From the 2007–09 Great Recession to the onset of the coronavirus disease 2019 pandemic, the new-vehicle market in the United States changed significantly. Consumer and producer price trends examined in this article show how dealers’ profits on new vehicles declined and, subsequently, how dealers successfully expanded financial services to improve revenue and profit.

New-vehicle production and sales are important to the U.S. economy. Vehicle dealerships are the primary intermediary between consumers and manufacturers in the new-vehicle supply chain. From 2007 to 2009, these dealerships, facing declining profits from vehicle sales, adjusted their business models to increase revenues from other lines of business, especially finance and insurance (F&I). The automotive market started to change during the 2007–09 Great Recession, when profit margins on new-vehicle sales began declining. Subsequently, dealerships expanded offerings of financial products to offset reduced profit margins in vehicle sales. The volume of these services steadily increased, reaching record levels by the end of 2019. The changes in the automotive sector are reflected in U.S. Bureau of Labor Statistics (BLS) price indexes. Using these indexes, this article describes the competitive challenges in the automotive sector that resulted in changes in automotive dealerships’ profit-maximizing strategies from 2007 through 2019.

Industry and theoretical background

BLS publishes several producer price indexes (PPIs) that track monthly price changes of services provided by vehicle dealerships. As part of the retail trade sector, these services have price indexes that primarily reflect margin prices (i.e., the difference or spread between the selling price and the acquisition price of a good). The overall industry PPI for new-car dealers measures the change in prices for all goods sold and other services performed by dealerships. Within the overall industry index, the more specific PPI for new-vehicle sales tracks the retail selling prices received by dealerships for new cars and trucks (regardless of whether the vehicles were manufactured in the United States or imported) less their acquisition prices. Other services price indexes that constitute the PPI for new-car dealers include the indexes for used-vehicle sales, service labor and parts, and other receipts. The latter index tracks the retail markup of other services performed by dealerships, including the sale of financial products.

Because PPIs for trade services are based on acquisition and sales prices, goods price indexes—such as consumer price indexes (CPIs) and PPIs for the output of domestic manufacturing industries—complement service margin indexes in retail service trade. For example, in the case of the PPI for new-vehicle sales, the acquisition price of new vehicles is similar to the price underlying the PPI for domestic motor vehicles manufacturing, and the retail selling price of new vehicles is similar in definition to the price underlying the CPI for new cars and trucks, which may include domestically produced and imported vehicles. The difference between these two prices is the gross-margin price, which reflects the value added by the establishment for services such as marketing, storing, displaying goods, and making the goods easily available for customers to purchase—this is the margin captured by the PPI for new-vehicle sales.

Applying this analysis to the data presented in chart 1 reveals that the trends in the PPI for motor vehicles and the CPI for new cars and trucks are reflected in the movements of the margin PPI for new-vehicle sales. An increase in the prices received by vehicle manufacturers without commensurate increases in consumer prices results in lower new-vehicle margins, whereas an increase in consumer prices without a commensurate increase in producer manufacturing prices results in an increase in the margin on new vehicles realized by dealerships.


Click legend items to change data display. Hover over chart to view data.

Note: The estimated margin index is the residual of an ordinary least squares regression of the CPI for new cars and trucks on the PPI for motor vehicles. CPI = Consumer Price Index; PPI = Producer Price Index.

A further illustration of the relationship between the PPI for motor vehicles and the CPI for new cars and trucks comes from the estimated margin index in chart 1, which plots the residuals of an ordinary least squares regression of the CPI for new cars and trucks on the PPI for motor vehicles. The regression is estimated as

\[ \text{New Cars and Trucks CPI}_t = \beta_0 + \beta_1 \text{Motor Vehicles PPI}_t + \epsilon_t. \]

In the regression, \( \beta_0 \) and \( \beta_1 \) capture the average difference between the two indexes over period \( t \), a difference reflecting the average markup of car dealers. The residual of this regression, \( \epsilon_t \), represents deviations of dealer markups from this average. A positive residual indicates that dealer margins have risen, whereas a negative residual indicates that margins have fallen. A plot of this residual (the estimated margin index in chart 1) closely mirrors the margin PPI for new-vehicle sales, indicating that the three indexes are internally consistent.

