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APRIL 2021

To work from home or not to work from home? That is the question

Maya B. Brandon

The coronavirus disease 2019 (COVID-19) era has ushered in a new look and feel for the workplace. With the fear of infection, of self or loved ones, many people are breathing a sigh of relief with the expansion of permissions to work from home, whereas others are holding their breath in the aftermath of widespread lockdowns and economic uncertainty. In "Who should work from home during a pandemic? The wage-infection trade-off" (National Bureau of Economic Research, Working Paper 27908, October 2020), authors Sangmin Aum, Sang Yoon (Tim) Lee, and Yongseok Shin explore an optimal policy: "the economic costs of containing a pandemic can be minimized by only sending home those jobs that are highly exposed but easy to perform from home."

How we think about interacting with others, avoiding illness, and establishing a new normal are top subjects today. In many cases, people must weigh the risks of exposure and infection against the benefits of wages. We assume that with these widespread health disparities, the workplace is a breeding ground of infection and shutting it down will reduce infection. Actions to contain pandemic-level contagions often require the cooperation of people at multiple levels, but these actions come at a cost, especially to low-wage workers who are "bearing the brunt of the pandemic economically and in terms of infection risks." Businesses and workers have difficult choices to make, and these choices come with a laundry list of economic, social, and health tradeoffs.

Many workers are safely able to work from home during the pandemic, but many are not. Aum, Lee, and Shin have constructed two indexes—one of occupational exposure risk and another of time spent working from home. Their indexes use data from O*NET (the Occupational Information Network that is the primary source of occupational information for the United States), the American Time Use Survey, and the American Community Survey to find that jobs with workers who have less ability to work from home and higher exposure to infection are not tightly correlated. "Infection risks vary widely even among jobs with the same WFH [working from home]: for example, neither medical therapists nor experimental physicists can work from home, but the latter pose almost no risk of contagion." The authors argue that the ability to work from home is not the be-all and end-all for who should work from home, because the nature of the work and possibility of exposure should also be considered. Jobs have been classified as essential or nonessential. These classifications, however, are too broad because the scope of work and the exposure risk better indicate who should be allowed to work from home on the basis of need. The authors report that closing and locking down all businesses are more harmful economically at micro- and macrolevels than operating under the optimal policy of sending home workers who have jobs that are highly exposed but easy to perform from home.

In the face of widespread business closures, high levels of exposure to the COVID-19, and uncertainty of employment, low-wage workers have been greatly affected globally by the lockdowns. High-wage workers have been less affected by the lockdowns and continued to work with modifications and increased options to telework. Aum, Lee, and Shin's optimal policy provides a realistic view of the job world during the COVID-19 pandemic but uses a conceptual view of the real world. Their goal is to provide a blueprint for pandemic lockdowns that is simple, implementable, and optimal for workers, employers, and the overall economy.

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Measuring industry employment, 1990–2018: a look at the auxiliary-unit concept

The North American Industry Classification System (NAICS) replaced the Standard Industrial Classification (SIC) system in 1997. Since the change, some analysts have expressed concerns about the elimination in NAICS of the concept of auxiliary units, which are now classified with other worksites that perform similar functions. This article examines how employment trends by broad industry groups would have differed over the past few decades if the auxiliary-unit concept had been used to estimate employment in those units as it was in the SIC system.

In the United States, Canada, and Mexico, businesses (and hence business employment) are classified and reported in industries according to the North American Industry Classification System (NAICS).[1] NAICS was implemented in the United States in 1997, replacing its predecessor, the Standard Industrial Classification (SIC) system. A major criticism of this change, over time, has involved the treatment of auxiliary units. In the SIC system, an auxiliary unit was defined as a worksite that was part of a firm and provided management or support services for other worksites within the firm. At the U.S. Bureau of Labor Statistics (BLS), in practice, this meant that an auxiliary unit

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was a worksite reported with other worksites as part of a multiworksite unemployment insurance account. Typical examples of auxiliary units include headquarters and warehouses associated with a manufacturing plant. Under NAICS, the auxiliary-unit concept was eliminated, and these units are now classified with other worksites performing similar functions.[2]

In this article, I use data from the BLS Quarterly Census of Employment and Wages (QCEW) to look at how employment trends over the past few decades would differ if we were to approximate the auxiliary-unit concept. Would making this change lead to different trends in certain industries over that period?

Background

In 2018, there were about 10 million business establishments in the United States. Each of these establishments produces a good or provides a service. The product or service that a company produces or provides leads to its classification in a specific industry in which similar businesses are also classified. This grouping of businesses by industry allows for a consistent definition to be used across statistical agencies for the collection and publication of economic statistics. It also allows economists, academics, and businesses to compare features of similar and dissimilar businesses, and it allows federal, state, and local governments to develop policies targeted at businesses within specific industries.

Prior to 1997, businesses were classified into industries on the basis of the 1987 SIC system. A notable feature of the SIC system was the inclusion of special rules for coding "auxiliary" establishments, which the SIC manual defined as follows:

> Auxiliary establishments are distinguished from operating establishments that primarily produce goods and from those that primarily provide services for personal or household use or for other enterprises. Some examples of activities commonly performed by auxiliaries are management and other general administrative functions, such as accounting, data processing, and legal services; research, development, and testing; and warehousing.[3]

The 1987 SIC manual further clarified how auxiliary establishments were assigned industry codes: "Auxiliary establishments are assigned four-digit industry codes on the basis of the primary activity of the operating establishments they serve."[4] Since 1997, businesses have been classified into industry groups using NAICS. The NAICS 2017 manual includes the following explanation in its preface:

> The North American Industry Classification System is unique among industry classifications in that it is constructed within a single conceptual framework. Economic units that have similar production processes are classified in the same industry, and the lines drawn between industries demarcate, to the extent practicable, differences in production processes. This supply-based, or production-oriented, economic concept was adopted for NAICS because an industry classification system is a framework for collecting and publishing information on both inputs and outputs, for statistical uses that require that inputs and outputs be used together and be classified consistently.[5]

The NAICS 2017 manual also describes auxiliary establishments, as follows:

> Although all establishments have output, they may or may not have receipts. In large enterprises, it is not unusual for establishments to exist to solely serve other establishments of the same enterprise (auxiliary, or enterprise support, establishments). In such cases, these units often do not collect receipts from the establishments they serve. This type of support (captive) activity is found throughout the economy and involves goods-producing activities as well as services. Units that carry out support activities for the enterprise to which they belong are classified, to the extent feasible, according to the NAICS code related to their own activity. This means that warehouses providing storage facilities for their own enterprise are classified as warehouses.[6]

Businesses evolve; they grow, change, and decline. A company may start with only one or two workers, and over time it may grow to have thousands of employees, with worksites located in multiple states and industries. Some of the worksites in other industries may partially or fully support the main company activity. A company may change vendors for the inputs it needs to develop and sell its product or service, and over time it may decide to outsource

part of its product development or service delivery to other companies—sometimes even in other countries. This decision process also applies to worksites that would have been classified as auxiliary establishments under the SIC system.

With a few assumptions about the auxiliary relationship, we can explore how important this concept might be in measuring employment change, particularly by industry. This article focuses on exploring employment trends by various industry groups in order to identify how these trends would have differed if an auxiliary-unit concept was used in the estimation process. (See the box that follows for basic definitions of some of the relevant terms used in this article.)

Definitions

Industry. BLS and other federal statistical agencies classify industries according to the North American Industry Classification System (NAICS). NAICS is hierarchical, with broad industry groups comprising more and more detailed groups.

Worksite. BLS defines a worksite as a single physical location of work. A worksite is also frequently referred to as an *establishment*. If there is more than one economic activity at the site, the economic activity that generates the most revenue is typically used to determine its primary industry for classification under NAICS.

Unemployment insurance (UI) account. Virtually all employers in the United States are required to register with the appropriate agency in the state in which they are located in order to receive a UI account number. State agencies assign this number to employers to track their mandatory participation in state and federal UI programs. Employers can have multiple worksites within one UI account but are limited to only those within the same state. The employer can choose to have more than one UI account, but a single worksite can only have one UI account.

Employer identification number (EIN). The EIN is a unique nine-digit number issued by the Internal Revenue Service (IRS) to identify a business entity. An EIN can identify a single worksite, or it can identify a group of worksites within one state or across states. (See exhibit 1 for a basic relationship structure.) In this article, the EIN is also referred to as a *firm identifier*. A firm is an establishment or a combination of establishments that sells goods or services for a profit. Firms can operate in one industry or in multiple industries.*

Quarterly Census of Employment and Wages (QCEW). Data from the BLS QCEW are the product of a federal–state cooperative program. The data are derived from summaries of the employment and total pay of workers covered by state and federal UI legislation and are provided to BLS by state workforce agencies. In addition, employers who operate multiple establishments within a state complete a questionnaire called the "Multiple Worksite Report," which provides detailed information on employment, wages, and industry for each of their establishments.

QCEW data cover about 97 percent of business employment in the United States, and data are published by county, metropolitan area, state, and the nation for detailed industry groups. The QCEW also collects the UI account number and the federal EIN for each of these employers. Major exclusions from UI coverage include self-employed workers, most agricultural workers on small farms, all members of the Armed Forces, elected officials in most states, most student workers at schools, employees of certain small nonprofit organizations, and railroad workers covered by the railroad unemployment insurance system.
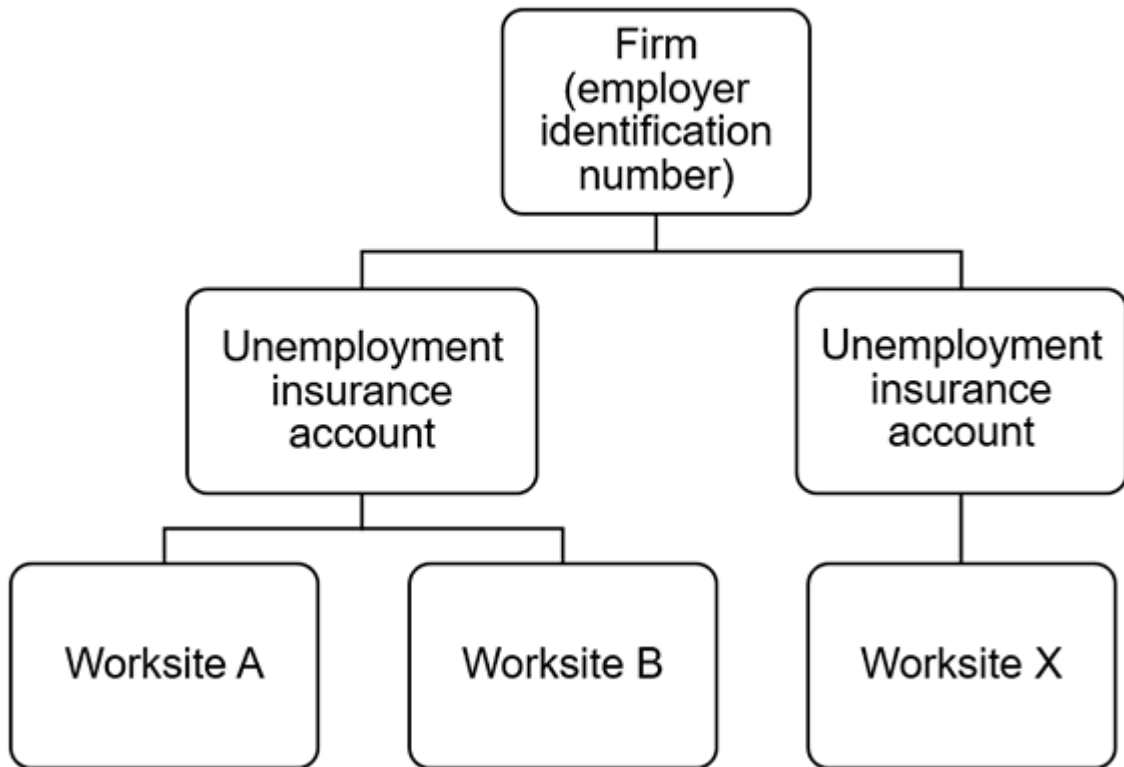
* For more on the "firm" concept, see Akbar Sadeghi, David M. Talan, and Richard L. Clayton, "Establishment, firm, or enterprise: does the unit of analysis matter?" *Monthly Labor Review*, November 2016, https://www.bls.gov/opub/mlr/2016/article/establishment-firm-or-enterprise.htm.

A methodology to account for auxiliary units

BLS no longer collects data in such a way as to identify auxiliary units. However, we can classify all worksites within an unemployment insurance (UI) account or a federal employer identification number (EIN) on the basis of the dominant industry of the account. Note that this approach serves as a proxy for the auxiliary-unit concept, but it will not capture exactly what a direct coding would.

The QCEW program collects data each quarter for all business worksites in the United States, including the number of employees and the total quarterly wages paid.[7] The QCEW also collects information on the worksite location, its UI account number, its federal EIN, and the industry in which it is classified (according to NAICS). With some straightforward assumptions, I assigned the dominant economic activity at the UI account level and at the firm level (i.e., for each group of establishments with the same EIN). The assumptions are that all activity at each worksite is associated with its assigned NAICS code and that the aggregate revenue of the UI account or firm is proportional to the employment at each worksite. With these assumptions, I identified the industry sector that has the most employment within a UI account or within a firm for the third month of each quarter and assigned that industry sector to the entire UI account or firm (for that quarter). (See exhibit 1 for a basic relationship diagram and exhibit 2 for an example.)

