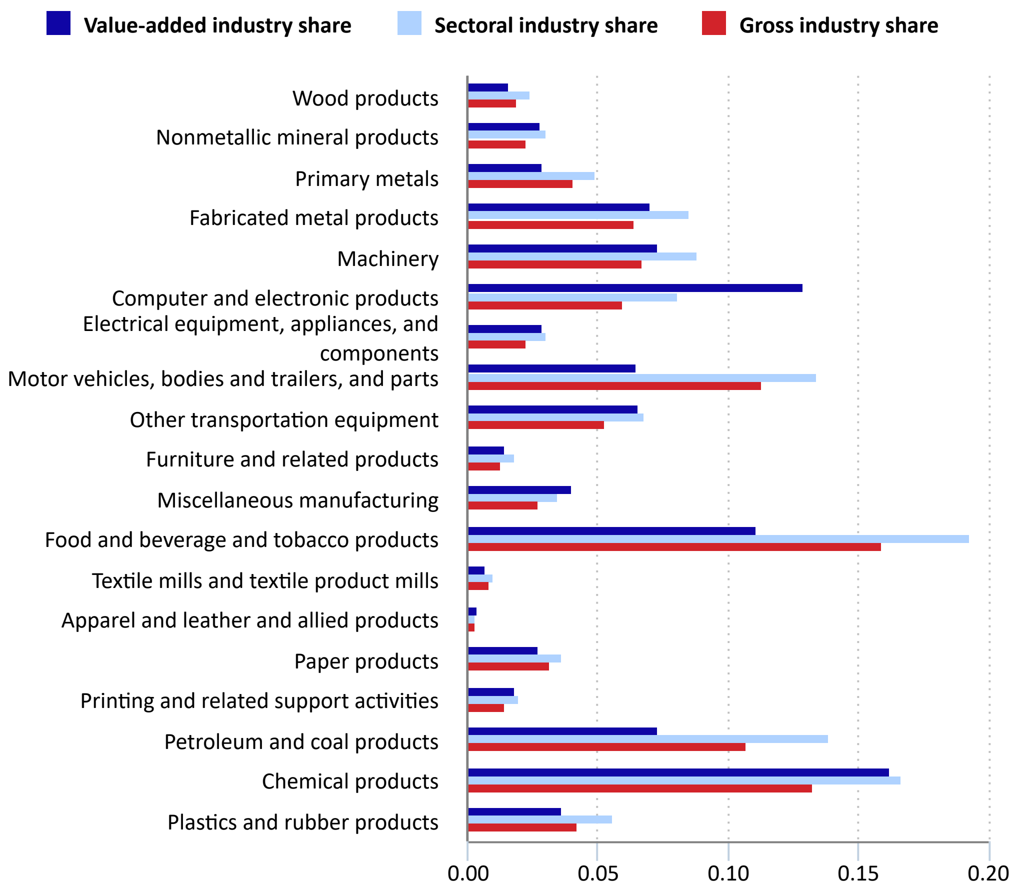
As equation (2) shows, measures of TFP growth in the sectoral model are proportionally smaller than measures of TFP growth in the value-added model, by the ratio of value-added output to sectoral output for that industry. Similarly, equation (3) reveals that gross-output TFP will have proportionally smaller growth than value-added TFP, by the ratio of nominal value-added output to nominal gross output. Gross-output TFP will also have proportionally smaller growth than sectoral-output TFP, by the ratio of sectoral output to gross output, as described in equation (4).[15]

To estimate how an industry *j* contributes to manufacturing sector (MN) TFP, we construct weights for each industry as the industry's current-dollar output share of the manufacturing sector on the basis of the concept being used. For example, when using the value-added framework to estimate industry contributions to manufacturing sector TFP, we construct industry weights as the industry's current-dollar value-added-output share of value-added output for the manufacturing sector, VA_j/VA_{MN}.[16] In the gross-output framework, weights for each industry are the industry's current-dollar gross-output share of manufacturing sector gross output, GO_j/GO_{MN}.[17] The gross-output model double counts the value of intermediate inputs produced and sold within an industry, both when sold to another producer for use in production and when sold to be consumed as a final product. For this reason, the gross-output model is seldom recommended for industry contribution analysis. In the value-added-output and gross-output models, industry weights will sum to 1.

Within the sectoral framework, weights for each industry are the industry's current-dollar sectoral-output shares of sectoral output for the manufacturing sector, SO_j/SO_{MN}. As just noted in our BLS published measures, the industry weights in the sectoral-output model will sum to a value greater than 1 because TFP growth in any one industry will augment productivity growth in other industries.[18]

Chart 5 compares industry shares by using the three different output concepts, for 2019. Note that because sectoral-output shares will sum to a value greater than 1, sectoral-output shares tend to be larger than the value-added and gross-output-based industry shares for most industries. This result is true throughout the 2000–21 period. In addition, because gross output for the manufacturing sector double counts the value of intermediate inputs and is quite large, gross-output industry shares are uniformly and substantially less than sectoral-output shares.[19] As evident in chart 5, sectoral-output shares in 2019 were higher than value-added shares for 16 of the 19 industries. For example, the sectoral-output share in food and beverage was much greater than the value-added-output share in 2019. This difference can be explained by noting that food and beverage had the highest share of sectoral intermediate inputs among all manufacturing industries, at 30 percent. However, it only had the third-highest share of capital costs, at 12 percent, and the second-highest share of labor costs, at 11 percent, among manufacturing industries in 2019.