The 5-year period over which vehicle prices experienced large fluctuations illustrates these implicit relationships. Both the CPI for new cars and trucks and the PPI for new-vehicle sales fell from January 2007 to January 2009, and prices recovered in subsequent years. The PPI for motor vehicles steadily outpaced the CPI for new cars and trucks. The gap between manufacturer and consumer prices was indicative of higher production costs relative to sales prices and is reflected in the decline of the margin PPI for new-vehicle sales and mirrored by the estimated margin index. The decline in the margin PPI for new-vehicle sales represents price changes that dealers do not fully pass through from producers to consumers. The jump in the PPI for motor vehicles in October 2008, at a time when consumer prices dipped, is reflected in a steep decline in the margin PPI for new-vehicle sales and the estimated margin index. Subsequently, consumer prices for new vehicles rose and manufacturing prices flattened out. The shift in these trends reversed the steep decline in the margin PPI for new-vehicle sales and the estimated margin index, although fluctuations persisted throughout the period.

Price transmission is the process by which price changes in one part of a supply chain are passed through to intermediaries and final consumers. In the automotive sector, market imperfections such as oligopoly, information barriers, irrationality, and financial liquidity constraints can cause asymmetrical, delayed, and incomplete price transmission. Price transmission in the sector is dependent on two markets—the manufacturer-dealer market (the manufacturer can be either foreign or domestic) and the dealer-consumer market. Different conditions in the two markets can cause fluctuations in profit margins for dealerships.

In the automotive sector, manufacturers and dealers are interdependent. Manufacturers hold relatively greater market power than dealerships. For example, when a manufacturer—the supplier—raises the price paid by a dealership for a vehicle, the dealership cannot switch to another manufacturer. The dealership may or may not be able to pass the higher manufacturer price to the consumer. If consumers are unwilling to buy higher priced cars, the dealership—as the intermediary—incurs a reduced profit margin. Chart 1 shows the price transmission mechanism in both markets through the PPI for new-vehicle sales and the estimated margin index. The steep decline in the margin for new vehicles precipitated a major change in the business model for dealerships.

Dealerships selling new cars and trucks are the primary intermediary between consumers and manufacturers in the automotive supply chain and thus are a crucial component in the supply chain through which prices are transmitted. During the period analyzed here, dealerships had little flexibility in setting the price of vehicles, given their intermediary role between manufacturers who were raising prices and consumers whose purchasing behavior was highly sensitive to income and prices. After the Great Recession, this constraint compressed profit margins for dealerships. However, by adding ancillary services (such as service contracts and insurance) to new-vehicle sales, dealerships actively innovated to expand their value proposition.

Besides managing inventory and selling vehicles to consumers, dealerships opted for vertical and horizontal integration, expanding their offerings of ancillary products and services alongside vehicle sales. These product and service innovations, previously offered by banks, insurance companies, manufacturers, and independent repair shops, provided more options to consumers and affected consumer purchasing behavior. Accordingly, the innovations merit consideration when analyzing the price dynamics of services offered at dealerships.

### Data analysis
This section presents the changes in prices for new-vehicle goods and services over the business cycle beginning in 2007, describes how falling margins for vehicle sales contributed to changes in dealerships’ business models, and analyzes price indexes to describe the impetus for these changes. BLS price indexes are complemented with annual reports from publicly traded dealerships to explain how the financial services offered by these dealerships buoyed their profits.

Because the automotive industry tracks business cycles, the analysis period starts in 2007, close to the industry peak before the recession, and ends in 2019. As seen in chart 2, there were two noteworthy changes to retail margins for new-vehicle sales over this period—a precipitous drop that occurred during the recession of 2008 and a steady decline from 2012 through 2019. The decline in later years coincides with diverging trends in the producer and consumer manufacturing price indexes for vehicles. In both periods, the commodity indexes and the margin PPI for new-vehicle sales reveal the same phenomenon—prices dealerships paid for vehicles were increasing at a higher rate than prices paid by consumers. Examining the factors that precipitated both changes will illustrate, in the sections that follow, the dealerships’ competitive environment and market challenges that contributed to innovations over the 2007–19 period, up until the coronavirus disease 2019 (COVID-19) pandemic. As manufacturers used their market power to pass price increases onto dealerships, the latter generated new revenues from the expanded sale of finance and insurance products, in lieu of passing vehicle price increases to consumers.
The Great Recession and short-term margins drop