Exhibit 1. The basic relationship between a firm and its worksites

```
                        ┌─────────────────┐
                        │      Firm        │
                        │   (employer      │
                        │  identification  │
                        │     number)      │
                        └────────┬─────────┘
                 ┌───────────────┴──────────────┐
        ┌────────┴────────┐            ┌─────────┴───────┐
        │  Unemployment    │            │  Unemployment    │
        │   insurance      │            │   insurance      │
        │    account       │            │    account       │
        └────────┬────────┘            └─────────┬───────┘
        ┌────────┴────────┐                      │
┌───────┴──────┐ ┌────────┴──────┐      ┌────────┴───────┐
│  Worksite A   │ │  Worksite B    │      │  Worksite X    │
└──────────────┘ └───────────────┘      └────────────────┘
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Source: U.S. Bureau of Labor Statistics.

Exhibit 2. Example of auxiliary units in a retail trade firm classified according to the primary worksite activity

Source: U.S. Bureau of Labor Statistics.
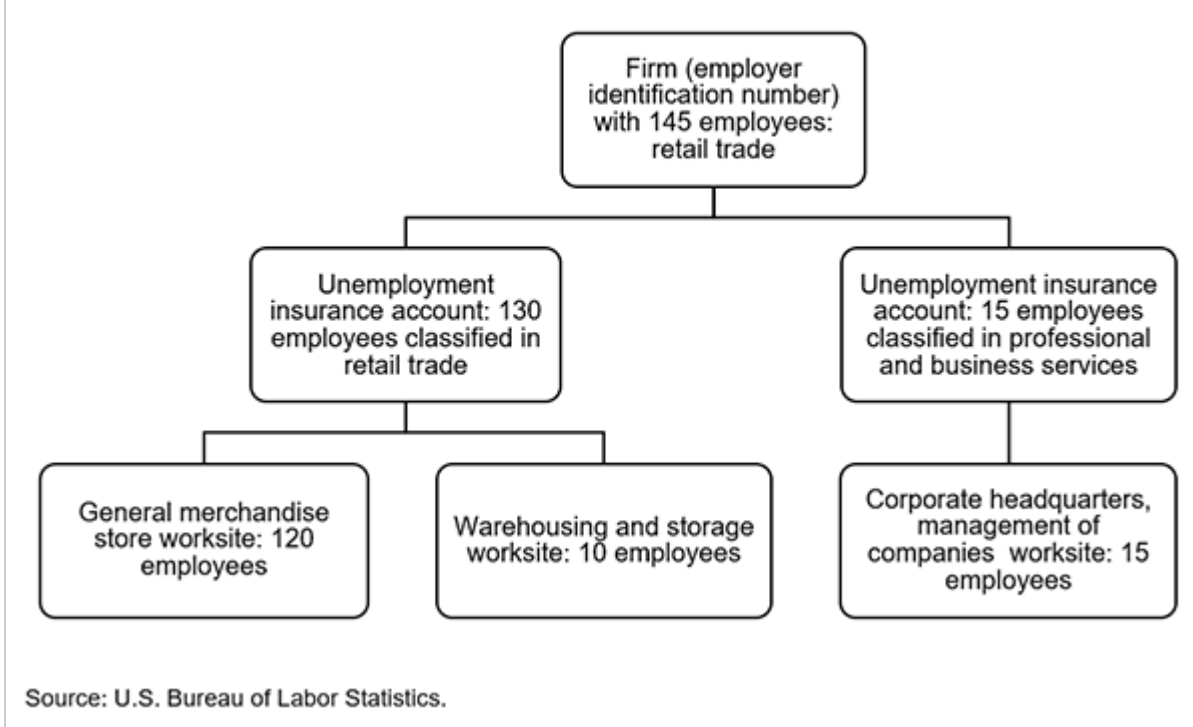
The analysis presented in this article shows data for employment change classified by industry at the worksite level, by UI account, and by EIN. Clearly, assigning industry classification at a more aggregate company level will produce an employment level that differs from the employment level produced by industry classification at the worksite level. My main interest here is to see if the long-run industry employment story is changed by the reclassification. Therefore, I indexed these data to 1990. (Appendix table A-1 provides the employment levels for the first quarter of 1990, and table A-2 shows index data for all of the industry groups analyzed in this article for the worksite, UI account, and EIN assignment of industry for the 1990–2018 period.) This analysis should help data users identify industries in which the more aggregate trends have deviated substantially from those given by the official worksite-classified statistics.

Note that this analysis allows us to see if aggregate economic trends would have been different if employment in company- and firm-owned worksites in other industries had been included in the primary industry. Total employment, as measured by the QCEW, is not changed by this reassignment, which simply moves selected establishments and their employment from their officially assigned industry group into another one. Therefore, this analysis provides a specific view of employment changes at a broad industry level and examines whether the inclusion of an auxiliary-unit proxy concept changes the economic story in each industry group. Different trends over time could result from several factors outside the scope of this analysis. Principally, this analysis does not determine whether changes in trends are due to aggregate changes in ownership of auxiliary-like worksites or changes in employment in the auxiliary-like industries. What this analysis explores is how much employment is directly attributable to firms whose aggregate primary activity is within a specific industry group, plus the employment associated with worksites owned by those firms that are classified outside of that industry group.

Potential errors associated with reclassification

There are a number of potential errors associated with this reclassification methodology. Among them are the following:

- NAICS codes are rarely in error at the two-digit level. However, when errors are identified during QCEW processing, they are corrected for the current and future quarters, but no historical corrections are made. This analysis accepts the QCEW NAICS six-digit codes as reported each quarter.
- Worksites with multiple economic activities are instructed to select the primary activity in order to assign a NAICS code. The activity associated with the highest revenue stream is usually selected as the primary activity. This analysis assumes that the aggregate revenue of the UI account or firm is associated with its worksites proportional to the employment at each worksite. This assumption is reasonable, and it generally will provide reasonable results; however, there are certainly isolated cases in which it will not. For example, when examining a firm that has an e-commerce worksite and a fulfillment center (i.e., a warehouse) worksite, the highest revenue is likely to be associated with the e-commerce site, whereas the highest employment may be associated with the warehouse site. This analysis does not attempt to make any corrections for such situations.
- This reclassification is based on ownership of worksites and does not include a detailed examination to determine relevance. Therefore, this reclassification may assign relevant worksites outside of the core industry (e.g., it could move a small retail worksite out of retail trade and into wholesale trade), and it could assign to the industry worksites that are completely unrelated to the primary industry.
- Although an EIN usually identifies all of the worksites within a business organization, a single business can obtain multiple EINs. For the purposes of this article, each EIN is treated as an independent firm.

These errors are expected to be small enough not to change the broad results contained in this analysis.

BLS organizes NAICS sectors into broader groupings for some publications. These groupings are natural resources and mining; construction; manufacturing; trade, transportation, and utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality; other services, except public administration; public administration; and an "unclassified" category. The analysis in this article uses these broader industry groupings, with two exceptions—natural resources and mining; and trade, transportation, and utilities are analyzed at the more detailed NAICS-sector level. The analysis omits the unclassified category. Therefore, this article examines the following industry groups: agriculture, forestry, fishing, and hunting; mining, quarrying, and oil and gas extraction; construction; manufacturing; wholesale trade; retail trade; transportation and warehousing; utilities; information; financial activities; professional and business services; education and health services; leisure and hospitality; other services, except public administration; and public administration.
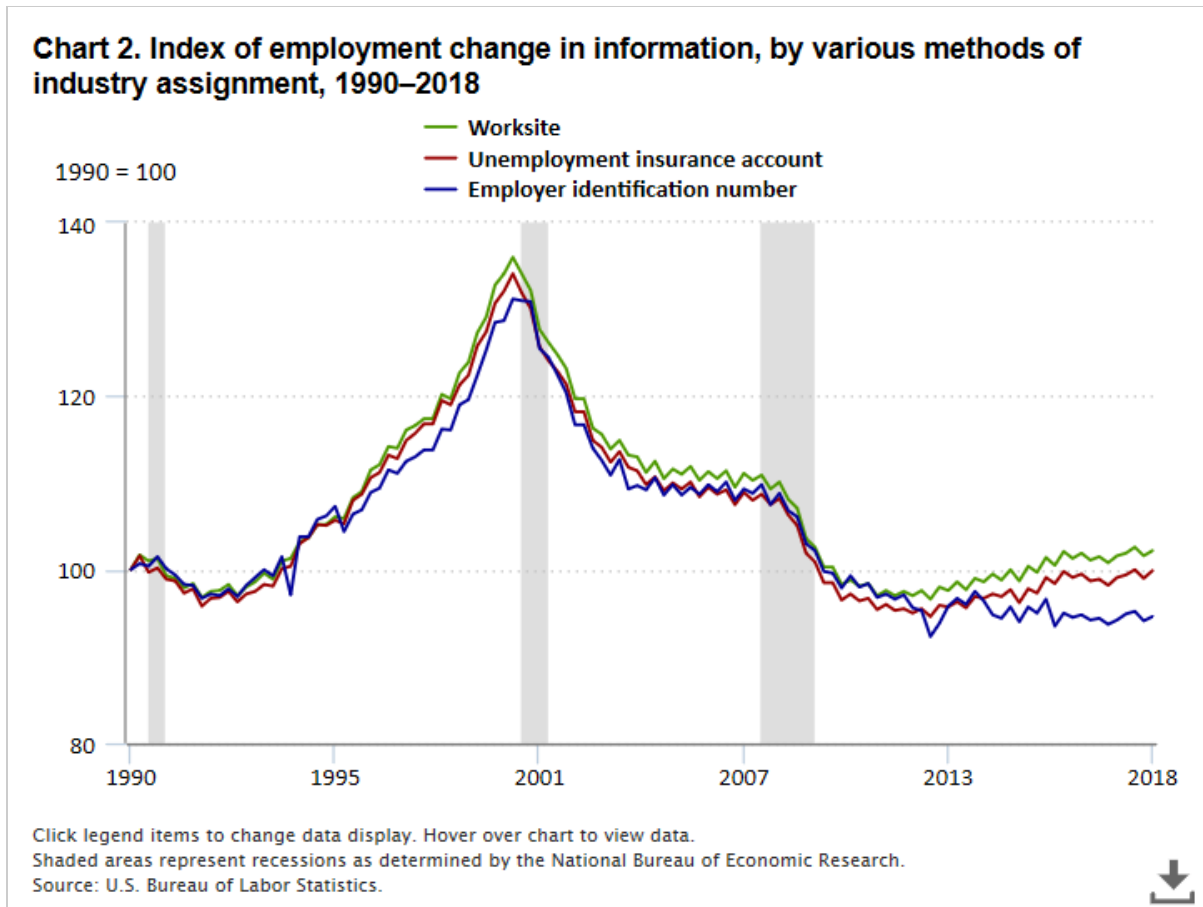
Results

The analysis in this article includes a reassignment of industry at both the UI account level and the EIN (firm) level. As expected, the assignment of industry at the UI account level results in employment trends that are closer to the trends seen at the worksite-assigned level, because the aggregation of worksites is on a smaller scale. For this reason, this analysis focuses on comparing data with an assignment of industry at the EIN or firm level by using data that have been categorized with the official worksite industry assignment. The analysis focuses mostly on the

end points of the various indexes that were created for this purpose, in order to identify industry sectors in which the economic story would be most similar and most different under this proxy auxiliary assignment procedure.
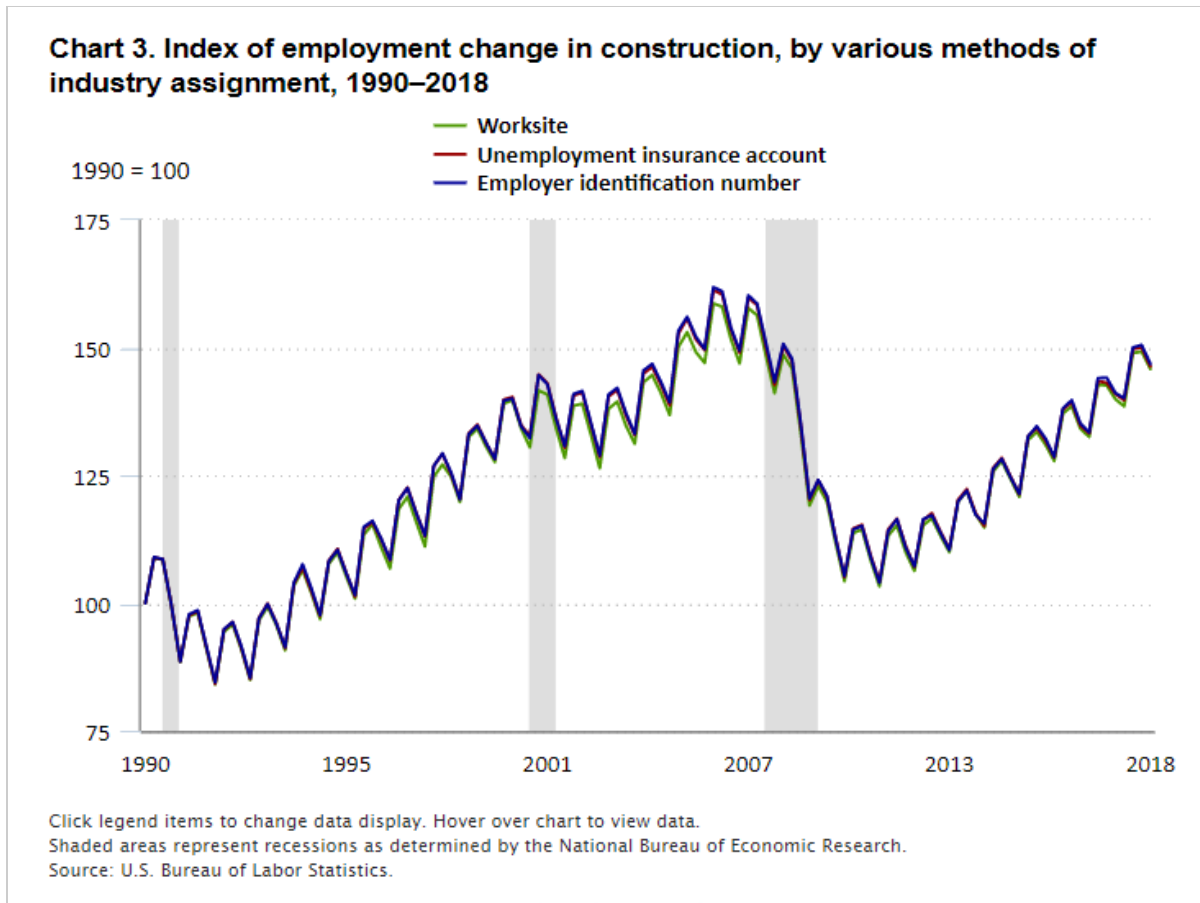
The industry with the largest positive percent difference between the EIN index and the worksite index over the 1990–2018 period is wholesale trade. Chart 1 shows a continually stronger trend in the EIN index, except around recessions. The data show that the EIN index grew 8.6 percent more than the worksite index over the period. This finding indicates that firms in the wholesale trade industry expanded their ownership of (and employment in) worksites outside of the wholesale trade industry during the study period.

Chart 1. Index of employment change in wholesale trade, by various methods of industry assignment, 1990–2018
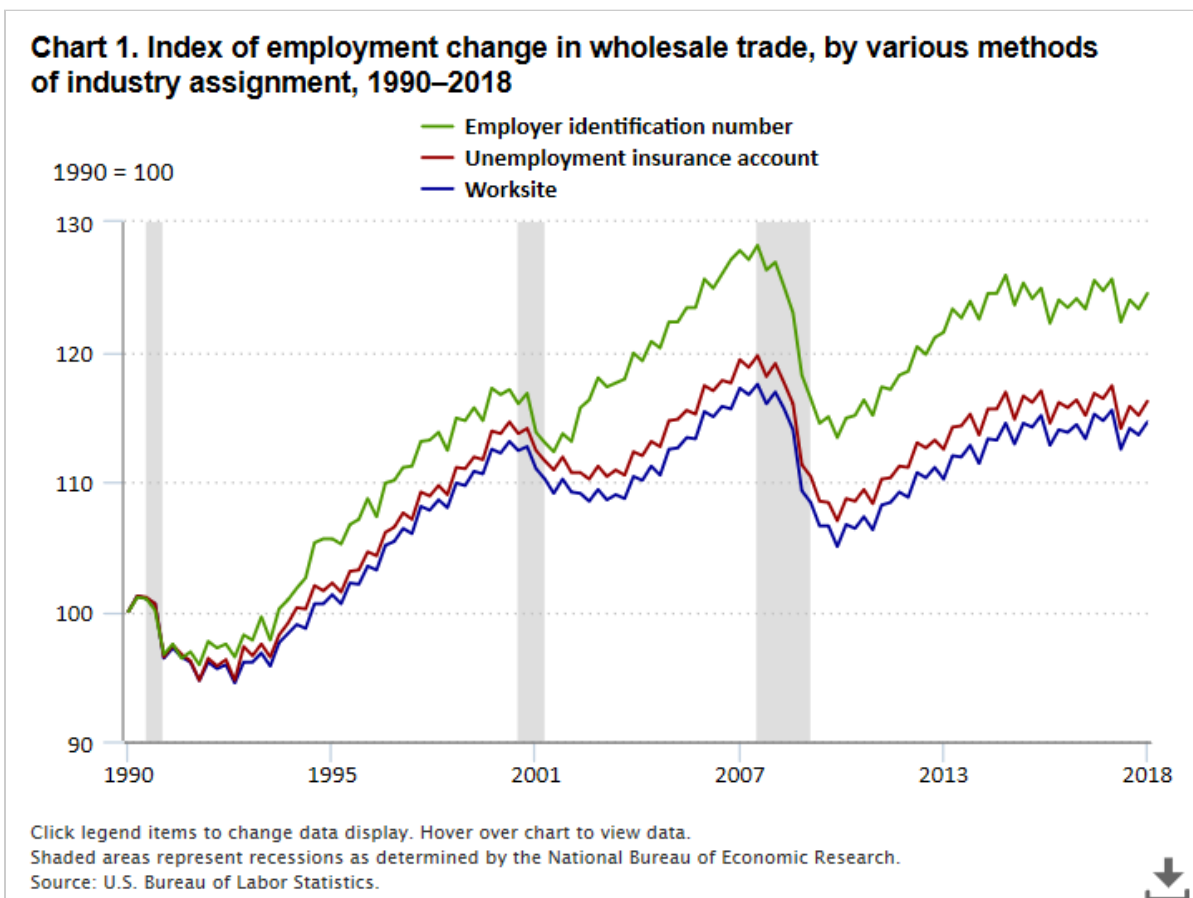
The industry with the largest negative percent difference between the EIN index and the worksite index over the 1990–2018 period is information. (See chart 2.) There was some limited deviation early in the period, but it moderated in early 2000. The deviation returned in early 2014 and mostly widened each quarter until the end of the period. The result is an EIN index that was 7.5 percent lower than the worksite index in 2018. This finding indicates that firms in the information industry reduced their ownership of (and employment in) worksites outside of the information industry over the 1990–2018 period.

Chart 2. Index of employment change in information, by various methods of industry assignment, 1990–2018

1990 = 100

Legend:
- Worksite
- Unemployment insurance account
- Employer identification number

Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

By contrast, as shown in table 1, the industries with the least deviation between the EIN index and the worksite index over the period are other services (+0.4 percent), utilities (−0.6 percent), and construction (+0.7 percent). Among these three industries, construction had the most employment. The index of employment change for construction is shown in chart 3. Visually, we see very little deviation between the EIN index and the worksite index for the construction industry over the entire 1990–2018 period.

Chart 3. Index of employment change in construction, by various methods of industry assignment, 1990–2018

Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

Charts 1, 2, and 3 show, respectively, positive, negative, and "no change" deviations between worksite and EIN industry coding. Table 1 provides information on the relative percent difference in the index values (at the end of the period) between the EIN NAICS reassignment and the original worksite NAICS code assignment, the difference in employment change, and the relative percent employment change (taking the difference in employment change divided by the final employment level of the worksite NAICS assignment).[8]

Table 1. Measures of employment change, by industry, between EIN-assigned industry and worksite-assigned industry

Industry	Relative percent difference in index values: (EIN − WS) / WS	Difference in employment change (EINΔ − WSΔ)	Relative percent employment change, (EINΔ − WSΔ) / WS
Agriculture, forestry, fishing and hunting	2.2	16,885	1.5
Mining, quarrying, and oil and gas extraction	−5.1	−34,787	−5.1
Construction	0.7	37,409	0.5
Manufacturing	−1.8	−684,757	−5.4
Wholesale trade	8.6	316,505	5.4
Retail trade	3.0	521,647	3.2
Transportation and warehousing	−3.0	−278,485	−5.0

See footnotes at end of table.

Table 1. Measures of employment change, by industry, between EIN-assigned industry and worksite-assigned industry

Industry	Relative percent difference in index values: (EIN − WS) / WS	Difference in employment change (EIN∆ − WS∆)	Relative percent employment change, (EIN∆ − WS∆) / WS
Utilities	−0.6	−11,768	−2.1
Information	−7.5	−219,373	−7.8
Financial activities	1.1	99,178	1.2
Professional and business services	5.3	−6,448	0.0
Education and health services	2.4	379,854	1.7
Leisure and hospitality	1.1	189,686	1.2
Other services, except public administration	0.4	−25,979	−0.6
Public administration	−1.6	−271,911	−1.2

Note: EIN = employer identification number; WS = worksite.

Source: U.S. Bureau of Labor Statistics.

Table 1 shows that the industries with the largest positive difference in employment change between the worksite- and EIN-based industry assignments over the 1990–2018 period are retail trade (+521,647), education and health services (+379,854), and wholesale trade (+316,505). The industries with the largest negative difference in employment change in this reassignment are manufacturing (−684,757), transportation and warehousing (−278,485), public administration (−271,911), and information (−219,373). The industries in which employment change was the least affected by this reassignment are professional and business services (−6,448), utilities (−11,768), and agriculture, forestry, fishing and hunting (+16,885)

The analysis presented in this article identifies industries whose firms changed their pattern of other-industry worksite ownership and employment over the 1990–2018 period. For example, as classified by the official worksite industry assignment, employment in retail trade grew by about 3.3 million over the period. However, when the data are reclassified at the firm level, employment growth in retail trade during this period increases to about 3.8 million. Therefore, a firm-level industry classification strategy shows somewhat stronger growth for retail trade plus retail-owned firms than the growth shown by the original worksite industry assignment. Based on this strategy of identifying deviations in employment change between worksite and EIN industry assignment, the following industries changed the most over the period from the first quarter of 1990 to the fourth quarter of 2018: manufacturing, wholesale trade, information, retail trade, and transportation and warehousing. (See appendix table A-2 for index data for all of the industry groups examined in this article at the worksite, UI account, and firm level.)

A deeper look at the two industries that changed the most over the 1990–2018 period after reclassification

This section takes a deeper look at some of the most substantial compositional changes identified in the earlier analysis of broad industry employment trends. Recall that, under NAICS, industry assignment is determined by the worksite's dominant economic activity. Hence, the majority of employment in a firm with multiple worksites

generally will be in the industry originally assigned to the firm in the QCEW.[9] In this article, this employment is referred to as *core* industry employment. The firm may also own establishments and have employment in other industries, and this is referred to as *noncore* employment. In this section, I briefly explore the distribution of noncore employment in wholesale trade and retail trade, the two industries that showed the most difference between worksite and EIN industry assignment in the earlier analysis.

Wholesale trade

In the fourth quarter of 2018, core wholesale trade employment (i.e., employment in worksites and firms that shared the same industry classification) represented 87.2 percent of total employment in the industry. The noncore employment in firms connected to wholesale trade was most concentrated in management of companies and enterprises (1.8 percent), professional and technical services (1.5 percent), and warehousing and storage (1.0 percent), computer and electronic products manufacturing (0.8 percent), chemical manufacturing (0.7 percent), and building material and garden supply stores (0.6 percent). An additional 6.4 percent of noncore employment was spread among many other three-digit industries. (See table 2.)

Table 2. Noncore employment as a percentage of total firm employment in wholesale trade, by three-digit NAICS subsector, fourth quarter 2018

Industry	Percent
Total	12.8
Management of companies and enterprises	1.8
Professional and technical services	1.5
Warehousing and storage	1.0
Computer and electronic products manufacturing	0.8
Chemical manufacturing	0.7
Building material and garden supply stores	0.6
Remaining	6.4

Note: The "remaining" category consists of smaller shares of employment spread among many other three-digit industries. NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics.

In wholesale trade, the noncore industries in which employment increased the most over the 1990–2018 period when they were reclassified at the EIN level included auxiliary worksites in professional and business services (+2.5 percent),[10] manufacturing (+0.9 percent),[11] and transportation and warehousing

(+0.9 percent).[12] In total, firms in the wholesale trade industry reduced the employment share of the core industry by 4.7 percent. At the three-digit level, these firms mainly added additional worksites and employment in management of companies and enterprises (+1.1 percent), professional and technical services (+1.0 percent), and warehousing and storage (+0.8 percent). (See table 3.)

Table 3. Largest noncore industry employment changes in wholesale trade when industries are reclassified at the EIN level, 1990–2018

Noncore industry	Percent change in employment share

See footnotes at end of table.

Table 3. Largest noncore industry employment changes in wholesale trade when industries are reclassified at the EIN level, 1990–2018

Noncore industry	Percent change in employment share
Management of companies and enterprises	1.1
Professional and technical services	1.0
Warehousing and storage	0.8

Note: Changes measured from fourth quarter 1990 to fourth quarter 2018. EIN = employer identification number.

Source: U.S. Bureau of Labor Statistics.

Retail trade

In the fourth quarter of 2018, core employment in retail trade represented 93.3 percent of total employment for the industry. The noncore employment in firms connected to retail trade was primarily found in warehousing and storage (2.3 percent) and management of companies and enterprises (1.9 percent). (See table 4.)

Table 4. Noncore employment as a percentage of total firm employment in retail trade, by three-digit NAICS subsector, fourth quarter 2018

Industry	Percent
Total	6.7
Warehousing and storage	2.3
Management of companies and enterprises	1.9
Merchant wholesalers, nondurable goods	0.3
Merchant wholesalers, durable goods	0.3
Telecommunications	0.3
Administrative and support services	0.3
Remaining	1.3

Note: The "remaining" category consists of smaller shares of employment spread among many other three-digit industries. NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics.

In retail trade, the noncore industries in which employment increased the most over the 1990–2018 period when they were reclassified at the EIN level included auxiliary worksites in transportation and warehousing (+1.7 percent), professional and business services (+1.1 percent), and information (+0.3 percent). The noncore industry with the largest decrease in employment over this period was worksites in manufacturing (−0.4 percent). In total, firms in the retail trade industry reduced the employment share of the core industry by 2.4 percent over these years. At the three-digit level, these firms mainly added more worksites and employment in warehousing and storage (+1.6 percent), management of companies and enterprises (+1.1 percent), and telecommunications (+0.3 percent). Although these changes do not fully encompass the e-commerce-related changes in and outside of this industry, they seem to support the e-commerce changes in retail trade that are well known—that is, a greater reliance on warehousing and storage, management of companies and enterprises, and telecommunications. (See table 5.)

Table 5. Largest noncore industry employment changes in retail trade when industries are reclassified at the EIN level, 1990–2018

Noncore industry	Percent change in employment share
Warehousing and storage	1.6
Management of companies and enterprises	1.1
Telecommunications	0.3

Note: Changes measured from fourth quarter 1990 to fourth quarter 2018. EIN = employer identification number.

Source: U.S. Bureau of Labor Statistics.

Conclusion

Several economic statistics can be used to measure industry change. BLS statistics used for this purpose include employment, hours, wages, turnover, industry productivity, and producer prices. This suite of statistics tells us much about the growth and decline of industries and about changes in prices, industry hires and separations, industry productivity, and average hourly, weekly, and annual wages paid to employees. These statistics can be supplemented by looking at employer size class, business age, the employment associated with expanding and contracting businesses, and other statistics readily available from BLS. Each of these statistics is mostly focused on telling us how industries are doing today, with some historical context to aid in understanding their contribution to the overall economy.

The statistics I have examined in this article are not focused on how much employment is in an industry or how much its employees are paid. Rather, the article examines data to identify industries in which employment trends would have been different if an auxiliary-like industry coding practice had been used, and then briefly explores the composition of industries in which those trends were most changed when the auxiliary-unit concept was used.

This article shows that, over the study period, several industries changed compositionally with respect to the noncore worksites that businesses own. Among the industries that changed the most over the period are wholesale trade and retail trade. The article also confirms that the worksite assignment of industry typically yields similar employment trend results to industry assignment made at the level of a UI account or an EIN, with some moderate deviations.

Appendix: recode data and index data

Table A-1. Recode data: levels for first quarter 1990 for data coded to NAICS by worksite, UI account, and EIN (in thousands)

Table A-2. Index data for all industries, worksite, UI account, and EIN assignment of industry, 1990–2018

NOTES

1 For more information on the North American Industry Classification System (NAICS), see https://www.census.gov/naics/. The use of NAICS as an industry classification system is mandated for federal statistical agencies by the Office of Management and Budget. Having a common classification system allows data users to compare data from various federal statistical agencies, knowing that each agency defines industries in the same way. NAICS also facilitates efficient sampling and estimation, because within detailed industry and size-class cells, the business activities, employment, and wages across worksites are relatively homogenous.

2 The former concept of the auxiliary unit from the Standard Industrial Classification (SIC) system was not ideal. The concept was based on ownership as well as function, which tended to reduce the clarity of economic reports. For example, consider a large retail firm that operates its own warehouse, and suppose that the warehouse was classified as part of a retail-owned business (as it would be under the SIC system). Now suppose that the retailer decides to make the warehouse part of a separate company, with the retailer purchasing warehousing services from it. In this scenario, employment would have declined in retail trade and increased in warehousing and storage. But the employment decline really had nothing to do with retail trade; rather, it was about a company's decision about which support services to own and which to purchase. By contrast, under NAICS, the warehouse would be assigned to the warehousing and storage industry, regardless of ownership. As a result, NAICS makes economic trends for warehousing and storage about that industry and its functions, rather than about who owns the warehouse. Nevertheless, note that this increased clarity of reporting about what is happening in individual industries can also obscure broader changes in businesses, especially in the longer term. Over the past few decades, for example, growth in e-commerce (retailers that do not operate in a traditional brick-and-mortar site) has led to that industry taking over a substantial portion of retail sales. This transformation of the retail sector affects employment in a number of industries that support e-commerce, including warehouses, and couriers and messengers.

3 See *Standard Industrial Classification Manual, 1987* (Executive Office of the President, Office of Management and Budget, 1987), p. 13, https://www.naics.com/wp-content/uploads/2017/05/SIC-Full-1987-Manual.pdf.

4 Ibid., p. 16.

5 See *North American Industry Classification System: United States, 2017* (Executive Office of the President, Office of Management and Budget, 2017), p. 3, https://www.census.gov/eos/www/naics/2017NAICS/2017_NAICS_Manual.pdf.

6 Ibid., pp. 19–20.

7 For more information, see the U.S. Bureau of Labor Statistics Quarterly Census of Employment and Wages page at https://www.bls.gov/cew/.

8 Note that some worksites enter the unemployment insurance system without having a NAICS industry code and are labeled "unclassified" until an industry code is assigned. Table 1 excludes a row for these records; therefore, the sum of the differences shown do not sum to zero.

9 In this article, the NAICS code is assigned as the two-digit industry with the single largest employment value among all two-digit industry employment values from worksites owned by the firm.

10 The professional and business services industry group includes the NAICS two-digit industries 54, 55, and 56.

11 The manufacturing industry includes the NAICS two-digit industries 31, 32, and 33.

12 The transportation and warehousing industry includes the NAICS two-digit industries 48 and 49.

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The U.S. productivity slowdown: an economy-wide and industry-level analysis

Labor productivity—defined as output per labor hour—has grown at a below-average rate since 2005, representing a dramatic reversal of the above-average growth of the late 1990s and early 2000s. The productivity slowdown during these years has left many economic observers wondering why this situation has occurred and what factors may have contributed. To clarify potential sources of the productivity slowdown, this article presents an analysis of labor productivity and its component series—multifactor productivity, contribution of capital intensity, and contribution of labor composition—at both the economy-wide and industry levels, complemented with a survey of the contemporary productivity literature.

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The figure—$10.9 trillion—represents the cumulative loss in output in the U.S. nonfarm business sector due to the labor productivity slowdown since 2005, also corresponding to a loss of $95,000 in output per worker.[1]

These figures show that, when there is consistently below-average productivity growth, year after year, a substantial effect can result over an extended period. How could this situation have occurred, in a modern and technically advanced economy such as in the United States? Well, not only has the productivity slowdown been one of the most consequential economic phenomena of the last two decades, but it also represents the most profound economic mystery during this time, and though many economists have grappled with the issue for over a decade and even created some innovative research approaches to address the question, we still cannot fully explain what brought on this situation.

One of the more perplexing aspects of the current slowdown is its genesis: that it came immediately following a historic productivity boom in the United States, and represented a swift rebuke of the popular idea of that time that we had entered a new era of heightened technological progress. The suddenness and size of the reversal were difficult to comprehend. For some background, in the late 1990s, when that much-cited productivity boom had begun, U.S. labor productivity growth had accelerated to rates of change that had not been seen since the late 1960s and early 1970s. This late 1990s surge surprised many economic observers, who had become accustomed to the below-average productivity growth rates of the mid-to-late 1970s through the early 1990s. In addition, the

situation in the United States was even more startling due to the fact that the rest of the more-developed economies of the world were not similarly experiencing a speedup in growth rates.[2]

A debate ensued among economists: Was the tremendous productivity growth of the late 1990s here to stay—a fundamental change generated by the computing and internet-related innovations that were all around us—or was it a temporary phenomenon that would pass? The fact that the productivity speedup persisted through the recession of 2001, and then became even more pronounced in 2002, convinced many observers that perhaps something had changed.[3] The acceleration of U.S. productivity growth is shown in figure 1, illustrated by the growth rates during 1998 through 2005, which rise above the long-term average rate since 1947, denoted by the dashed blue line. Over these high-growth years, U.S. labor productivity grew at an average rate of 3.3 percent,[4] which is markedly higher than the cumulative 2.1-percent average rate from 1947 to 2018.

Figure 1. Labor productivity growth: annual percent changes, nonfarm business sector, 1994–2018
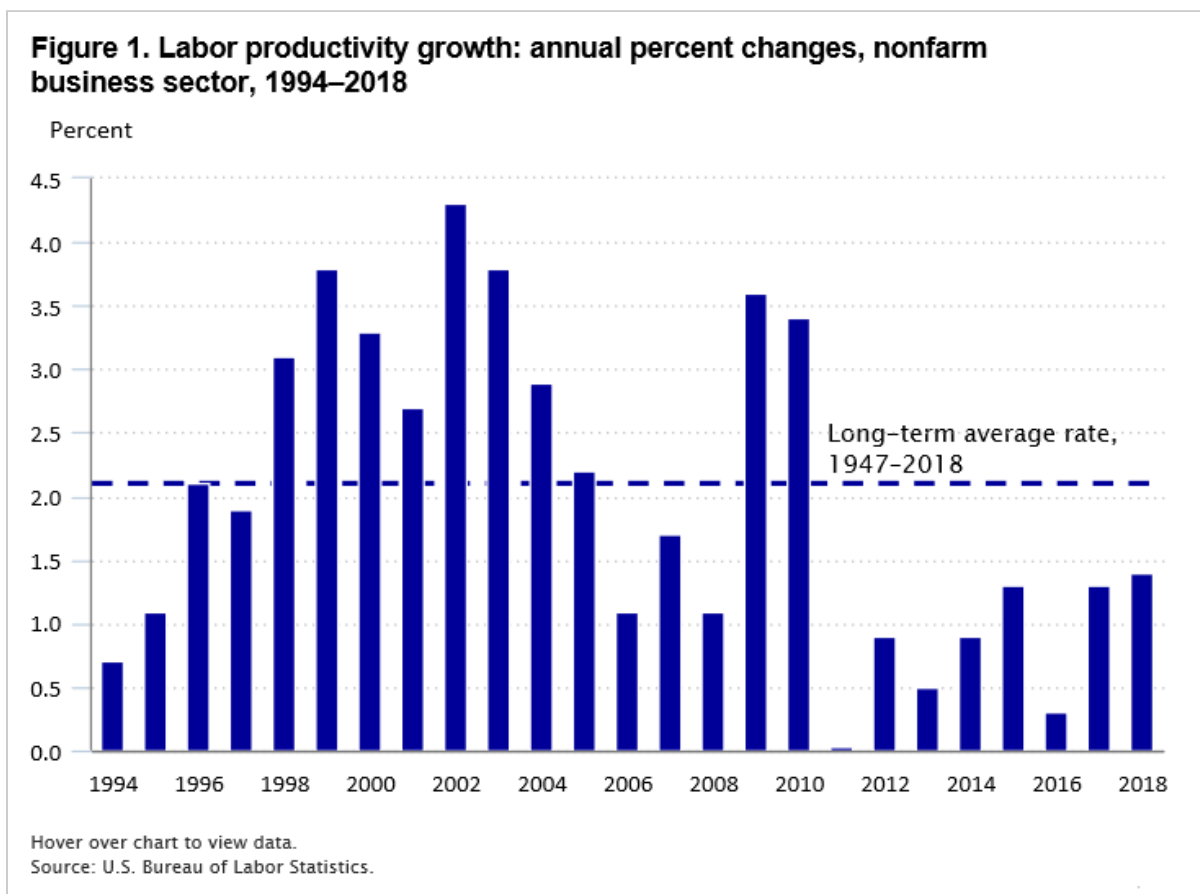
This high-growth period came to an end during the mid-2000s, when U.S. labor productivity growth rates began to stumble, and in 2006 receded below the long-term average trend line for the first time in a decade. And, notwithstanding 2 years of high growth in 2009 and 2010 following the Great Recession, productivity growth rates have remained stubbornly low in subsequent years. Many economic observers were yet again surprised, in this case at just how drastically growth rates slowed, given the recently observed high rates of growth and the continued technological innovations that were proliferating throughout the economy. In the years since 2005, labor productivity has grown at an average annual rate of just 1.3 percent, which is lower than the 2.1-percent long-term

average rate from 1947 to 2018. The slow growth observed since 2010 has been even more striking: labor productivity grew just 0.8 percent from 2010 to 2018.

As the slowdown in labor productivity growth has steadily held on throughout the past decade, economic observers have been trying to understand this phenomenon, which has the effect of placing downward pressure on economic growth, worker compensation gains, profits growth, and gains in living standards of Americans. Many observers began to wonder: Why has U.S. labor productivity growth been so consistently low in recent years, and why is it so markedly different from the strong growth observed relatively recently? This article presents two approaches to address these questions, with each approach including an analysis of the U.S. Bureau of Labor Statistics (BLS) productivity data and a review of the contemporary productivity literature. First, the economy-wide slowdown in labor productivity growth is analyzed by breaking out the series into its three component series: multifactor productivity (MFP) growth, the contribution of capital intensity, and the contribution of labor composition. Second, industry-level productivity data are used to identify the industries that made notable contributions to the economy-wide labor productivity slowdown.

Economy-wide analysis of the U.S. labor productivity slowdown

This section presents an analysis of the economy-wide slowdown in labor productivity growth that decomposes the series into its three component series: multifactor productivity growth, the contribution of capital intensity, and the contribution of labor composition. This section also presents a dollar and time cost analysis of the slowdown, and an analysis of how U.S. regions impacted the economy-wide slowdown.

Decomposition of labor productivity growth

Labor productivity is a measure of economic performance that compares the amount of goods and services produced (output) with the number of labor hours used in producing those goods and services. It is defined mathematically as output per hour of work, and growth occurs when output increases faster than labor hours. For example, if output is rising by 3 percent and hours are rising by 2 percent, then labor productivity is growing by 1 percent.

Labor productivity growth is vitally important to present and future prospects for economic growth, because it represents the only path by which economic growth can rise above what would be possible by simply increasing labor hours (as, by definition, economic growth can only come from either hours growth or labor productivity growth). The economic gains brought about by labor productivity growth make it possible for an economy to achieve higher growth in labor income,[5] profits and capital gains of businesses, and public sector revenue; these economic gains also hold the potential to lead to improved living standards for those participating in an economy, in the form of higher income, greater leisure time, or a mixture of both. In addition, as labor productivity rises, all of these factors may increase simultaneously, without gains in one coming at the cost of one of the others.

Given the importance of labor productivity growth, it is worth delving into the measure in more detail to see what underlying factors are making this growth possible. As such, in addition to labor productivity growth being defined as a residual—the difference between output growth and hours growth—we can also analyze it as a sum, built up from the contributions of its three component series.

Components of labor productivity growth

The following equation allows us to quantify the sources of labor productivity growth and helps us better understand the measure by looking into its three component series:

labor productivity growth = multifactor productivity growth + contribution of capital intensity + contribution of labor composition

Multifactor productivity (MFP) growth represents the portion of output growth that is not accounted for by the growth of capital and labor inputs and is due to contributions of other inputs, such as technological advances in production, the introduction of a more streamlined industrial organization, relative shifts of inputs from low to high productivity industries, increased efforts of the workforce, and improvements in managerial efficiency. Similar to labor productivity growth, MFP growth can also be defined as a residual—output growth minus the growth of the combined inputs of labor and capital.

The **contribution of capital intensity** is defined as the capital-weighted change in the capital-labor ratio. The measure is computed as capital's share of current dollar costs multiplied by the growth in capital services per labor hour. The contribution of capital intensity—also called capital deepening—reflects businesses' decision-making process between hiring more workers and purchasing more or higher-quality equipment, or of substituting equipment for workers or vice versa.* In cases in which firms increase their usage of capital relative to labor, or where capital costs rise relative to labor costs, there will be an increase in the contribution of capital intensity to labor productivity growth.
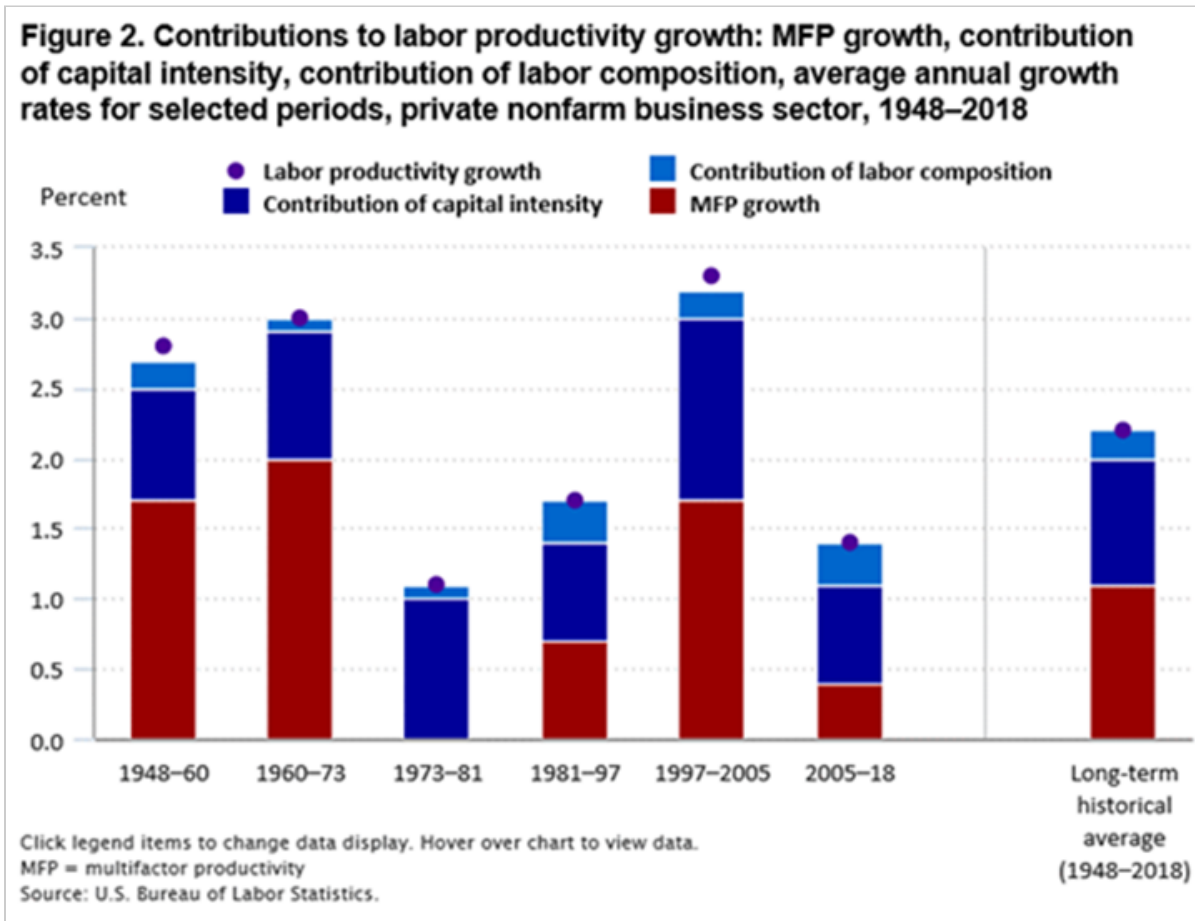
The **contribution of labor composition** is defined as the labor-weighted change in a measure—labor composition—which reflects shifts in the level of skills and experience of the workforce. It is computed as labor's share of current dollar costs multiplied by labor composition.** The contribution of labor composition helps us gauge the productive capacity of the workforce at a given point in time. When firms hire more workers with higher skills and more experience or lay off workers with lower skills or less experience, or when labor costs rise relative to capital costs, the contribution of labor composition to labor productivity growth increases.

* Specifically, the contribution of capital intensity is defined as $w_k \left[\left(\ln \frac{K_t}{K_{t-1}} \right) - \left(\ln \frac{L_t}{L_{t-1}} \right) \right]$, where w_k is the 2-year average cost share of capital and K_t and L_t are capital services and labor hours at a given time t.