Chart 5. Industry shares of manufacturing sector output, by output type, 2019



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

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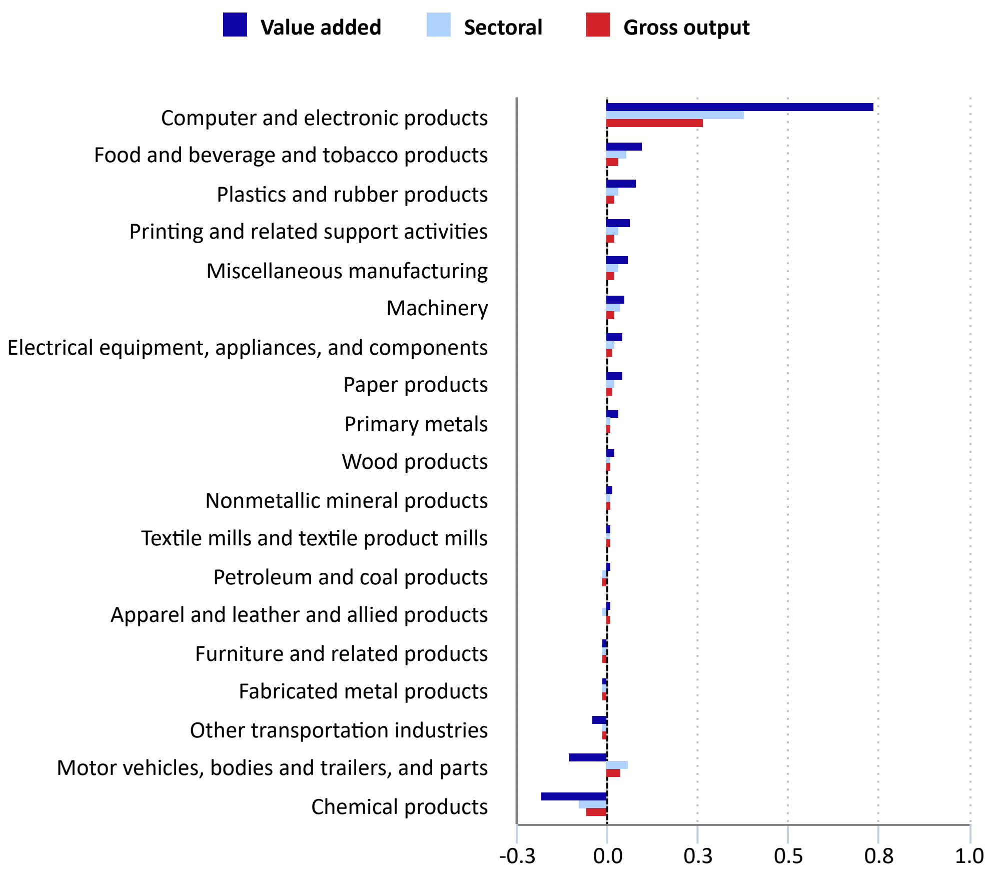
Chart 5 also shows, by comparison, the value-added share for the computer industry was larger than the sectoral-output share in 2019. In this year, the computer industry had the third-lowest share of sectoral intermediate inputs among manufacturing industries and the first- and second-highest shares of labor and capital costs, respectively, among manufacturing industries. Also note that in an industry, as the relative use of capital, labor, and sectoral intermediate inputs changes over time, the relationship between sectoral and value-added-output shares in the industry may vary. In the computer industry, for instance, sectoral shares over the 1988–2003 period initially exceeded value-added shares. Then, as a result of a continuous, dramatic decline in purchases of intermediate inputs from outside the sector, accompanied by more moderate variation in capital and labor costs, value-added shares over the 2004–21 period became larger than sectoral shares. Gross-output shares similarly may be larger or smaller than value-added-output shares, depending on the relative shares of primary and intermediate inputs among the manufacturing industries. For 2019, gross-output shares were larger than value-added-output shares in 8 industries and smaller in 11 industries.

Impact of output concepts, 2000–21

We estimate the contribution of individual industries to overall manufacturing sector TFP growth by using each of the output concepts: value-added output, sectoral output, and gross output. Chart 6 summarizes the relative contribution of each industry to manufacturing sector TFP growth for the 2000–21 period as measured by using each output concept. In this longer period, in general, the rankings of industry contributions were similar.