During the Great Recession, dealerships’ margins for new-vehicle sales dropped suddenly because producer prices rose abruptly while prices consumers paid for vehicles declined. U.S. producer manufacturing prices increased rapidly for high-fixed-cost firms with tight financial conditions, and the situation for vehicle manufacturers was no different. To remain solvent and cover their rigid cost structures and interest payments, these manufacturing firms increased producer prices during the recession. Retailers—dealerships, in the case of automobiles—had no option but to accept the price increases given their interdependence with manufacturers. But falling consumer demand during the recession left dealerships unable to pass high prices to cash-strapped and indebted consumers. Producer manufacturing and consumer prices diverged, leaving dealerships caught in the middle, with shrinking margins.

The trend of shrinking margins is apparent in chart 2. From 2007 to mid-2009, the margin PPI for new-vehicle sales dropped precipitously. Then, consumer prices increased in the last half of 2009 while producer manufacturing prices remained flat, with the PPI for new-vehicle sales recovering in the beginning of 2010. The PPI for new-vehicle sales dipped again later in 2010, as weak consumer demand and inventory buildup contributed to low dealership margins. The quick drop in dealerships’ margins at the beginning of the recession illustrates how vehicle manufacturer costs were pushed through to dealerships, regardless of the dealerships’ ability to push them onto consumers.

Long-term margin compression

After the volatility coinciding with the recession and other external factors, the PPI for new-vehicle sales and the CPI for new cars and trucks diverged once again. From January 2012 to December 2019, producer manufacturing prices for vehicles increased 9.6 percent while consumer prices increased only 2.2 percent. As producer prices steadily outpaced consumer prices, the margin PPI for new-vehicle sales fell 34.7 percent over the 8-year period.

Financial data on profit margins reported to the U.S. Securities and Exchange Commission (SEC) by publicly traded dealerships in the United States corroborate the historic trends in the PPI for new-vehicle sales. Chart 3 shows annual vehicle margin indexes from the five largest publicly traded dealerships in the United States. These indexes declined rapidly during the period in which the PPI for new-vehicle sales decreased. The SEC accounting data show volatility within a small range during the recession and shortly after—from 2007 to 2011—followed by a rapid decline thereafter. The average new-vehicle margin based on SEC data declined 25.6 percent from 2007 through 2019, mirroring the 34.3-percent decline posted by the PPI for new-vehicle sales over the same period. The margin on a new-vehicle sale for the publicly traded companies in 2019 averaged 5.2 percent, with one company’s margin reported as low as 4.1 percent.

Dealerships expand other lines of business

Chart 2. CPI for new cars and trucks, PPI for motor vehicles, and PPI for new-vehicle sales, January 2007–December 2019

Chart 3. New-vehicle margin indexes for publicly traded dealerships, 2007–19
Facing low consumer prices and higher producer prices in the immediate aftermath of the Great Recession, dealerships sustained profitability by offsetting declining new-vehicle margins with increased profits on the sale of add-on ancillary goods and services. New profit opportunities were sought because vehicle sales cratered and tight credit conditions stunted traditional financial profit sources such as interest rate markups. Many dealerships created new ancillary finance and insurance (F&I) products and found ways to market existing products more effectively. Dealerships enjoyed unprecedented success in selling products ranging from traditional Guaranteed Asset Protection (GAP) insurance and extended warranties to credit cards, credit repair services, and even products like disability and unemployment insurance. GAP insurance products can be more prudent for consumers who take out high loan-to-value loans, because these products protect borrowers and lenders when the value of debt owed on a wrecked or traded-in vehicle is higher than the actual value of the vehicle. In addition, point-of-purchase sales emerged as good profit sources, providing immediate profits from fees and commissions and recurring profits in the forms of contracted repairs, deductibles, and premiums. Furthermore, services that were rolled into an auto loan resulted in larger principal and interest payments.