** The BLS labor composition methodology can be found at https://www.bls.gov/mfp/mprlabor.htm.

The three components of labor productivity growth are displayed in figure 2 for the slowdown period (2005–18), the speedup period (1997–2005), as well as other selected post-World War II (WWII) periods and the long-term historical average.[6] Labor productivity growth, corresponding to the purple dots, represents the sum of the three stacked bars of MFP growth,[7] contribution of capital intensity, and contribution of labor composition. It is apparent that the labor productivity growth rate (1.4 percent) of the slowdown period has slackened relative to the rate of the

speedup period and is also below the long-term historical average. Furthermore, we can see from the diminished red and dark-blue stacked bars of the slowdown period relative to the bars of the speedup period that MFP growth and the contribution of capital intensity are the sources of the U.S. labor productivity slowdown. (The contribution of labor composition was approximately the same as that of the speedup period and did not contribute to the slowdown.[8]) MFP grew 0.4 percent during the slowdown period, which is *less than one-fourth* the growth of the speedup period and is also well below the long-term historical average. In addition, the contribution of capital intensity in the slowdown period, 0.7 percent, is around half that of the speedup period and is also below the long-term historical average.

Figure 2. Contributions to labor productivity growth: MFP growth, contribution of capital intensity, contribution of labor composition, average annual growth rates for selected periods, private nonfarm business sector, 1948–2018
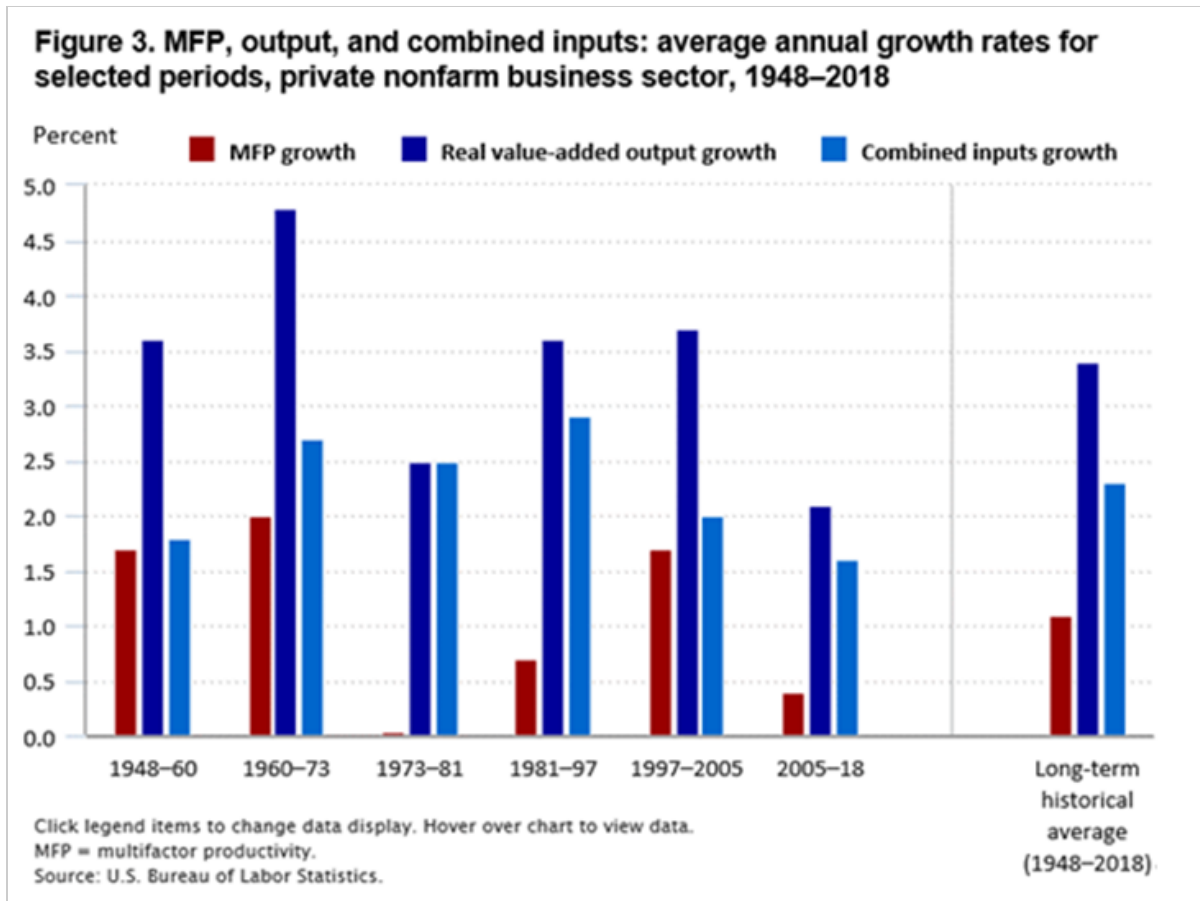
The deceleration in MFP growth—the largest contributor to the slowdown—explains 65 percent of the slowdown relative to the speedup period; it also explains 79 percent of the sluggishness relative to the long-term historical average rate. The massive deceleration in MFP growth is also emblematic of a broader phenomenon shown in figure 2. We can see that throughout the historical period since WWII, the majority of the variation in labor productivity growth from one period to the next was from underlying variation in MFP growth, rather than from the other two components. While the contribution of labor composition varied only between a range of 0.1 percent to 0.3 percent during the entire post-WWII era and the contribution of capital intensity varied between 0.7 percent and 1.3 percent, MFP growth varied within a wider range, between 0.0 percent and 2.0 percent.[9]

At the same time, in addition to the notable variation in MFP growth during the recent periods, something unprecedented about these recent periods was the additional contribution from variation in the contribution of capital intensity. The contribution of capital intensity had previously remained within a relatively small range (0.7 percent to 1.0 percent) during the first five decades of post-WWII periods, but then in the 1997–2005 period, the measure nearly doubled, from 0.7 percent up to 1.3 percent, followed by nearly halving to 0.7 percent in the 2005–18 period. This unprecedented variation in the contribution of capital intensity was the factor that combined with the variation in MFP growth to bring about such historic speedup and slowdown periods in recent years, increasing the size of the overall labor productivity slowdown to rival the widely noted 1970s slowdown. The contribution of capital intensity accounts for 34 percent of the labor productivity slowdown relative to the speedup period and explains 25 percent of the sluggishness relative to the long-term historical average rate.
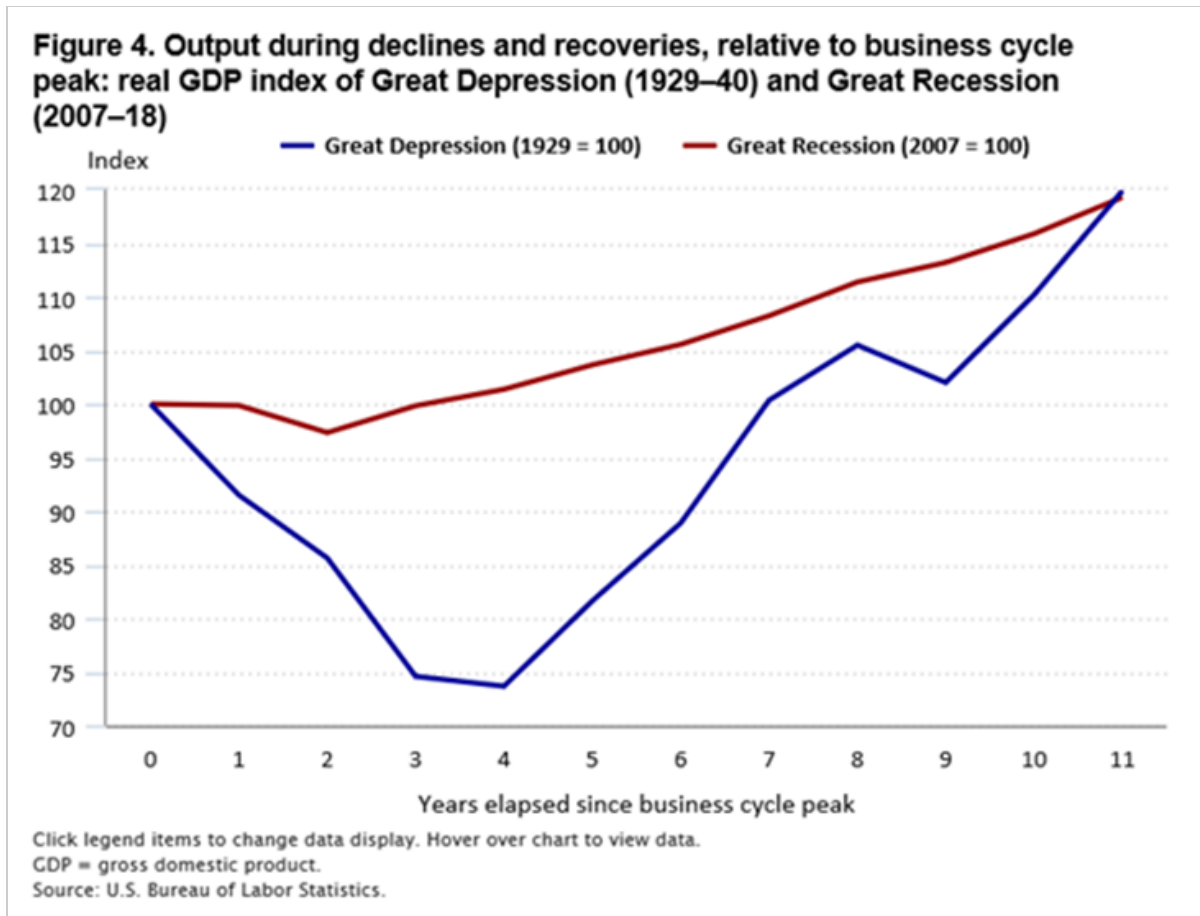
The slowdown in MFP growth

Now let us take a deeper look into the two contributors to the labor productivity slowdown. For MFP growth, let us start out by noting the inherent difficulty in attempting to quantify the sources, components, or causes of MFP growth or lack thereof. This difficulty arises because MFP growth itself cannot be measured or identified on its own but can only be ascertained as the leftover output growth that remains after all measurable inputs to production—in this case, labor and capital[10]—have already been taken into account. With MFP growth, we are actually measuring something that is unidentifiable, similar to how cosmologists can measure the extent of dark matter and its influence on the universe even as they do not know what this matter comprises.[11] This is the reason that the question of what is driving the slowdown in MFP growth has puzzled so many economic observers in recent years and still remains incompletely explained following more than a decade of work on the issue.

However, there are a few approaches that can be taken to help us gain a foothold on what might be happening to MFP growth, both by using BLS data as well as by looking at some clever approaches of the numerous researchers working on this issue. As a first step in our analysis, let us look at the BLS series used in calculating MFP growth, in order to provide some background and context on the economy in which the MFP slowdown took place. As just noted, MFP growth is a residual: output growth minus the growth of the combined inputs of capital and labor. Figure 3 reveals that, although both output growth and combined input growth atrophied in the slowdown period relative to their higher rates of the speedup period, output growth succumbed to a much more serious retrenchment. Namely, while combined input growth slowed by 0.4 percentage point, output growth slowed 4 times as much, by 1.6 percentage points. The fact that output growth retreated so much further than combined inputs during the slowdown period is reflected in the notably low MFP growth rate of 0.4 percent during this period, and is a key fact connected with the productivity slowdown. For this reason, as we begin our investigation of the MFP slowdown, we will first be looking closely at the historically weak output growth and getting a sense of the state of the economy during this period.

Figure 3. MFP, output, and combined inputs: average annual growth rates for selected periods, private nonfarm business sector, 1948–2018

Percent

■ MFP growth   ■ Real value-added output growth   ■ Combined inputs growth

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

Historically weak output growth of the post-2005 slowdown period

The rate of output growth during the 2005–18 slowdown period (2.1 percent) is a historically weak growth rate. Not only does this rate pale in comparison to the 3.7-percent growth of the speedup period, but it also represents a historically slow rate for the entire post-WWII period, well below the historical average growth rate of 3.4 percent (see figure 3). Of course, a large portion of the below-average output growth in the slowdown period reflects the fact that this period encompasses the global financial crisis and Great Recession of 2007–09 and the subsequent recovery. It might surprise some to discover that the post-2007 business cycle, which contains this historic downturn, not only had slower cyclical growth than all previous business cycles since WWII, but it even recorded a slower overall growth rate than the Great Depression of the 1930s (see figure 4). In the case of the Great Depression, output plummeted by 26 percent—a much more severe decline than the 3-percent decline during the Great Recession.[12] However, the recent cycle exhibited a much weaker recovery than that of the Great Depression, with output growth from 2009 to 2018 being less than *one-third* of the 7.2-percent rate posted during the peacetime recovery from 1933 to 1940.[13] Because of this extended weak recovery, as of 2018, the post-2007 cycle's growth rate came in slightly below what had occurred during the 1930s—even more striking when one considers that the population growth rate was the same in these two periods.[14]

Figure 4. Output during declines and recoveries, relative to business cycle peak: real GDP index of Great Depression (1929–40) and Great Recession (2007–18)

Index

— Great Depression (1929 = 100) — Great Recession (2007 = 100)

Years elapsed since business cycle peak

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

The historically low output growth of the post-2007 business cycle—and particularly the anemic recovery—was not wholly unexpected. Valerie Cerra and Sweta Chaman Saxena, Carmen M. Reinhart and Kenneth S. Rogoff, and Carmen M. Reinhart and Vincent R. Reinhart show that a permanent loss of output and a lack of rebound to the long-term growth trend often follow financial crises such as the one the United States experienced in 2008.[15] Similarly, the International Monetary Fund (IMF) asserts that output losses arising from banking crises are usually substantial, stating that "typically, output does not recover to its precrisis trend. On average, output falls steadily below its precrisis trend until the third year after the crisis and does not rebound thereafter," although the IMF also clarifies that following this permanent output loss, "medium-term growth rates tend to eventually return to the precrisis rate."[16] Daisuke Ikeda and Takushi Kurozumi offer a story that may underlie this phenomenon, suggesting that an "adverse financial shock tightens firms' financing and thereby dampens their activities, which in turn has a significant negative impact on the economy as a whole by decreasing activities not only on the demand side but also on the supply side of the economy. The effect on the supply side, such as the sectors of research and development (R&D) and technology adoption, induces a persistent decline in [MFP] and thus can cause a permanent decline in output relative to a pre-shock balanced growth path."[17]

James H. Stock and Mark W. Watson look even further back in time, to before the financial crisis, claiming that more than half of the weakness of the recovery is from slower long-term trend growth—due to changing demographics—that was already apparent before the Great Recession.[18] However, they also note that particularly slow government spending (specifically from the phaseout of the American Recovery and

Reinvestment Act and the budget sequestration of 2013, as well as from slow state and local government hiring during the entire recovery) and faltering international demand following the recession also played a role. Ray C. Fair also cites sluggish government spending following the Great Recession, asserting that it was the central factor underlying the weak recovery.[19]

In addition to researchers citing weak fiscal stimulus, other researchers have pointed to limitations on monetary stimulus. Robert E. Hall offers that the zero lower bound on interest rates following the financial crisis presented a limiting factor that had not been operative in prior U.S. recessions.[20] Robert J. Barro also claims that monetary stimulus was insufficient to spur a vigorous recovery.[21]

The drag on MFP growth from the Great Recession

Now that we have an understanding of the recent trends in the measures used to compute MFP growth (in particular the unusually slow output growth of recent years), our first task is to attempt to use this basic information to help us better understand the slowdown in MFP growth. Specifically, we may ask: Could the state of the economy during the slowdown period, as indicated by the atypically low output growth, especially with it running below its potential and capacity during and following the Great Recession, have helped to cause the low MFP growth?

Yes, according to several authors, the weakened state of the economy during much of the 2005–18 slowdown period could be one factor underlying the low MFP growth. As noted earlier, Ikeda and Kurozumi argue that when an economy is operating below its potential, firms may pull back on investment in R&D and new technology.[22] David M. Byrne, Stephen D. Oliner, and Daniel E. Sichel concur, noting that one possible explanation for the productivity slowdown is that "the economy has taken a long time to recover from the financial crisis and Great Recession, as the repair of balance sheets has proceeded slowly and as uncertainty about the pace of the recovery has held back investment."[23] Romain Duval, Gee Hee Hong, and Yannick Timmer agree, postulating that "the combination of pre-existing firm-level financial fragilities and tightening credit conditions made an important contribution to the post-crisis productivity slowdown,"[24] and also that "while most forms of physical capital can be pledged as collateral to get a loan, intangible assets such as R&D or workforce training cannot. Furthermore, investments in intangible assets tend to translate more slowly into sales and to be riskier. Therefore, [their] hypothesis is that credit-constrained firms cut their investment in intangible assets, contributing in part to a sharper productivity slowdown after the crisis."[25]

Waning dynamism: reduced responsiveness to productivity gains at the firm level

At the same time, although the Great Recession and its aftermath have substantially affected recent economic trends, the data clearly show that the productivity slowdown started *before* the global financial crisis and Great Recession.[26] Looking back at figure 1, we can see that labor productivity grew at a successively lower rate in each consecutive year from 2002 through 2006, descending to well below the long-term average trend by 2006. So, a second question emerges: What might have led to this initial slowing and commencement of the slowdown period, or, more broadly, what factors might have contributed to the productivity slowdown of the entire 2005–18 period, other than the Great Recession and its deficient recovery?

One major finding is that the businesses that have been spurring recent innovations are having difficulty expanding, and thus, their innovations are failing to make a bigger impact on the economy as a whole than would otherwise be the case. Ryan A. Decker, John C. Haltiwanger, Ron S. Jarmin, and Javier Miranda show that, despite the broad slowdown in productivity growth, many firms are actually still seeing strong productivity gains, with innovation having continued to occur at the "productivity frontier" during the slowdown period since the early 2000s, among the firms that are the productivity leaders in their respective industries.[27] The authors reveal this indirectly, by observing that productivity dispersion in the United States has expanded in recent years, which means that a wider gap exists between these leading firms and the laggards. The authors claim that, within the framework of Michael Gort and Steven Klepper, this increased productivity dispersion implies that there has *not* been a declining pace of innovation.[28]

So then, why are the innovations that have been sparking at these higher-productivity firms not translating into solid economy-wide productivity gains? The answer has to do with how these firms have responded to their productivity windfall. Namely, Decker et al. observe decreased responsiveness to these firm-level productivity bursts as a potential source of the aggregate productivity slowdown, as evidenced by falling rates of job reallocation among these firms.[29] In other words, many of the firms that have been innovating have not similarly been able to scale up and hire more employees commensurate with their improved productivity.

This slump in firm-level reallocation coincides with the timeline of the aggregate productivity slowdown, with Decker et al. finding that "reallocation has declined in all sectors—particularly the high-tech sector—since the early 2000s."[30] In terms of quantifying the impact of this phenomenon, the authors observe that "counterfactual exercises imply that the decline in responsiveness yields a significant drag on aggregate (industry-level) productivity, as much as 2 log points in high-tech manufacturing and more than 5 log points economy-wide in recent years."[31] (Note that we will further explore in depth the slowdown in high-tech manufacturing in the "Industry-level analysis of the U.S. labor productivity slowdown" section of this article, particularly the dramatic slowdown in the computer and electronic products industry.) As for the underlying sources, which may be resulting in these lower rates of reallocation, Decker et al. cite several potential factors: rising adjustment costs, globalization, increased regulation, and declining competition.

The factor of declining competition—as potentially having a stultifying effect upon productivity-enhancing job reallocation—has been of particular interest in the literature, with Jan De Loecker, Jan Eeckhout, and Gabriel Unger outlining this phenomenon in the United States, offering as evidence that average markup costs have nearly tripled—from 21 percent as of 1980 to a level of 61 percent in 2016—in addition to the rate of profits expanding by 8 times its size, from 1 percent to 8 percent.[32] The authors claim that "because passthrough [of cost savings from productivity growth to lower prices for consumers] is lower in the presence of higher market power, the rise in market power will give rise to [a] lower degree of adjustment of the variable inputs, including labor, for the same [productivity] shock process. The rise in market power thus can rationalize the decrease in labor reallocation across firms, even if the observed shocks to firm productivity [have] remained constant."[33]

Gustavo Grullon, Yelena Larkin, and Roni Michaely echo De Loecker et al.'s data and analysis on increasing market power, stating that such findings "are robust to the inclusion of private firms and factors that account for foreign competition, as well as the use of alternative measures of concentration. Overall, [their] findings suggest that the nature of US product markets has undergone a structural shift that has weakened competition."[34]

Furthermore, undergirding these findings regarding expanded market power are findings of not only rising concentration across firms but also rising concentration in ownership across firms, with a few large shareholders in multiple companies in a given industry.[35] Other related findings include relaxed antitrust enforcement, increased mergers and acquisitions, and other restraints on competition, including increases in occupational licensing by states, the growth of land use restrictions, a greater scope of intellectual property law, and increases in lobbying and political rent seeking.[36]

Additionally, it might be of interest that, in a slightly different analysis of the widening productivity dispersion of high-growth and low-growth firms found by Decker et al., Dan Andrews, Chiara Criscuolo, and Peter N. Gal have proposed that "stalling technological diffusion" may be a possible source of this widening productivity dispersion, theorizing that low-growth firms may be having a difficult time integrating new technologies.[37] However, Decker et al. caution and clarify that "while the diffusion hypothesis could play a role, [their] estimates of [MFP] persistence suggest that the group of 'frontier firms' is sufficiently fluid to somewhat limit the diffusion story's explanatory power. Increased adjustment frictions is an alternative, but not mutually exclusive, explanation."[38]

Income inequality

Escalating income inequality may also be a factor underlying the productivity slowdown, according to Jason Furman and Peter Orszag.[39] Namely, though low productivity growth may be leading to rising inequality, it may also be that rising inequality is reducing productivity growth, by stifling "the ability to harness the talents of potential innovators across the income spectrum." The authors caution, however, that "any plausible magnitude for such an effect would fall well short of explaining the 1.0- to 1.5-percentage-point drop in productivity growth."[40] Furman and Orszag further qualify that rising income inequality and low productivity growth may both "have a common cause, namely that reduced competition and reduced dynamism—in part caused by specific policy changes—have contributed to both issues."[41] Some empirical support for Furman and Orszag's hypothesis that income inequality may be a potential factor in sluggish productivity growth has been offered by Ruchir Agarwal and Patrick Gaulé, who examine income disparities on a global scale and observe that "talented individuals born in low- or middle-income countries are systematically less likely to become knowledge producers."[42]

The debate over innovation possibilities in the 21st century

At this point, it should be noted that a weighty qualifier exists with regard to all the foregoing material regarding the MFP slowdown, on the basis of a notably different perspective on the recent data taken by several economists, such as Robert J. Gordon and John G. Fernald.[43] These authors have hypothesized that a productivity slowdown has not occurred per se in recent years. Rather, they contend that a productivity *reversion* to the "new normal" of lower productivity growth, established in the early 1970s, has occurred.

More specifically, these economists assert that the information technology (IT)-based innovations of recent decades are no match for the world-changing impacts of widespread electricity, the internal combustion engine, and indoor plumbing that emerged in the late 1800s and early 1900s. They claim that productivity growth cannot be expected to sustainably continue on the same high-growth trend that previously had been seen as of the mid-20th century. Furthermore, they regard the productivity speedup of the late 1990s and early 2000s as the true

outlier and the subsequent low productivity growth as merely the expected case in this relatively lower innovation era.

One underlying rationale for this potential story is provided by Joseph A. Tainter.[44] This author offers that, in general, as complexity in a society increases following initial waves of innovation, further innovations become increasingly costly because of diminishing returns. As a result, productivity growth eventually succumbs and recedes below its once torrid pace: "As easier questions are resolved, science moves inevitably to more complex research areas and to larger, costlier organizations," clarifying that "*exponential* growth in the size and costliness of science, in fact, is necessary simply to maintain a *constant* rate of progress." Nicholas Bloom, Charles I. Jones, John Van Reenen, and Michael Webb offer supporting evidence for this view regarding the United States, asserting that given that the number of researchers has risen exponentially over the last century—increasing by 23 times since 1930—it is apparent that producing innovations has become substantially more costly during this period.[45]

However, at the same time, some other economists have a few qualifiers of their own regarding the hypothesis that we have long been in an essentially low-productivity era. Chad Syverson reminds us that productivity slowdowns did occur between the waves of innovation during the late 1800s and early 1900s, as seminal technologies such as electricity and the internal combustion engine emerged.[46] Ana Paula Cusolito and William F. Maloney add that "while this prior diffusion hardly implies that a second IT wave is imminent, it does show that productivity accelerations from general-purpose technologies do not have to be one-off events. Just because their resultant productivity growth sped up in the late 1990s and early 2000s does not mean it cannot speed up again."[47]

To sum up this section, from an economy-wide perspective, we can identify several plausible explanations for the slowdown in MFP growth, including

- declining rates of productivity-enhancing job reallocation,
- rising market power and industry concentration,
- greater restraints on competition,
- growing income inequality,
- the drag from the global financial crisis and Great Recession and its weak recovery,
- diminishing returns to innovation relative to that of the late-19th and early to mid-20th centuries, and
- a historically wavelike tendency of innovations.

It appears likely that the MFP slowdown is coalescing from a combination of these factors, though it may not be possible to place them into an integrated framework or decomposition, given that they address the issue of the MFP slowdown from widely different perspectives—some cyclical, some noncyclical, and some more qualitative in nature than quantitative—and as there may be other factors, which have not yet been discovered. However, these factors do provide us with an overall sense of what may be undergirding the slowdown.

It should also be noted that the story of the MFP slowdown does not end here. In the "Industry-level analysis of the U.S. labor productivity slowdown" section of this article, we will analyze the slowdown from an industry-level perspective, investigating the

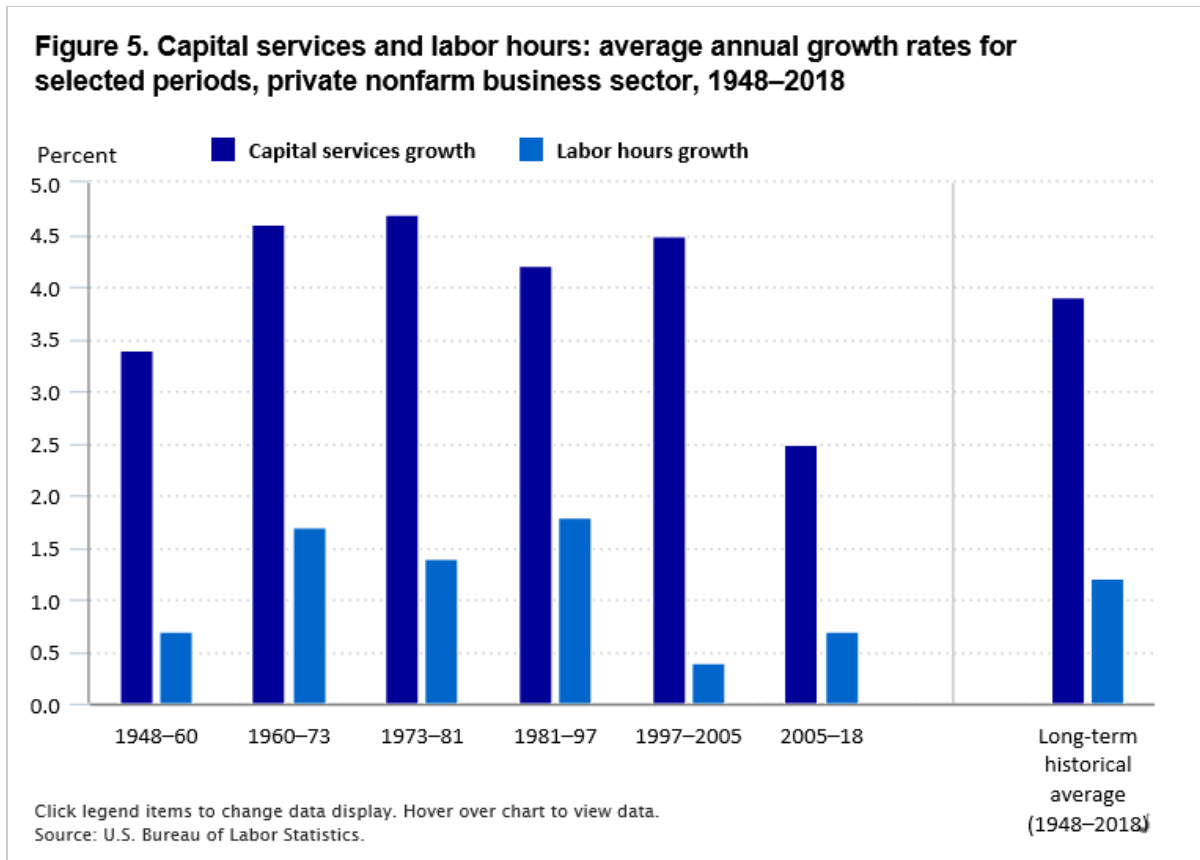- large negative contribution from the computer and electronic products industry,

- large negative contributions from the retail and wholesale trade industries, and

- small negative contributions from most other industries.

The slowdown in the contribution of capital intensity

Alongside the slowdown in MFP growth is the other contributor to the labor productivity slowdown: the contribution of capital intensity. This measure has exhibited an unprecedented variation and, from 2005 to 2018, was cut by nearly half relative to the 1997–2005 speedup period. As noted previously, the contribution of capital intensity grew just 0.7 percent during the 2005–18 slowdown period, which is lower than the 1997–2005 speedup period (1.3 percent) and the historical average rate (0.9 percent). As was also noted, the measure accounts for 34 percent of the labor productivity slowdown relative to that of the speedup period, explains 25 percent of the sluggishness relative to the long-term average percentage rate, and had the lowest growth among all the selected post-WWII periods (see figure 2).[48]

Given that the contribution of capital intensity is calculated as the difference in growth rates between capital and labor inputs, multiplied by the capital cost share, we can determine how much each of these three underlying factors contributed to its slowdown. As shown in figure 5, capital services grew during the slowdown period at a rate of 2.5 percent, which is well below both its rate for the speedup period (4.5 percent) and its long-term average (3.9 percent). Labor hours grew at a rate of 0.7 percent, which lies between its rate for the speedup period (0.4 percent) and its long-term average (1.2 percent). Capital's cost share was 38 percent during the slowdown period, which is higher than during the speedup period (33 percent) and the long-term average rate (34 percent).

Figure 5. Capital services and labor hours: average annual growth rates for selected periods, private nonfarm business sector, 1948–2018
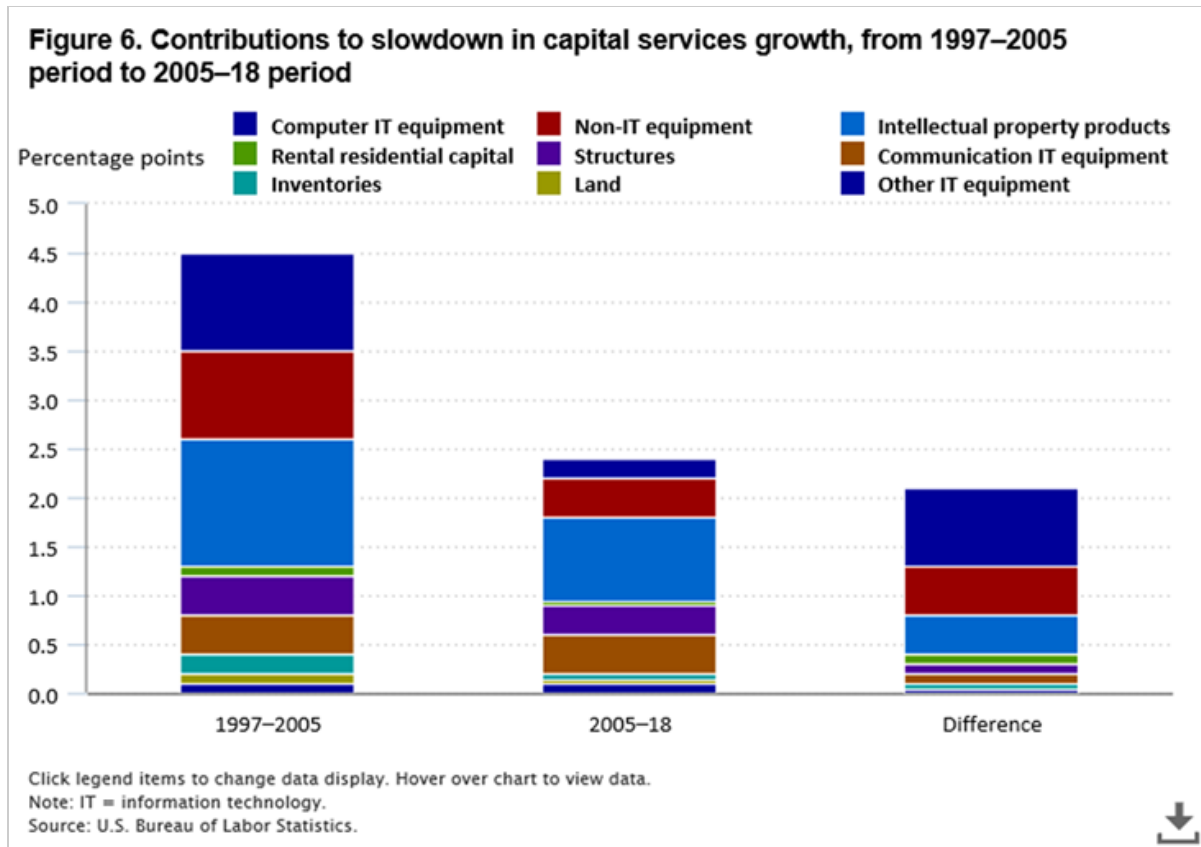
Thus, we can say that it was the combination of a large deceleration in capital services growth with a slight acceleration in labor hours growth that drove down the change in the capital-labor ratio in the slowdown period. This dual effect overwhelmed a slight increase in the capital cost share and diminished the contribution of capital intensity to 0.6 percentage point below what it had been in the speedup period.

At the same time, relative to its long-term trend rate, the sluggishness in the contribution of capital intensity in the slowdown period was comparatively modest—just 0.2 percentage point below its long-term trend rate (see figure 2). Furthermore, the contribution of capital intensity in the slowdown period was not as much of an outlier as it had been during the speedup period, in which it was 0.4 percentage point *above* the long-term trend during these high-growth years. Nonetheless, both periods exhibited rates that were outside the norm. So, a question arises: What led to such a dramatic acceleration in the contribution of capital intensity and then led to a similarly sized deceleration not just back to normal during the slowdown period, but to slightly below the norm?

To answer the first part of this question, we must look back at the capital and labor components of the contribution of capital intensity during the 1981–97 pre-speedup period (see figure 5). What this reveals is that the vast majority of the acceleration in the contribution of capital intensity from the pre-speedup period to the speedup period was not due to capital services growth expanding but to labor hours growth shrinking. While capital services growth sped up slightly, from 4.2 percent to 4.5 percent, labor hours slowed substantially, from 1.8 percent to 0.4 percent. This drop in labor hours growth is not altogether surprising, given that the speedup period contained both the recession of 2001 and the "jobless recovery" of the early 2000s.

So, it can be said that the change in the capital-to-labor ratio—and thereby the contribution of capital intensity—during the speedup period was boosted up to such a high degree from unusually low labor hours growth, with capital services growth lying not far outside the norm. In contrast, for the slowdown period, it was the inverse: most of the slowing in the measure came from unusually low capital services growth, with labor hours growth not far outside the norm.

We can identify the contributions toward the recent slowdown in capital services growth, which are found in the far right stacked bar in figure 6. As previously noted, capital services growth slowed from 4.5 percent to 2.5 percent during the slowdown period. Of this 2.0-percentage-point deceleration, 0.8 percentage point was from a massive slowdown in computer IT equipment, which shrunk from providing a contribution of 1.0 percentage point in the speedup period to just making a 0.2-percentage-point contribution in the slowdown period. The other two notable contributors to the slowdown were from non-IT equipment (0.5 percentage point) and intellectual property products (0.4 percentage point). In addition, 0.1-percentage-point contributions were from rental residential capital, structures, communication IT equipment, and inventories.

Figure 6. Contributions to slowdown in capital services growth, from 1997–2005 period to 2005–18 period

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

So, what factors may have undergirded such below-average capital services growth during the slowdown period? As noted earlier, Byrne, Oliner, and Sichel assert that the fragile financial condition of the economy following the Great Recession may have hindered investment during the recovery.[49] Robert E. Hall agrees, stating that "at the end of 2013 [the capital stock] was 13.2 percent below its trend path. The crisis and Great Recession, including amplification mechanisms, appear to be responsible for the shortfall."[50] Also, the work of Ravi Bansal, Mariano Max Croce, Wenxi Liao, and Samuel Rosen indicates specifically that uncertainty during and following the Great Recession may have also played a role and, especially, hurt innovative and productivity-driving firms, observing that "volatility shocks are more disruptive for innovation-oriented firms both in terms of market valuation and contraction in their investments. According to the data, when uncertainty increases, there exists a relative reallocation effect that penalizes investments in R&D-intensive firms, that is, investments that are important to sustain long-term growth."[51]
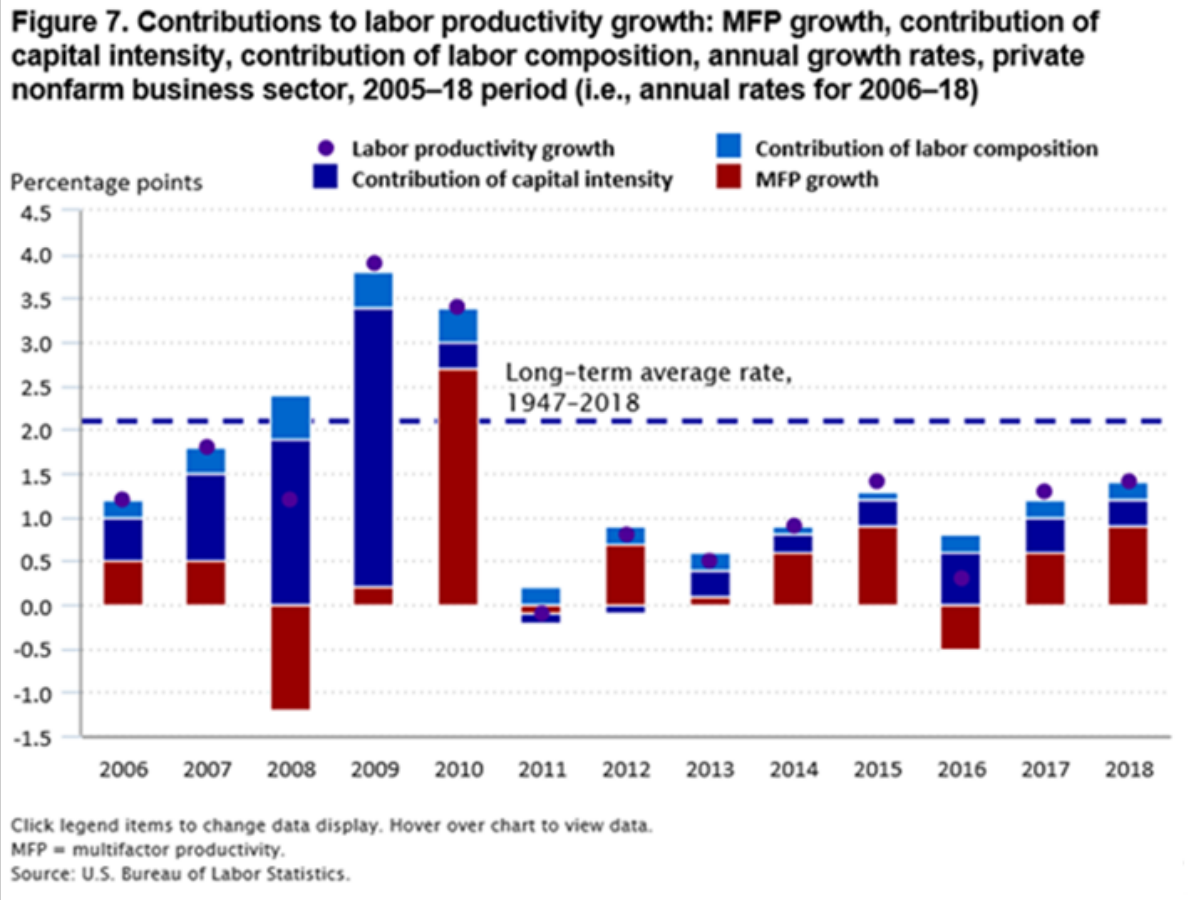
Taking a slightly longer view and analyzing the entire 2005–18 slowdown period, Germán Gutiérrez and Thomas Philippon point out that the U.S. business sector has underinvested relative to "measures of profitability and valuation, particularly Tobin's Q, and that this weakness starts in the early 2000's."[52] In terms of a theoretical underpinning that could explain this phenomenon, the authors specify that although it is possible for firms to underinvest either because of a low Q or despite a high Q, the data do not support the first case. So instead, the authors focus on the latter case, in which they find evidence of three main drivers: "rising intangibles, decreased competition, and changes in corporate governance that encourage payouts instead of investment."[53]

Regarding the rise of intangibles (intellectual property including software, R&D, patents, trademarks, and goodwill) as a share of overall capital investment, Gutiérrez and Philippon estimate that this component "can explain a quarter to a third of the observed investment gap."[54] This is because these assets are both difficult to measure, which may lead to their undercounting, and also "difficult to accumulate, due to higher adjustments costs," leading to "a higher equilibrium value of Q, even if intangibles are correctly measured."[55]

The remainder of the underinvestment likely comes from some combination of decreased competition and changes in corporate governance, according to Gutiérrez and Philippon. Regarding the former, the evidence indicates that "industries with more concentration and more common ownership invest less, even after controlling for current market conditions. Within each industry year, the investment gap is driven by firms that are owned by quasi-indexers and located in industries with more concentration and more common ownership.[56] These firms spend a disproportionate amount of free cash flows buying back their shares."[57] And, in terms of the latter, Gutiérrez and Philippon cite increased shareholder oversight, particularly in guarding against managers' desire to expand capital investments beyond an amount that would be in shareholders' best interests, as well as short-termism, in which "stock-based compensation incentivizes managers to focus on short-term capital gains" via share buybacks rather than making long-term capital investments in their firm.[58]

Annual contributions to the productivity slowdown

In addition to analyzing the labor productivity slowdown from a full-period perspective, as we have done thus far, we can also look at the individual years of the slowdown period itself, to determine how the path of each component developed over time. Figure 7 illustrates how the three series underlying labor productivity growth—MFP growth, the contribution of capital intensity, and the contribution of labor composition—progressed over the course of the slowdown period, from 2005 to 2018.

Figure 7. Contributions to labor productivity growth: MFP growth, contribution of capital intensity, contribution of labor composition, annual growth rates, private nonfarm business sector, 2005–18 period (i.e., annual rates for 2006–18)

In the first year of the slowdown period—2006, which in figure 7 indicates the growth observed from 2005 to 2006, as we are displaying the growth from one year to the next—MFP growth and the contribution of capital intensity not only had the same rate of growth but they were also similarly below their respective long-term rates. A 0.5-percent increase in MFP in 2006 was below its long-term average of 1.1 percent, and a 0.5-percent increase in contribution of capital intensity was below its long-term average of 0.9 percent. However, over the next few years, it is remarkable how each of these measures diverged as the Great Recession began and wore on. In each year from 2006 through 2009, the contribution of capital intensity incrementally expanded, reaching a series-high 3.2 percent in 2009 and composing the majority of the above-trend labor productivity growth in that year. This acceleration in the contribution of capital intensity was due to an outsized decline in underlying labor hours; although capital services growth slowed from 3.7 percent in 2006 to 1.1 percent in 2009, labor hours growth plummeted from 2.3 percent in 2006 to –7.2 percent in 2009. This difference in magnitudes makes sense, given that it is easier for businesses to lay off workers than sell capital equipment during a recession.