Chart 6. Contributions to manufacturing sector TFP growth, by manufacturing industry and output type, annual percent change, 2000–21



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

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However, for a few industries, the choice of output measure still had a large impact on the estimated contribution to manufacturing sector TFP growth. Table 5 compares manufacturing industry contributions, shares, and TFP across the three alternative output measures. Under the value-added-output framework, the motor vehicles, bodies and trailers, and parts industry was a drag on manufacturing sector TFP, with a negative industry contribution of 0.105 percentage point. Conversely, using either the sectoral or gross-output frameworks moved the motor vehicle industry from 18th- to 2nd-highest contributing industry, with positive contributions of 0.058 and 0.038 percentage point, respectively. Thus, the impact of including purchases of intermediate inputs on industry contribution measures was especially evident for the motor vehicle industry. This movement reflects both higher average industry share values and small but positive growth in TFP when intermediate inputs are included, to some degree, in the output measure. This industry was the second-largest user of intermediate inputs, the third largest user of within sector intermediate inputs, and the second-largest user of intermediate inputs outside the sector in 2021.

Table 5. Manufacturing industry TFP growth and related contribution components, 2000–21

NAICS codes	NAICS industry	Value-added output			Sectoral output			Gross output		
		Industry contribution (annual percent change)	Industry share (average)	Industry TFP (annual percent change)	Industry contribution (annual percent change)	Industry share (average)	Industry TFP annual percent change	Industry contribution (annual percent change)	Industry share (average)	Industry TFP (annual percent change)
31–33	Manufacturing sector	0.920	[1]	1.03	0.599	[1]	0.59	0.415	[1]	0.41
321	Wood products	0.024	0.02	1.33	0.011	0.02	0.44	0.007	0.02	0.37
327	Nonmetallic mineral products	0.015	0.03	0.63	0.009	0.03	0.36	0.006	0.02	0.31
331	Primary metals	0.035	0.03	1.24	0.009	0.05	0.21	0.007	0.04	0.18
332	Fabricated metal products	–0.012	0.07	–0.09	–0.001	0.08	0.01	–0.002	0.06	–0.02
333	Machinery	0.049	0.07	0.84	0.036	0.09	0.45	0.024	0.07	0.40
334	Computer and electronic products	0.740	0.13	6.20	0.383	0.10	3.74	0.269	0.08	3.41
335	Electrical equipment, appliances, and components	0.045	0.03	1.56	0.022	0.03	0.63	0.015	0.02	0.60
3361–3363	Motor vehicles, bodies and trailers, and parts	–0.105	0.07	–3.36	0.058	0.12	0.44	0.038	0.10	0.34
3364–3369	Other transportation equipment	–0.040	0.06	–0.54	–0.007	0.06	–0.09	–0.006	0.05	–0.09
337	Furniture and related products	–0.007	0.02	–0.43	–0.002	0.02	–0.11	–0.002	0.01	–0.12
339	Miscellaneous manufacturing	0.059	0.04	1.44	0.030	0.04	0.71	0.022	0.03	0.70
311, 312	Food and beverage and tobacco products	0.096	0.11	0.75	0.053	0.18	0.26	0.032	0.15	0.19
313, 314	Textile mills and textile product mills	0.007	0.01	0.55	0.003	0.01	0.16	0.003	0.01	0.17
315, 316	Apparel and leather and allied products	0.001	0.01	–1.83	–0.004	0.01	–0.79	0.000	0.01	–0.62
322	Paper products	0.043	0.03	1.49	0.021	0.04	0.54	0.015	0.03	0.44
323	Printing and related support activities	0.065	0.02	2.69	0.033	0.03	1.20	0.023	0.02	1.15
324	Petroleum and coal products	0.006	0.07	1.09	–0.011	0.13	0.06	–0.004	0.10	0.09
325	Chemical products	–0.181	0.16	–1.13	–0.074	0.16	–0.43	–0.053	0.13	–0.37
326	Plastics and rubber products	0.081	0.04	2.08	0.031	0.05	0.53	0.022	0.04	0.51

[1] This measure is not applicable to the manufacturing sector.
Note: NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

As illustrated in chart 6, under the value-added-output framework, food and beverage and tobacco products was the second most important contributing industry to TFP growth, with a contribution of 0.096 percentage point. When sectoral output was used to measure TFP, the industry fell to the third most important contributing industry and the industry contribution to overall manufacturing sector TFP declined to 0.053. This result reflects the inclusion of intermediate inputs that are purchased from outside the industry in the calculation. Under the gross-output model that adds intermediate inputs produced within and outside the food industry, the industry remained the third-highest contributing industry with a smaller positive contribution of 0.032 to manufacturing sector TFP growth.

Similarly, the plastics and rubber products industry was the third highest to contribute to the manufacturing sector TFP growth, contributing 0.081 percentage point, under the value-added model. When intermediate inputs are considered by using either sectoral or gross output to measure TFP, this industry's rank changed to seventh-highest contributing industry, with corresponding contributions of 0.031 and 0.022.

The degree to which industry contributions to manufacturing sector TFP growth vary by the choice of output concept is somewhat muted over an extended period such as 2000–21. This dampening of variation reflects the averaging of cyclical changes over a longer period. We next examine the effect of output choice on variation in TFP growth, industry shares, and industry contributions across business cycles.