By opening this new product area, dealerships saw their revenues rise continuously from the immediate postrecession period through the end of 2019. As shown in chart 4, the BLS aggregate PPI for new-car dealers increased steadily over this timeframe, despite the decline in the margin prices represented by the PPI for new-vehicle sales. This increase was due to advances in the PPI for other receipts and the PPI for service labor and parts. The PPI for other receipts tracks price changes in the F&I products described above.

From January 2007, when the margin PPI for new-car dealers peaked before the recession, to December 2019, the PPI for other receipts increased 70.8 percent, outpacing the price increase of all other services provided by dealerships. The PPI for service labor and parts increased as well, rising 50.0 percent over the same period. The steady price increase in dealers' labor and parts sales is largely a function of the number of vehicles sold in previous years. The expansion of F&I sales and the growth of service contracts allowed dealerships to remain profitable and withstand low margins on new vehicles through 2019.

For an overall industry index composed of component indexes, relative-importance values (determined by prices and quantities sold) show the portion of that index attributable to each component index. Examining these values over time shows the change in the composition of the overall index. From December 2008 to December 2019, the relative importances of the indexes composing the PPI for new-car dealers decreased from 27.2 percent to 17.4 percent for vehicle sales, rose from 2.3 percent to 26.1 percent for other services (a category including financial services), and decreased from 70.5 percent to 56.4 percent for service labor and parts. These trends in relative importance provide additional evidence of the shift in industry composition outlined above.

The profit contributions of major business segments of publicly traded dealerships reflect the decline in margins described by BLS price indexes. The expansion of the F&I segment dominated profit growth from 2009 to 2019. The amount of gross profit attributable to F&I sales for publicly traded dealerships grew by 134.6 percent from 2007 through 2019, making F&I sales the fastest growing profit contributor. Conversely, gross profits from new-vehicle sales decreased by 1.8 percent. This decrease coincided with record growth in the number of vehicles sold; together with falling margins, this trend resulted in decreased profits per vehicle over the 2007–19 period.
Chart 6 illustrates these stark trends of F&I sales overtaking new-vehicle sales as a bigger source of gross profits. From 2012 through 2019, the same period during which the margin PPI for new-vehicle sales declined, F&I profits reported to the SEC either matched or exceeded profits from new-vehicle sales. In 2007, new-vehicle sales constituted 26.6 percent of gross profits, F&I sales constituted 19.9 percent, and parts, labor, and service constituted 40.1 percent. By 2019, these shares were reversed, with new-vehicle sales constituting 15.9 percent of gross profits, F&I sales constituting 28.4 percent, and parts, labor, and service constituting 43.4 percent.

Chart 6 also shows that gross profits did not return to their 2007 levels until 2012. From that point on, F&I sales accounted for 41.5 percent of growth in gross profits, whereas new-vehicle sales saw their profit contribution stagnate. (See chart 7.) Although parts, labor, and service had the largest percent contribution to gross-profit growth over the 2007–19 period, they also represented the largest segment of dealerships’ business. In other words, F&I sales contributed disproportionately to profit growth over the 12-year period.
Without the disproportionate growth in F&I sales over the 2007–19 period, publicly held dealerships’ net profits would have declined. Gross profits generated from all major business segments cover fixed costs and financing costs. Chart 8 presents a hypothetical example highlighting how F&I sales sustained dealership profits over the period. The chart compares annual growth in net profits of five publicly held dealerships (2007 is the relative base year) with an estimate of net profits for which F&I sales are assumed to have remained a constant percentage of new-vehicle sales. If F&I sales had held at that constant percentage, net profit for the five publicly traded dealerships would have declined or risen less from 2007 to 2019. Some companies would have experienced net losses.

Dealership services and the CPI

The expansion of F&I sales is crucial to understanding the lack of price transmission from producer to consumer prices in the new-vehicle market. The F&I innovations helped dealerships stay in business, because dealerships had neither the bargaining power to negotiate lower vehicle prices with manufacturers nor the consumer demand that would have allowed them to charge higher vehicle prices. Since innovations in services do not factor into a vehicle’s price, they can explain how dealerships withstood the gap between higher and rising prices for new vehicles supplied by manufacturers and new-vehicle prices paid by consumers.