At the same time as the contribution of capital intensity was expanding during the Great Recession, MFP growth was stagnating. After posting a below-average value in 2007 (0.5 percent), the measure sank well into negative territory in 2008 and then edged barely back into positive territory in 2009. What may have brought about this below-average MFP growth during the Great Recession? John G. Fernald notes that "Factor utilization . . . 'explains' the plunge and rebound in [MFP]. Utilization fell below the range of historical experience in the recession, [and] then recovered rapidly during the recovery."[59] Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry cite uncertainty, noting that "plant-level [MFP] shocks increased in

variance by 76 percent during the recession" and that "bad times, defined in terms of low growth rates of output, are also uncertain times in terms of increased cross-sectional dispersion of [MFP] shocks."[60] In addition, Lucia Foster, Cheryl Grim, and John Haltiwanger claim that the Great Recession was an atypically detrimental recession in terms of its effect on MFP growth, in that there was not the usual boost from increased reallocation, which most recessions offer; the authors show that "the intensity of reallocation fell rather than rose and the reallocation that did occur was less productivity enhancing than in prior recessions."[61]

Following the end of the Great Recession in 2009, we observe another year of strong labor productivity growth (3.4 percent) in 2010, though with a sudden reversal in the underlying contributions: MFP growth and the contribution of capital intensity were virtually mirror images of one another in those 2 years, with MFP growth accelerating from 0.2 percent in 2009 to 2.7 percent in 2010 and the contribution of capital intensity slowing from 3.2 percent in 2009 to 0.3 percent in 2010. What might have brought about this result? As noted earlier, Fernald cites increased utilization as a potential explanation for the rebound in MFP growth during this early phase of the recovery.[62] Also, it is often the case when emerging from a recession—especially one as severe as the Great Recession—that firms may still remain apprehensive about hiring until the recovery begins in earnest, with a lag in employment recovery relative to output recovery. This was the case with the recovery from the Great Recession, with labor hours falling for an additional quarter more than output, in the third quarter of 2009, and then remaining virtually flat for two additional quarters—while output was simultaneously rising—and hours not beginning to recover in earnest until the second quarter of 2010.[63] This lag in the labor hours recovery contributed to both the dramatic increase of MFP growth in 2010 as well as the diminution of the contribution of capital intensity in that year.[64]

In the years following 2010, labor productivity growth stagnated, with an average rate of just 0.8 percent—well below the 2.1-percent long-term average rate since 1947. These early years of the recovery were particularly weak for the underlying measures, with the contribution of capital intensity receding into slightly negative territory in both 2011 and 2012, and MFP posting a decline in 2011 and a 0.1-percent increase in 2013. More recently, the situation has improved somewhat compared with those early years, with labor productivity rising above 1.0 percent during 3 of the last 4 years, though still remaining below the long-term historical trend and thus extending the productivity slowdown for over a decade.[65]

A noteworthy fact about the growth during the historically weak recovery period—specifically, after 2011—is how consistent and steady the growth rates have been during these years, with labor productivity growth staying within a historically narrow range of between 0.3 percent and 1.4 percent. This phenomenon reflects the combination of a steadily weak output recovery and a consistently moderate labor hours recovery. And, in terms of labor productivity growth's underlying series, MFP growth was below average during these years as weak output growth was paired with moderate combined-input growth from labor and capital. And, the contribution of capital intensity was also low throughout these years, as moderately increasing labor hours were paired with similarly moderate capital services growth.
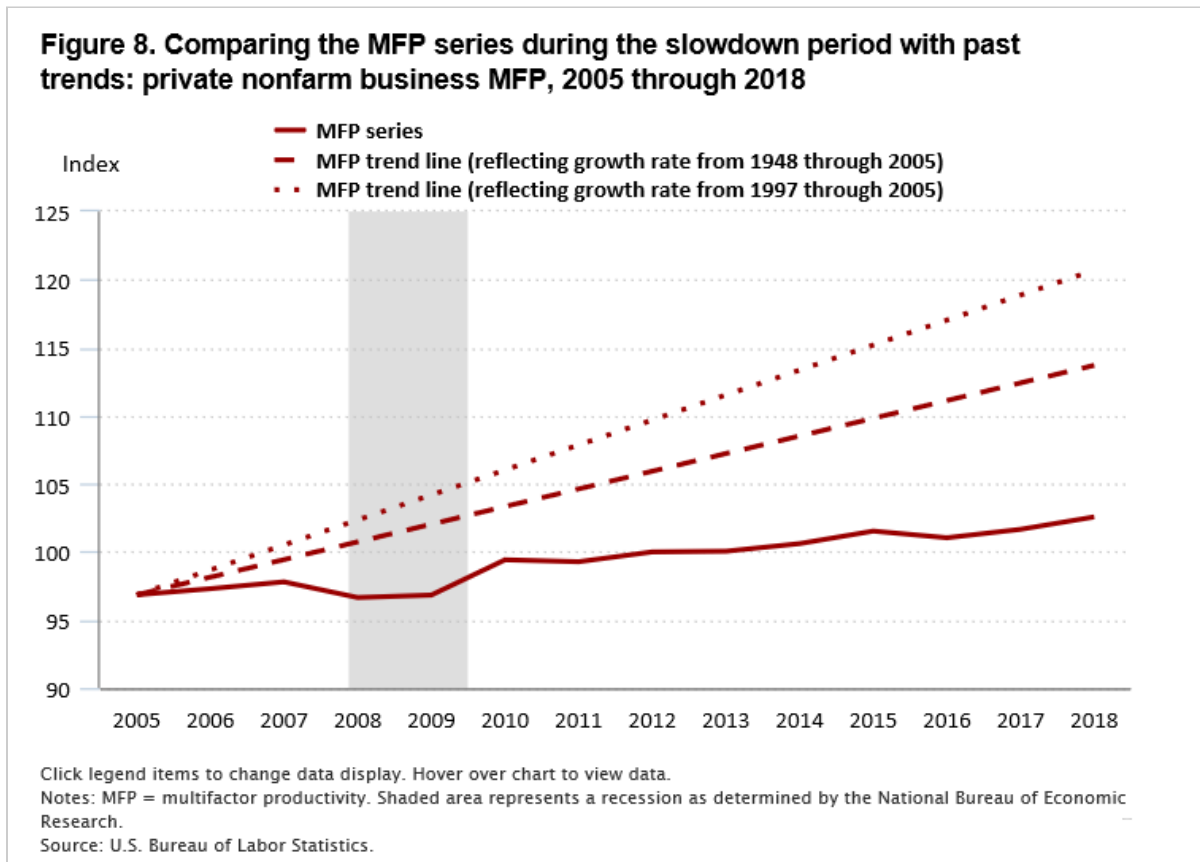
Also, note that, in contrast to its typical steadiness during the full periods (see figure 2), the contribution of labor composition exhibited some within-period variation during the slowdown period from 2005 to 2018 (see figure 7) and thereby slightly amplified the swings in labor productivity during this period. Specifically, the contribution of labor composition rose at above-average rates during the Great Recession, with a high of 0.5 percent in 2008, and then grew at below-average rates since, of 0.1 or 0.2 percent. These shifts in the contribution of labor composition over the slowdown period—particularly within the post-2007 business cycle—are not surprising, given that lower-

skilled or less-experienced workers are more likely to be laid off during recessions and then may gradually be reintegrated into the workforce as a recovery progresses.[66]
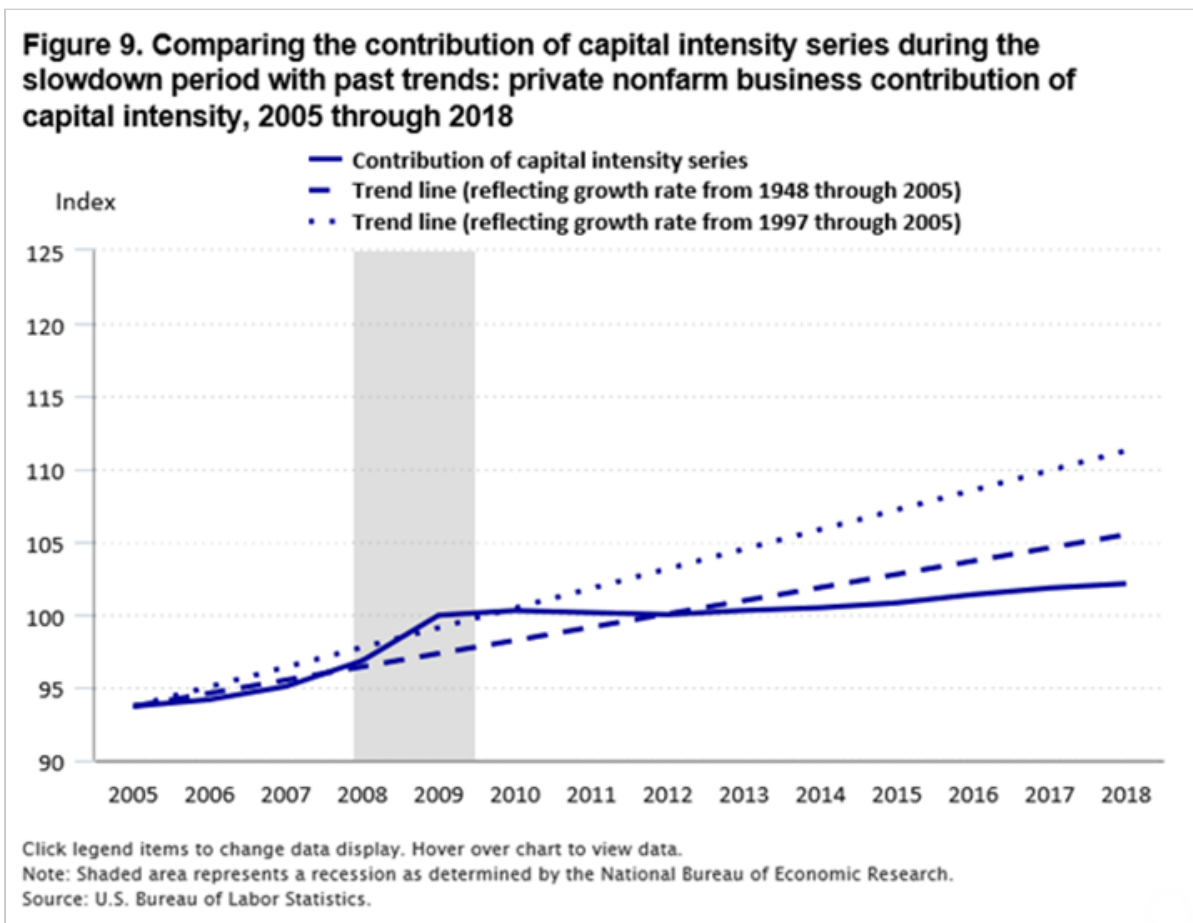
Trend comparisons for MFP and the contribution of capital intensity

In addition to determining the extent to which each component series contributed to labor productivity growth within each year of the slowdown period, we can also determine how each of these component series tracked during these years compared with its own previously observed growth trends, particularly its speedup period trend rate (1997–2005) and its long-term trend rate (1948–2005). This analysis allows us to see how much the movements after 2005 either stayed on course with, or diverged from, the growth trends that had been previously and historically observed for these series. We will do this for the two contributors to the slowdown: MFP growth and the contribution of capital intensity.

The path of the MFP index series over the slowdown period, as well as the long-term trend rate and the speedup period trend rate for this series, is shown in figure 8. We see that in 2006 and 2007, MFP was already falling slightly behind both the speedup period and long-term period trend lines, and this gap widened substantially during the recession. Then, in 2010, 1 year of high MFP growth partially shrank the gap, but subsequently, from 2011 to 2018, below-average MFP growth widened the gap substantially. Strikingly, we can see from the figure that every annual movement from 2005 to 2018 other than the gain in 2010 acted to widen the gap, either with a negative annual change or a positive change that was slower than the historical trend.

Figure 8. Comparing the MFP series during the slowdown period with past trends: private nonfarm business MFP, 2005 through 2018

Click legend items to change data display. Hover over chart to view data.
Notes: MFP = multifactor productivity. Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

The contribution of capital intensity index series took a much different path through the slowdown period, as is illustrated by figure 9. As just discussed, the contribution of capital intensity took an inverse path relative to MFP during the Great Recession, with an increase in 2008 and a surge in 2009 that sent the series above both the long-term and speedup period trend lines by 2009. However, the subsequent stagnation in the series, with virtually no growth over the next 4 years, submerged it below both trend lines by 2013 and widened the gap from that point onward. At the same time, note that this cumulative gap in the growth of the contribution of capital intensity was, as of 2018, less than that of MFP, which is cumulatively much further behind its historical trends (see figure 8).

Figure 9. Comparing the contribution of capital intensity series during the slowdown period with past trends: private nonfarm business contribution of capital intensity, 2005 through 2018

Click legend items to change data display. Hover over chart to view data.
Note: Shaded area represents a recession as determined by the National Bureau of Economic Research.
Source: U.S. Bureau of Labor Statistics.

Dollar and time costs of the productivity slowdown

In addition to analyzing the productivity slowdown in terms of percent changes, as we have done up to this point, we may also wonder: how much of a real-world impact did the labor productivity slowdown have in terms of dollars of lower output or hours of lost leisure time, for participants of the U.S. economy? Before undertaking this analysis, we should clarify that it is not possible to know in what combination the additional productivity growth—if growth had continued at average historical rates following 2005, rather than at the low rates we have observed—would have translated into greater output and additional leisure time. However, these calculations give us a sense of the losses that have been incurred by Americans, due to the productivity slowdown.

We will first estimate the loss from the productivity slowdown by assuming that the additional productivity growth (representing the difference between recorded productivity growth and what productivity growth would have been if

rates had continued at average historical rates following 2005) would have all contributed to producing additional output, and we will then make an analysis assuming that the added productivity growth would have all contributed to accumulating additional leisure time.

To estimate the total loss in output, we first ascertain how much total output was produced during the slowdown period. This amount is $175.2 trillion. We can then calculate a hypothetical total output, incorporating a consistent 2.3-percent labor productivity growth rate.[67] This amount is $186.1 trillion. So, the difference in output, representing the loss due to the productivity slowdown, is $10.9 trillion. Furthermore, as there were, on average, 114.6 million workers in the nonfarm business sector during these years, this result translates into a loss of $95,000 in output per worker.[68]

The productivity slowdown can also be framed in terms of lost time, specifically the lost leisure time that could have been available for workers to consume if a slowdown had not occurred.[69] To do this analysis, we first add up all hours worked during the slowdown period, which comes to 2.51 trillion. Then, assuming that labor productivity grew at a consistent rate of 2.3 percent throughout the period and that all of the effect of the added productivity growth contributed to a reduction in hours worked, this calculation would yield a total of 2.37 trillion hypothetical hours worked. Then, subtracting this hypothetical hours figure from the actual hours figure (2.51 trillion) would result in a hypothetical gain of leisure time of 138.5 billion hours, or 1,209 per worker. And, given that the average weekly hours during these years would have been 30.7 in this case,[70] this would result in a total of 39.4 weeks of leave lost because of the slowdown in productivity growth during this period or, correspondingly, 3.0 additional weeks of leave per year.

Did the productivity slowdown progress differently in U.S. regions?

Before we move on to the industry-level analysis, it might be of interest to some readers to know that there was some variation in how the economy-wide productivity slowdown progressed between states and regions of the United States. BLS publishes data on U.S. state and regional labor productivity for 2007 forward, and we can use these data to illustrate how the slowdown progressed in these areas for this portion of the post-2005 slowdown period.*

Box figure 1 tracks the progress of the labor productivity series for the private nonfarm sector in the four U.S. regions during the 2007–18 period. What this figure shows is that the Western United States outperformed the other three regions (Midwest, South, and Northeast) during these years. The West not only outperformed the other regions throughout and following the Great Recession, but its outperformance expanded during the recovery.

Box figure 1. Comparing labor productivity in U.S. regions: output per hour, West, Midwest, South, and Northeast regions, private nonfarm sector, 2007–18
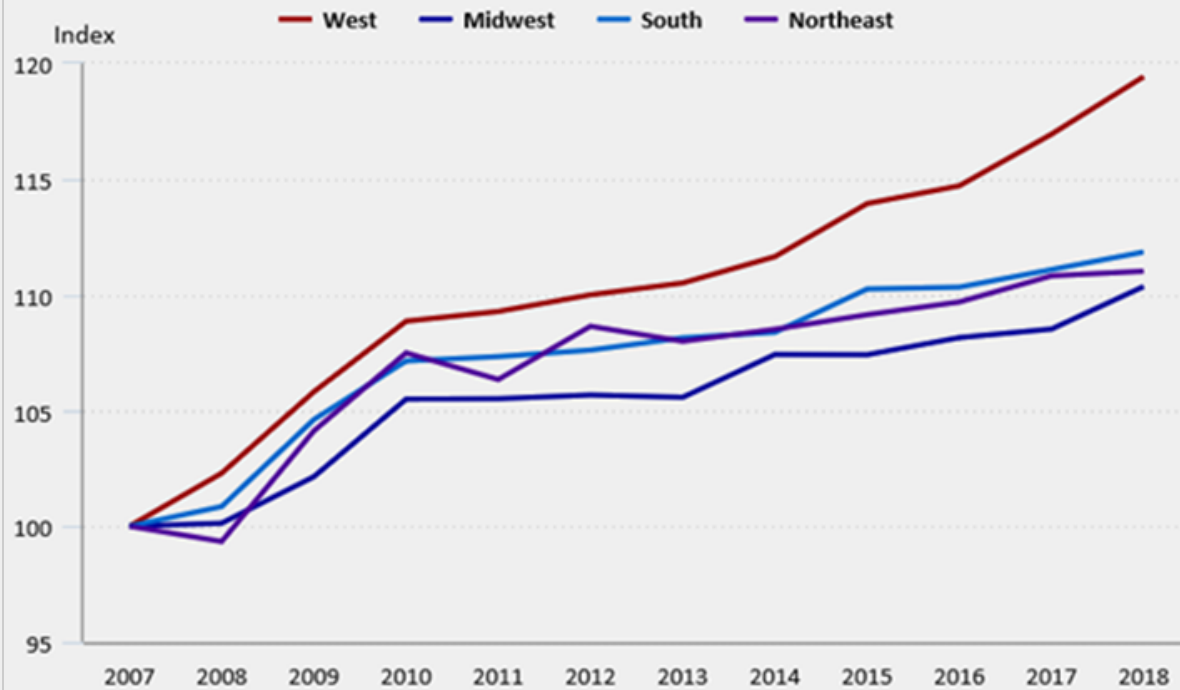

Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

The West realized a 1.6 percent rate of labor productivity growth during these years, whereas the Midwest, South, and Northeast posted rates of 0.9 percent, 1.0 percent, and 1.0 percent, respectively. Given that the national rate for these years is 1.3 percent, we can see that, if not for the faster growth of the West during these years, the overall U.S. slowdown would have been around 0.3 percentage point lower than the already low rate observed during this period. This insight may offer researchers a potential avenue for future research, to look into what potential factors may have contributed to the somewhat higher productivity growth in the Western United States as compared with the rest of the country. At the same time, it is still the case that all four regions posted below-average growth, compared with the national long-term average rate since 1948 of 2.2 percent.

As for the individual states, box figure 2 reveals that, in addition to having the highest overall growth, the Western United States also had the most outliers, both on the high and low end (the figure shows the top six and bottom six state productivity growth rates). Washington, California, Oregon, and Colorado had four of the top six rates, which buoyed the overall growth of the West and more than counterbalanced very low growth in Arizona and Alaska and a decline in Wyoming. North Dakota took the top state rate, at 3.1 percent, and was the only state that had a growth rate that placed above the long-term average U.S. rate of 2.2 percent. As noted by YiLi Chien and Paul Morris, North Dakota underwent an oil boom during these years, "bringing a large influx of capital" to the state, with the authors concluding that the above-average labor productivity growth in this state "is very likely associated with the boom of the oil industry."** (The turnaround

in this industry, as well as the results of other notable industries, will be discussed in detail in the next section.)

Box figure 2. Labor productivity growth: selected U.S. states, private nonfarm sector, average annual growth rates, 2007–18 period
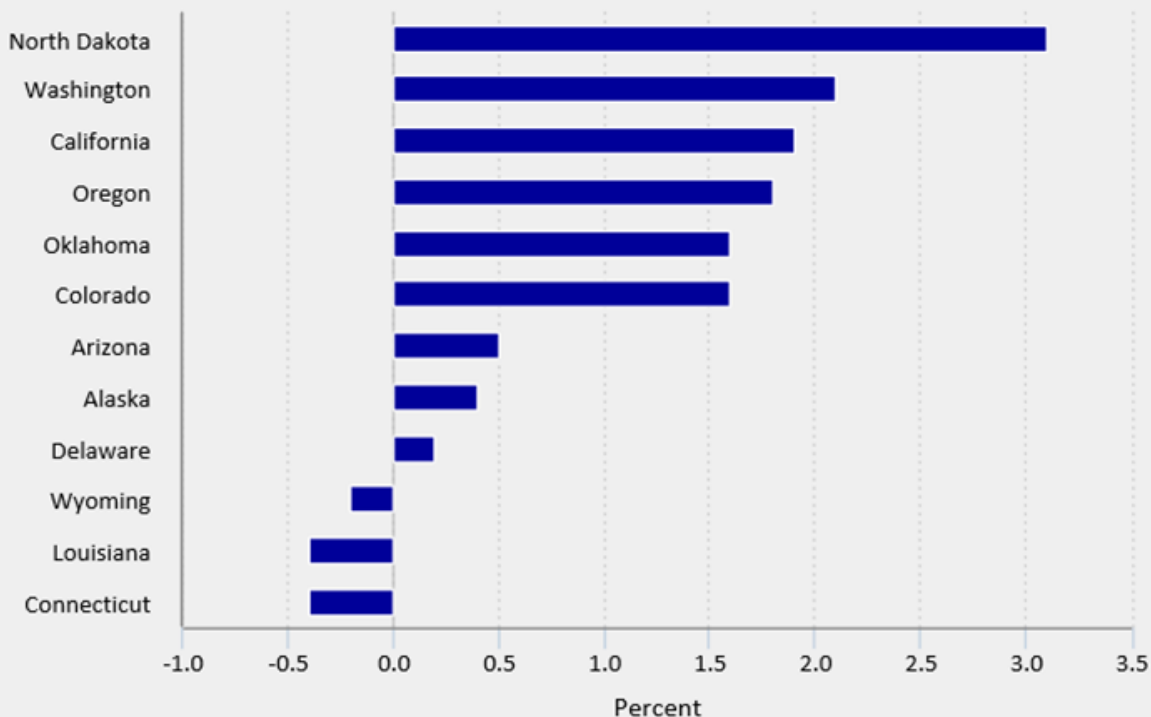
Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics.

* For more information on BLS state-level productivity data, see Sabrina Wulff Pabilonia, Michael W. Jadoo, Bhavani Khandrika, Jennifer Price, and James D. Mildenberger, "BLS publishes experimental state-level labor productivity measures," *Monthly Labor Review*, June 2019, https://www.bls.gov/opub/mlr/2019/article/pdf/bls-publishes-experimental-state-level-labor-productivity-measures.pdf. In addition, the data can be found at the BLS state productivity home page at https://www.bls.gov/lpc/state-productivity.htm.

** YiLi Chien and Paul Morris, "Slowdown in productivity: state vs. national trend," The Regional Economist (Federal Reserve Bank of St. Louis, first quarter 2017).

Industry-level analysis of the U.S. labor productivity slowdown

Up to this point, we have analyzed the U.S. labor productivity slowdown from an economy-wide perspective. We can also examine more detailed, industry-level data to extend our analysis and identify the industries that contributed the most to the slowdown in productivity growth from the 1997–2005 period to the 2005–18 period. In

breaking out the U.S. labor productivity slowdown into its industry-level components, we will investigate the two series contributing to the slowdown—MFP growth and the contribution of capital intensity—to determine which industries contributed most to the economy-wide slowdown via these two factors. This can be done by calculating Domar-weighted growth rates of these two factors, for all the industries that make up the private nonfarm business sector.[71] First, we will be looking at the industry contributions to the MFP slowdown, followed by the industry contributions to the slowdown in the contribution of capital intensity.

Industry contributions to the MFP slowdown

When we break out the economy-wide MFP slowdown into its components, it is instructive for us to disaggregate the data into both sectors and industries, because each of these approaches provides a slightly different perspective and can deepen our understanding of the issue. As such, we will first look at contributions at the 14-sector level and then at contributions at the 60-industry level.[72]

The sector-level contributions to the economy-wide MFP slowdown are shown in figure 10, along with the corresponding contributions of the overall goods sector and services sector. First, we notice that the goods sector made a contribution (0.63 percentage point [ppt.]) to the MFP slowdown that is larger than the contribution made by the services sector (0.49 ppt.). The fact that the goods sector made a larger contribution is at first glance somewhat surprising, given that it is much smaller than the services sector and produces just 25 percent of private nonfarm business output. The potency of the contribution from the goods-producing sector can be isolated to the manufacturing sector and, most prominently, durable goods manufacturing, which itself contributed 0.51 ppt., or nearly half the overall contributions to the private nonfarm business sector (1.11 ppt.).[73] When the durable goods sector contribution is combined with the nondurable goods sector contribution, the total manufacturing sector accounted for 65 percent of the private nonfarm business MFP slowdown.
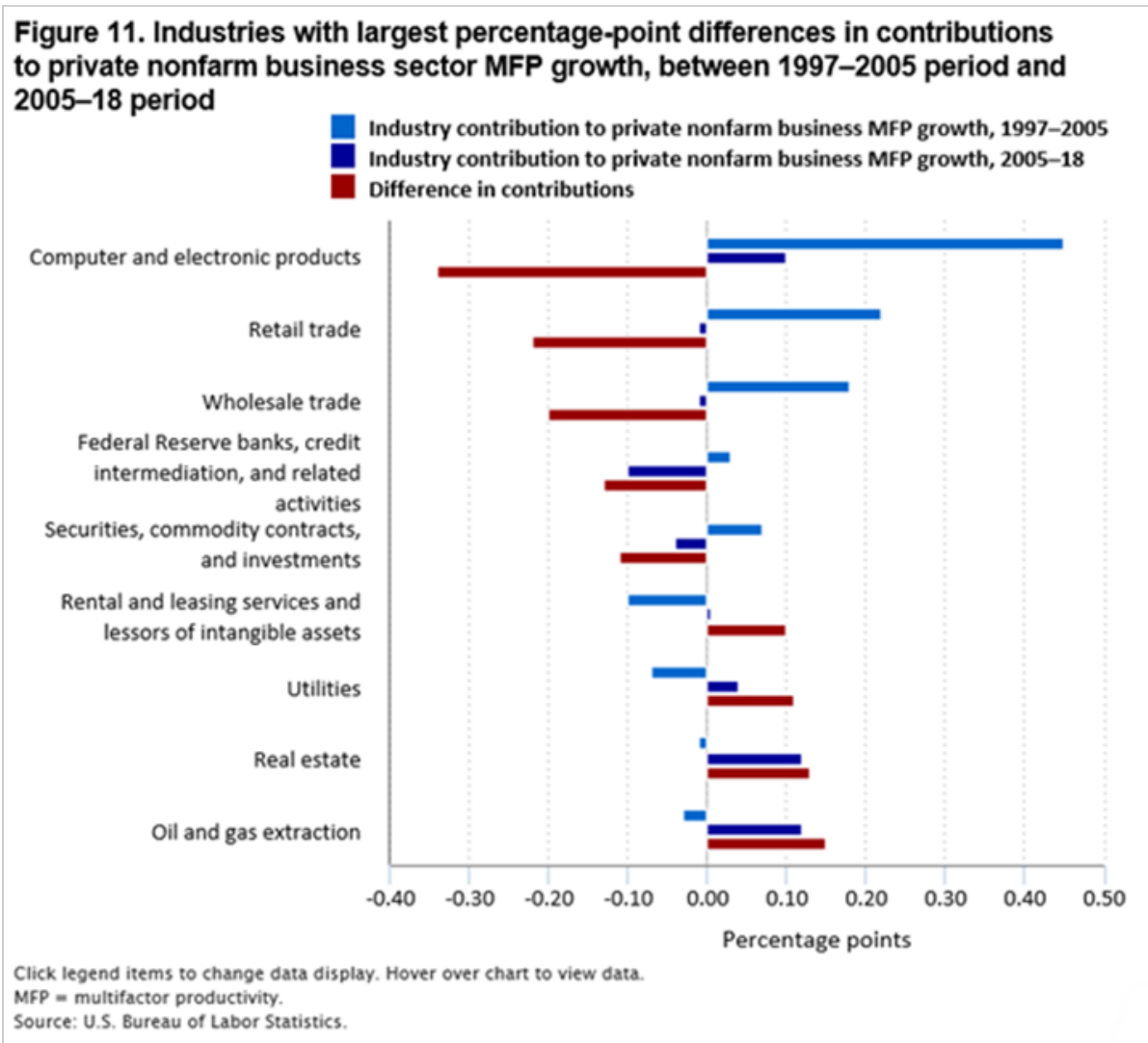
Figure 10. Contributions of sectors to slowdown in MFP growth in private nonfarm business sector, from 1997–2005 period to 2005–18 period
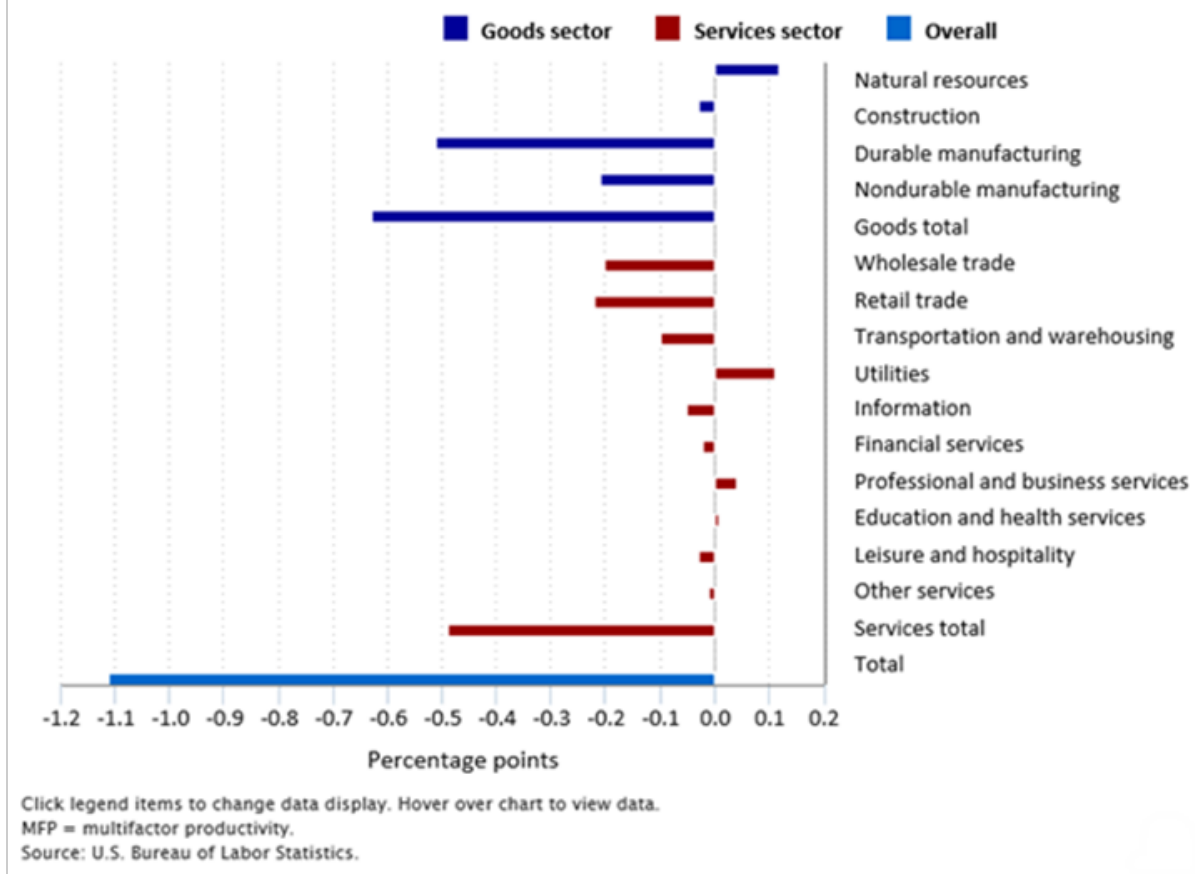
For the services sector, the largest contributors to the slowdown were retail trade (0.22 ppt.), wholesale trade (0.20 ppt.), and transportation and warehousing (0.10 ppt.). These three sectors together more than explain the overall contribution to the MFP slowdown coming from the services sector (0.49 ppt.), as they made a combined contribution of 0.52 ppt. It is also worth pointing out that two sectors had notable productivity speedups, especially considering their small size—natural resources and mining (0.12 ppt.) and utilities (0.11 ppt.); natural resources and mining makes up just 2.7 percent of the private nonfarm business sector, and utilities makes up just 2.3 percent. Also, though the financial services sector and the professional and business services sector made relatively flat contributions to the slowdown, there were a number of industries within those two sectors that made notable contributions to the slowdown (these industries are discussed below). However, when these industry-level slowdowns are summed with speedups in other industries within the same sector, only a small overall contribution to the slowdown remains for these two sectors.

The industry-level contributions to the economy-wide MFP slowdown are shown in figure 11, specifically for a selection of the largest contributions (positive or negative). (Also, see appendix, table 1, for a full list of industry contributions to the MFP slowdown and industry contributions to the slowdown in the contribution of capital intensity, in the private nonfarm business sector.) It is not surprising that the largest industry-level contributor to the slowdown (computer and electronic products) is from within the largest sector-level contributor to the slowdown (durable manufacturing). Computer and electronic products incurred a massive slowdown, with a contribution to

MFP growth of 0.45 ppt. from 1997 to 2005 dwindling to 0.10 ppt. from 2005 to 2018. A startling fact about this industry is that, even after having the largest MFP slowdown among all the industries, computer and electronic products still possessed a positive contribution and, in fact, the third-largest contribution among all 60 industries during the 2005–18 period, behind only real estate (0.12 ppt.) and oil and gas extraction (0.12 ppt.).[74] The MFP slowdown in computer and electronic products represents 66 percent of the slowdown in durable manufacturing and 31 percent of the slowdown in the private nonfarm business sector.

Figure 11. Industries with largest percentage-point differences in contributions to private nonfarm business sector MFP growth, between 1997–2005 period and 2005–18 period

Numerous researchers have focused on the historic acceleration and subsequent moderation in the growth of the computer and electronic products industry as being a major driver of the economy-wide productivity slowdown. Many had been aware of the remarkable growth of computer and electronic products in the late 1990s and early 2000s, with Stephen D. Oliner and Daniel E. Sichel observing that the trend at that time was already apparent and strong. They note that "the multifactor productivity contributions from computer and semiconductor producers moved up sharply during 1996–99, reaching 0.26 and 0.39 percentage point per year, respectively," and that "the increases largely reflect the faster decline in the relative prices of computers and semiconductors . . . and the rising output shares of computer and semiconductor producers."[75] David M. Byrne and Carol Corrado also

emphasize the rapidly declining prices during those years: "the greatest computer [price] declines, and the greatest gap, occurs [sic] in the 1994 to 2000 period, when [microprocessor unit] prices were falling especially fast."[76]

Then, however, during the mid-2000s, the pace of microprocessor unit price declines began to stall.[77] And, more recently, price declines have shrunk in size even more, with Byrne and Corrado citing "*extremely* small declines of late, after having gradually lost force since 2004."[78] At the same time, Byrne, Oliner, and Sichel argue that there has not been a slowdown in technological progress that the paltry price declines might indicate, clarifying that "technical progress in the semiconductor industry has continued to proceed at a rapid pace."[79] So, might there be some mismeasurement occurring with regard to these prices? Yes, there was, argue David M. Byrne, John G. Fernald, and Marshall B. Reinsdorf, who say that in "IT-related hardware and software . . . mismeasurement is sizable."[80]

However, these authors also caution that this measurement was not a new issue in the mid-2000s and that IT price mismeasurement was evident even before the productivity slowdown, clarifying that they "find no evidence that the biases have gotten worse since the early 2000s."[81] In fact, they point out that, if one were to consistently adjust for mismeasurement across time, it would actually make the labor productivity slowdown worse, given that "mismeasurement of IT hardware [was] significant prior to the slowdown," and also given that "the domestic production of these products has fallen, [and thus] the quantitative effect [of mismeasurement] on productivity was larger in the 1995–2004 period than since, despite mismeasurement worsening for some types of IT."[82]

Chad Syverson concurs with Byrne, Fernald, and Reinsdorf, agreeing that mismeasurement is unlikely to be a driver of the productivity slowdown,[83] and observes that "the productivity slowdown has occurred in dozens of countries, and its size is unrelated to measures of the countries' consumption or production intensities of information and communication technologies [ICTs]," further contending that "if measurement problems were to account for even a modest share of this missing output, the properly measured output and productivity growth rates of industries that produce and service ICTs would have to have been multiples of their measured growth in the data."

So, what factors might have led to the slowdown in the productivity growth of IT goods? Decker et al. point out that a dwindling of the "marginal employment growth response of businesses to idiosyncratic productivity draws . . . is especially large in the high-tech sector, with the responsiveness of young firms in the post-2000 period only about half (manufacturing) to two thirds (economy-wide) of the peak responsiveness in the 1990s." The authors conclude that "the timing of reallocation and responsiveness patterns in high-tech is consistent with the timing of the productivity slowdown, which evidence indicates was driven by ICT-producing and using industries."[84]

The waning responsiveness of young high-tech firms that is cited by Decker et al. could potentially be explained, at least in part, by the work of Mordecai Kurz, who finds growing market power in the IT sector, which may be stifling the entry and growth of young firms.[85] Kurz reports that "declining or slow growing firms with broadly distributed ownership have been replaced by IT based firms with highly concentrated ownership," and that "IT innovations enable and accelerate the erection of barriers to entry and once erected, IT facilitates maintenance of restraints on competition."[86] Foster, Grim, Haltiwanger, and Wolf also reference the concentration within high-tech industries, noting that, in contrast to the late 1990s, when "the productivity surge in the high-tech sectors [had] a high contribution of increased within-industry covariance between market share and productivity . . . the productivity slowdown in the post-2000 period in high tech is due to both a decrease in within-firm productivity growth but also

a decrease in this covariance."[87] Titan Alon, David Berger, Robert Dent, and Benjamin Pugsley offer further evidence to support this finding, noting that "over the last three decades, the U.S. business sector has experienced a collapse in the rate of new startups alongside an enormous reallocation of economic activity from entrants and young firms to older incumbents."[88] Alon et al. clarify that this finding is not just particular to high-tech industries but is "widespread across industries and geographic markets,"[89] so that while this could be relevant in high-tech industries, it could also help explain the productivity slowdowns in other industries. And, more generally, Grullon et al. observe that "more than 75% of U.S. industries have experienced an increase in concentration levels over the last two decades."[90]

Beyond the concentration argument, David Autor, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu propose another potential contributor to the productivity slowdown in IT, particularly in IT-intensive manufacturing industries, which is a reduction in U.S. innovation caused by increased foreign competition from China.[91] The authors observe that "despite accounting for less than one-tenth of U.S. private non-farm employment, U.S. manufacturing still generates more than two-thirds of U.S. R&D spending and corporate patents," and claim that "increased imports from China ramped up competitive pressure on publicly listed U.S. firms" and that "this increase in competitive pressure caused U.S. firms to *decrease* their output of innovations as measured by patent grants."[92] However, this phenomenon is more long-term and may not apply only or specifically to the 2005–18 slowdown period, although it could potentially be a contributor.

Now, shifting gears a bit, let us look beyond the large slowdown in the computer and electronic products industry and examine some other sizable contributors, located in the trade sector. Specifically, retail trade and wholesale trade contributed 0.22 ppt. and 0.20 ppt., respectively, to the MFP slowdown, and when combined, they actually exceed the size of the slowdown in computer and electronic products. These trade sectors transitioned from making sizeable positive contributions to MFP growth during the speedup period to being virtually flat during the slowdown period.

Might the size and coincidence of these slowdowns in the trade sectors and those in the IT-related industries be related? The answer is likely yes, according to several researchers, at least regarding the retail trade sector. Lucia Foster, John Haltiwanger, and C. J. Krizan assert that "the retail trade sector underwent a massive restructuring and reallocation of economic activity in the 1990s. Retail businesses changed their ways of doing business with intensive adoption of advanced information technology, including everything from improvements in inventory control to the introduction and widespread use of scanners and rapid credit card processing technologies. Structural changes occurred with entering establishments from large multiunit national firms displacing single-establishment firms."[93]

These changes were widely seen in the economy, with the proliferation of "big box" stores such as Wal-Mart, Home Depot, and Best Buy that swept the country and displaced many small businesses that could not compete with the advanced IT that these corporations were using.[94] Emek Basker argues that the effect was particularly powerful regarding Wal-Mart, "because Wal-Mart competes with retailers across many categories, including general merchandise stores, drugstores, apparel stores, and grocery stores."[95]
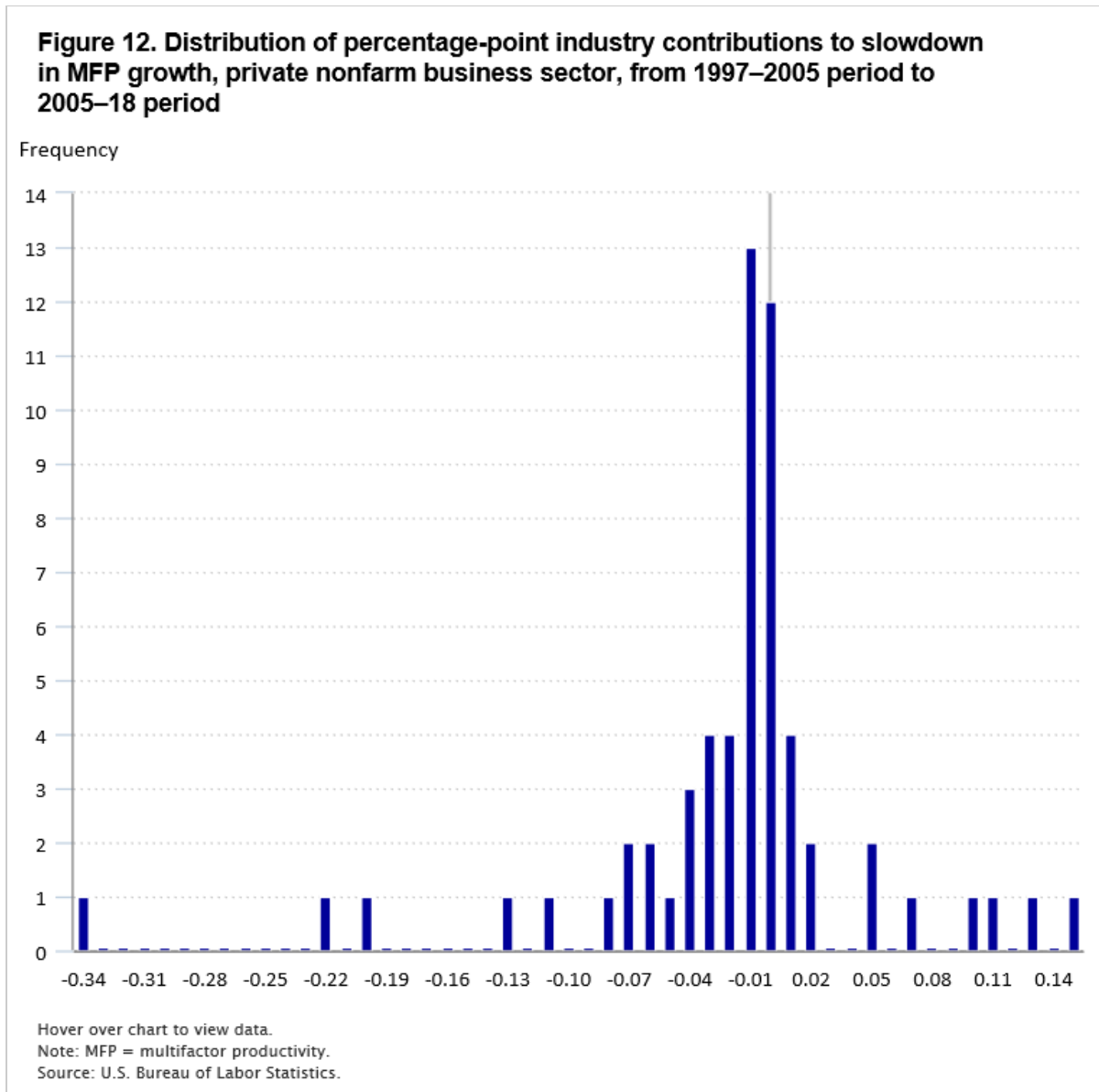
Moreover, Foster et al. contend that, in their firm-level analysis of the dispersion and reallocation dynamics within the retail trade sector, "virtually all of the productivity growth in the retail trade sector over the 1990s is accounted for by more productive entering establishments displacing much less productive exiting establishments," which

they clarify is due to a combination of "selection effects and post-entry learning effects. That is, establishments that enter might be immediately more productive than the establishments they are displacing, or it may take time for the productivity gap to widen or emerge."[96]

Also, looking beyond the trade sectors and the computer and electronic products industry, we see several other notable downward contributors to the slowdown in MFP growth: Federal Reserve banks and credit intermediation (0.13 ppt.), securities, commodity contracts, and investments (0.11 ppt.), and broadcasting and telecommunications (0.08 ppt.).
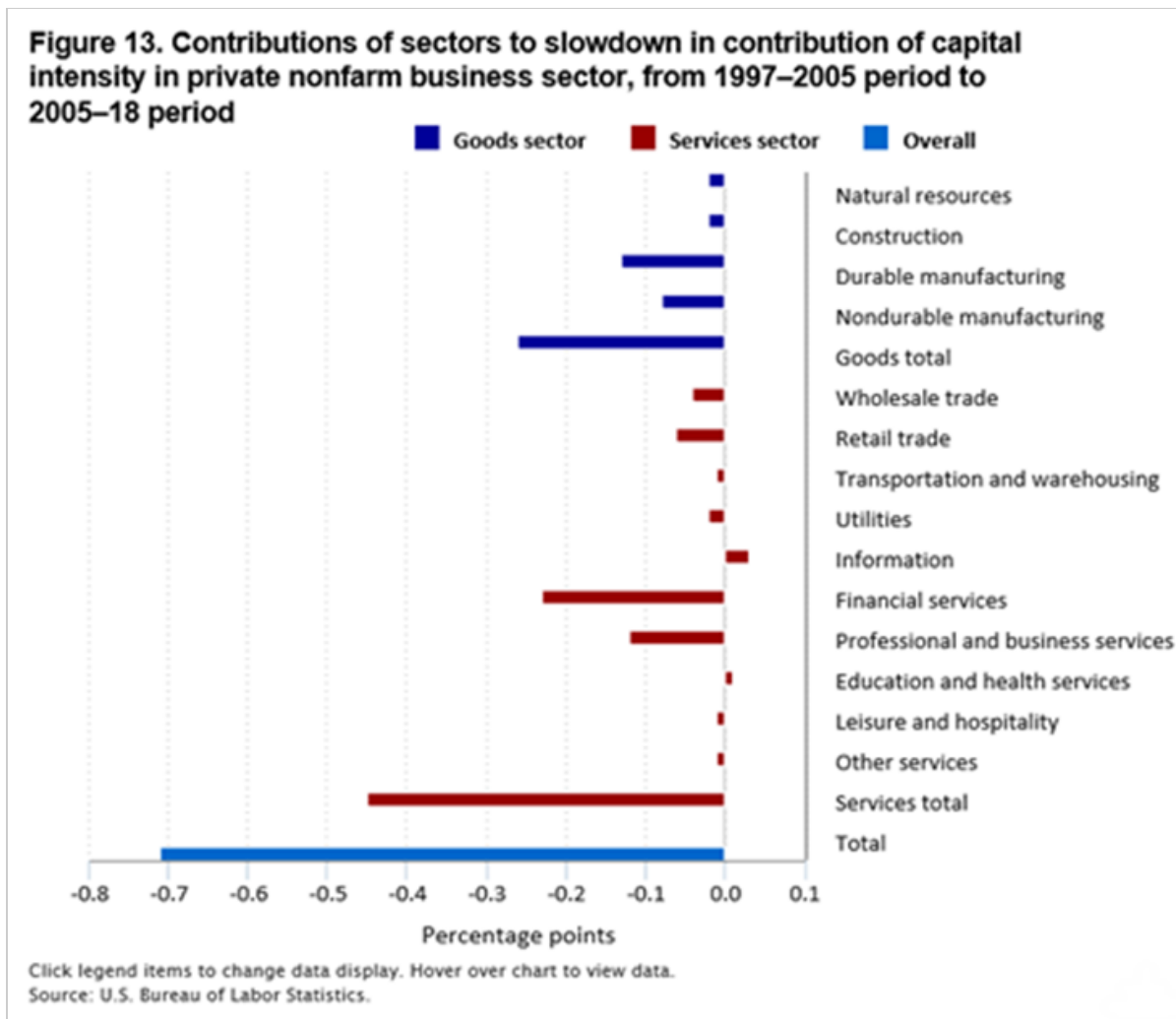
In addition, a few industries worked in the opposite direction of the overall slowdown and posted accelerations in MFP growth during this period: oil and gas extraction (0.15 ppt.), real estate (0.13 ppt.), utilities (0.11 ppt.), and rental and leasing services and lessors of intangible assets (0.10 ppt.). The increase for the oil and gas extraction industry during the slowdown period catapulted it from being the 56th ranked industry among all 60 industries as of the speedup period, to a rank of 2 as of the slowdown period. This astounding turnaround, note David Popp, Jacquelyn Pless, Ivan Haščič, and Nick Johnstone, may reflect technological innovations in this industry, in which the "rise of hydrofracturing lowered fossil fuel prices so much that natural gas is now the primary fuel for electricity generation in the U.S."[97] The real estate industry had a similarly extraordinary turnaround in its MFP growth contribution, rising from a rank of 51 to 1.

Given that there were both negative and positive contributors to the MFP slowdown, with sizable contributors on both sides, it may be of interest to look at the distribution of these industry-level data (see figure 12). The first item to note is that there were more large negative contributors (those slowing by 0.05 ppt or more) than large positive contributors (those expediting by 0.05 ppt. or more). The net slowdown of the large-contributing industries was 0.74 ppt., with 1.39 ppts. of the large contributors on the negative side and 0.66 ppt. on the positive side. The second item worth noting is that the remaining 0.38 ppt. of the slowdown comes from the small contributors— specifically, many more small negative contributors existed than small positive contributors. While just 6 industries contributed between 0.01 and 0.04 ppt., *24* contributed between –0.01 and –0.04 ppt. These negative small contributors had a combined slowdown of 0.44 ppt., greatly outweighing the positive small contributors, which had a combined speedup of just 0.08 ppt. So, we can say that, although there were numerous large contributors to the overall slowdown on the negative side (particularly computer and electronic products and the trade industries), there was also a widespread, generalized negative slide among the vast majority of the industries, which also helped bring about the historic decline in MFP growth.

Figure 12. Distribution of percentage-point industry contributions to slowdown in MFP growth, private nonfarm business sector, from 1997–2005 period to 2005–18 period

Hover over chart to view data.
Note: MFP = multifactor productivity.
Source: U.S. Bureau of Labor Statistics.

Industry contributions to the slowdown of the contribution of capital intensity

The slowdown in the contribution of capital intensity came more from the services sector than the goods sector. This finding can be seen in figure 13, which shows the sector-level contributions to the overall slowdown in the contribution of capital intensity. The services sector accounted for 0.45 ppt. of the overall slowdown in this measure, with the goods sector contributing 0.26 ppt.

Figure 13. Contributions of sectors to slowdown in contribution of capital intensity in private nonfarm business sector, from 1997–2005 period to 2005–18 period

The largest sector contribution to the slowdown was from the financial services sector, with a contribution of 0.23 ppt. There were also noteworthy contributions from professional and business services (0.12 ppt.), durable manufacturing (0.13 ppt.), and nondurable manufacturing (0.08 ppt.).

Figure 14 shows the large industry-level contributions to the slowdown in the contribution of capital intensity, including those with contributions of 0.05 or greater in either direction, positive or negative. Five of the six large contributors were negative and were of similar sizes. The four largest outliers each had slowdowns of 0.06 ppt.; these were rental and leasing services and lessors of intangible assets, retail trade, computer and electronic products, and insurance carriers and related activities. Miscellaneous professional, scientific, and technical services slowed by 0.05 ppt. The broadcasting and telecommunications industry had a speedup of 0.05 ppt.

Figure 14. Industries with largest differences in contributions to private nonfarm business contribution of capital intensity, between 1997–2005 period and 2005–18 period

- ■ Industry contribution to private nonfarm business contribution of capital intensity, 1997–2005
- ■ Industry contribution to private nonfarm business contribution of capital intensity, 2005–18
- ■ Difference in contributions

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

The distribution of industry contributions to the economy-wide slowdown in the contribution of capital intensity skews heavily negative (see figure 15), with 31 negative contributors and just 4 positive contributors. At the same time, the net contribution to the slowdown from the large contributors (0.24 ppt.) was lower than the net contribution from the small contributors (0.46 ppt.), indicating that there were relatively few outliers with regard to the slowdown in the contribution of capital intensity, especially when compared with the case of the MFP slowdown, which had some substantial outliers. To summarize this section, the bulk of the slowdown in the economy-wide contribution of capital intensity came from relatively small slowdowns in this measure that occurred in a substantial number of industries.

Figure 15. Distribution of percentage-point industry contributions to slowdown in contribution of capital intensity, private nonfarm business sector, from 1997–2005 period to 2005–18 period