Impact of output concepts across business cycles

Table 6 presents TFP growth rates by output measure for the 2000–07, 2007–19, and 2019–21 business cycles. At the industry level, sectoral and gross TFP measures are similar because they differ only by the intermediate inputs produced and consumed within the industry. However, when TFP is measured using the value-added model, only capital and labor are included in the model. Because all intermediate inputs are removed from the value-added model, value-added TFP may differ widely from sectoral and gross TFP. For the manufacturing sector, TFP grew in all three models during the 2000–07 and 2019–21 business cycles and declined during the 2007–09 business cycle. However, this pattern is not present for all industries. For example, the petroleum industry had slower or negative TFP growth in the 2000–07 and 2019–21 business cycles than in the 2007–19 period.

Table 6. Total factor productivity growth by output measure, selected business cycles, annual percent change

NAICS codes	NAICS industry	Value-added output			Sectoral output			Gross output		
		2000–07	2007–19	2019–21	2000–07	2007–19	2019–21	2000–07	2007–19	2019–21
31–33	Manufacturing sector	3.43	–0.84	4.10	1.75	–0.27	1.70	1.21	–0.20	1.30
321	Wood products	2.51	–0.10	5.93	0.89	0.07	1.11	0.74	0.05	1.00
327	Nonmetallic mineral products	0.04	0.44	3.87	0.13	0.25	1.83	0.08	0.22	1.67
331	Primary metals	1.33	1.83	–2.53	0.63	0.53	–3.06	0.49	0.45	–2.48
332	Fabricated metal products	1.44	–1.79	5.04	0.66	–0.67	1.80	0.57	–0.62	1.59
333	Machinery	3.78	–1.21	3.11	1.60	–0.44	1.82	1.42	–0.39	1.57
334	Computer and electronic products	12.14	3.49	2.46	6.50	2.41	2.30	5.81	2.24	2.16
335	Electrical equipment, appliances, and components	4.46	–0.27	2.67	1.71	–0.12	1.40	1.64	–0.10	1.20
3361–3363	Motor vehicles, bodies and trailers, and parts	5.91	–7.88	–6.52	1.92	–0.34	–0.03	1.54	–0.29	–0.06
3364–3369	Other transportation equipment	2.36	–1.44	–5.05	1.31	–0.50	–2.48	1.17	–0.47	–2.19
337	Furniture and related products	–0.03	–0.06	–3.92	–0.10	0.03	–1.00	0.01	–0.04	–1.09
339	Miscellaneous manufacturing	3.37	0.44	0.82	1.59	0.13	1.12	1.46	0.24	0.79
311, 312	Food and beverage and tobacco products	2.49	–2.08	12.58	0.71	–0.48	3.23	0.60	–0.45	2.71
313, 314	Textile mills and textile product mills	2.16	–0.35	0.34	0.56	–0.14	0.62	0.61	–0.14	0.48
315, 316	Apparel and leather and allied products	3.03	–0.71	–22.54	–1.24	0.68	–7.71	0.44	0.06	–8.06
322	Paper products	2.25	0.13	7.21	0.87	0.04	2.38	0.72	0.04	1.87
323	Printing and related support activities	6.09	1.06	0.84	2.66	0.53	0.10	2.57	0.52	0.05
324	Petroleum and coal products	0.64	1.38	0.94	–0.08	0.18	–0.12	0.00	0.19	–0.15
325	Chemical products	1.92	–4.43	9.02	0.87	–1.85	3.64	0.76	–1.62	3.30
326	Plastics and rubber products	2.12	–0.49	18.76	0.61	–0.06	3.88	0.63	–0.07	3.58

Note: The 2019–21 period is an incomplete business cycle. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Industry shares of aggregate sector output under the value-added-, sectoral-, and gross-output measurement frameworks, respectively, are presented in table 7 for the three business cycle periods.[20] Industry shares change over time as the value of the industry's output relative to the sector increases or decreases. For example, the computer industry's sectoral and gross-output shares of manufacturing sector output averaged 0.13 and 0.10, respectively, in the 2000–07 business cycle, before declining rapidly, arriving at values of 0.08 and 0.06 in the 2019–21 business cycle. With the use of the value-added model, the share of the computer industry was relatively stable over time. Similarly, the petroleum industry's output shares had greater volatility across business cycles when the sectoral and gross-output models were used as compared with the value-added model.

Table 7. Industry shares by output measure, selected business cycles, share averages for selected periods