Given the penetration of financial products and GAP insurance in the new-vehicle market, the spread between the CPI for new cars and trucks and the PPI for motor vehicles does not describe the actual consumer expenditure for a new car. The price definition used in the CPI for new cars and trucks refers to the final price of a vehicle paid by a consumer to a dealership and includes taxes and transportation costs, and excludes finance charges. Because GAP insurance and other F&I revenues are not part of a vehicle’s price as measured by the CPI for new cars and trucks, the true economic cost to consumers who purchased these products for a new vehicle likely rose more than that index. With record levels of low- and no-downpayment sales during this period, GAP insurance substituted as underwater-loan protection for consumers and was extremely popular. Thus, part of the difference between the PPI for motor vehicles and the CPI for new cars and trucks is the unaccounted cost to the consumer of additional F&I services, beyond the cost of a new vehicle.

Conclusion

Between the 2007–09 Great Recession and the onset of the COVID-19 pandemic, car and truck dealerships faced an economic shock and compressed profit margins on new-vehicle sales. Many dealerships weathered these challenges by providing more F&I products and continuing to expand other services such as parts and repair. This article uses
The industry PPI for new-car dealers to illustrate these changes. This industry index (which separately measures price change for new-car sales, service labor and parts, and other receipts) shows that, from 2007 to 2019, the automotive industry offset declining margins on new-vehicle sales by increasing prices for service labor and parts and for other receipts. Relative-importance values from industry indexes also indicate a shift from vehicle sales toward other activities. Within the industry, the relative importance of vehicle sales decreased from 27.2 percent to 17.4 percent from December 2008 to December 2019, and the relative importance of other services (a category including financial services) rose from 2.3 percent to 26.1 percent over the same period.

The shift in strategy toward the sale of F&I products and services was common for dealerships through 2019, but subsequent events reestablished the dominant market influence of economic shocks. A case in point was the 2021 supply chain disruption affecting the automotive industry, which shifted dealership operations and recalibrated profit maximization. In April 2021, the industrial production index for motor vehicles and parts manufacturing declined 70.8 percent. Over the same period, the PPI for new-vehicle sales advanced 26.4 percent, the largest monthly increase since the series was first published in December 1999. In other words, acute supply shortages coincided with a record increase in dealer margins. Notwithstanding the unique economic climate in 2021, the recent trends indicate dealers need to innovate to find new areas of profit. The BLS producer and consumer price indexes help tell the story of how those innovations unfolded in response to a changing business environment.

SUGGESTED CITATION:

Notes
1 For details on the Producer Price Index (PPI) coverage of the retail trade sector, see https://www.bls.gov/ppi/factsheets/ppi-coverage-of-the-retail-trade-sector.htm.
2 The PPI for new-vehicle sales (and all other dealership services) is based on an industry classification system and is not seasonally adjusted. For this price index, we use an industry classification system as opposed to a commodity-based classification system, because the product mix captured by industry classification indexes is closer to that reflected in the Consumer Price Index (CPI) for new cars and trucks and the PPI for motor vehicles (both of which are commodity indexes).
3 In this article, all references to PPIs for motor vehicles refer to manufacturing indexes from a commodity-based classification system; the seasonally adjusted version of these indexes is used. CPIs for vehicles measure the final price for a finished vehicle paid by the consumer to the dealership or other retailer and include taxes and transportation costs; the indexes exclude finance charges. PPI measurement also subtracts any rebates the consumer receives from the price. PPIs for both car and truck manufacturing measure the prices received by manufacturers of domestically produced vehicles sold to retailers and intermediaries. Manufacturers typically sell new vehicles to dealerships, so the price used for the PPI for motor vehicles is the dealer net price, which subtracts taxes, fees, and any incentives or rebates provided to the dealership.


18 Here margins are defined by subtracting the costs of goods sold from total new-vehicle revenue and dividing the result by total new-vehicle sales. The cost of goods sold is a common accounting term referring to the variable costs associated with selling a particular item. In microeconomics language, this metric is very close to $p \times q$ – AVC $\times q$/$p \times q$, where $p$ is price, $q$ is output, and AVC is average variable cost; however, opportunity cost is not considered in financial statements and is considered in the microeconomic concept of AVC.