Frequency

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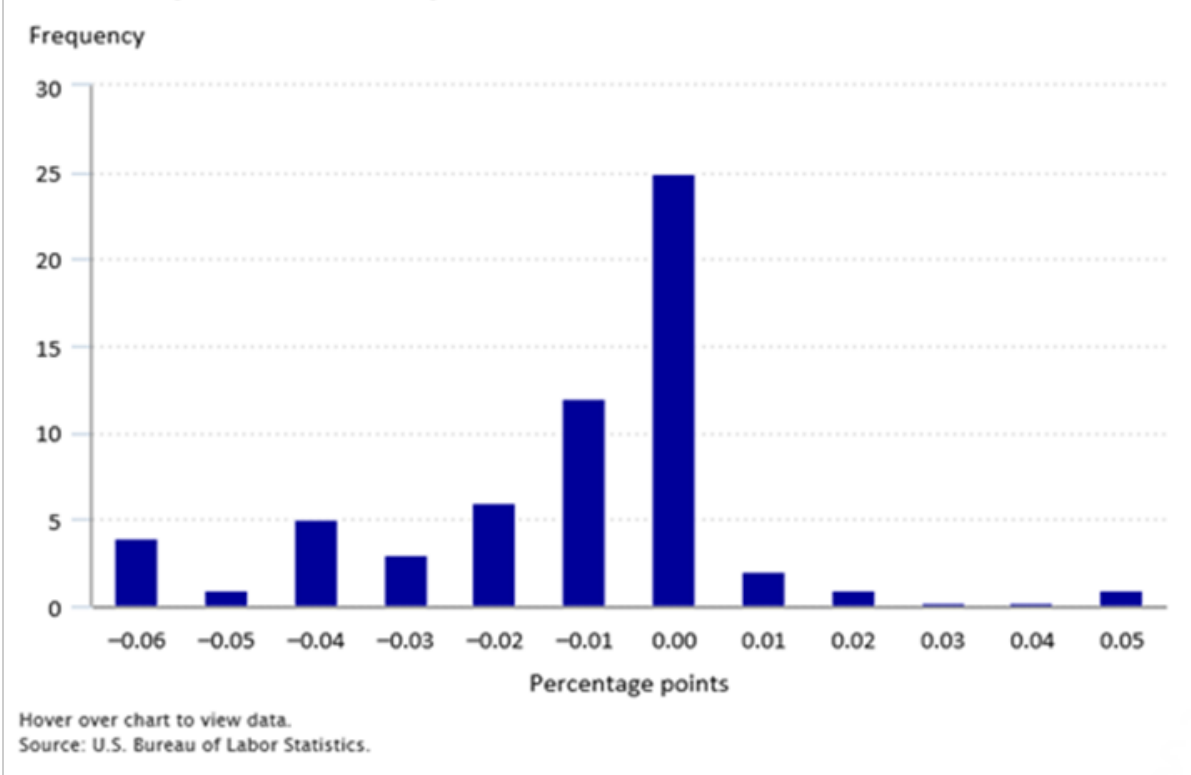
Conclusion

At this point, we have a general understanding of the many factors—at both the economy-wide and industry levels—which may underlie the productivity slowdown since the mid-2000s. However, some questions remain, perhaps the most central one being: Is the U.S. economy now, as some researchers have suggested, in an intermittent lull in between waves of high growth, or, as others contend, in a "new normal" of lower growth that has resulted from fundamentally diminished returns to innovation? The answer is not known at the moment, and only time—and additional data in our time series—will tell us.

At the same time, one thing that we can say for certain about our present situation is that the productivity slowdown of the past decade and a half has left the U.S. economy in a weaker position—yielding a sizable loss of potential output during these years—and perhaps even more importantly, it has also left the economy in a weaker position going forward. This is because the productivity slowdown has resulted in a lower base of output from which to grow onward from here, relative to the more elevated starting position that the economy would instead now have if productivity had continued to grow at the long-term historical trend after 2005.

Thus, it will be important for participants of the U.S. economy to keep an eye on productivity data in coming years, to determine whether the slowdown since 2005 simply represented a periodic variation in trend, which can be explained from recent cyclical and noncyclical factors, as some observers have claimed, or whether it comes to be seen as a continuation of the low-growth economy of the last few decades of the 20th century. BLS productivity

data, including labor productivity, multifactor productivity, and capital and labor data, at both the economy-wide and industry levels, will continue to shed light on this issue.

Appendix. Full list of industry contributions

Table 1. Industry contributions to slowdown in private nonfarm business labor productivity growth, from 1997–2005 period to 2005–18 period, percentage points

Industry	Contributions from industry MFP growth			Contributions from industry contribution of capital intensity		
	1997–2005 period	2005–18 period	Difference	1997–2005 period	2005–18 period	Difference
Forestry, fishing, and related activities	0.011	–0.001	–0.012	0.002	0.002	0.001
Oil and gas extraction	–0.029	0.122	0.15	0.004	–0.035	–0.039
Mining, except oil and gas	0.014	–0.020	–0.034	0	0.014	0.014
Support activities for mining	–0.004	0.016	0.02	–0.004	–0.001	0.003
Utilities	–0.067	0.042	0.109	0.044	0.029	–0.015
Construction	–0.091	–0.122	–0.031	0.036	0.014	–0.023
Food and beverage and tobacco products	0.019	–0.020	–0.039	0.022	–0.001	–0.023
Textile mills and textile product mills	0.007	–0.001	–0.008	0.004	0.001	–0.004
Apparel and leather and applied products	0	–0.002	–0.002	0.007	0	–0.007
Wood products	0.001	0.004	0.003	0.002	0.001	–0.001
Paper products	0.003	0	–0.004	0.01	0.003	–0.007
Printing and related support activities	0.022	0.009	–0.013	0.006	0.003	–0.003
Petroleum and coal products	0.019	–0.021	–0.040	0.014	0.018	0.004
Chemical products	–0.001	–0.075	–0.074	0.103	0.071	–0.032
Plastics and rubber products	0.027	–0.002	–0.028	0.016	0.002	–0.014
Nonmetallic mineral products	0.003	–0.004	–0.006	0.005	0.003	–0.002
Primary metal products	0.027	0.004	–0.023	0.004	0.004	0.001
Fabricated metal products	0.007	–0.015	–0.022	0.014	0.006	–0.007
Machinery	0.027	–0.004	–0.030	0.023	0.007	–0.016
Computer and electronic products	0.445	0.104	–0.341	0.09	0.032	–0.058
Electrical equipment, appliances, and components	0.008	0.003	–0.006	0.009	0.003	–0.006
Motor vehicles, bodies and trailers, and parts	0.076	0.001	–0.074	0.037	0.001	–0.036
Other transportation equipment	0.009	0.015	0.006	0.01	0.009	–0.001
Furniture and related products	0	–0.003	–0.002	0.004	0.002	–0.002
Miscellaneous manufacturing	0.023	0.006	–0.017	0.012	0.007	–0.005
Wholesale trade	0.181	–0.015	–0.196	0.1	0.059	–0.041
Retail trade	0.216	–0.007	–0.223	0.099	0.041	–0.058
Air transportation	0.042	0.033	–0.009	0.009	0.005	–0.004
Rail transportation	0.014	0	–0.014	0.003	0.003	0
Water transportation	–0.005	0.008	0.012	–0.003	0.001	0.004
Truck transportation	–0.008	–0.007	0.001	0.007	0.008	0
Transit and ground passenger transportation	0.003	–0.003	–0.007	0.003	–0.001	–0.004
Pipeline transportation	0.009	0.007	–0.002	0.004	0.005	0.001
Other transportation and support activities	0.029	–0.035	–0.065	0.001	–0.004	–0.005
Warehousing and storage	0.015	–0.003	–0.017	–0.001	–0.002	–0.001

See footnotes at end of table.

Table 1. Industry contributions to slowdown in private nonfarm business labor productivity growth, from 1997–2005 period to 2005–18 period, percentage points

Industry	Contributions from industry MFP growth			Contributions from industry contribution of capital intensity		
	1997–2005 period	2005–18 period	Difference	1997–2005 period	2005–18 period	Difference
Publishing industries, except internet (includes software)	–0.006	0.042	0.048	0.073	0.053	–0.020
Motion picture and sound recording industries	0.025	0.021	–0.004	0.018	0.005	–0.012
Broadcasting and telecommunications	0.121	0.044	–0.077	0.125	0.173	0.048
Data processing, internet publishing, and other information services	0.027	0.015	–0.013	0.046	0.063	0.017
Federal reserve banks, credit intermediation, and related activities	0.03	–0.096	–0.126	0.112	0.071	–0.041
Securities, commodity contracts, and other financial investments and related activities	0.069	–0.042	–0.111	0.011	0.003	–0.009
Insurance carriers and related activities	0.05	0.046	–0.004	0.073	0.018	–0.055
Funds, trusts, and other financial vehicles	0.008	–0.003	–0.011	0.006	–0.020	–0.026
Real estate	–0.009	0.124	0.133	0.022	–0.015	–0.037
Rental and leasing services and lessors of intangible assets	–0.098	–0.002	0.095	0.117	0.057	–0.061
Legal services	0.006	–0.033	–0.039	0.012	0.006	–0.006
Miscellaneous professional, scientific, and technical services	–0.052	0.02	0.072	0.078	0.026	–0.052
Computer systems design and related services	0.047	0.095	0.048	0.019	–0.006	–0.024
Management of companies and enterprises	0.002	0.023	0.021	0.008	–0.003	–0.011
Administrative and support services	0.08	0.023	–0.057	0.046	0.019	–0.026
Waste management and remediation services	0.007	–0.003	–0.010	–0.002	–0.001	0.002
Educational services	–0.015	–0.007	0.008	–0.005	0.002	0.007
Ambulatory health care services	0.035	0.034	–0.002	0.004	0.002	–0.002
Hospitals and nursing and residential care facilities	–0.011	–0.015	–0.003	0.009	0.011	0.003
Social assistance	0.005	–0.003	–0.008	0	0	–0.001
Performing arts, spectator sports, museums, and related activities	0.006	0.011	0.005	0.005	0.002	–0.003
Amusements, gambling, and recreation industries	–0.014	0	0.014	0.006	0.004	–0.002
Accommodation	0.007	0.006	–0.001	0.015	0.008	–0.007
Food services and drinking places	0.041	–0.007	–0.048	–0.006	–0.008	–0.001
Other services, except government	–0.023	–0.032	–0.009	0.009	0.003	–0.005

Note: MFP = multifactor productivity.

Source: U.S. Bureau of Labor Statistics.

NOTES

[1] The overall estimated output loss figure ($10.9 trillion) represents the difference between (1) the sum of annual real output amounts in the nonfarm business sector from 2006 to 2018 and (2) the sum of annual real output amounts during this period assuming that labor productivity had continued to grow at the same long-term average rate observed from 1947 to 2005 and that all of the additional gains in labor productivity contributed to higher output rather than higher nonwork time. For more information on the estimation of this figure, as well as an example in which the additional gains in labor productivity contributed to higher nonwork time rather than higher output, see the section "Dollar and time costs of the productivity slowdown" in this article. Also, note that the loss for the entire U.S economy is likely sizably greater than the presented output loss figure. However, because we cannot measure the productivity of the noncovered sectors that represent the difference (including general government, nonprofit institutions, and private households, which include owner-occupied housing), since the output data for these sectors are not suitable for productivity measurement, we can only estimate what the effect would have been for the 76 percent of the U.S. economy covered by the nonfarm business sector. Also note that the estimated output loss per worker figure ($95,000) does not represent the loss in compensation per worker due to the slowdown, which would have been sizably less than that figure, given that only a portion of output accrues to workers as compensation for their labor. For more information on this aspect, see Michael D. Giandrea and Shawn A. Sprague, "Estimating the U.S. labor share," *Monthly Labor Review*, February 2017, https://www.bls.gov/opub/mlr/2017/article/estimating-the-us-labor-share.htm.

[2] See figure 2 of Martin Neil Baily and Nicholas Montalbano, "Why is U.S. productivity growth so slow? Possible explanations and policy responses," Hutchins Center Working Paper 22 (Washington, DC: Brookings Institution, September 2016), p. 4. Baily and Montalbano provide an excellent overview of the productivity slowdown and also offer potential policy responses. In addition, other overviews of the slowdown include Alexander Murray, "What explains the post-2004 U.S. productivity slowdown?" *International Productivity Monitor*, no. 34, Spring 2018, p. 81–109; and Emily Moss, Ryan Nunn, and Jay Shambaugh, "The slowdown in productivity growth and policies that can restore it," *The Hamilton Project* (Washington, DC: Brookings Institution, June 2020).

[3] In Dale W. Jorgenson, Mun S. Ho, and Kevin J. Stiroh, "A retrospective look at the U.S. productivity growth resurgence," *Journal of Economic Perspectives*, no. 1, vol. 22, Winter 2008, p. 4, the authors offer an anecdote illustrating the changed perspective during this period: "in just four years, from 1997 to 2001, the Congressional Budget Office more than doubled its ten-year projection of nonfarm business productivity growth from 1.2 to 2.7 percent!"

[4] All percent changes in this article, unless otherwise noted, refer to average annual percent changes.

[5] Although labor productivity growth theoretically provides a foundation for potential gains in worker compensation, it has historically been the case that commensurate gains in worker compensation do not necessarily accompany gains in labor productivity. Since the early 1970s, real hourly compensation growth has lagged far behind labor productivity growth. For more information, see 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.

[6] There are two main ways of dividing time periods when one is doing a historical productivity analysis such as the one in this article: using business cycles or using variation in trends that are apparent in the data. For the present article, I use variation in trends to define the speedup period (1997–2005) and the slowdown period (2005–18). I selected these two periods because they correspond to the periods that are generally discussed in the literature on this issue and because it is apparent from the data that the question at hand ("What were the sources of the slowdown?") could not be addressed by operating strictly within the macroeconomic business cycle framework. One reason for this is that the industry-level sources of the slowdown exhibited their own trends that did not necessarily fit within the economy-wide business cycles. Another reason is that although using either a cyclical or trend approach for the slowdown period made little difference (because the business cycle that began in 2007 began just 2 years following the beginning

of the trend-based period [2005]), for the speedup period, it appeared to be preferable to use a trend-based approach. This preference was due to the fact that using the business-cycle break (in 2001) would have split the widely cited speedup period (1997–2005) roughly in half, disallowing for a one-to-one comparison of a speedup and slowdown period. If a business cycle approach had been taken instead, then the comparison would have been between two speedup periods (1990–2001 and 2001–07) and one slowdown period (2007–18), as parts of each of those two preceding periods contain a portion of the speedup in the trend, and the industry-level and broad-based changes in the economy during the speedup period from 1997 to 2005 would have been split into two separate periods. It is notable that this disjuncture between business cycles and trend-based periods in terms of the current productivity slowdown did not occur with the last major productivity slowdown, in the 1970s. This widely cited slowdown, which was apparent in the data beginning in 1973, represented both a business cycle break and a clear demarcation between extended periods of high growth (before 1973) and low growth (after 1973). This result contrasts the present slowdown, the period selection of which was not as clear-cut. As for defining the periods since 1947 that occurred before the speedup period (1997–2005), I use a grouped business cycle approach (by grouping adjacent business cycles with similar trends) to make the interperiod comparisons in the figures more concise and make the broad trends over the past 70 years easier to absorb. The fact that the last major productivity slowdown (in the 1970s) had a match between business cycle breaks and trend-period breaks makes the 1948–1997 period somewhat easier to break up into periods. Also, for a strictly business cycle analysis of the present slowdown, see Shawn Sprague, "Below trend: the U.S. productivity slowdown since the Great Recession," *Beyond the Numbers: Productivity*, vol. 6, no. 2 (U.S. Bureau of Labor Statistics, January 2017), https://www.bls.gov/opub/btn/volume-6/below-trend-the-us-productivity-slowdown-since-the-great-recession.htm.

7 Multifactor productivity (MFP) data for the U.S. private nonfarm business sector are available on an annual basis, beginning with data for 1948. This sector accounted for approximately 74 percent of the total U.S. economic output (gross domestic product [GDP]) as of 2017. As denoted by the term "business" in the series name, three nonbusiness sectors are excluded from GDP: general government, nonprofit institutions, and private households (including owner-occupied housing). These three sectors are excluded because their output is measured largely with the use of compensation data, which measure an input to production rather than an output from production, thus rendering these sectors inappropriate for productivity measurement. Also, farm sector data are excluded to reduce volatility in the overall measure. And, as denoted by the term "private" in the series name, government enterprises are excluded, because satisfactory capital measures are unavailable for this sector. In addition, note that the term "MFP" is synonymous with "TFP" or total-factor productivity, which is used throughout the economic literature and refers to the same measure. (For more information on this, see the U.S. Bureau of Labor Statistics (BLS) Division of Productivity Research and Program Development Frequently Asked Questions (FAQs) page at https://www.bls.gov/dpr/faqs.htm#Q01). On another note, although for this article we are looking at private nonfarm business MFP growth, which only includes labor and capital as inputs, BLS also publishes other measures of MFP growth, one of which is referred to as KLEMS (K-capital, L-labor, E-energy, M-materials, and S-purchased services), which includes additional inputs as well.

8 Although figure 2 shows a slight shift in the contribution of labor composition (from 0.2 percent to 0.3 percent) from the speedup period to the slowdown period, looking at these data with more precision reveals a trivial shift in the contribution of labor composition during the slowdown, with an upward shift of just 0.01 percentage point, from 0.24 percent in the speedup period to 0.25 percent in the slowdown period.

9 Alistair Dieppe, Neville Francis, and Gene Kindberg-Hanlon observe this phenomenon in both advanced economies and emerging market economies, in the period from 1980 to 2018: "The volatility of labor productivity is largely accounted for by [MFP] across both advanced economies and EMDEs, where [MFP] accounts for 75–80 percent of labor productivity variance. The high proportion of volatility present in [MFP] reflects its role as a residual, explaining all productivity variation not driven by slower-moving developments in the capital stock and human capital." Alistair Dieppe, Neville Francis, and Gene Kindberg-Hanlon, "A tale of two dynamics: exploring productivity and business-cycle drivers of developed and emerging market economies," working paper, July 24, 2020, p. 6.

10 For this article, we are looking at private nonfarm business MFP growth, which only includes labor and capital as inputs. However, BLS also publishes other measures of MFP growth that include other inputs, referred to as KLEMS (capital, labor, energy, materials, and services).

11 See Brian Resnick, "Dark matter, humility, and coming to grips with the unknown," *Vox*, November 25, 2020.

12 From 1929 to 1933, GDP fell by a cumulative 26.3 percent, whereas from 2007 to 2009, GDP fell by a cumulative 2.7 percent. For more information, see National Data, National Income and Product Accounts (NIPA), Table 1.1.6. Real gross domestic product, chained dollars (U.S. Bureau of Economic Analysis).

13 From 1933 to 1940, GDP grew at an average annual rate of 7.2 percent, and from 2009 second quarter to 2018 fourth quarter, GDP grew at an average annual rate of 2.3 percent. NIPA, Table 1.1.6.

14 The U.S. population grew at an average annual rate of 0.7 percent from 1929 to 1940 and from 2007 to 2018. NIPA, Table 7.1 Selected per capita product and income series in current and chained dollars, line 18 (U.S. Bureau of Economic Analysis).

15 Valerie Cerra and Sweta Chaman Saxena, "Growth dynamics: the myth of economic recovery," *American Economic Review*, vol. 98, no. 1, March 2008, pp. 439–57; Carmen M. Reinhart and Kenneth S. Rogoff, *This Time is Different: Eight Centuries of Financial Folly* (Princeton, NJ: Princeton University Press, 2009); and Carmen M. Reinhart and Vincent R. Reinhart, "After the fall," Working Paper 16334 (Cambridge, MA: National Bureau of Economic Research, September 2010).

16 International Monetary Fund, *World Economic Outlook, October 2009: Sustaining the Recovery* (Washington: International Monetary Fund, 2009), p. 125.

17 Daisuke Ikeda and Takushi Kurozumi, "Slow post-financial crisis recovery and monetary policy," Working Paper 347 (Federal Reserve Bank of Dallas Globalization Institute, October 2018), p. 4. As noted in endnote 7, in this article, I use MFP to refer to multifactor productivity, although others in the literature refer to the measure as TFP or total factor productivity. These acronyms and names refer to the same measure. For more information, see the BLS Division of Productivity Research and Program Development FAQ page at https://www.bls.gov/dpr/faqs.htm#Q01.

18 These changes in demographics "include, most prominently, the demographic shifts of the surge of women into the labor force in the 1970s–1990s and, more recently, the baby boom[ers] beginning to retire." James H. Stock and Mark W. Watson, "Why has GDP growth been so slow to recover?" (draft paper presented at the Boston Federal Reserve's conference, "The elusive 'great recovery': causes and implications for future business cycle dynamics," October 2016), p. 1.

19 Ray C. Fair, "Explaining the slow U.S. recovery: 2010–2017," Business Economics, vol. 53, no. 4, pp. 184–194, October 2018.

20 Robert E. Hall, "The routes into and out of the zero lower bound," in Proceedings—Economic Policy Symposium—Jackson Hole (Federal Reserve Bank of Kansas City, 2013), p. 3.

21 Robert J. Barro, "The job-filled non-recovery" (Cambridge, MA: Harvard University, September 2016), p. 6.

22 Ikeda and Kurozumi, "Slow post-financial crisis recovery and monetary policy," p. 4.

23 David M. Byrne, Stephen D. Oliner, and Daniel E. Sichel, "Is the information technology revolution over?" *International Productivity Monitor*, vol. 25, Spring 2013, p. 21.

24 Romain Duval, Gee Hee Hong, and Yannick Timmer, "Financial frictions and the great productivity slowdown," Working Paper 17/129 (International Monetary Fund Working Papers, May 2017), p. 1.

25 Duval et al., "Financial frictions and the great productivity slowdown," p. 17. Intangible assets are nonphysical assets such as intellectual property, including software, research and development, patents, trademarks, and goodwill. Germán Gutiérrez and Thomas Philippon, in "Investment-less growth: an empirical investigation," abstract, Working Paper 22897 (Cambridge, MA: National Bureau of Economic Research, December 2016), also cite decreased investment in intangibles; see section (in this article) "The slowdown in the contribution of capital intensity." In addition to having an indirect effect on the MFP growth measure, as noted by Duval et al., a slowdown in intangibles would also have a direct effect on the contribution of capital intensity measure, by explicitly reducing the numerator of the change in the capital-labor ratio. In addition, the fallout from the Great Recession may have also hampered rates of reallocation—the process of moving more resources toward high-productivity firms and away from low productivity firms—according to Lucia Foster, Cheryl Grim, and John Haltiwanger, "Reallocation in the Great Recession: cleansing or not?" abstract, Working Paper 20427 (Cambridge, MA: National Bureau of Economic Research, August 2014). These authors observe faltering rates of reallocation during the Great Recession, which is the inverse of the typical case for recessions, perhaps indicating that the magnitude of this recession adversely affected prospects for productivity growth. Even worse, they state that "the reallocation

that did occur [during the Great Recession] was less productivity enhancing than in prior recessions." Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry also cite weak rates of reallocation, which they claim is undergirded by an increase in uncertainty during recessions, contending that "increased uncertainty also reduces productivity growth because it reduces the degree of reallocation in the economy. Higher uncertainty leads productive plants to pause expanding and unproductive plants to pause contracting, which in the . . . U.S. economy drives much of aggregate productivity growth." Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen J. Terry, "Really uncertain business cycles," Working Paper 18245 (Cambridge, MA: National Bureau of Economic Research, July 2012), p. 1–2.

26 John G. Fernald downplays the importance of the Great Recession in the post-2005 productivity slowdown, claiming that "the Great Recession seem[s] less important than trends related to information technology (IT) that predated the Great Recession." See his paper, "Productivity and potential output before, during, and after the Great Recession," Working Paper 2014–15 (Federal Reserve Bank of San Francisco, June 2014). (Note that the effect of IT-intensive industries on the slowdown will be addressed in the "Industry-level analysis of the U.S. labor productivity slowdown" section of this article.)

27 Ryan A. Decker, John C. Haltiwanger, Ron S. Jarmin, and Javier Miranda, "Changing business dynamism and productivity: shocks vs. responsiveness," Working Paper 24236 (Cambridge, MA: National Bureau of Economic Research, January 2018). Also, in addition to the works cited in this section on the topic of productivity dispersion, note that data on productivity dispersion are now available from BLS and the Census Bureau, via the Collaborative Micro-Productivity Project (CMP), which has developed and published experimental statistics on within-industry dispersion. The public-use statistics (referred to as the Dispersion Statistics on Productivity) developed via this project, were released in fall 2019 and cover all four-digit North American Industry Classification System industries in the manufacturing sector. Restricted-use establishment-level data with microbased estimates of productivity as well as its underlying components (e.g., output and input measures) are also available to qualified researchers on approved projects in secure Federal Statistical Research Data Centers. More information on these data can be obtained at https://www.bls.gov/lpc/productivity-dispersion.htm.

28 Michael Gort and Steven Klepper, "Time paths in the diffusion of product innovations," *Economic Journal*, vol. 92, no. 367, September 1982, pp. 630–653.

29 Decker et al., "Changing business dynamism and productivity."

30 Decker et al., "Changing business dynamism and productivity," p. 27. An in-depth discussion of high-tech industries, and their relationship to the economy-wide productivity slowdown, is in the "Industry-level analysis of the U.S. labor productivity slowdown" section of this article.

31 Ibid.

32 Jan De Loecker, Jan Eeckhout, and Gabriel Unger, "The rise of market power and the macroeconomic implications," working paper, 2018.

33 Ibid., p. 52.

34 Gustavo Grullon, Yelena Larkin, and Roni Michaely, "Are US Industries becoming more concentrated?" abstract, working paper, 2017.

35 Miguel Antón, Florian Ederer, Mireia Giné, and Martin C. Schmalz, "Common ownership, competition, and top management incentives," Finance Working Paper 511/2017 (Brussels: Belgium, European Corporate Governance Institute), February 2018; and José Azar, Sahil Raina, and Martin C. Schmalz, "Ultimate ownership and bank competition," working paper (SSRN, March 17, 2016).

36 John E. Kwoka, Jr. "Mergers, merger control, and remedies: a response to the FTC critique," working paper (SSRN, March 2017); Bruce A. Blonigen and Justin R. Pierce, "Evidence for the effects of mergers on market power and efficiency," Working Paper 22750 (Cambridge, MA: National Bureau of Economic Research, October 2016); Council of Economic Advisers, "Occupational licensing: a framework for policymakers," The White House: Washington, DC, July 2015; Jason Furman, "Barriers to shared growth: the case of land use regulation and economic rents" (remarks at The Urban Institute, November 20, 2015); Jason Furman, "Market concentration —note by Jason Furman" (paper presented at Organisation for Economic Cooperation and Development [OECD], Directorate for

Financial and Enterprise Affairs Competition Committee Hearing on Market Concentration, June 7, 2018); and Brookings Institution, "The productivity puzzle: How can we speed up the growth of the economy?" panel discussion (Washington, DC, September 9, 2016). In addition, Ernest Liu, Atif Mian, and Amir Sufi theorize that the low interest rates of the past decade have helped increase concentration, asserting that "low interest rates encourage market concentration by raising industry leaders' incentive to gain a strategic advantage over followers, and this effect strengthens as the interest rate approaches zero." For more information, see Ernest Liu, Atif Mian, and Amir Sufi, "Low interest rates, market power, and productivity growth" abstract, Working Paper 25505 (Cambridge, MA: National Bureau of Economic Research, August 2019).

37 Dan Andrews, Chiara Criscuolo, and Peter N. Gal, "The global productivity slowdown, technology divergence and public policy: a firm level perspective," Hutchins Center Working Paper 24 (Washington, DC: Brookings Institution, September 2016), https://www.brookings.edu/research/the-global-productivity-slowdown-technology-divergence/, p. 3.

38 Decker et al., "Changing business dynamism and productivity," p. 24. Additionally, there is another widely cited firm-level theory that has been offered to explain the increased productivity dispersion, which is from Adalet McGowan, Andrews, and Millot. Müge Adalet McGowan, Dan Andrews, and Valentine Millot, "Insolvency regimes, zombie firms and capital reallocation," OECD Economics Department Working Papers No. 1399, June 28, 2017. Adalet McGowan et al. remark that the prevalence of so-called "zombie firms," or low-productivity firms that are unable to properly service their debts, have increased in OECD countries since the mid-2000s. The authors hypothesize that the stubborn persistence of these low-growth firms is potentially not only keeping resources from reallocating to high-growth firms, but it is also creating entry barriers and inhibiting the growth of new firms. However, this theory appears not to be relevant specifically for the United States, which, unlike other OECD countries and especially European countries, has actually had a decline in the share of zombie firms in recent years. For more information, see Dan Andrews and Giuseppe Nicoletti, "Confronting the zombies: policies for productivity revival" slide 7, OECD Economic Policy Papers, no. 21 (presented at the Peterson Institute for International Economics, January 23, 2018).

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40 Ibid., p. 2. See also Alexander M. Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenan, "Who becomes an inventor in America? The importance of exposure to innovation," Working Paper 24062 (Cambridge, MA: National Bureau of Economic Research, November 2017); Frederico Cingano, "Trends in income inequality and its impact on economic growth," OECD Social, Employment and Migration Working Papers, no. 163 (Paris: Organisation for Economic Cooperation and Development Publishing, December 9, 2014); and Jonathan D. Ostry, Andrew Berg, and Charalambos G. Tsangarides. "Redistribution, inequality, and growth," Staff Discussion Note (Washington, DC: International Monetary Fund, February 2014).

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46 Chad Syverson, "Will history repeat itself? Comments on 'Is the information technology revolution over?'" *International Productivity Monitor*, no. 25, Spring 2013, pp. 37–40.

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48 Though figure 2 shows that both the 2005–18 slowdown period and the 1981–97 period posted the same low 0.7-percent rate, at slightly more precision, the 2005–18 rate (0.66 percent) was nearly a percentage point lower than the 1981–97 period rate (0.74 percent).

49 Byrne et al., "Is the information technology revolution over?" p. 21.

50 Robert E. Hall, "Quantifying the lasting harm to the U.S. economy from the financial crisis," Working Paper 20183 (Cambridge, MA: National Bureau of Economic Research, May 2014), p. 13.

51 Ravi Bansal, Mariano Max Croce, Wenxi Liao, and Samuel Rosen, "Uncertainty-induced reallocations and growth," Working Paper 26248 (Cambridge, MA: National Bureau of Economic Research, September 2019), p. 1.

52 Gutiérrez and Philippon, "Investment-less growth," abstract. Tobin's Q was first introduced by Nicholas Kaldor in 1966. For more information, see Nicholas Kaldor, "Marginal productivity and the macro-economic theories of distribution: comment on Samuelson and Modigliani," *Review of Economic Studies*, vol. 33, no. 4, October 1966, pp. 309–319. It was popularized a decade later, however, by James Tobin, who describes its two quantities: "One, the numerator, is the market valuation: the going price in the market for exchanging existing assets. The other, the denominator, is the replacement or reproduction cost: the price in the market for newly produced commodities. We believe that this ratio has considerable macroeconomic significance and usefulness, as the nexus between financial markets and markets for goods and services." James Tobin and William C. Brainard, "Asset markets and the cost of capital," in *Economic Progress, Private Values, and Public Policy* (Amsterdam: North-Holland Publishing Company, 1977).

53 Germán Gutiérrez and Thomas Philippon, "Investment-less growth: an empirical investigation," *Brookings Papers on Economic Activity* (Washington, DC: Brookings Institution, September 7, 2017), p. 90.

54 Ibid., p. 93.

55 Ibid., p. 136.

56 Regarding quasi-indexers, Gutiérrez and Philippon state, "Quasi-indexers have diversified holdings and low portfolio turnover—consistent with a passive, buy-and-hold strategy of investing portfolio funds in a broad set of firms." Gutiérrez and Philippon, "Investment-less growth," December 2016, p. 3.

57 Ibid., abstract.

58 Ibid., 2016, p. 19. See also Michael Jensen, "Agency costs of free cash flow, corporate finance, and takeovers," *American Economic Review*, vol. 76, no. 2, 1986, p. 323. Gutiérrez and Philippon, "Investment-less growth," September 7, 2017, p. 109. See also Christine Jolls, "Stock repurchases and incentive compensation," abstract, Working Paper 6467 (Cambridge, MA: National Bureau of Economic Research, March 1998).

59 Fernald, "Productivity and potential output before, during, and after the Great Recession," p. 9.

60 Bloom et al., "Really uncertain business cycles," p. 1.

61 Foster et al., "Reallocation in the Great Recession: cleansing or not?" abstract.

62 Fernald, "Productivity and potential output before, during, and after the Great Recession."

63 Sprague, "Below trend," https://www.bls.gov/opub/btn/volume-6/below-trend-the-us-productivity-slowdown-since-the-great-recession.htm.

64 In 2010, labor hours jumped up by more than 7 percentage points in a single year and transitioned from a 7.2-percent decline in 2009 to a 0.1-percent decline in 2010. This much smaller decline in labor hours growth for 2010 helped shrink the contribution of capital intensity and expand MFP growth compared with what they had been in 2009. Specifically, labor hours growth lowered the contribution of capital intensity in 2010 relative to that of 2009 because its low rate in 2010 (–0.1 percent) was then more similar to the rate for capital services (0.8 percent), thus shrinking the capital-to-labor ratio relative to the ratio of the prior year. In addition, MFP growth was dramatically accelerated as the below-average gains in both labor and capital in that year were paired with rapidly recovering output growth (3.3 percent).

65 Also, note that the low productivity growth of the 2005–18 period itself reduced the long-term rate since 1947 from 2.3 percent— what it had been as of 2005—to 2.1 percent as of 2018.

66 The data underlying the labor composition series bear this phenomenon out during the Great Recession: the labor cost share of workers under 45 and workers without a college degree plunged much more than it did for workers over 45 and workers with a college degree, during the Great Recession.

67 In this case, I use the long-term historical trend rate from 1947 to 2005, which is 2.3 percent, rather than the rate from 1947 to 2018, which is 2.1 percent. This is because, in this exercise, we are attempting to determine what growth would have been after 2005 if it had continued at the rate observed prior to 2005.

68 This per-worker loss in output technically should be viewed in terms of productivity analysis, with the output loss being represented relative to this input to production. Furthermore, the loss in output per worker does not equate to the loss in compensation per worker, which would have been a lesser amount, as only a portion of output accrues to workers as compensation for their labor. Giandrea and Sprague, "Estimating the U.S. labor share," https://doi.org/10.21916/mlr.2017.7.

69 Note that, in this hypothetical case, some of this additional leisure or nonwork time could have been the result of layoffs (which could have resulted in unemployment, voluntary retirement from work, or, for some workers, another job), to the extent that the reduction in overall hours was distributed inequitably among workers and reduced employment rather than average weekly hours. To the extent that average weekly hours were reduced, this could have come in the form of increased vacation or sick leave offered and taken, a reduction in the workweek, or a transition from full-time to part-time work for some workers.