NAICS codes	NAICS industry	Value-added output			Sectoral output			Gross output		
		2000–07	2007–19	2019–21	2000–07	2007–19	2019–21	2000–07	2007–19	2019–21
321	Wood products	0.02	0.01	0.02	0.03	0.02	0.03	0.02	0.02	0.02
327	Nonmetallic mineral products	0.03	0.03	0.03	0.03	0.03	0.03	0.02	0.02	0.02
331	Primary metals	0.03	0.03	0.03	0.05	0.05	0.05	0.04	0.04	0.04
332	Fabricated metal products	0.07	0.07	0.07	0.08	0.08	0.09	0.06	0.06	0.06
333	Machinery	0.07	0.07	0.07	0.09	0.09	0.09	0.07	0.07	0.07
334	Computer and electronic products	0.12	0.13	0.13	0.13	0.09	0.08	0.10	0.07	0.06
335	Electrical equipment, appliances, and components	0.03	0.03	0.03	0.04	0.03	0.03	0.03	0.02	0.02
3361–3363	Motor vehicles, bodies and trailers, and parts	0.08	0.06	0.06	0.13	0.11	0.13	0.11	0.10	0.11
3364–3369	Other transportation equipment	0.05	0.07	0.06	0.06	0.07	0.06	0.04	0.05	0.05
337	Furniture and related products	0.02	0.01	0.01	0.03	0.02	0.02	0.02	0.01	0.01
339	Miscellaneous manufacturing	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03	0.03
311, 312	Food and beverage and tobacco products	0.10	0.11	0.12	0.17	0.19	0.20	0.14	0.15	0.17
313, 314	Textile mills and textile product mills	0.01	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
315, 316	Apparel and leather and allied products	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
322	Paper products	0.04	0.03	0.03	0.04	0.04	0.04	0.04	0.03	0.03
323	Printing and related support activities	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.01
324	Petroleum and coal products	0.06	0.07	0.05	0.10	0.16	0.12	0.07	0.12	0.09
325	Chemical products	0.14	0.16	0.17	0.15	0.17	0.17	0.12	0.14	0.14
326	Plastics and rubber products	0.04	0.04	0.04	0.06	0.05	0.06	0.04	0.04	0.04

Note: The 2019–21 period is an incomplete business cycle. NAICS = North American Industry Classification System.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

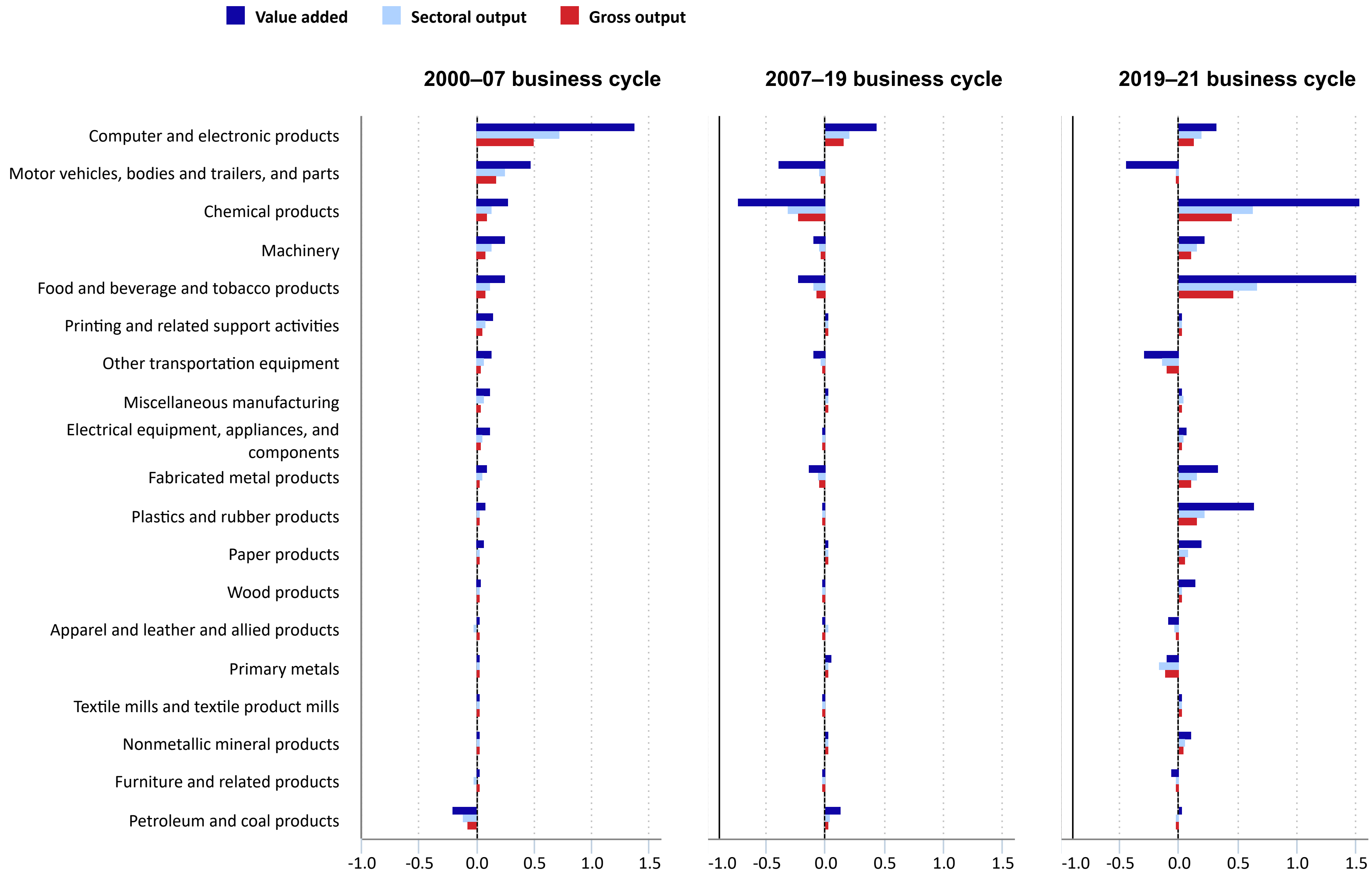
Table 8 and chart 7 compare industry contributions with manufacturing sector TFP across business cycles by using the three output concepts. The data in chart 7 are ranked by using the 2000–07 contribution values from the value-added model.