19 This analysis is of the five largest dealerships that exclusively operate in North America.


Company-specific information is from the 10-K forms filed with the U.S. Securities and Exchange Commission (SEC), which are stored in the SEC EDGAR database (https://www.sec.gov/edgar/search).

Net income before taxes is calculated by subtracting fixed costs, depreciation, and interest expenses from total gross profits.

Chart 8 truncates the data values at −100 percent despite 2008 values falling below that level, for two reasons. First, having a 2008 data point fully displayed in the chart distorts the visualization and makes the difference between the actual and estimated profits difficult to observe. Second, the level of −100 percent is a meaningful cutoff because any point below it is a net loss. The calculation begins by taking total finance and insurance (F&I) sales for each company in 2007 and dividing each figure by total new-vehicle sales in 2007. Then, to arrive at the estimated counterfactual net profit for each company, the proportion obtained from the previous step is held constant over the 11-year period by multiplying it by new-vehicle sales each year and then subtracting the difference between actual F&I sales and the estimated counterfactual from actual net profits.


Michael Havlin is an economist at the U.S. Federal Maritime Commission.


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The positive effects of the measles vaccine on long-term labor market outcomes

Summary written by: Lawrence H. Leith

The development of vaccines and their systematic and widespread use in the United States represent an important advancement in the nation’s public health. Smallpox, for example, has been largely eradicated because of vaccines, not only in the United States but also throughout the rest of the world. Similarly, the development of vaccines for cholera and anthrax have nearly eliminated their occurrence among humans. The measles vaccine was introduced in 1963, and vaccination rates rose quickly, which reduced morbidity and mortality from the disease. Although several studies have examined the public health advantages of the measles vaccine, its effects on long-term labor market outcomes have not been addressed. In a recent article titled “The long-term effects of measles vaccination on earnings and employment” (American Economic Journal: Economic Policy, May 2022), economist Alicia Atwood evaluates changes in employment and earnings in the United States after the measles vaccine was introduced.

Using data from the U.S. Census Bureau and the Centers for Disease Control and Prevention, Atwood analyzes the effects that the measles vaccination had on U.S. labor market outcomes during the 2000–17 period. She looks at measles incidence rates by state for the 1952–75 period and compares them with state vaccination rates after 1963. Because evidence shows that people are more susceptible to other infectious childhood diseases for up to 5 years after having had the measles, Atwood also examines statewide incidence rates for mumps, rubella, pertussis, and chicken pox—before and after the measles vaccine. For her labor market analysis, Atwood uses data from the Census Bureau’s American Community Survey (ACS) for 2000 to 2017. She limits her study to people who were ages 25 to 60 at the time of the survey. The ACS has the added advantage of providing the birth state of the survey participants. This advantage allows Atwood to connect her labor market analysis to her data on statewide measles incidence and vaccination rates during the 1952–75 period.

Atwood's research design allows her to exploit the notable change in the measles incidence rate that occurred after the vaccine was introduced. She uses a “difference-in-difference identification strategy,” which takes advantage of differences across states in pre- and postvaccine measles incidence and vaccination rates. Atwood evaluates labor market outcomes for people by their birth year and the state in which they were born. This approach enables her to connect survey participants with the data on incidence and vaccination rates. She argues that differences across the states and regions in prevaccine measles incidence rates and the resulting differences in the incidence of measles and other infectious diseases after the vaccine was introduced affected human capital accumulation considerably. For example, children who do not contract measles and other diseases are more likely to be healthier in general during their childhoods, which leads to more productive school years, compared with children who do contract these diseases.

Atwood estimates that people who were born in a state with average measles prevaccine incidence rates and who had lifetime exposure to the measles vaccine earned, on average, $447 more per year than those without exposure to the vaccine, a 1.1-percent increase in their annual income as adults. In addition, she finds that exposure to the measles vaccine lowers the probability of living in poverty, increases people’s chances of being employed, and does not affect the number of hours worked in a week. The latter finding suggests that workers’ income gains are achieved through increased productivity, rather than by working more hours. Atwood concludes her article by calculating the potential economic benefits of the measles vaccine. She estimates that if all 171 million people ages 25 to 65 in 2019 experienced herd immunity from measles as children, then as much as $76.4 billion in personal income that year could be attributed to productivity gains resulting from the measles vaccine.
Beyond BLS briefly summarizes articles, reports, working papers, and other works published outside BLS on broad topics of interest to MLR readers.