70 For this computation of hypothetical average weekly hours, we are assuming that all the reduction in overall hours went to a reduction in average weekly hours and not to employment. This approach was taken to show the additional leisure or nonwork time that would have been hypothetically available for this group of workers who were employed during 2005–18.

71 Evsey D. Domar, "On the measurement of technological change," *Economic Journal*, vol. 71, no. 284, December 1961, pp. 709– 729. In his article, Domar developed a method for estimating industry contributions to overall MFP growth for an aggregate sector. I use this approach for breaking out industry contributions to private nonfarm business MFP growth. Domar showed that a given industry's contribution to an aggregate MFP growth rate is equal to the MFP growth rate for that industry, multiplied by a two-period average of the ratio of output in the industry to value-added in the sector. The sum of the Domar-weighted industry MFP growth rates approximates the private nonfarm business MFP growth rate. Also, to calculate the industry contributions to the private nonfarm business contribution of capital intensity, I use an approach that uses Domar's general approach and allows for the breakout of this component. For more information regarding this approach, see Robert Inklaar, Mary O'Mahony, and Marcel Timmer, "ICT and Europe's productivity performance industry-level growth account comparisons with the United States," Groningen Growth and Development Centre (GGDC) Research Memorandum GD-68 (Netherlands: University of Groningen, GGDC, December 2003), pp. 12–13.

72 Farm industries are excluded from our analysis in this article, as we are looking at the contributions to the private nonfarm business sector.

73 The summed MFP contributions, using the Domar method, add to 1.11 percentage points, which is slightly different from the top-line private nonfarm business slowdown of 1.27 percentage points. For this section of the article, I use the 1.11 figure as the overall value because it is consistent with the summed contributions.

74 Byrne et al. report that "since 2004 IT has continued to make a significant contribution to U.S. labour productivity growth, though it is no longer providing the boost that it did during the productivity resurgence from 1995 to 2004." See Byrne et al., "Is the information technology revolution over?" abstract.

75 Stephen D. Oliner and Daniel E. Sichel, "The resurgence of growth in the late 1990s: Is information technology the story?" *Journal of Economic Perspectives*, vol. 14, no. 4, Autumn 2000, p. 16.

76 David M. Byrne and Carol Corrado, "ICT prices and ICT services: What do they tell us about productivity and technology?" Working Paper 2017-015 (Board of Governors of the Federal Reserve System Finance and Economics Discussion Series, February 10, 2017), p. 21.

77 According to Byrne et al., "the official price indexes for semiconductors developed by BLS show that quality-adjusted semiconductor prices are not falling nearly as rapidly as they did prior to the mid-2000s." See Byrne et al., "Is the information technology revolution over?" p. 23.

78 Byrne and Corrado, "ICT prices and ICT services," p. 1.

79 Byrne et al., "Is the information technology revolution over?" p. 23.

80 David M. Byrne, John G. Fernald, and Marshall B. Reinsdorf, "Does the United States have a productivity slowdown or a measurement problem?" *Brookings Papers on Economic Activity* (draft paper presented at BPEA conference, March 10–11, 2016), p. 1, https://www.brookings.edu/wp-content/uploads/2016/03/ByrneEtAl_ProductivityMeasurement_ConferenceDraft.pdf.

81 Ibid.

82 Ibid., abstract. The authors also qualify that "the effect on [MFP of their adjustment] is more muted."

83 Chad Syverson, "Challenges to mismeasurement explanations for the U.S. productivity slowdown," abstract, Working Paper 21974 (Cambridge, MA: National Bureau of Economic Research, February 2016).

84 Decker et al., "Changing business dynamism and productivity," p. 27.

85 Mordecai Kurz, "On the formation of capital and wealth," Discussion Paper 17-016 (Stanford Institute for Economic Policy Research, June 25, 2017).

86 Ibid., abstract.

87 Lucia Foster, Cheryl Grim, John Haltiwanger, and Zoltan Wolf, "Innovation, Productivity Dispersion, and Productivity Growth," U.S. Census Bureau Center for Economic Studies Working Paper 18-08, February 2018, p. 4.

88 Titan Alon, David Berger, Robert Dent, Benjamin Pugsley, "Older and slower: the startup deficit's lasting effects on aggregate productivity growth," Working Paper 23875 (Cambridge, MA: National Bureau of Economic Research, September 2017), p. 2.

89 Ibid., p. 2.

90 Grullon et al., "Are US industries becoming more concentrated?" abstract.

91 David Autor, David Dorn, Gordon H. Hanson, Gary Pisano, and Pian Shu, "Foreign competition and domestic innovation: evidence from U.S. patents," working paper, September 2018.

92 Ibid., p. 2.

93 Lucia Foster, John Haltiwanger and C. J. Krizan, "Market selection, reallocation, and restructuring in the U.S. retail trade sector in the 1990s," *Review of Economics and Statistics*, vol. 88, no. 4, November 2006, p. 748.

94 On this topic, also see Ronald S. Jarmin, Shawn D. Klimek, and Javier Miranda, "The role of retail chains," in Timothy Dunne, J. Bradford Jensen, and Mark J. Roberts, eds., *Producer Dynamics: New Evidence from Micro Data* (Chicago: University of Chicago Press, January 2009), chap. 6.

95 Foster et al., "Market selection, reallocation, and restructuring in the U.S. retail trade sector in the 1990s," p. 748, as cited in Emek Basker, "Job creation or destruction? Labor-market effects of Wal-Mart expansion," *Review of Economics and Statistics*, vol. 87, no. 1, February 2005, pp. 174–183.

96 Foster et al., "Market selection, reallocation, and restructuring in the U.S. retail trade sector in the 1990s," p. 749.

97 David Popp, Jacquelyn Pless, Ivan Haščič, and Nick Johnstone, "Innovation and entrepreneurship in the energy sector," abstract, Working Paper 27145 (Cambridge, MA: National Bureau of Economic Research, May 2020).

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Are temporary layoffs becoming permanent during COVID-19?

Cody Parkinson

Job loss during the coronavirus disease 2019 (COVID-19) pandemic has been catastrophic. Firm–worker relationships are important in determining how quickly the U.S. economy will recover. In "Temporary layoffs and unemployment in the pandemic" (*FRBSF Economic Letter*, Federal Reserve Bank of San Francisco, November 16, 2020), Erin Wolcott, Mitchell G. Ochse, Marianna Kudlyak, and Noah A. Kouchekinia examine unemployment data relating to temporary versus permanent layoffs during the current pandemic and other recent recessions to assess the shape and speed of economic recovery.

Data and definitions from the Current Population Survey (CPS) are used for the analysis. During the survey process, people classified as unemployed are asked a series of questions to determine the reasons for their unemployment. These reasons include being on temporary layoff, permanent layoff, quitting their job, reentering the labor force, and so forth. People on temporary layoff have either received a date to return to work by their employer or expect to be recalled to their job within 6 months. When firms and workers have preestablished relationships, the process for returning to work is generally less time consuming and less costly than situations in which firms and workers need to establish a new employment relationship.

During periods of high unemployment, a higher aggregate share of people on temporary layoff generally signals a more rapid recovery. The authors present data showing that temporary layoffs were the main contributor to the high unemployment rate of 14.7 percent in April 2020. Temporary layoffs contributed 11.5 percent to the total rate, which was the highest contribution of temporary layoffs to total unemployment since at least 1967. In October 2020, temporary layoffs accounted for 2.0 percent of the 6.9 percent unemployment rate. Data from the Survey of Business Uncertainty also confirmed that temporary layoffs contributed to the increase in the unemployment rate. However, reasons for unemployment other than temporary layoffs have increased. If people continue to cycle through periods of joblessness, hold short-term jobs, or remain out of the labor force entirely, then future unemployment could remain persistently elevated.

Using CPS data, the authors can track changes in the labor market status of workers from one month to the next. The data show that the probability of someone moving from temporary layoff to permanent layoff increased during the COVID-19 pandemic but remains low by historical standards. Other than temporary layoffs, the April 2020 unemployment increase was largely attributable to people moving from employed to permanent layoff. However, the proportion of people moving from employed to permanent layoff fell in May and June. The proportion of people moving from out of the labor force to unemployed increased in May and June and has remained around the same level through at least September 2020. The data show that temporary layoffs are generally not turning into permanent layoffs. In addition, while the number of people who are considered long-term unemployed is still lower than the number during the 2007–09 recession, that amount may increase if the pandemic continues.

The authors close by summarizing their findings, stating that despite unemployment being well above prepandemic levels, data do not show that temporary layoffs are becoming permanent. However, as the crisis continues, recovery may slow as people battle persistent types of joblessness.

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Has COVID-19 affected mothers' labor market outcomes?

Demetrio Scopelliti

The coronavirus disease 2019 (COVID-19) pandemic has posed several challenges to parents continuing to work while also taking care of children who are unable to attend school or daycare because of safety regulations. While some parents are able to stay with their children by working from home, many work in industries and occupations that require them to work away from home. Because of the duration of the pandemic, childcare concerns have caused some parents in single-parent and multiparent households to consider leaving the labor force, limiting the hours they work in their current jobs, or changing jobs to work in occupations that allow them to work from home.

In "Did Covid-19 disproportionately affect mothers' labor market activity?" authors Daniel Aaronson, Luojia Hu, and Aastha Rajan (*Chicago Fed Letter*, Federal Reserve Bank of Chicago, January 2021) argue that COVID-19 has adversely affected parents' labor force participation that has disproportionately affected working mothers. Aaronson and colleagues acknowledge that other studies have shown that COVID-19 has not substantially affected parents' labor force participation. However, their assessment of labor market activity of parents (ages 25 to 54) through fall 2020 shows that labor force participation of mothers was 0.6 percentage point lower in the spring and 0.3 percentage point lower in the fall than that of adults in the same age group without kids. This finding means that approximately 120,000 mothers left the labor force in spring 2020 and approximately 60,000 left in fall 2020. In analyzing the demographics of those mothers who chose to leave the labor force beginning in March 2020, the authors found that the negative affect was disproportionately experienced by Black, single, and noncollege-educated mothers, reflecting disparities in the broader labor market over the same period.

Aaronson, Hu, and Rajan note that, while they assert gender disparity in labor market activity during COVID-19, their findings are not consistent with a trend toward the convergence of men's and women's labor market activity in the United States. Although the authors do not discuss the reasons why a gender disparity in labor market activity exists during COVID-19, they suggest that the disparity may be attributed to a higher proportion of women working in service industries, such as leisure and hospitality, that have been drastically affected by COVID-19. Another reason may be that mothers are still predominantly viewed as primary caregivers and more likely to be affected by the absence of children from schools and childcare. The impact on primary caregivers has been further complicated by the duration of the pandemic and safety concerns that have made relying on extended family for assistance more difficult. Regardless, the impact of the COVID-19 pandemic on labor market activity going forward remains to be seen.

How does the labor market for parents change during the COVID-19 pandemic?

Lisa N. Huynh

Differences in labor force participation rates between genders are prevalent within the labor market, but these differences have been amplified with the onset of the coronavirus 2019 disease (COVID-19) pandemic, especially for mothers. In a working paper titled "Parents in a pandemic labor market" (Federal Reserve Bank of San Francisco, Working Paper 2021-04, February 4, 2021), authors Olivia Lofton, Nicolas Petrosky-Nadeau, and Lily Seitelman identify the different labor market outcomes between working men and women and working parents.

Lofton and coauthors find that, overall, employment of men declined by 12 percent compared with 15 percent of women in April 2020 (relative to February 2020). While the initial fall and recovery in employment were similar between nonparent men and women, the initial fall in employment was smaller for fathers than for mothers and nonparents. In addition, recovery prospects for mothers stalled compared with fathers and nonparents. Once the new school year started, recovery halted and the gender employment gap for parents continued to rise, whereas the labor force participation for nonparent women and men remained similar. The authors note that this finding would mean that the employment gap itself was driven more by parent status than by gender differences.

In addition, the authors discover that the labor force participation rates and employment to population ratio disproportionately affected both women and mothers. After controlling for demographic characteristics, the authors observe that these data show that the pandemic had a greater effect (2 times as large) on mothers with less education compared with the effect on college-educated mothers. These data also show that mothers in the lowest income tercile were largely affected (5 times as large) by the pandemic as compared with mothers in the highest income tercile. Interestingly, the age of the youngest child in the household appears not to have affected any labor market outcomes for parents.

Jobs with flexible working hours have helped cushion the overall effect of the pandemic on employment prospects, limiting the decline in employment numbers among mothers. However, simply having the ability to telework has not changed outcomes for either mothers or fathers. The authors find that jobs with flexible working hours are more important than telework capability during a pandemic when parents need to prioritize childcare. Disruptions to a child's schooling can also affect the labor force participation rates of mothers because of the absence of childcare options. In general, the authors note a negative relationship between the degree of the disruption of schooling and the change in the labor force participation rates among mothers and nonparent women.

Unlike its role in previous recessions, the role of childcare during the pandemic recession has been critical in introducing mothers back into the workforce, which suggests that childcare obligations could hold recovery back.

The authors suggest that reopening schools and daycare centers and increasing job flexibility would help recover the labor force participation rates to prepandemic levels and assist the growth prospects during the pandemic.

Consumer inflation during the COVID-19 pandemic

Richard Works

The coronavirus disease 2019 (COVID-19) outbreak of 2020 created an awareness among financial media, academics, and bankers regarding the challenges of measuring inflation during a pandemic. While consumption patterns were affected by social distancing and lockdown mandates, these sudden changes can introduce biases in inflation measures. In "Inflation with Covid consumption baskets" (National Bureau of Economic Research, Working Paper 27352, July 2020), author Alberto Cavallo investigates the impact on inflation measures from changes in expenditures patterns because of the 2020 coronavirus pandemic. The author suggests that "the welfare implications are particularly relevant for lower-income households and [also] extend to countries experiencing a divergence [across] sectoral inflation rates" due to price movements. The term "sectoral inflation" refers to the rise in prices occurring in different commercial sectors of a country. For example, the industries under the transportation sector include new vehicles, motor fuels, used cars and trucks, and car and truck rental.

For this research, Cavallo used data collected on debit and credit card transactions from the Opportunity Insights Tracker (a mechanism that measures the daily change in U.S. consumption patterns). To produce COVID-19 consumer price index (CPI) indexes, he combined real-time expenditure estimates with official inflation measures from January 2019 to May 2020 that were not seasonally adjusted. This data collection was done for several countries, including the United States in which the index data used were produced by the U.S. Bureau of Labor Statistics (BLS). However, Cavallo found that matching data from the Opportunity Insights Tracker to data from various statistical offices from around the world was not always straightforward. For example, some countries that were investigated use a different classification system than the North American Industry Classification System that the United States uses. Thus, to match data from country to country, the author made mathematical assumptions to adjust for the differences in classifications. In addition, he employed Opportunity Insights Tracker data to obtain real-time estimates of expenditures.

From his results, Cavallo discovered that the official CPI from BLS and his calculated COVID-19 CPI were nearly identical in the United States in January and February 2020. But in March of that year (the start of the pandemic's initial outbreak in the United States), the COVID-19 inflation estimate was higher than the official CPI, although both showed deflation. As the pandemic grew, so did the difference between the two inflation rates. The official CPI fell 0.69 percent between March and April compared with the COVID-19 CPI, which decreased only 0.09 percent. Also, in May 2020, the official CPI experienced deflation, whereas the COVID-19 CPI had a positive rate of inflation. Some countries had higher COVID-19 inflation because vastly different price movements occurred across items (and the price divergence happened simultaneously with shifting weights).

Most of the differences between the official inflation measures and the COVID-19 inflation measures were found in spending on food and fuel. One reason for the difference is from expenditure weights that are generally lagged, whereas the COVID-19 CPI used real-time expenditure data. (BLS CPI data, however, are updated every 2 years

for weights.) As Cavallo explains, the "Core CPI" index excludes food and fuel, but the "Covid core" was still higher than the official *All items less food and energy* CPI in May 2020. These differences were due to less expenditure weight on nonenergy transportation sector subcategories, such as public transportation or new and used motor vehicles, with higher deflation.

The author's findings suggest that during the coronavirus pandemic, the cost of living increased faster than the cost of living of the official CPI. To examine the household impact, the author used data from the 2018 BLS Consumer Expenditure Survey and then updated weights using monthly data of income quintiles from the Opportunity Insights Tracker. The results showed that low-income households spent more on food than on transportation, which exacerbated the difference in the inflation measures during the beginning of the pandemic. Cavallo suggests that low-income households had higher rates of COVID-19 inflation (1.12 percent in May 2020) during the pandemic when compared with higher income households (only 0.57 percent).

Why has the employment–population ratio declined in the United States?

Lawrence H. Leith

For the past two decades, the employment–population ratio—the percentage of the population that is employed—has been slowly declining in the United States among people of prime working age (ages 25 to 54). The employment–population ratio has declined the most among less educated men, but it has declined among other groups as well. The ratio for prime-age women, for example, rose steadily throughout the post-World War II period and peaked in 2000; it has gradually declined since then. Although the 2001 and 2007–09 recessions—and the impact of the COVID-19 pandemic beginning in early 2020—have exacerbated these declines, they have been driven largely by more long-term economic factors. In a recent article titled "Explaining the decline in the U.S. employment-to-population ratio: a review of the evidence" (*Journal of Economic Literature*, September 2020), former Commissioner of the U.S. Bureau of Labor Statistics Katharine G. Abraham and her coauthor, economist Melissa S. Kearney, examine these trends for the period from 1999 to 2018 and seek to explain the economic factors driving them.

Abraham and Kearney quantify and rank some of the factors that contributed to the declines in the employment–population ratios among prime-age men and women over the 1999–2018 period. The authors warn that none of the factors they examine work in isolation and are, in fact, interrelated; moreover, they were unable to quantify some of the factors because the evidence was too sparse. Nevertheless, Abraham and Kearney find that "labor demand factors are the most important drivers" of the overall decline in the employment–population ratio among 25- to 54-year-olds over the period. In particular, they cite the marked increased in imported goods from China as the single most important factor driving the decline, reducing the ratio by approximately 0.92 percentage point. The second-largest factor is the increase in automation in the U.S. economy—especially robot technology—which reduces the demand for human labor. The authors estimate that this factor reduced the employment–population ratio for prime-age workers by another 0.43 percentage point over the 20-year period. Other things equal, the more that machines can do what human beings used to do, the more that the percentage of employed people will continue to decline.

Abraham and Kearney also find that labor supply factors have been less important than labor demand factors in the decline of the employment–population ratio for 25- to 54-year-olds over the past two decades. They examine the increase in the number of people receiving Social Security Disability Insurance during the period, for example, and find that it reduced the ratio by 0.09 percentage point. Similarly, the authors look at the Veterans Affairs Disability Compensation program and estimate that its growth reduced the ratio by 0.07 percentage point. The authors note that other "social safety net" programs, such as the Supplemental Nutrition Assistance Program

(formerly known as food stamps) and the Earned Income Tax Credit, had negligible effects on the decline in the employment–population ratio over the 1999–2018 period.

The authors suggest that several other factors warrant further research to determine how much they might also have contributed to the decline in the prime-age employment–population ratio over the past two decades. One such factor involves the challenge that many parents face in reconciling their family and work responsibilities. This challenge is especially relevant for lower wage workers, many of whom often have unpredictable and inflexible schedules. For many parents, the relatively high cost of childcare can make not working more attractive than working. As a result, one parent might choose not to work and instead stay home to care for children. Other factors that Abraham and Kearney suggest warrant further research include increased incarceration rates, stricter licensing requirements, and certain changing social norms, such as young adults in their twenties and beyond living with their parents or other relatives.

Immigration and innovation

The impact of foreign-born workers on the U.S. labor market remains a primary focus of immigration policy and research. In a recent book titled *The Roles of Immigrants and Foreign Students in U.S. Science, Innovation, and Entrepreneurship*, editors Ina Ganguli, Shulamit Kahn, and Megan MacGarvie offer a collection of eight novel papers presenting recent findings in the literature on immigration economics. The collection provides evidence that (1) foreign-born students still want to work in the United States, although this may be changing for Chinese students, (2) foreign-born students who remain to work in the United States after graduation are positively selected by ability, and (3) the presence of more foreign-born entrepreneurs or employees in a firm is associated with more productivity growth and innovation by most measures.

Many foreign-born students come to the United States to attend top-rated academic institutions. A relevant question with implications for student visa policies is how many foreign students who build human capital in the United States actually remain in the country to use that capital in the U.S. labor market. In chapter 2, Ina Ganguli and Patrick Gaulé estimate that, among Ph.D. students, foreign-born students are more likely to accept postdoctoral appointments in the United States than are native-born students. This difference is robust to test scores and career preferences, suggesting that American educational institutions select students interested in living in the United States. Similarly, in chapter 8, Michael Roach, Henry Sauermann, and John Skrentny show that about 42 percent of foreign-born Ph.D. students wish to stay in the United States permanently and about 37 percent wish to work in the country for some time before returning home. These rates are similar across degree fields, but the average is pulled down by Chinese students, only about 17 percent of whom intend to stay in the United States permanently. The authors urge further study of this difference between

THE ROLES OF IMMIGRANTS AND FOREIGN STUDENTS IN US SCIENCE, INNOVATION, AND ENTREPRENEURSHIP

Edited by Ina Ganguli, Shulamit Kahn, and Megan MacGarvie
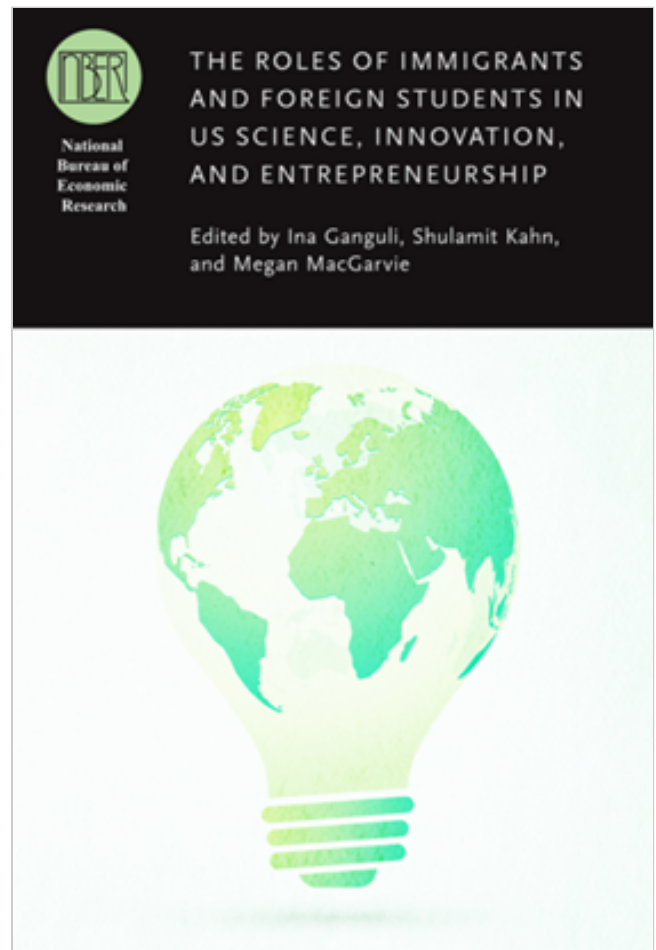
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Chinese and other foreign-born students, but they provide ample evidence that immigrants sourced from institutions of higher education have a lasting presence in the United States.

In chapter 1, Stefano Breschi, Francesco Lissoni, and Ernest Miguelez examine why some foreign-born students stay to work in the United States, whereas others return to their home countries. The chapter explores this question by using a novel dataset (based on a data-linkage project between LinkedIn and PatentsView) of patent-holding Indian immigrants employed in the U.S. information and communications technologies (ICT) industry. Using PatentsView, the authors pull data on patents from the top 179 ICT companies. After linking patent holders from these companies to LinkedIn profiles and restricting the sample to Indian inventors whose first move outside of India was to the United States, the authors arrive at a dataset containing around 5,500 such individuals. The analysis explores differences between those who return home and those who stay in the United States, distinguishing between "education" migrants (those who studied at an educational institution at the time of migration) and "work" migrants (those who worked at the time of migration). Breschi, Lissoni, and Miguelez find evidence that return migrants in both the education and work categories are negatively selected with respect to education; that is, those who stay in the United States tend to have higher educational attainment, on average. On the other hand, the authors also find that work migrants who return home are positively selected by the number of patents, implying that those with more patents are more likely to return to India. The authors urge caution in interpreting this mixed result in the absence of further research, but they do demonstrate that many of the latter migrants publish patents and work in the United States for a considerable time.

Given the evidence that many immigrants come to the United States for work, what is their effect on innovation and the firms that hire them? The other papers in the book seek to answer this question. Chapters 3, 4, and 6 explore the relationship between immigration and innovation at the firm level. Because much of the high-skilled immigration to the United States occurs through the H-1B work visa program, which allows the admission of a limited number of immigrants with a college degree up to an annual cap, chapters 3 and 4 focus on the impact of those immigrants.

Using Labor Condition Applications (LCAs), which are documents filed by firms seeking to employ an H-1B worker, Gaurav Khanna and Munseob Lee (chapter 3) compare the performance of firms that file LCAs with the performance of firms that do not. The authors stress that, since filing an LCA is the first step involved in the H-1B program and because not all LCAs are approved, their data reflect a firm's tendency to hire high-skilled immigrants. For their dependent variable, Khanna and Lee construct a measure of product reallocation that reflects how many products come off and on the market—a measure of creative destruction. The authors find that LCAs are positively associated with product reallocation, with firms that apply for foreign workers more dynamically bringing in new products and taking out old ones. Although causation is difficult to establish, the authors do find that increased LCAs precede greater product reallocation, but periods of greater product reallocation have no correlation with later LCAs.

Anna Maria Mayda et al. (chapter 4) take a similar approach by using a firm's number of approved H-1B workers as a treatment variable. Through a Freedom of Information Act request filed with the U.S. Citizenship and Immigration Services, the authors obtained data on the entire universe of approved H-1B applications from 1997 to 2012. Their findings, like those reported in chapter 3, suggest that larger companies (based on revenue) have a

higher propensity to employ H-1B workers and that greater revenue growth follows the introduction of more such workers.

Taking a different approach, J. David Brown et al. (chapter 6) examine immigrant-owned tech firms with data from the U.S. Census Bureau American Survey of Entrepreneurs. Since tech firms have relatively high rates of innovation and employ many foreign-born workers, the authors try to estimate the effect of immigrant ownership on innovation. Their measures include product and process innovation, intellectual property, and R&D spending. All measures are positively associated with immigrant ownership, and except for intellectual property, they are significant. Many of the innovation measures, most notably R&D spending, are robust to a myriad of controls.

Academics interested in the relationship between immigration and U.S. scientific and technological innovation should explore the evidence presented in this book. Although the book applies some advanced econometric concepts and may challenge nontechnical audiences, it is a welcome advance in the literature on immigration economics. Those with academic or policy interests concerned with the effects of foreign-born workers on the labor market may find it valuable, and those who wish to add to the literature may benefit from learning more about the novel datasets created by some authors.

Employee access to sick leave before and during the COVID-19 pandemic

In response to the coronavirus disease 2019 (COVID-19) pandemic, many private industry employers implemented changes to their sick leave policies. Using data from the U.S. Bureau of Labor Statistics (BLS) National Compensation Survey and two BLS supplemental surveys, this article examines changes to sick leave provisions and use before and during the pandemic.

The National Compensation Survey (NCS), collected by the U.S. Bureau of Labor Statistics (BLS), is used to produce multiple data outputs, including the Employment Cost Index, employer compensation costs, and employee benefits. The survey is unique in collecting compensation information from employers, gathering data not only on worker wages and salaries but also on employer-provided benefits.[1] Among the benefits collected are various types of employee leave, including sick leave. Information on the incidence and provision of benefits is published annually.

The coronavirus disease 2019 (COVID-19) pandemic resulted in many employers changing their leave policies, affecting sick leave provisions shortly after the NCS reference period in March 2020. To capture data on these pandemic-induced changes, BLS collected two additional surveys: (1) a supplement to the NCS and (2) an establishment survey, called the Business Response Survey (BRS).[2] In this article, we present and analyze data on sick leave provisions and use before and during the pandemic.

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Prepandemic information on paid sick leave

To contextualize sick leave changes due to the COVID-19 pandemic, we first provide information on employer-provided sick leave in private industry before the pandemic, relying on NCS data from March 2020. Table 1
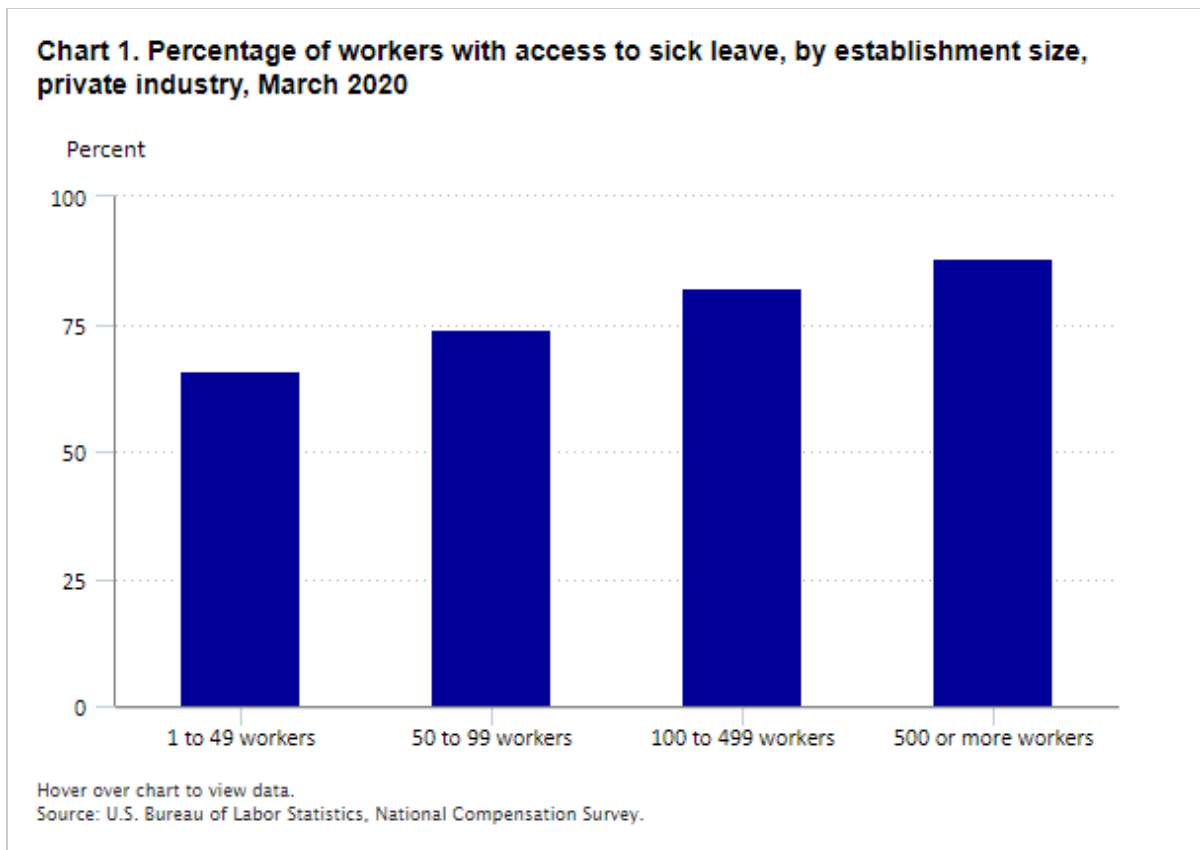
presents data—by occupational characteristics, industry, and establishment size—on employee access to sick leave, types of sick leave provisions, and leave combinations.

Table 1. Sick leave access, provision type, and combinations of leave benefits, private industry, March 2020

Access to paid sick leave

In March 2020, 75 percent of all private industry workers had access to paid sick leave. Paid sick leave was more prevalent among full-time workers (86 percent) than among part-time workers (45 percent), and it was also more prevalent among union workers (88 percent) than among nonunion workers (74 percent). In addition, access to sick leave varied by occupation, with workers in management, professional, and related occupations having the highest access rate (92 percent) and workers in service occupations having the lowest rate (59 percent).[3]

In terms of establishment characteristics, access to sick leave tended to increase with establishment size. (See chart 1.) In establishments with 1 to 49 workers, 66 percent of workers had access to sick leave, compared with 74 percent in establishments with 50 to 99 workers, 82 percent in establishments with 100 to 499 workers, and 88 percent in establishments with 500 or more workers.[4]

Chart 1. Percentage of workers with access to sick leave, by establishment size, private industry, March 2020

Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