Table 8. Industry contributions to manufacturing sector TFP growth by output measure, selected business cycles, annual percent change

NAICS codes	NAICS industry	Value-added output			Sectoral output			Gross output		
		2000–07	2007–19	2019–21	2000–07	2007–19	2019–21	2000–07	2007–19	2019–21
321	Wood products	0.044	–0.008	0.146	0.024	–0.001	0.037	0.016	–0.001	0.027
327	Nonmetallic mineral products	0.001	0.007	0.112	0.004	0.004	0.057	0.001	0.003	0.040
331	Primary metals	0.033	0.059	–0.099	0.026	0.028	–0.162	0.016	0.020	–0.110
332	Fabricated metal products	0.098	–0.135	0.341	0.052	–0.058	0.155	0.034	–0.040	0.103
333	Machinery	0.256	–0.100	0.221	0.135	–0.042	0.155	0.090	–0.028	0.103
334	Computer and electronic products	1.377	0.439	0.320	0.728	0.214	0.195	0.506	0.154	0.134
335	Electrical equipment, appliances, and components	0.128	–0.009	0.075	0.059	–0.004	0.045	0.041	–0.003	0.029
3361–3363	Motor vehicles, bodies and trailers, and parts	0.470	–0.384	–0.435	0.253	–0.042	–0.017	0.170	–0.029	–0.017
3364–3369	Other transportation equipment	0.131	–0.098	–0.292	0.074	–0.033	–0.138	0.050	–0.024	–0.095
337	Furniture and related products	0.000	–0.002	–0.059	–0.001	–0.001	–0.019	0.001	–0.001	–0.015
339	Miscellaneous manufacturing	0.129	0.023	0.030	0.065	0.009	0.040	0.044	0.010	0.022
311, 312	Food and beverage and tobacco products	0.253	–0.227	1.505	0.122	–0.090	0.670	0.081	–0.070	0.471
313, 314	Textile mills and textile product mills	0.025	–0.003	0.002	0.010	–0.001	0.006	0.009	–0.001	0.004
315, 316	Apparel and leather and allied products	0.038	–0.007	–0.082	–0.008	0.002	–0.028	0.007	–0.001	–0.023
322	Paper products	0.070	0.002	0.193	0.036	0.001	0.087	0.025	0.001	0.061
323	Printing and related support activities	0.156	0.021	0.011	0.079	0.011	0.001	0.054	0.008	0.000
324	Petroleum and coal products	–0.207	0.130	0.006	–0.108	0.047	–0.016	–0.074	0.038	–0.014
325	Chemical products	0.282	–0.733	1.539	0.142	–0.316	0.627	0.101	–0.227	0.451
326	Plastics and rubber products	0.087	–0.017	0.648	0.036	–0.004	0.222	0.027	–0.003	0.155

Note: The 2019–21 period is an incomplete business cycle. NAICS = North American Industry Classification System, and TFP = total factor productivity.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

Chart 7. Contributions to manufacturing sector total factor productivity, by manufacturing industry and output type, annual percent change



Click legend items to change data display. Hover over chart to view data.
Note: The 2019–21 period is an incomplete business cycle.
Source: U.S. Bureau of Labor Statistics unpublished manufacturing production account.

View Chart Data

In the 2000–07 business cycle, the computer industry was the highest contributor to manufacturing sector TFP growth while the motor vehicles industry was the second-highest contributor in all three output models. The computer industry retained its position as the greatest contributor to manufacturing sector TFP growth in the next business cycle period, 2007–19. However, the contribution of the motor vehicle industry fell to among the lowest four contributing industries. In addition, the petroleum and coal industry rose from the least contributing industry in the 2000–07 cycle to the second-highest contributor, in all three models, during the 2007–19 period. Industry TFP growth in all output models was typically slower in the 2007–19 cycle that included the Great Recession (2007–09) than in the 2000–07 period. Numerous industries that previously contributed positively to manufacturing TFP growth instead had a negative or diminishing effect in this second business cycle period, including the chemical industry and the food industry. In the still incomplete 2019–21 business cycle, the choice of output model more greatly affected industry contribution than it did in the prior two cycles. Under the value-added-output model, the chemical products industry ranked as the greatest contributor to manufacturing sector TFP, with the food industry as the second-highest contributor. These two rankings, although quite close, were reversed under the sectoral- and gross-output models. In addition, during this period, the ranking of industry contributions by output measure exhibited much more variation among the top 12 industries.