OCTOBER 2023
COVID-19 has unfairly hurt the reputation of global supply chains

Summary written by: Jonathan Yoe

Until around 1990, U.S. public opinion of globalization was largely positive because it was associated with economic growth. Globalization brought consumers more selection of products at cheaper prices. However, after 1990, technology allowed firms to send certain parts of the production process to other nations, which means we sent our production know-how to low-wage nations. This process helped China replace the United States as the world’s largest manufacturer and increased reliance on global supply chains (GSCs). Since the beginning of the coronavirus disease 2019 (COVID-19) pandemic, policymakers have heavily scrutinized GSCs publicly.

In their article “Risks and global supply chains: what we know and what we need to know” (National Bureau of Economic Research, Working Paper 29444, October 2021), Richard Baldwin and Rebecca Freeman examine GSCs in the context of COVID-19. Increased demand for personal protective equipment (masks) and medical supplies (ventilators, respirators, and dialysis machines) together with worker shortages and government-mandated shutdowns of production facilities caused serious goods shortages worldwide. Now, some policymakers are recommending shorter and more domestic GSCs to limit international exposure to foreign shocks, whether these shocks are specific to a country’s geographic region (environmental or geopolitical incidents) or are broader like COVID-19. Policymakers believe that GSCs should be made more diverse, for example by firms finding multiple suppliers. The authors address the risks associated with GSCs and discuss the likelihood that policies will be passed for shorter and more domestic GSCs. Also, the authors consider the effectiveness of these policies.

Risks to GSCs take the form of supply risks (geopolitical instability, natural disasters, cyberattacks), demand risks (macroeconomic crises, like recessions), or transportation risks (shortage of drivers). The authors consider whether GSCs are too risky. Baldwin and Freeman cite studies on COVID-19-related GSC shocks, which concluded that dismantling GSCs and shortening and domesticating them will not protect a country from shocks. Rather, this reshaping of supply chains will merely concentrate the risk to the domestic economy. In addition, the authors find that getting more information about GSCs and making them more diverse can help mitigate risk. A policy of increased information and supply chain transparency is called a no-regrets policy. The authors conclude that there is no downside to having more information.

The authors also address the effectiveness and likelihood of GSC-related policies. Addressing the effectiveness of any potential policy, they first argue that a policy is only effective if it properly targets the problem. For example, the shortage of personal protective equipment was due to a sudden spike in demand. Reshaping the GSC would have had no effect. Second, a no-regrets policy encourages countries to develop contingency plans (e.g., stockpiling goods and diversifying suppliers). Third, policy will be either a tax or subsidy (gasoline taxes and agricultural subsidies) or a regulation (financial markets) or will be controlled directly by government (public goods, such as self-defense). Fourth, a country resilient at the macro level can make it resilient at the micro level. For example, good monetary and fiscal policy can help mitigate the effects of economic shocks.

Certain producers in GSCs are too specialized to change them easily or even feasibly. The authors write that any firm can produce masks, but very few have the technology and scale to produce semiconductors. The government would need to believe that an economic shock is long term for it to introduce a policy meant to promote substantial changes to GSCs. Baldwin and Freeman argue that the government would need to enact policies that would subsidize U.S. production or tax foreign production to make GSCs for manufacturing more domestic. If not this, the government would need to regulate industry or take over production. For example, medical supplies and semiconductors can be considered part of our national defense and could justify policy like this. A policy reclassified as essential to national security could be serious enough to reshape GSCs for these products.
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OCTOBER 2022

Traditional retail in retreat

Summary written by: Yavor Ivanchev

Over the last two decades, the U.S. retail landscape has been shaped by the steady encroachment of e-commerce on traditional retail, a process largely propelled by technological innovation. At the turn of the 21st century, e-commerce accounted for less than 1 percent of total retail sales in the United States, but by 2021, that share had reached nearly 15 percent. Given this marked shift in a major sector of the U.S. economy, researchers have increasingly turned their attention to examining the impacts of e-commerce on the economic behavior of brick-and-mortar retail establishments and the labor market experiences of their workers.