Before the pandemic, sick leave access rates also differed by industry. Although table 1 shows that these rates did not vary significantly between goods-producing establishments (74 percent) and service-providing establishments (76 percent), they did vary considerably by industry segment. Looking at two-digit North American Industry Classification System industry sectors, one sees that, in several sectors, about 90 percent of workers had access

to sick leave. These sectors include finance and insurance (97 percent), utilities (96 percent), and professional and technical services (93 percent).

Sick leave provisions

As shown in the leave provisions columns of table 1, among workers with access to sick leave in March 2020, 63 percent were in plans providing a fixed number of days per year, 34 percent were in consolidated leave plans,[5] and 3 percent could take sick leave days as needed, meaning that their plans did not specify a maximum number of days. Plans allowing workers to take days as needed were relatively rare. Six percent of workers in educational services had this plan feature, and this rate was the highest across all published industry sectors.

Access to consolidated leave plans varied by worker and establishment characteristics. Among production, transportation, and material-moving workers with access to sick leave, 24 percent received this benefit as part of a consolidated leave plan, a rate significantly lower than the rates for service workers (30 percent), sales and office workers (37 percent), and workers in management, professional, and related occupations (37 percent).

Consolidated leave plans also were more prevalent at larger establishments. In establishments with 1 to 99 workers, 31 percent of workers with sick leave access had a consolidated leave plan, compared with 36 percent of workers in establishments with 100 or more workers. Among industry sectors, the rates of access to consolidated leave plans were 20 percent for workers in leisure and hospitality and 40 percent for workers in financial activities.

How much sick leave did workers receive?

Table 2 presents estimates of mean and median days of paid sick leave by length of service and establishment size. As seen in the table, in March 2020, there was little variation in the amount of leave offered by length of service, especially among smaller establishments. In fact, the mean and median days for establishments with 1 to 49 workers and establishments with 50 to 99 workers were mostly the same across the various categories for length of service. For this reason, we focus on differences in paid sick leave by establishment size for workers with more than 1 year of service. (See chart 2.)

Table 2. Number of annual days of paid sick leave, by service requirement and establishment size, private industry, March 2020

Chart 2. Number of annual days of paid sick leave after 1 year of service, by establishment size, private industry, March 2020

Number of days

Legend: ■ Mean ■ Median

Click legend items to change data display. Hover over chart to view data.
Source: U.S. Bureau of Labor Statistics, National Compensation Survey.
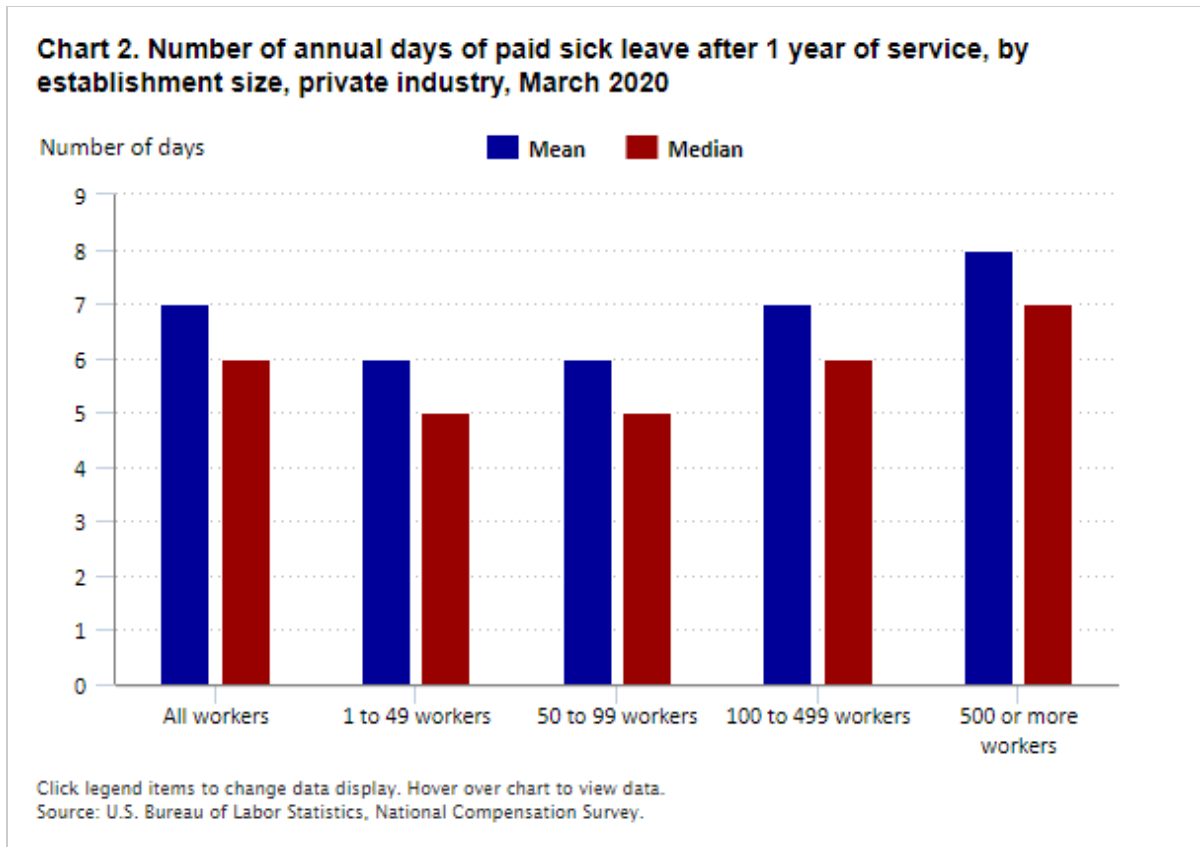
Employees at establishments with 1 to 49 workers and 50 to 99 workers were offered an average of 6 days of sick leave per year, with a median of 5 days. Employees at establishments with 100 to 499 workers were offered an average of 7 days of sick leave, with a median of 6 days. Employees at establishments with 500 or more workers had the most generous sick leave, an average of 8 days per year, with a median of 7 days.

Leave combinations

The data on sick leave provisions indicate that, in March 2020, roughly one-third of private industry workers were offered consolidated leave plans. Other workers may have been offered a more traditional leave package distinguishing among different types of paid leave. The last four columns of table 1 focus on access to different combinations of paid leave.

Much like access to sick leave, access to leave combinations varied by establishment size. Before the pandemic, the rate of access to personal leave, sick leave, paid family leave, or vacation was 77 percent at establishments with 1 to 49 workers, 85 percent at establishments with 50 to 99 workers, and 92 percent at establishments with 100 or more workers.

Access to leave including personal leave, sick leave, paid family leave, or vacation also varied by industry, but slightly differently than did access to sick leave alone. (See chart 3.) Although access rates in utilities, finance and insurance, and professional and technical services were relatively high (in the mid- to high 90-percent range), they were found to increase by only a few percentage points with the inclusion of additional forms of leave. This pattern is not surprising, particularly in the case of finance and insurance and professional and technical services, because these industries have relatively high offerings of consolidated leave plans. Workers in manufacturing had access to

sick leave at a rate of 81 percent, but once other leave types were included in the measure, the access rate increased to 97 percent.

Chart 3. Sick leave access and combinations of leave benefits, selected private industries, March 2020

■ Access to sick leave ■ Access to personal leave, sick leave, or paid family leave
■ Access to personal leave, sick leave, paid family leave, or vacation

Construction (NAICS 23)
Manufacturing (NAICS 31-33)
Wholesale trade (NAICS 42)
Retail trade (NAICS 44-45)
Transportation and warehousing (NAICS 48-49)
Utilities (NAICS 22)
Information (NAICS 51)
Finance and insurance (NAICS 52)
Real estate and rental and leasing (NAICS 53)
Professional and technical services (NAICS 54)
Administrative and waste services (NAICS 56)
Educational services (NAICS 61)
Healthcare and social assistance (NAICS 62)
Accommodation and food services (NAICS 72)
Other services (except public administration) (NAICS 81)

Percent (0, 25, 50, 75, 100)

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, National Compensation Survey.

Workers in accommodation and food services and in construction had relatively low rates of access to sick leave. As seen in table 1, however, with the inclusion of other types of paid leave, the former's rate of leave access rises to 59 percent, an increase of 9 percentage points, and the latter's rate increases to 83 percent, a jump of 21 percentage points.
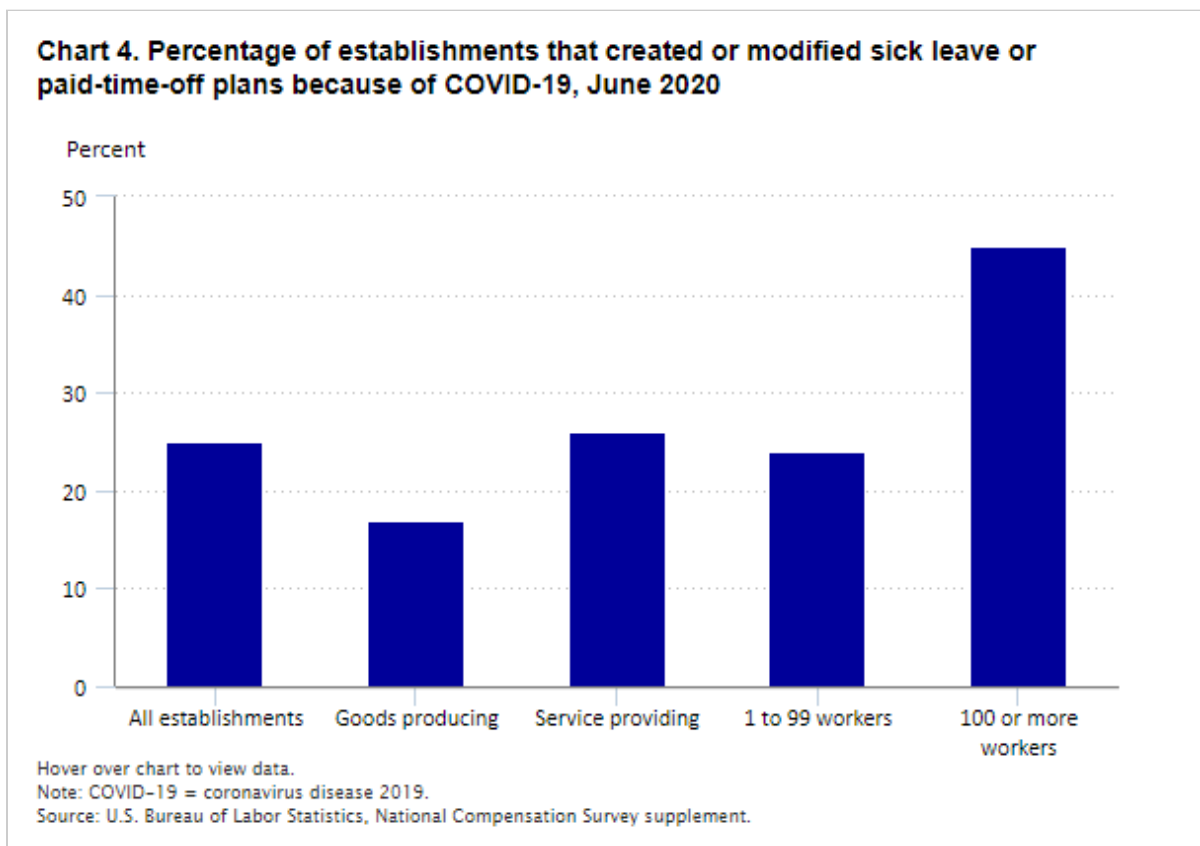
NCS COVID-19 supplement

In response to the COVID-19 pandemic, BLS added supplemental questions to the NCS, asking employers about leave plan changes due to the pandemic. These questions focused on whether private industry establishments

changed their leave policies and on whether employees used sick leave between March 1 and May 31, 2020. Survey data were collected from June 1 to July 21, 2020, representing about 6.5 million private industry establishments from approximately 1,500 responding units in the United States. The response rate was roughly 25 percent.

Unlike the NCS estimates, which capture the share of workers receiving benefits, the supplemental estimates capture establishment shares, because the supplemental data were collected at the establishment, not at the job, level. Since the sample size of the NCS supplement is relatively small, the level of detail provided in the supplemental data is limited. Estimates are presented for all private industry establishments, goods-producing establishments, service-providing establishments, establishments with 1 to 99 workers, and establishments with 100 or more workers.

Changes to paid sick leave or paid-time-off plans

As shown in chart 4, 25 percent of all private industry establishments created or modified paid sick leave or paid-time-off plans because of the COVID-19 pandemic. This rate was 45 percent among establishments with 100 or more workers and 24 percent among establishments with fewer than 100 workers.

Chart 4. Percentage of establishments that created or modified sick leave or paid-time-off plans because of COVID-19, June 2020

Hover over chart to view data.
Note: COVID–19 = coronavirus disease 2019.
Source: U.S. Bureau of Labor Statistics, National Compensation Survey supplement.

How many days of paid leave did establishments add? Table 3 presents the distribution of these additions for the subset of establishments that modified existing paid leave plans or created new plans. Of these establishments, 34 percent added 1 to 5 paid leave days to their plans, 20 percent added 6 to 10 days, and 37 percent added more than 10 days. (The remaining 8 percent had an unknown number of days added.) Among goods-producing establishments, 44 percent added 1 to 5 paid days, 34 percent added 6 to 10 days, and 19 percent added more

than 10 days. Among service-providing establishments, 33 percent added 1 to 5 paid days, 19 percent added 6 to 10 days, and 39 percent added more than 10 days.

Table 3. Percentage of establishments that added paid days to new or existing leave plans because of COVID-19, by number of days added, June 2020

Category	1 to 5 days	6 to 10 days	More than 10 days	Unknown
All establishments	34	20	37	8
Sector				
Goods producing	44	34	19	3
Service providing	33	19	39	9
Establishment size				
1 to 99 workers	37	17	39	8
100 or more workers	9	61	20	10

Note: COVID-19 = coronavirus disease 2019.

Source: U.S. Bureau of Labor Statistics, National Compensation Survey supplement.

Use of sick leave

For the period between March 1 and May 31, 2020, 42 percent of all establishments reported that the average number of sick leave days (paid and unpaid) used per employee was zero. Twenty percent of establishments reported that the average employee used between 1 and 5 sick leave days during the same period, and 10 percent of establishments reported that the average employee used more than 5 sick leave days. Nineteen percent of establishments with 100 or more workers indicated that the average employee used more than 5 sick leave days, compared with 9 percent of establishments with less than 100 workers who reported the same.

Among establishments that modified existing paid and unpaid sick leave plans or created new plans, 90 percent indicated that their plan changes were temporary. The remaining 10 percent either reported that their plan changes were permanent or indicated that they could not provide information on whether the changes would be permanent.

Business Response Survey information on sick leave

The Business Response Survey (BRS) was collected between July 20 and September 30, 2020, leveraging the existing BLS internet data collection portal used for a variety of establishment-level data collections, including the Annual Refiling Survey of the Quarterly Census of Employment and Wages (QCEW). The BRS uses the QCEW as its sampling frame and has a scope of private industry establishments in the 50 states, the District of Columbia, and Puerto Rico.[6] The NCS also uses the QCEW as its sampling frame, but its scope is somewhat different from that of the BRS, most notably in that it excludes agriculture. The usable response rate for the BRS was 27.2 percent, comparable to that of the NCS sick leave supplement.

The reference period for the BRS was from January 1, 2020, to the time the respondent completed the survey. The BRS asked the following question related to sick leave: "As a result of the coronavirus pandemic, did this business location increase the amount of paid sick leave provided to employees?" The answer options included "yes, provided paid sick leave to employees who did not have paid sick leave prior to the coronavirus pandemic"; "yes,

increased amount of paid sick leave for employees who already had sick leave prior to the coronavirus pandemic"; "no change to paid sick leave or no paid sick leave provided"; and "don't know."

Our analysis focuses on the combined "yes" responses, aiding a comparison with the NCS supplement, which aggregated both newly created leave plans and modified existing plans. BRS estimates are presented both as the percentage of establishments adding sick leave and as the percentage of employment in establishments adding sick leave. The former measure is similar to that in the NCS supplement, and the latter is comparable to the March estimate on percentage of workers from the NCS.

Table 4 provides a set of BRS estimates by industry and establishment size. Among all private industry establishments, 14 percent increased sick leave because of COVID-19. This percentage is lower than the NCS supplement estimate of 25 percent. Despite this difference, the patterns by establishment size are similar between the NCS supplement and the BRS, which, because of its larger sample size, provides more granular estimates by establishment size.

Table 4. Sick leave increases due to COVID-19, by industry and establishment size, 2020

Category	Establishments with increased paid sick leave		Employment in establishments with increased paid sick leave	
	Percent	Standard error	Percent	Standard error
Industry				
U.S. total, private sector	14	0.2	28	0.4
Agriculture, forestry, fishing, and hunting (NAICS 11)	11	1.9	42	3.8
Mining, quarrying, and oil and gas extraction (NAICS 21)	13	1.2	23	3.2
Utilities (NAICS 22)	26	3.4	49	1.8
Construction (NAICS 23)	11	0.3	25	1.1
Manufacturing (NAICS 31-33)	19	0.4	36	1.0
Wholesale trade (NAICS 42)	19	0.9	34	1.9
Retail trade (NAICS 44-45)	15	0.4	29	1.6
Transportation and warehousing (excluding scheduled air transportation and truck transportation) (NAICS 48-49A)	17	2.0	27	3.2
Scheduled air transportation (NAICS 4811)	20	2.6	31	3.1
Truck transportation (NAICS 484)	11	2.1	24	2.4
Information (NAICS 51)	12	1.6	30	3.4
Finance and insurance (NAICS 52)	21	1.1	36	2.0
Real estate and rental and leasing (NAICS 53)	13	1.2	27	2.4
Professional and technical services (NAICS 54)	11	0.6	25	2.2
Management of companies and enterprises (NAICS 55)	21	2.8	41	2.6
Administrative and waste services (NAICS 56)	12	0.9	21	2.3
Educational services (NAICS 61)	10	1.5	31	2.4
Healthcare (NAICS 621-623)	17	0.4	32	1.2
Social assistance (NAICS 624)	20	5.7	30	1.9
Arts, entertainment, and recreation (NAICS 71)	7	1.3	17	2.2

See footnotes at end of table.

Table 4. Sick leave increases due to COVID-19, by industry and establishment size, 2020

Category	Establishments with increased paid sick leave		Employment in establishments with increased paid sick leave	
	Percent	Standard error	Percent	Standard error
Accommodation and food services (NAICS 72)	11	0.4	19	0.8
Other services (except public administration) (NAICS 81)	8	0.6	17	1.2
Establishment size				
Small (1 to 499 workers)	14	0.2	26	0.5
1 to 4 workers	9	0.4	9	0.4
5 to 9 workers	14	0.4	14	0.4
10 to 19 workers	19	0.6	19	0.6
20 to 49 workers	25	0.7	25	0.7
50 to 99 workers	30	1.3	30	1.3
100 to 249 workers	36	1.7	36	1.7
250 to 499 workers	36	1.8	36	1.8
Large (500 or more workers)	36	0.8	37	1.0
500 to 999 workers	35	1.0	35	1.0
1,000 or more workers	38	1.5	38	1.5

Note: COVID-19 = coronavirus disease 2019; NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics, Business Response Survey.

As seen in table 4, initial increases in establishment size correspond to increases in the percentage of establishments that expanded sick leave because of the pandemic. Among establishments with 50 to 99 workers, 30 percent increased the amount of paid sick leave provided to employees. Although the point estimates in the table tend to increase with establishment size, the increases between adjacent size classes are not statistically significant.

While the sample size of the NCS supplement was not large enough to provide estimates by industry, such estimation was possible with the BRS. A pandemic-induced expansion of sick leave was relatively uncommon among establishments in the arts, entertainment, and recreation industry (7 percent) and more common among establishments in the utilities (26 percent) and finance and insurance (21 percent) industries.

As was shown in table 1, workers in utilities and in finance and insurance had relatively high rates of access to sick leave before the pandemic. Chart 5 combines, for selected private industries, the prepandemic sick leave access rates from the NCS with the establishment- and employment-level estimates from the BRS. Industries are sorted by the percentage of employment in establishments that increased sick leave during the pandemic. As seen toward the top of the chart, industries such as utilities and finance and insurance, which had prepandemic sick leave access of 96 and 97 percent, respectively, also had relatively high rates of sick leave expansion during the pandemic. Shown at the bottom of the chart, industries in which employees had relatively low rates of

prepandemic sick leave access, such as administrative and waste services, accommodation and food services, and other services, also had relatively low rates of sick leave expansion during the pandemic.

Chart 5. Access to sick leave and increases in sick leave due to COVID-19, selected private industries
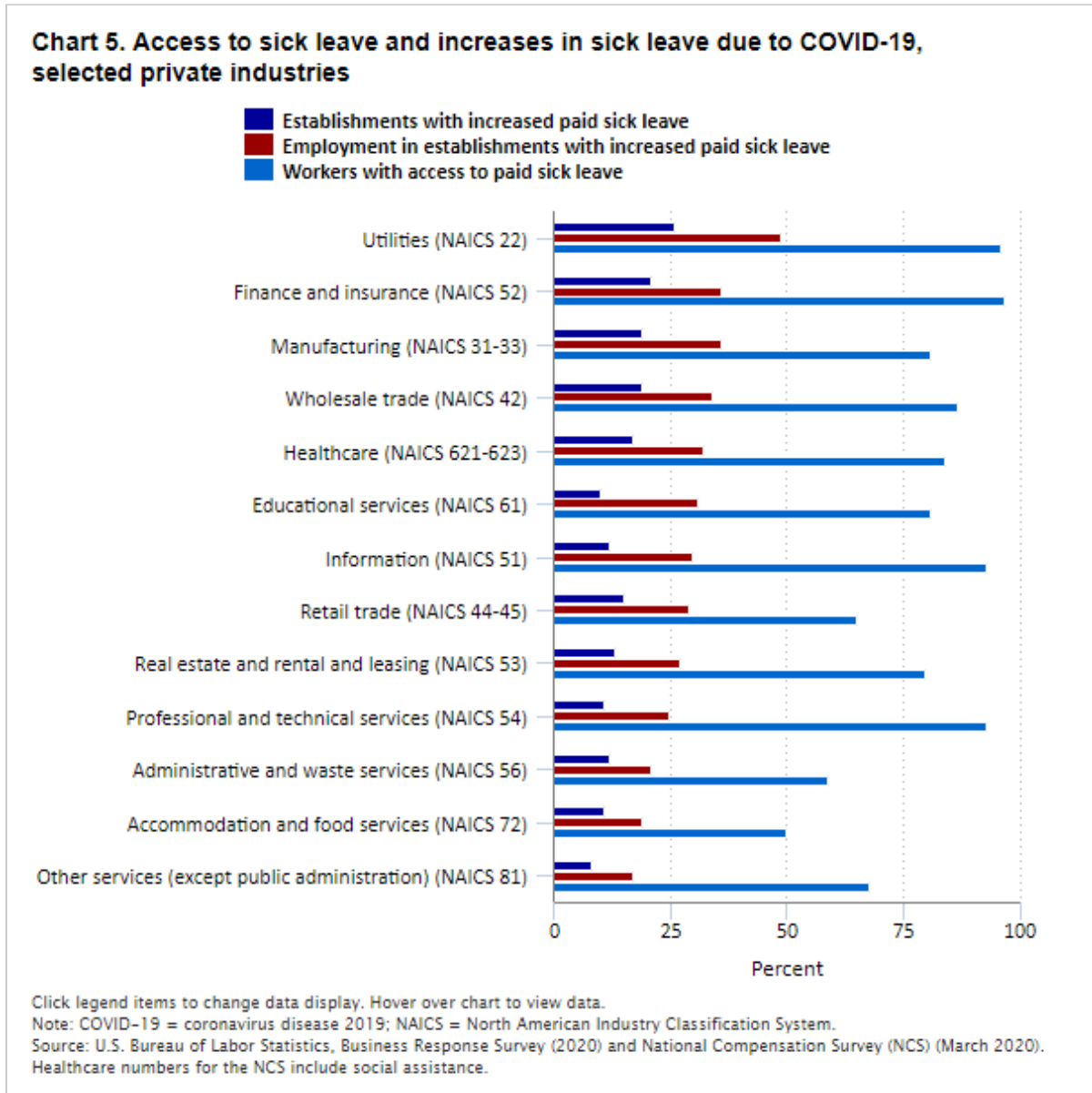
There are exceptions to this pattern. For example, although 93 percent of workers in professional and technical services had access to sick leave before the pandemic, only 11 percent of establishments in this industry sector, covering 25 percent of employment, expanded sick leave access because of COVID-19. In retail trade, 65 percent of workers had access to sick leave before the pandemic—one of the lowest industry access rates—but 15 percent of establishments in this industry sector, covering 29 percent of employment, expanded sick leave access because of COVID-19, which places retail trade roughly in the middle of the industry distribution.

Taken as a whole, however, the numbers suggest that establishments that had relatively generous leave benefits before the pandemic were also more likely to expand sick leave during the pandemic.

Conclusion

In this article, we used data from the NCS and two supplemental surveys to examine how sick leave provisions in the private industry changed in response to the COVID-19 pandemic. Our analysis suggests that, after the pandemic hit, 25 percent of private industry establishments created or modified paid sick leave or paid-time-off plans, with 90 percent of these establishments indicating that plan changes would be temporary. In addition, we found that about 14 percent of private industry establishments increased the amount of paid sick leave in response to the pandemic.

Tables

Table 1. Sick leave access, provision type, and combinations of leave benefits, private industry workers, March 2020

Category	Access to sick leave (all workers = 100 percent)		Type of provision (all workers with paid sick leave = 100 percent)						Combinations (all workers = 100 percent)			
			Fixed number of days		As needed		Part of consolidated leave plan		Personal leave, sick leave, or paid family leave		Personal leave, sick leave, paid family leave, or vacation	
	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error
All workers	75	0.9	63	1.0	3	0.2	34	0.9	78	0.9	85	0.7
Occupation												
Management, professional, and related	92	0.7	59	1.7	4	0.5	37	1.6	93	0.6	95	0.6
Service	59	2.0	68	2.5	2	0.4	30	2.5	61	2.0	69	1.8
Sales and office	77	1.1	60	1.3	3	0.2	37	1.2	79	1.0	86	1.0
Natural resources, construction, and maintenance	68	1.6	64	2.3	5	1.2	32	2.2	72	1.9	85	1.7
Production, transportation, and material moving	72	1.6	74	1.4	2	0.4	24	1.5	76	1.3	90	1.0
Job status												
Full time	86	0.7	61	1.1	3	0.3	35	1.1	88	0.6	94	0.5
Part time	45	1.6	76	2.0	1	0.4	23	1.9	49	1.7	57	1.6
Union status												
Union	88	1.4	62	1.1	3	0.3	35	1.1	91	1.2	94	1.0
Nonunion	74	1.0	—	—	—	—	—	—	77	0.9	84	0.8
Sector												
Goods producing	74	1.3	65	2.0	4	0.7	30	1.9	78	1.4	92	1.1
Service providing	76	1.1	63	1.1	3	0.3	34	1.1	78	1.0	83	0.8
Industry												
Construction (NAICS 23)	62	2.0	64	3.0	2	0.7	34	2.8	66	2.2	83	2.9
Manufacturing (NAICS 31-33)	81	1.5	—	—	—	—	—	—	85	1.4	97	0.6

See footnotes at end of table.

Table 1. Sick leave access, provision type, and combinations of leave benefits, private industry workers, March 2020

Category	Access to sick leave (all workers = 100 percent)		Type of provision (all workers with paid sick leave = 100 percent)						Combinations (all workers = 100 percent)			
			Fixed number of days		As needed		Part of consolidated leave plan		Personal leave, sick leave, or paid family leave		Personal leave, sick leave, paid family leave, or vacation	
	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error
Trade, transportation, and utilities (NAICS 22, 42, 43, 48-49)	74	1.2	68	1.6	3	0.5	29	1.4	78	1.0	85	0.8
Wholesale trade (NAICS 42)	87	1.4	71	2.4	4	1.1	24	1.9	90	1.2	95	1.3
Retail trade (NAICS 44-45)	65	1.1	63	1.8	2	0.5	35	1.6	70	1.2	79	0.9
Transportation and warehousing (NAICS 48-49)	83	2.9	75	3.9	2	0.6	23	4.0	85	2.8	93	1.5
Utilities (NAICS 22)	96	2.8	—	—	—	—	—	—	98	1.1	99	0.8
Information (NAICS 51)	93	2.2	62	4.3	4	1.3	34	4.1	93	2.2	94	2.1
Financial activities (NAICS 52-53)	93	1.0	56	1.0	5	0.9	40	1.2	94	0.9	96	0.8
Finance and insurance (NAICS 52)	97	0.5	51	1.7	4	0.7	45	1.8	98	0.4	98	0.4
Real estate and rental and leasing (NAICS 53)	80	3.6	70	5.1	—	—	—	—	83	3.1	90	2.5
Professional and business services (NAICS 54-56)	79	2.1	—	—	—	—	—	—	81	2.0	87	1.7
Professional and technical services (NAICS 54)	93	1.8	56	5.1	3	1.4	41	5.0	95	1.7	95	1.7
Administrative and waste services (NAICS 56)	59	3.5	—	—	—	—	—	—	61	3.3	74	3.2
Education and health services (NAICS 61-62)	84	2.8	55	2.7	1	0.2	44	2.7	85	2.9	88	2.3
Educational services (NAICS 61)	81	3.0	83	3.1	6	1.4	11	2.9	83	3.0	84	3.1
Healthcare and social assistance (NAICS 62)	84	3.2	51	3.0	—	—	—	—	85	3.3	89	2.6

See footnotes at end of table.

Table 1. Sick leave access, provision type, and combinations of leave benefits, private industry workers, March 2020

Category	Access to sick leave (all workers = 100 percent)		Type of provision (all workers with paid sick leave = 100 percent)						Combinations (all workers = 100 percent)			
			Fixed number of days		As needed		Part of consolidated leave plan		Personal leave, sick leave, or paid family leave		Personal leave, sick leave, paid family leave, or vacation	
	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error	Percent	Standard error
Leisure and hospitality	52	2.6	78	3.4	2	1.0	20	3.5	54	2.5	60	2.3
Accommodation and food services (NAICS 72)	50	3.3	81	3.0	2	0.8	17	3.0	52	2.6	59	3.1
Other services (NAICS 81)	68	3.0	66	5.0	4	1.2	30	4.9	71	2.6	79	3.1
Establishment size												
1 to 99 workers	67	1.2	65	1.4	3	0.4	31	1.3	70	1.1	79	1.1
1 to 49 workers	66	1.4	65	1.8	4	0.5	31	1.7	68	1.3	77	1.3
50 to 99 workers	74	2.2	66	2.4	1	0.4	33	2.4	77	1.9	85	1.4
100 or more workers	85	1.2	62	1.3	2	0.4	36	1.3	87	1.1	92	1.0
100 to 499 workers	82	1.4	62	1.8	2	0.5	36	1.8	85	1.3	91	1.2
500 or more workers	88	2.0	62	1.9	3	0.6	35	1.8	90	1.9	93	1.6

Note: NAICS = North American Industry Classification System.

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

Table 2. Number of annual days of paid sick leave, by service requirement and establishment size, private industry, March 2020

Category	After 1 year of service				After 5 years of service				After 10 years of service				After 20 years of service			
	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error

See footnotes at end of table.

Table 2. Number of annual days of paid sick leave, by service requirement and establishment size, private industry, March 2020

Category	After 1 year of service				After 5 years of service				After 10 years of service				After 20 years of service			
	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error	Mean	Standard error	Median	Standard error
All workers	7	0.1	6	0.0	7	0.1	6	0.0	7	0.1	6	0.0	7	0.2	6	0.0
Establishment size																
1 to 99 workers	6	0.2	5	0.1	6	0.2	5	0.2	6	0.2	5	0.3	6	0.2	5	0.3
1 to 49 workers	6	0.2	5	0.1	6	0.2	5	0.2	6	0.2	5	0.2	6	0.2	5	0.2
50 to 99 workers	6	0.3	5	0.2	6	0.3	5	0.7	6	0.3	5	0.8	7	0.3	5	0.8
100 or more workers	7	0.1	6	<0.05	8	0.1	6	<0.05	8	0.2	6	<0.05	8	0.2	6	0.1
100 to 499 workers	7	0.2	6	0.0	7	0.2	6	0.0	7	0.2	6	0.0	7	0.3	6	0.0
500 or more workers	8	0.2	7	0.3	8	0.2	8	0.7	8	0.2	8	0.7	9	0.2	8	0.6

Source: U.S. Bureau of Labor Statistics, National Compensation Survey.

NOTES

1 For additional information, see "National compensation measures," *Handbook of Methods* (U.S. Bureau of Labor Statistics), www.bls.gov/opub/hom/ncs/home.htm.

2 For information on the National Compensation Survey (NCS) supplement, see www.bls.gov/ncs/effects-of-coronavirus-on-sick-leave-policies.htm. For information on the Business Response Survey (BRS), see www.bls.gov/brs/.

3 While the NCS publication of annual benefits contains information on occupational and work characteristics, the NCS supplement and the BRS do not contain this information.

4 The increase in sick leave access is not statistically significant between establishments with 250 to 499 workers and establishments with 500 or more workers.

5 A consolidated leave plan combines multiple forms of leave that employees can allocate as they choose.

6 For additional information on BRS sampling and estimation, see www.bls.gov/brs/methods/technical-notes.htm.

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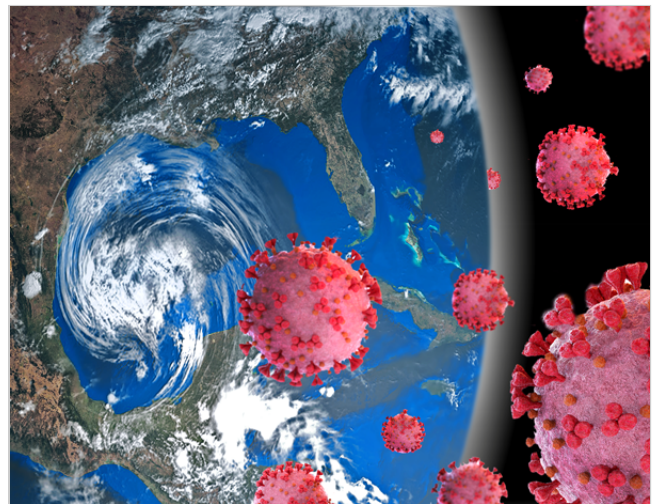
Estimating state and local employment in recent disasters—from Hurricane Harvey to the COVID-19 pandemic

Natural disasters, including hurricanes, floods, wildfires, and the coronavirus disease 2019 (COVID-19) pandemic, have challenged the standard practices used to produce state and area employment estimates. In some cases, these challenges have led to modifications to the handling of reported business closures, assumptions regarding nonresponse, and the techniques used for modeling employment in domains with small samples for state and metropolitan areas. This article examines how a series of major hurricanes in 2017 and 2018 affected the estimation of state and metropolitan area payroll employment and how lessons learned from these disasters provided a playbook for producing estimates during the COVID-19 pandemic.

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The U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) program produces some of the timeliest economic indicators each month, both for the nation as a whole and for varying levels of geographic detail. The CES program conducts a monthly survey of about 144,000 businesses and government agencies representing about 697,000 individual worksites. Respondents to the CES survey provide information on the number of employees, total payroll, and hours paid for the pay period that includes the 12th day of the month. The CES program uses these data to produce estimates of industry employment, hours, and earnings. BLS typically publishes national data within a week of the end of the reference month; data for the 50 states; Washington, DC; Puerto Rico; the U.S. Virgin Islands; and about 450 metropolitan areas are released approximately 2 weeks later.

Natural disasters challenge assumptions built into the employment estimation process regarding nonresponse and the relationship between business openings and closures, and the CES program must address this issue in order to produce accurate data. This article provides an overview of three aspects of the CES methodology that natural disasters confront. It then provides case studies of how the CES program dealt with these questions in developing state and metropolitan area estimates following five recent hurricanes—Harvey, Irma, and Maria in 2017, and

Florence and Michael in 2018—and how the lessons learned from the earlier experience were applied to producing estimates in the early months of the coronavirus disease 2019 (COVID-19) pandemic. (See table 1.)

Table 1. Selected natural disasters that affected state and local employment data

Disaster	Analyzed effect in Current Employment Statistics estimates
Hurricane Harvey	September 2017, Texas
Hurricane Irma	September 2017, Florida
Hurricane Maria	October 2017, Puerto Rico
Hurricane Florence	September 2018, North Carolina and South Carolina
Hurricane Michael	October 2018, Florida and Georgia
COVID-19 pandemic	March and April 2020, 50 states, plus Washington, DC, and Puerto Rico

Source: U.S. Bureau of Labor Statistics.

Note: COVID-19 = coronavirus disease 2019.

CES methodology and natural disasters

The CES program surveys businesses each month and uses the data and a consistent, objective methodology to produce estimates of industry employment, hours, and earnings. The methodology relies on assumptions that are continually evaluated and generally hold in normal times. However, natural disasters are extreme events, and this section explores three ways that such disasters raise questions about the usual CES methodological underpinnings.

Are survey respondents different from nonrespondents?

The CES survey is designed as a probability-based survey.[1] The BLS Quarterly Census of Employment and Wages (QCEW), which contains information on all employers required to participate in the unemployment insurance (UI) system and covers about 97 percent of all nonfarm payroll employment, provides both a sampling frame and the main benchmark source for the CES program.[2] In developing the QCEW as a sample frame, BLS stratifies the data by state, industry, and establishment size. The CES survey randomly selects businesses within these strata, with the inverse of the probability of selection used as the sample weight in estimation. The survey estimates are benchmarked to the administrative QCEW data annually. The difference between the benchmark data and the survey-based estimates—the benchmark revision—is regularly used to assess the accuracy of the CES estimates. After setting benchmark employment levels each year, the CES program estimates monthly employment growth rates with a weighted link-relative estimator. The estimator is essentially the ratio of the current month's weighted employment to that of the prior month in the set of matched respondents that reported nonzero employment for the pay period containing the 12th of both months. The generally small number of active survey units reporting zero employment in either the current or prior month is not used because of assumptions in the business birth–death model (discussed in the next subsection).

Equation 1 provides the weighted link-relative estimate ($\hat{R}_t$) for time t, where ae_i is reported employment for a matched respondent i in n matched sample establishments, w is the sampling weight, and d is a nonresponse weight adjustment (calculated for industries identified to respond at substantially higher or lower rates)[3]:

(1)
$$\hat{R}_t = \frac{\sum_{i=1}^{n} w_i \times d_i \times ae_{i,t}}{\sum_{i=1}^{n} w_i \times d_i \times ae_{i,t-1}}.$$

Within each estimating domain (an area or industry combination in which the estimate calculation is performed—other published cells are summaries of estimating cells), the estimator implicitly imputes data for nonrespondents as well as businesses reporting zero employment in the current or prior month by using the growth rates of the matched units. State-level estimates are produced for "estimation supersectors," high-level industries (such as construction or leisure and hospitality) that are estimated directly and control the sum of estimates of more detailed industries. The sample size in these estimation supersectors is large enough to avoid using small-area modeling techniques in most cases, but domain estimates use respondents in businesses from quite different industries (for example, clothing stores, gas stations, and grocery stores mixed together in retail trade).

The implicit imputation follows from the form of the estimator, which does not require explicit imputation, and a missing-at-random assumption within each estimating cell (conditioned on the industries in d_i). The survey respondents stand in for the nonrespondents, and this assumption works well when they are similar, on average.[4]

Natural disasters challenge the missing-at-random assumption. Certain types of businesses—for example, those in federally designated disaster areas—might have more job losses than others in their state because of business disruptions, and they might respond to the CES survey at a lower rate, as other matters take a higher priority. Similarly, certain industries within an estimation supersector may fare differently from one another during a disaster in a way that correlates with response rates, and the same may be true for differences in employment trends and response rates between large and small establishments.

Are business births and deaths properly captured?

The ability to use the QCEW as a frame with a close match to the target population of all nonfarm payroll jobs is one of the CES program's greatest strengths. Two of the program's biggest challenges are accounting for businesses that have opened and closed since the frame was established. It is impossible to sample, enroll, and collect data on business births in real time because the QCEW lags the CES survey by several months. Establishment deaths—defined as worksites that no longer have any payroll employees, which may be temporary or permanent—present a challenge because businesses generally stop reporting when there are no employees. A small number of businesses report establishment deaths; however, they are mainly firms with multiple worksites. These two components of job growth generally offset one another, and the degree to which CES procedures do not capture the residual growth when applied to historical QCEW population data is known as the "net birth–death residual." This value is generally small and stable, and therefore the CES program forecasts historical values with a time-series model for use in estimation. Equation 2 provides the formula for the employment estimate ($\hat{Y}_t$):

(2)
$$\hat{Y}_t = \hat{Y}_{t-1} \times \hat{R}_t + BD_t.$$

The CES program multiplies the prior month's employment level ($\hat{Y}_{t-1}$) by the weighted link relative ($\hat{R}_t$) and then adds the current month's forecast value (BD_t).[5]

Natural disasters strain the usual assumptions about business births and deaths. Disaster conditions may halt the formation of new businesses, while forcing many existing businesses to cease operations. But despite disruptions —and sometimes even severe damage to physical locations—many businesses continue to pay employees

through the hardship, mitigating the number of business deaths by CES definitions. Still, the net birth–death residual calculated from the QCEW is often noticeably lower in domains affected by natural disasters, and the forecast error tends to be positive in these cases.

Are small-area models adequate?

The CES program produces estimates with a version of the Fay-Herriot model for estimation supersectors and for many metropolitan areas with small sample sizes.[6] The model estimate is a weighted combination of the direct weighted link-relative estimate and a synthetic component consisting of a historical trend value corrected by a coefficient derived from the regression model in equation 3:

(3) $$Y1_{i,j} = \beta_i \times Y2_{i,j} + e_{i,j}.$$

$Y1_{i,j}$ represents the statewide weighted link-relative estimates for a given industrial supersector (i) and state (j), $Y2$ represents the corresponding historical trend values, β_i is an estimated coefficient, and $e_{i,j}$ is a model residual. The regression modeling is performed at a statewide supersector level, and the correction factor (β_i) from the state-level model is linked to detailed metropolitan areas. The Fay-Herriot estimate for metropolitan area k is displayed in equation 4:

(4) $$\hat{Y}_{i,k} = W_{i,k} \times Y1_{i,k} + (1 - W_{i,k}) \times \beta_i \times Y2_{i,k}.$$

The weight ($W_{i,k}$) assigned to the direct estimate ($Y1_{i,k}$) is a function of the variance of the direct and trend ($Y2_{i,k}$) components as well as the variance from the state-level model. When the relationship between the direct estimates and the historic trend is looser, the direct estimates receive a higher weight. The correction factor adjusts the historic trend values to the direct estimates roughly on average across the country, but it does not account for any clusters of heterogeneity among states or areas.