The values of industry contributions to manufacturing sector TFP growth derived from the value-added model are markedly different from industry contributions derived from the sectoral and gross-output models in several industries. This pattern reflects the variation in TFP growth for each output model, across industries, and the differences in industry shares among the value-added-, sectoral-, and gross-output models.

Summary

To understand the performance of the U.S. manufacturing sector, we must look beyond sector-level data and explore the performance of individual industries. Using BLS published data, we have shown that any one industry's influence on sector-level performance is a function of both its size in the sector and its TFP growth. Both the industry share of output and industry TFP growth will vary during different periods, reflecting the underlying dynamics of production in any given industry. For example, over the entire period from 2000 to 2021, the computer and electronic products industry contributed over half of the growth in manufacturing sector TFP. However, in the recent 2019–21 period, the food, beverage, and tobacco products industry contributed the most.

By tracing the contribution of industries to manufacturing sector TFP over three different business cycles, we clearly show the rise and fall of industries' importance to overall manufacturing sector performance and their link to technological innovations, changing economic needs, and global economic patterns. The dramatic increase in U.S. oil and natural gas production because of the development of revolutionary hydraulic fracturing and horizontal drilling techniques increased the average industry share of manufacturing output produced by the petroleum industry by 60 percent, from 0.10 in 2000–07 to 0.16 in the 2007–19 period. This rise in industry share, combined with increased, positive TFP growth of 0.21 percent per year in the 2007–19 period, resulted in a petroleum industry contribution of 0.053 percentage point to manufacturing sector TFP growth. This industry's positive contribution compares with its earlier impact as a drag on manufacturing sector TFP growth, with an industry contribution of negative 0.111 percentage point in the 2000–07 period.

Similarly, innovations in the chemical and food industries resulted in large increases in TFP growth in the recent 2019–21 period compared with the 2007–19 period, repositioning these industries as the top two contributing industries to manufacturing sector TFP growth in 2019–21 versus the two lowest industries with negative contributions to overall sector TFP in the 2007–19 period. This dramatic shift in the ranking of these two industries occurred despite a slight increase in the food industry's average share (0.19 to 0.20) and a larger decrease in the petroleum industry's average share (0.16 to 0.12) from the 2007–19 period to the most recent period.

By using three different output concepts (value-added output, sectoral output, and gross output), our comparison of industry contributions to manufacturing sector TFP growth shows that the choice of output measure directly affects productivity analysis both through implicit differences in the resulting empirical measures of TFP and through the estimation of industry contribution to TFP growth in any given sector.

First, the choice of output measure affects the measurement of TFP growth. Second, it affects the estimate of an industry's contribution to aggregate TFP growth via both the output-based share weighting scheme, which varies depending on the output concept selected, and the measure of TFP growth. A TFP measure based on value-added output reflects only the effect of primary inputs—capital and labor—on the production of output. TFP measures based on sectoral output reflect the effect of intermediate inputs purchased *outside an industry* on the production of output, while TFP measures based on gross output reflect the effect of intermediate inputs purchased *both outside and within an industry* on output production. Each of the respective TFP measures—value-added output, sectoral output, and gross output—can be interpreted differently because of the inherent constraints embedded in the related growth accounting model. In addition, the selection of the output concept will affect the value of the industry's share of sector output. Even over a longer term such as 2000–21, the choice of output model had a notable effect. The motor vehicles industry moved from the second-lowest negative contributor to manufacturing TFP growth under a value-added model to the second-highest contributing industry under either a sectoral or gross-output model. The use of alternative output measures across shorter business cycle periods revealed more pronounced variability in industry ranking by contribution to sector TFPs.

By expanding on the differences among the three output measures and how these differences affect the related TFP growth rates, industry share weights, and industry contribution measures, we show that careful deliberation is warranted before selecting a value-added-, sectoral-, or gross-output framework for TFP and contribution analysis. Using a sectoral output framework not only avoids the double-counting issues that render the gross-output framework difficult to interpret and of little analytical value but also reflects the effect on productivity of capital, labor, and intermediate inputs purchased outside a given industry. Although using the value-added-output framework also avoids the double counting inherent in the gross-output model, the value-added output captures only the increase in TFP resulting from the use of capital and labor inputs in production. Industry shares in the value-added framework reflect only differences in the use of capital and labor inputs by industry, whereas sectoral shares reflect changes in the relative use of capital, labor, and intermediate inputs. For these several reasons, BLS selected the sectoral-output framework as the most informative and least compromised output framework in analyzing productivity of the manufacturing sector and industries.

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Notes

1 *Total Factor Productivity for Major Industries—2021*, USDL-22-2181 (U.S. Bureau of Labor Statistics, November 18, 2022, updated annually), https://www.bls.gov/news.release/prod5.nr0.htm.

2 The most recent business cycle period we consider, 2019–21, is not complete but began in 2019 with the recession that resulted from the onset of the COVID-19 pandemic.

3 See Lucy P. Eldridge and Susan G. Powers, "The importance of output choice: implications for productivity measurement," *Monthly Labor Review*, September 2023, https://doi.org/10.21916/mlr.2023.22.