This model relies on assumptions about the similarity of industry behavior between areas in order to "borrow strength" across those areas; the model also relies on assumptions about the relationship between statewide and metropolitan area trends.[7] Hurricanes bring these assumptions into stark relief, as some affected states may be dissimilar to the nation as a whole, and even within those states some areas face devastation while others remain unscathed. Similarly, the COVID-19 pandemic affected jobs in states and cities to widely different degrees, despite broad-based shutdowns and job losses.

Five major hurricanes

Although the CES survey began in 1915, and the program has faced many natural disasters since then, the survey has evolved substantially over the years. The CES program fully implemented a probability-based design for the 50 states and Washington, DC, in 2003, BLS assumed responsibility for producing the state and local estimates in 2011, and estimation procedures and models have continued to evolve since then.[8] As a result, the 2017–18 hurricanes provided the best context in which to address estimation issues related to the COVID-19 pandemic.[9]

Several major hurricanes made landfall on the Gulf of Mexico and Atlantic coasts, as well as over U.S. territories in the Caribbean, during the 2017 and 2018 hurricane seasons.[10] The timing of these storms matters because anyone who worked or received pay for any portion of the pay period including the 12th day of the month was counted as employed. Hurricane Harvey made landfall at Port Aransas, Texas, as a category-4 storm, on Friday,

August 25, 2017, and produced heavy rainfall and severe flooding in coastal Texas and other parts of the Gulf Coast, most notably in Louisiana. The system that became Hurricane Irma also formed in August 2017 and made landfall over several Caribbean islands as a category-5 storm in early September; it struck the Florida Keys as a category-4 storm on Sunday, September 10, 2017, and reached the mainland later that day, continuing north along the Florida peninsula. Hurricane Maria formed in September 2017 and caused severe devastation as it made its way through the Caribbean that month. The center of the then-category-5 storm passed just south of St. Croix in the U.S. Virgin Islands on September 19, 2017, before moving diagonally across Puerto Rico the following day.[11] The next year, Hurricane Florence reached category-4 strength and weakened to a category-1 storm, before making landfall on Friday, September 14, 2018, near Wrightsville Beach, North Carolina; it then traveled into South Carolina, causing severe flooding and storm surges in both states. The following month, Hurricane Michael struck the Florida panhandle on Wednesday, October 10, 2018, as a category-5 hurricane.

Hurricanes Harvey and Irma both caused tragic loss of life and rank among the most severe U.S. natural disasters, in terms of property damage. Harvey caused 68 direct deaths in Texas and an estimated $125 billion in property damages in the region. Irma caused 10 direct deaths across three states—7 in Florida, 2 in Georgia, and 1 in South Carolina—and 3 direct deaths in the U.S. Virgin Islands, as well as $50 billion in property damages. The CES survey measured far fewer job losses associated with Harvey than with Irma, however. Texas employment grew in September 2017—adding 14,600 jobs, not far off the prior 12-month average growth of 16,900 jobs—with net job losses in coastal metropolitan areas such as Houston-The Woodlands-Sugar Land, TX (–8,800). The state added 39,300 jobs the following month as businesses bounced back. Florida, by contrast, lost 172,700 jobs in September 2017, before recovering 194,700 jobs the following month. The difference resulted from the timing of the storms. Irma struck Florida at the beginning of the week that included September 12, so workers on a weekly payroll who lost their shifts for 7 days showed up in the estimates as a job loss. By contrast, Harvey hit Texas more than 2 weeks earlier, so only prolonged layoffs resulted in a drop in measured employment in that state.[12] Hurricane Maria, despite hitting Puerto Rico and the Virgin Islands well before the October 2017 reference period, followed closely behind Irma's strike on the territories and caused lasting devastation that was evident in employment data for a prolonged period.

The birth–death model

In normal months, a small number of businesses report zero employment in the CES survey. The rate of reported establishment "deaths" generally follows a stable, seasonal pattern, and some of the deaths are temporary. Following Hurricanes Irma and Maria, the number of establishments reporting zero employment increased sharply. Table 2 shows the proportion of respondents that reported zero employment and compares the forecasted and actual birth–death residuals (later derived from the QCEW) in disaster months. In order to provide frames of reference, table 2 also shows the average proportion of business deaths in the sample over the 2-year period before the disaster and the average absolute monthly forecast error, in terms of employment. The proportion of reported establishment deaths was double the usual rate in Florida following Hurricane Irma and 7 times the usual rate in Puerto Rico following Hurricane Maria. This indicated that the usual birth–death relationship did not hold, and actual birth–death values from the QCEW—calculated several months after the initial release of the CES estimates—were substantially more negative than the forecast values. The forecast error of employment in Florida following Irma was nearly 4 times the average absolute monthly forecast error, while the forecast error for Puerto Rico following Maria was more than 8 times larger than average. Following other major hurricanes, the proportion

of reported establishment deaths was relatively normal, and the birth–death forecasts were closer to their mark and well within normal ranges. (See table 2.)

Table 2. Reported zeros and birth–death forecast errors

Event	Proportion of businesses reporting zero employment		Birth–death forecast error (mean absolute error, 2014–19)	
	Month	Percent	Month	Value (in thousands)
Harvey (Texas)	September 2017	0.23	September 2017	–0.3 (7.9)
	Average, September 2014, 2015, and 2016	0.15		
Irma (Florida)	September 2017	0.40	September 2017	28.4 (7.5)
	Average, September 2014, 2015, and 2016	0.19		
Maria (Puerto Rico)	October 2017	2.20	October 2017	13.8 (1.7)
	Average, October 2014, 2015, and 2016	0.32		
Florence (North Carolina)	September 2018	0.14	September 2018	4.9 (3.6)
	Average, September 2015, 2016, and 2017	0.16		
Florence (South Carolina)	September 2018	0.21	September 2018	–0.5 (2.1)
	Average, September 2 015, 2016, and 2017	0.20		
Michael (Florida)	October 2018	0.22	October 2018	4.5 (7.5)
	Average, October 2015, 2016, and 2017	0.18		
Michael (Georgia)	October 2018	0.13	October 2018	2.3 (5.0)
	Average, October 2015, 2016, and 2017	0.18		
COVID-19 (50 states, plus Washington, DC, and Puerto Rico)	March 2020	0.46	March 2020	Unavailable
	Average, March 2017, 2018, and 2019	0.18		
	April 2020	3.40	April 2020	Unavailable
	Average, April 2017, 2018, and 2019	0.22		

Source: U.S. Bureau of Labor Statistics.

Although reported establishment deaths generally are not used in the estimation process, the seven-fold increase in their rate in Puerto Rico following Hurricane Maria necessitated a different approach. BLS determined the risk of underestimating the number of business deaths to be substantial enough that reported zeros were treated the same as other matched reports and were used in the sample link relative. This change negatively affected the October 2017 employment estimates by 11,800 jobs, nearly offsetting the birth–death forecast error of 13,800. Because many of the closures were temporary, the returns from zero employment were also used in the estimates.

Following Hurricane Irma, the CES program did not initially use reported business deaths in the weighted link-relative estimator for Florida, but after benchmarking the September 2017 employment data, the program recognized that the initial sample-based estimates undercounted the extent of job loss.[13] The QCEW data contained a large increase in the number of establishments reporting zero employment, and had the sample-based estimates used the reported zeros, the estimated employment level would have been 35,000 lower—more closely tracking the population data—which would have accounted for the birth–death forecast error. (The actual value was 28,000 lower than the forecast value.) The CES program included the returns for businesses that had reported declines to zero following Irma in the sample-based estimates that were produced from the new September 2017 benchmark level, increasing Florida employment estimates in October 2017 by 32,000. Including these returns from zero and making other adjustments to account for reporting differences between the CES

survey and the QCEW resulted in October–December 2017 reestimates that would more closely track the eventual benchmark data released in March 2019.

Nonresponse analysis

Following several major hurricanes, concerns arose over the possibility of businesses in severely affected areas responding at lower rates than those in the rest of the state, which would result in a violation of the missing-at-random assumption. The CES program has investigated nonresponse weight adjustments following hurricanes and other disasters such as floods and wildfires dating back to Katrina, in 2005, in order to appropriately represent disaster areas in statewide estimates. Although these adjustments can be calculated for different levels of devastation—for instance using flood maps—the set of counties designated by the Federal Emergency Management Agency (FEMA) as eligible for individual and public assistance has typically defined disaster areas for purposes of nonresponse analysis. The program now regularly monitors response rates and the impact of differential nonresponse in states affected by natural disasters. However, response rates were not significantly lower in disaster areas following the 2017–18 hurricanes, in part because of dedicated data collection efforts. Applying nonresponse adjustments following the 2017–18 hurricanes would have changed estimates little, with no obvious benefit, and therefore the estimates were not adjusted for differential nonresponse.

Small-area estimation

The CES program widely uses variants of the Fay-Herriot model in producing employment estimates, particularly at the metropolitan-area level.[14] In areas affected by recent major hurricanes, the direct employment estimates were lower than the synthetic components 65 percent of the time. This indicates a breakdown in the assumptions of similarity across states and among areas within each state. Chart 1 shows a comparison of the link relatives for the direct and synthetic parts of Fay-Herriot models in metropolitan areas containing counties designated by FEMA as eligible for individual and public assistance. (Three outlier values are not displayed.) The reference line has a slope of 1, and values above that line indicate a direct estimate lower than the synthetic one.

Chart 1. Comparison of direct and synthetic components in Fay-Herriot model estimates
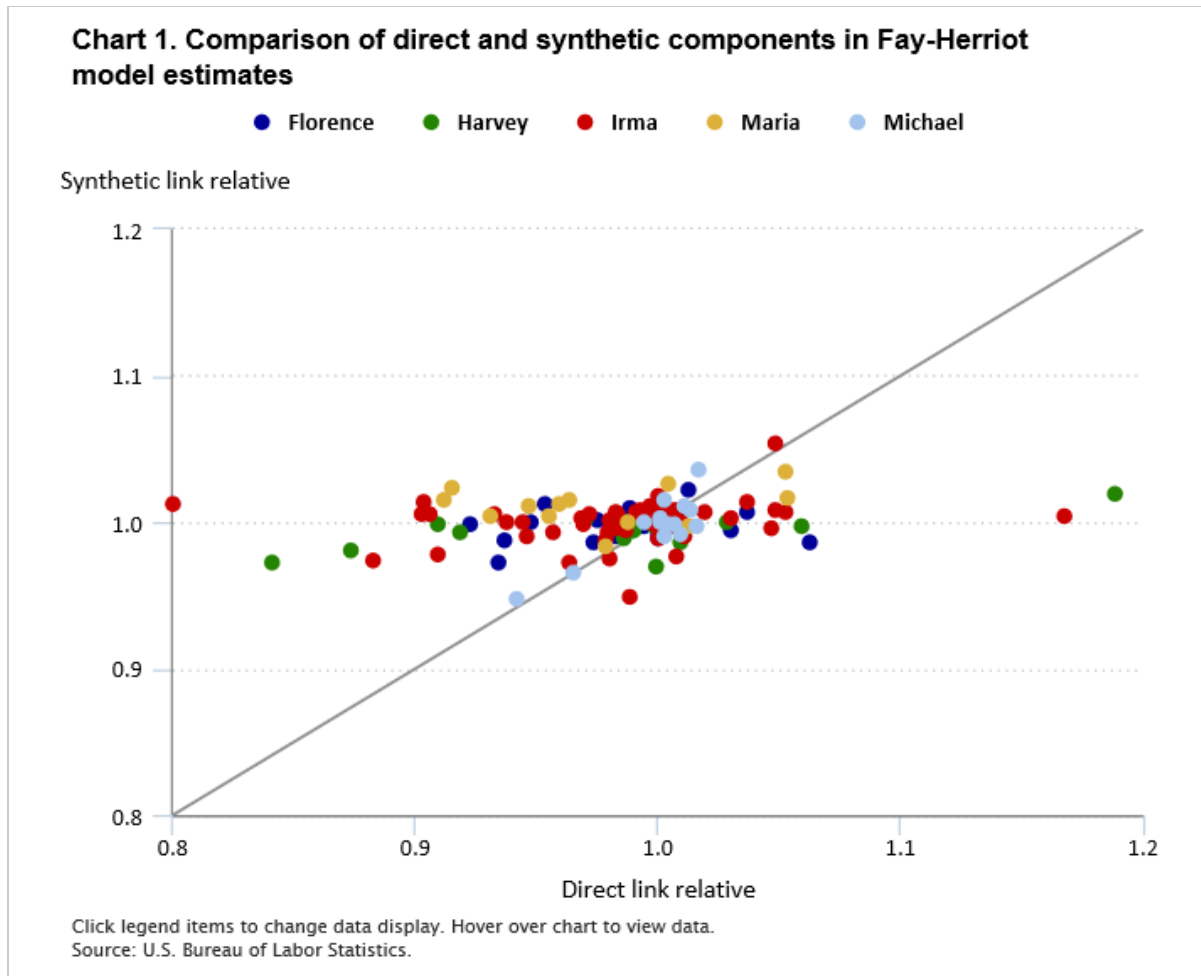
Although the direct estimates showed the job-losing effects of these hurricanes more, on average, than did the model as a whole, the sample in these domains is small and often quite volatile. Had the CES program used direct estimates instead of Fay-Herriot models, the root-mean-square benchmark revision to the link relatives would have been 37 percent higher.

Experiences following the 2017 and 2018 hurricanes led to the development of other modeling approaches that would generate better results and not violate important assumptions. Instead of modeling all statewide supersectors together and applying the results to metropolitan areas, the domains directly affected by hurricanes could be pooled and modeled together. Had it been used, this "hurricane variant" of the Fay-Herriot model would have produced benchmark revisions that were, on average, 12 percent lower, and it would have improved 64 percent of estimates. The variant model would have improved accuracy the most for the hurricanes with the largest effect on estimates, reducing benchmark revisions for Puerto Rico following Maria by 39 percent and for Florida following Irma by 11 percent. (The hurricane variant improved estimates 71 percent of the time for Puerto Rico and 74 percent of the time for Florida.) The hurricane variant model did not perform well for Texas following Harvey: although the correction factor better captured the drop in employment, worse model fit resulted in a much larger weight on the direct components, which would have resulted in higher benchmark revisions. (See table 3.)

Table 3. Root-mean-square benchmark revision of link relatives for Fay-Herriot modeled series in metropolitan areas during major hurricanes

Hurricane	Direct sample-based	Fay-Herriot	Fay-Herriot hurricane variant	Percentage improved by hurricane variant
All (n = 139)	0.056	0.041	0.036	64.7
Florence (n = 21)	0.031	0.027	0.026	61.9
Harvey (n = 22)	0.060	0.021	0.033	31.8
Irma (n = 68)	0.047	0.036	0.032	73.5
Maria (n = 14)	0.102	0.075	0.046	71.4
Michael (n = 14)	0.058	0.056	0.056	71.4

Source: U.S. Bureau of Labor Statistics.

Applying lessons learned to producing estimates during the COVID-19 pandemic

A historically unprecedented number of jobs were lost and regained in the months after the onset of the COVID-19 pandemic.[15] Health officials identified the first case of COVID-19 in the United States in Washington State on January 21, 2020.[16] However, it would be several weeks before community spread of the virus led to severe business disruptions and shutdowns. Many novel data sources show declining activity throughout the month of March 2020,[17] even before the issuance of formal shelter-in-place and stay-at-home orders.[18] The week of March 8–14 marked a turning point in business activity. Restaurant reservation data from OpenTable illustrate the evolving decline in business activity that week: as of Sunday, March 8, reservations were down only 2 percent over the year, but by the following Saturday (March 14), they showed a 42-percent decline.[19] Ohio was the first state to close all public schools on March 12, and by the end of the following week (March 15–21), nearly all public schools had closed,[20] air passenger travel had fallen by 75 percent,[21] and restaurant reservations had dropped by nearly 100 percent. The National Bureau of Economic Research (NBER) Business Cycle Dating Committee determined that the longest economic expansion in U.S history ended in February 2020 and a recession began in March.[22] Nationwide job losses in March (–1.7 million) and April (–20.7 million) marked the steepest employment decline in history, and were followed by the two largest monthly job gains ever in May (+2.8 million) and June (+4.8 million). The steepness and suddenness of these job losses, followed by a rapid (if partial) recovery, were more reminiscent to the losses seen after major hurricanes than those seen during a typical recession.

The birth–death model

The nationwide increases in the number of establishments reporting zero employment in March 2020 (2.6 times normal) and April 2020 (15 times normal) could only be compared with the spikes following Irma in Florida (2.1 times normal) and Maria in Puerto Rico (6.9 times normal). Evidence from Irma and Maria indicates that using reported zeros could reduce error. Beginning with the March final and April preliminary estimates, the CES state and area program incorporated "excess" reported zeros in the link relative in calculating the employment estimates. In order to avoid statistical bias, the program applied a weight-reduction adjustment value ranging between 0 and 1 to establishments reporting zero employment. In cases in which the proportion of reported zeros

at the state estimation supersector level was at or below normal, the factor was set to 0, and in those cases in which the proportion was many times the usual rate, the factor approached 1. The average weight adjustment factor for a reported zero was 0.603 in March and 0.954 in April. As with Hurricanes Irma and Maria, employment counts also needed to appropriately reflect returns from zero. Weight adjustment factors were also developed for returns, and they were first applied in the May preliminary estimates, as many business reopened. The use of excess reported drops-to and returns-from zero lowered the final sum of state employment estimates by 331,000 in March and 3.0 million in April, while increasing them by 1.0 million in May and 934,000 in June, as many businesses reopened.

In addition, the CES program augmented the time-series forecast component of the net birth–death model with information from the nonzero matched sample as an exogenous regressor in a regression model with autoregressive integrated moving average errors (regARIMA), beginning with the April values.[23] Earlier research indicated that this method could improve forecast accuracy during business cycle turning points, although it was not feasible to implement following hurricanes.[24] The CES program updated the forecast models at the national level and controlled the sum of the state subsector forecasts to the new national forecasts, incorporating sample information on the states and industries seeing spikes in reported zero employment to allocate the distribution of differences. This lowered the sum of state birth–death factors by 799,000 in April compared with what they would have been without the regressor. The models in turn processed more positive sample information in May and June 2020 into higher forecast values.

Nonresponse analysis

The COVID-19 recession led to nonresponse concerns about the state and area employment estimates that were different from but related to those explored after hurricanes. Subdividing states into affected and unaffected regions, as is done for a hurricane, was not a promising option because of the geographic pervasiveness of business disruption. The CES program explored making differential-response-rate adjustments based on business size (the hypothesis being that larger firms may be less disrupted and better able to continue paying employees), but the results were unclear and any adjustments may have exacerbated the effects of confounding factors. The program also explored conducting nonresponse analysis based on linked unemployment insurance filings, but doing so did not uncover notable differences between respondents and nonrespondents.

In producing the April 2020 state-level estimates, a major nonresponse problem appeared as certain detailed industries within the estimation supersectors were broadly underrepresented across states in the responding CES sample in a way that correlated with employment trends. In retail trade, clothing and clothing accessories stores closed almost everywhere in April 2020, and these establishments responded to the survey at relatively low rates, while general merchandise stores and building material and garden equipment stores had comparatively resilient employment and responded at higher rates. Within leisure and hospitality, full-service restaurants lost relatively more jobs and responded to the CES survey at lower rates than limited-service restaurants, while in the "other services" supersector, the laundry and personal care services industry showed steep losses and was underrepresented in the responding sample. This nonresponse issue did not arise in the national estimates because they are produced at a detailed industry level using samples from all states, in contrast to the approach used in the state and local estimates, where estimation supersectors pool samples from heterogeneous industries into a discrete geographic domain.[25]

The CES program took two approaches to nonresponse adjustments for these industries. If it was possible to do so, especially in very large states, the program calculated sample-based estimates at a more detailed level and summed them to replace the estimation supersectors.[26] In states for which this approach was infeasible, the CES program calculated nonresponse adjustments similar to those calculated (but not applied) following hurricanes and those obtained by using preidentified nonresponse factors in the link-relative estimator (d_i). Many of the response-rate differences were longstanding, but they had not substantially affected the estimates. In total, nonresponse adjustments served to lower the sum of April 2020 state employment estimates by 461,000 in leisure and hospitality, 413,000 in retail trade, and 73,000 in other services. As jobs returned, the differential nonresponse problem presented in the opposite direction, and correcting for it increased employment estimates.

Small-area estimation

The CES program explored an approach similar to the hurricane variant of the Fay-Herriot model in March 2020. The program considered a scenario in which certain states and metropolitan areas in the Northeast and Pacific Northwest that had early cases of COVID-19 might have substantially larger employment drops in March, in which case it could have been beneficial to pool those areas together and model them separately. This was not the case, however, as job losses that month presented along a continuum, with no clearly identifiable division, and were only loosely related to early case counts. The ordinary Fay-Herriot models were also problematic. The wide range of job losses among states resulted in very high model variance and subsequently near-total reliance on the direct estimates. Although the direct estimates are approximately unbiased, they tend to have high variability when sample sizes are small, and the poor performance of direct estimates following hurricanes in modeled cells indicated the potential for low accuracy.

Instead, BLS generated and in many cases used a small-area model that generalizes the Fay-Herriot model and relaxes many of its assumptions by jointly modeling variance and point estimates and clustering the data.[27] This model outperformed the existing Fay-Herriot model in simulations, in terms of benchmark revisions, during both the steep downturn of the 2007–09 recession and the subsequent recovery and expansion. When applied during the COVID-19 recession, metropolitan area estimates were more consistent with statewide values and showed a similar story: compared with the Fay-Herriot estimates, the new model reduced the root-mean-square difference between metropolitan and statewide estimates in the same state or industry by 29 percent in the April 2020 preliminary estimates. The combination of lessened reliance on volatile direct estimates (because of better model fit) and state-specific effects being captured in the synthetic component of the clustered model resulted in the tighter relationship among metropolitan area estimates and corresponding state-level estimates.

Conclusion

Timely economic data is needed to capture rapid shifts in business conditions shortly after they occur, and payroll employment estimates from the CES program are among the timeliest economic indicators available each month for states and metropolitan areas. Natural disasters often cause sudden, steep job losses, but the measurement of employment change following disasters presents challenges. The CES survey must accurately capture the relationship between business openings and closings, account for differences between respondents and nonrespondents, and use robust models to accurately estimate employment in small domains. Five major hurricanes that occurred in 2017 and 2018 brought these concerns to light and resulted in the development of potential solutions. Using reported zeros proved beneficial to the estimation process after the survey showed sharp

increases in their number. Modeled estimates could be improved by refining the pool of observations that are processed together.

When the COVID-19 pandemic caused the steepest job losses in U.S. history, the CES program applied the lessons learned from producing estimates following major hurricanes to better capture business deaths, properly represent industries experiencing the most severe declines, and incorporate models that capture important differences between, and commonalities among, states. Using reported zeros proved beneficial following Hurricanes Irma and Maria, and the CES program generalized their use with the wave of business closures that began in March 2020. Although nonresponse was not a major problem after the 2017–18 hurricanes, monitoring processes set up in the wake of those hurricanes helped BLS identify industry-based differential nonresponse adjustments when the steepest job losses in history occurred. Techniques pooling similar observations in Fay-Herriot models showed promise, and the CES program applied a model that more formally clustered the data to produce small-area estimates during the pandemic.

Although job losses during the COVID-19 recession have been far steeper and more sudden than those occurring in typical downturns, the associated measurement challenges highlight areas of potential improvement that could help the CES survey better capture future business-cycle turning points and sudden changes in state and area employment that result from disasters.

SUGGESTED CITATION

Steven M. Mance, "Estimating state and local employment in recent disasters—from Hurricane Harvey to the COVID-19 pandemic," *Monthly Labor Review,* U.S. Bureau of Labor Statistics, April 2021, https://doi.org/10.21916/mlr.2021.9.

NOTES

[1] For more information on the design of the U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey and its evolution, see Laura A. Kelter, "One hundred years of Current Employment Statistics—the history of CES sample design," *Monthly Labor Review*, August 2016, https://doi.org/10.21916/mlr.2016.35.

[2] For more information on the process for benchmarking state and local CES employment data, see Kirk Mueller, "Benchmarking the Current Employment Statistics state and area estimates," *Monthly Labor Review*, November 2017, https://doi.org/10.21916/mlr.2017.26.

3 This formula is simplified to remove components that are not relevant to this article. A robust estimation technique is used to identify "atypical" reporters, which are removed from the link and only represent themselves, and reduce the weight on other influential reporters. Employees of religious organizations, which are in scope for CES but not on the sampling frame, are addressed by removing their benchmark level from the prior month's employment before applying the weighted link relative and then added back to the current month's level.

4 Decompositions of benchmark revisions have indicated nonresponse to not be a principal driver of total survey error in the CES survey. See, for example, Larry L. Huff and Julie G. Gershunskaya, "Components of error analysis in the Current Employment Statistics survey," Proceedings of the Survey Research Methods Section, American Statistical Association, October 2009, http://www.asasrms.org/Proceedings/y2009f.html; the paper is also available on the BLS website at https://www.bls.gov/osmr/research-papers/2009/st090050.htm. Although the implicit imputation of the weighted link-relative estimator is generally used, there is some explicit imputation in state and area estimates for large nonrespondents that exhibit a stable, seasonal difference from the rest of the universe using historical QCEW data. These explicit imputations are often not made during disasters.

5 For more information about the CES net birth–death model, see Kirk Mueller, "Impact of business births and deaths in the payroll survey," Monthly Labor Review, May 2006, https://www.bls.gov/opub/mlr/2006/05/art4full.pdf.

6 Fay-Herriot models are commonly used in producing small-area estimates and were introduced by Robert E. Fay III and Roger A. Herriot in "Estimates of income for small places: an application of James-Stein procedures to census data," Journal of the American Statistical Association, vol. 74, no. 366, June 1979, pp. 269–277, https://www.jstor.org/stable/pdf/2286322.pdf.

7 More formally, this involves distributional assumptions linking the direct estimates, historical trend projections, and actual values from a high-level model to more detailed domains. For more detail, see Julie Gershunskaya, "Estimation for detailed publication levels in the Current Employment Statistics survey," Proceedings of the Survey Research Methods Section, American Statistical Association, October 2012, https://www.bls.gov/osmr/research-papers/2012/st120190.htm.

8 Puerto Rico transitioned from a quota-based design to the current probability-based design with the January 2014 estimates. Although the U.S. Virgin Islands were severely affected by Hurricane Maria, employment estimates for the Virgin Islands are not examined in this article because they employ a quota-based sample with an estimation methodology that differs from that of the rest of the CES program.

9 The handling of recent disasters was built upon past experiences, primarily Hurricane Katrina, a thorough examination of which can be found in Molly Barth Garber, Linda Unger, James White, and John Wohlford, "Hurricane Katrina's effects on industry employment and wages," Monthly Labor Review, August 2006, https://www.bls.gov/opub/mlr/2006/08/art3full.pdf.

10 Information on the track and development of these storms and estimates of the damage they caused are from the National Hurricane Center's Tropical Cyclone Reports; for more information, see https://www.nhc.noaa.gov/data/tcr/.

11 Devastation from Hurricanes Irma and Maria was severe enough that officials in the U.S. Virgin Islands were unable to collect establishment data for several months, resulting in a delay in the release of preliminary September, October, and November 2017 estimates for the territory. Unlike the 50 states and the District of Columbia, the workforce agencies in the U.S. Virgin Islands and Puerto Rico collect the majority of the microdata used in their CES estimates. More information is available at https://www.bls.gov/sae/notices/2017/hurricanes-irma-maria-september-october-november-december-2017-payroll-data-for-puerto-rico-and-the-us-virgin-islands.htm.

12 An analysis of credit card data by researchers at the Federal Reserve Board indicated that retail trade spending in the areas affected by Hurricanes Harvey and Irma dropped steeply but returned to normal within 2 weeks of the storms making landfall, which helps explain the comparatively smaller effect of Harvey on CES estimates. See Aditya Aladangady Shifrah, Aron-Dine, Wendy Dunn, Laura Feiveson, Paul Lengermann, and Claudia Sahm, "From transactions data to economic statistics: constructing real-time, high-frequency, geographic measures of consumer spending," Finance and Economics Discussion Series 2019-057 (Board of Governors of the Federal Reserve System, 2019), https://doi.org/10.17016/FEDS.2019.057.

13 Some large business deaths were accounted for in Florida following Hurricane Irma, but they solely represented themselves.

14 Fay-Herriot models are also used in some statewide estimation supersectors, mostly in smaller industries such as mining and logging. Another type of small-domain model is also used by the CES program, primarily in detailed industries.

15 Coronavirus disease 2019 (COVID-19) is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). For more information, see "COVID-19 science update" (Centers for Disease Control and Prevention, January 15, 2021), https://www.cdc.gov/library/covid19/01152021_covidupdate.html.

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16 Lena H. Sun and Lenny Bernstein, "First U.S. case of potentially deadly Chinese coronavirus confirmed in Washington state," *The Washington Post*, January 21, 2020, https://www.washingtonpost.com/health/2020/01/21/coronavirus-us-case/.

17 For example, researchers at the Federal Reserve Bank of Minneapolis used smartphone data to create indexes that measure changes in travel and social encounters, which showed broad declines through March and into April 2020. See Victor Couture, Jessie Handbury, Jonathan I. Dingel, Kevin R. Williams, and Allison Green, "Measuring movement and social contact with smartphone data: a real-time application to COVID-19," Institute Working Paper 35 (Federal Reserve Bank of Minneapolis, Opportunity and Inclusive Growth Institute, July 2020), https://doi.org/10.21034/iwp.35.

18 There is evidence that the formal shutdown orders only explain a small proportion of the decline in business activity. See Austan Goolsbee and Chad Syverson, "Fear, lockdown, and diversion: comparing drivers of pandemic economic decline 2020," Working Paper 27432 (Cambridge, MA: National Bureau of Economic Research, June 2020), https://doi.org/10.3386/w27432.

19 For more information on restaurant reservation data, see the "State of the Industry" page on the OpenTable website at https://www.opentable.com/state-of-industry.

20 Ohio became the first state to close schools on March 12, and 27 states and territories had done so by March 16. By March 25, all U.S. public schools were closed. See "The coronavirus spring: the historic closing of U.S. schools," *Education Week*, July 1, 2020, https://www.edweek.org/ew/section/multimedia/the-coronavirus-spring-the-historic-closing-of.html.

21 Data on passenger throughput during the COVID-19 pandemic from the Transportation Security Administration are available at https://www.tsa.gov/coronavirus/passenger-throughput.

22 The Business Cycle Dating Committee of the National Bureau of Economic Research determined that a peak in economic activity occurred in February 2020, marking the end of the economic expansion that began in June 2009 and the beginning of a recession. For more information, see "Determination of the February 2020 peak in U.S. economic activity" (Cambridge, MA: National Bureau of Economic Research, June 8, 2020), https://www.nber.org/cycles/june2020.html.

23 For more information on regression models with autoregressive integrated moving average (regARIMA), see Kathleen M. McDonald-Johnson and Catherine C. Hood, "Outlier selection for RegARIMA models" (U.S. Census Bureau, 2001), https://www.census.gov/ts/papers/asa2001kmm.pdf.

24 For more information on the regression model used to modify birth–death forecasts, see Victoria Battista, "Back to the future: using current regression variables to forecast forward from historical net birth/death employment," Proceedings of the Government Statistics Section, American Statistical Association, October 2013, https://www.bls.gov/osmr/research-papers/2013/st130140.htm.

25 See Huff and Gershunskaya, "Components of error analysis in the Current Employment Statistics survey."

26 In retail trade and other services, the post-stratified estimates were produced at the three-digit NAICS subsector level. In leisure and hospitality, the estimates became the sum of arts, entertainment, and recreation; accommodation; full-service restaurants; and the remainder of food services and drinking places. In some cases, QCEW ratios were applied to the March leisure and hospitality estimates to create a prior-month employment level from which to apply the weighted link relative.

27 For more details on the generalized small-area model, see Julie Gershunskaya and Terrance D. Savitsky, "Bayesian nonparametric joint model for point estimates and variances under biased domain variances," Proceedings of the Survey Research Methods Section, American Statistical Association, November 2019, https://www.bls.gov/osmr/research-papers/2019/st190020.htm.

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