4 Total factor productivity (TFP) is measured with the use of discrete estimates of growth rates—that is, growth rates derived from yearly data on output and inputs. As a result, measured TFP growth is a discrete approximation to true growth. For further description of this issue, see Robert M. Solow, "Technical change and the aggregate production function," *The Review of Economics and Statistics*, vol. 39, no. 3, August 1957, pp. 312–320. The U.S. Bureau of Labor Statistics (BLS) estimates the annual rate of growth of TFP as the percent change from the prior year.

5 Solow, "Technical change and the aggregate production function." Note that Solow's growth model assumes Hicks-neutral technical change and constant returns to scale.

6 BLS prioritizes the use of output measures that most accurately reflect movements in output for each specific industry. Manufacturing industry output measures are derived with the use of various data sources, including the U.S. Census Bureau Annual Survey of Manufactures, the Energy Information Administration, and industry trade associations. Data of intermediate inputs are obtained from the U.S. Bureau of Economic Analysis. The weights for the BLS manufacturing industry contributions relate industry sectoral output to sectoral output for the aggregate manufacturing sector. Each industry's relative contribution to aggregate manufacturing sectoral output reflects the industry's sectoral TFP growth weighted by the ratio of the industry-specific sectoral output to manufacturing sectoral output, in a given year.

7 For further discussion, see Evsey D. Domar, "On the measurement of technological change," *The Economic Journal*, vol. 71, no. 284, December 1961, pp. 709–729; and Charles R. Hulten, "Growth accounting with intermediate inputs," *The Review of Economic Studies*, vol. 45, no. 3, October 1978, pp. 511–518.

8 To preserve the additive quality of the growth rates, we calculated industry contributions to TFP growth by using the difference in natural logs of industry TFP in adjacent years.

9 Charles F. Mason, Lucija A. Muehlenbachs, and Sheila M. Olmstead, "The economics of shale gas development," Discussion Paper RFF DP 14-42-REV (Washington, DC: Resources for the Future, November 2014, revised February 2015), https://media.rff.org/documents/RFF-DP-14-42.pdf; and Robert Rapier, "How the shale boom turned the world upside down," *Forbes*, April 21, 2017, https://www.forbes.com/sites/rrapier/2017/04/21/how-the-shale-boom-turned-the-world-upside-down/?sh=5ae9810977d2.

10 Thomas H. Klier and James Rubenstein, "Detroit back from the brink? Auto industry crisis and restructuring, 2008–11," *Economic Perspectives*, vol. 36, no. 2 (Federal Reserve Bank of Chicago, 2012), pp. 35–54, https://www.chicagofed.org/publications/economic-perspectives/2012/2q-klier-rubenstein#:~:text=Detroit%20Back%20from%20the%20Brink%3F%20Auto%20Industry%20Crisis,has%20substantially%20changed%20the%20industry%20in%20the%20U.S.

11 Mason et al., "The economics of shale gas development"; and Rapier, "How the shale boom turned the world upside down."

12 For more information, see Eldridge and Powers, "The importance of output choice."

13 See TFP comparisons in Eldridge and Powers, "The importance of output choice."

14 For a discussion of the relationships among TFP measures constructed by using measures of value-added-, sectoral, and gross output, see Eldridge and Powers, "The importance of output choice."

15 See endnote 5 for more details on data sources for industry measures. As a result of these differences in data sources for outputs and inputs, the experimental measures of TFP growth constructed by using the value-added-, sectoral-, and gross-output concepts violate these relationships in a few instances.

16 The weights used in the value-added model relate industry value-added output to aggregate manufacturing sector value-added output. In this model, the weights are similar to Domar weights, as described by Domar in "On the measurement of technological change." This theoretical framework showed that the effective productivity growth rate for industries may be measured by weighting the multifactor productivity growth rates for each industry by the value of that specific industry's share of final output, measured as value-added output. A particularly

useful summary of the Domar method by provided William Gullickson is available in “Multifactor productivity in manufacturing industries,” *Monthly Labor Review*, October 1992, pp. 31–32, https://www.bls.gov/opub/mlr/1992/10/art4full.pdf.

17 The industry weights in the sectoral- and gross-output models relate industry sectoral (gross) output to sectoral (gross) output for the manufacturing sector. Although these shares differ from the standard Domar weights that relate industry sectoral (gross) output to aggregate value-added output, they are useful for comparing industry contribution results across output models. These share definitions were adopted to accommodate the BLS unpublished manufacturing database, which incorporates data from multiple datasets.

18 William Gullickson and Michael J. Harper, “Possible measurement bias in aggregate productivity growth,” *Monthly Labor Review*, February 1999, p. 50, https://www.bls.gov/opub/mlr/1999/02/art4full.pdf.

19 Value-added, sectoral, and gross industry shares are presented in Lucy P. Eldridge and Susan G. Powers, “Productivity measurement: does output choice matter?,” Working Paper 603, appendix tables A-7, A-8, and A-9 (U.S. Bureau of Labor Statistics, July 21, 2023).

20 To preserve the additive quality of the growth rates, one should calculate industry contributions to TFP growth by using the difference in natural logs of industry TFP in adjacent years.

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