This task is taken up in a recent article, “Creative destruction? Impact of e-commerce on the retail sector” (National Bureau of Economic Research, Working Paper 30077, May 2022), by Sudheer Chava, Alexander Oettl, Manpreet Singh, and Linghang Zeng. The authors surmise that, in coping with e-commerce competition, traditional retailers may adopt two starkly different, yet both rational, strategies. In one scenario, these retailers may choose to hire more workers, at higher pay, in an effort to improve the shopping experience of their customers and lure more of them through their doors. In another, less-labor-friendly scenario, traditional retailers may adopt the opposite strategy, choosing to cut their operating costs by laying off workers, reducing their hours and compensation, or closing up shop.

To assess how these possibilities hold up empirically, Chava et al. focus on a large U.S. e-commerce retailer, using its geographically diversified rollout of fulfillment centers (FCs) as a measure of e-commerce at the local level. This information, which goes back to 2000, is analyzed in conjunction with credit-bureau payroll data for 2.6 million retail workers, retail establishment sales data from the National Establishments Time-Series (NETS) database, and county-level employment data from the U.S. Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW).

The authors’ results point to traditional retail in retreat. With respect to labor impacts, the analysis indicates that the introduction of an FC in a county has a sizable negative effect on wages, leading to a 2.4-percent drop in the income of those employed in local retail, primarily through employer cuts to work hours. However, this effect is geographically bounded, disappearing at distances larger than 100 miles from FCs, and stronger among part-time hourly employees and those with less experience on the job. The authors’ analysis of QCEW data also shows that the presence of FCs in a county reduces that county’s employment growth in traditional retail by nearly 3 percent, and this decline is not offset by a compensating reallocation of labor to FCs or other retail-related sectors, such as transportation.

Similar e-commerce impacts transpire at the establishment level. Using NETS data, Chava et al. find that, after the introduction of an FC in a county, local retail stores suffer an average sales loss of 4 percent, a revenue hit that forces them to cut payroll by about 2 percent. Moreover, the probability of an establishment going out of business in the presence of FCs rises by an estimated 22 percent, with that risk being most pronounced among small and newly opened stores. The authors find no evidence that these results are an artifact of negative selection in the choice of FC locations; rather, the decline in traditional retail in areas affected by e-commerce seems to be driven mostly by the delivery efficiencies offered by FC shipping networks.
The “folk political economy” of Maine’s paper workers


Shredding Paper by Michael G. Hillard is an interesting chronicle of the economic and technological history of Maine’s paper industry. It highlights the plight of factory workers with the rise of U.S. industrial capitalism. The book tells the story of laborers who were an integral part of Maine’s industrial economy, describing their changing fortunes as they navigated through moral and technical challenges in rapidly changing markets. It includes firsthand accounts of the lives of factory workers and their families.

Using the backdrop of Maine’s paper industry, Hillard sheds light on the complex relationship between labor and firms, as well as on the different economic practices that shaped the U.S. manufacturing industry in the past century. Were the rise and demise of the paper industry inevitable consequences of capitalism, and could capitalism work in a way that would have allowed paper and other similar industries to flourish in the long term?

Hillard interviewed several previous employees of paper mills in the state, including Great Northern Paper, Oxford Paper, and S. D. Warren Company. The employees’ accounts bring these factories to life through nostalgic memories and provide vicarious glimpses of the hot and humid factory floors and the cold, harsh conditions of the forests where loggers lost limbs and life.

As one example, S. D. Warren Company of Westbrook, Maine, is fondly remembered as “Mother Warren” by its former employees, an enduring term associated with founder S. D. Warren’s paternalistic efforts to reinvest some of the company’s profits into research and development and to give back to the local community by building infrastructures such as churches and schools. Because of these efforts, workers overlooked the poor working conditions as they took pride in their work, had a close relationship with management, and enjoyed job security stretching across generations. For these reasons, the company was able to keep unionization at bay for a long time and maintained a good relationship with workers even after they became unionized.

Chapters 3, 4, and 5 focus on the rise of unions such as the United Paperworkers International Union Local 1069, describing various strikes and their outcomes. After S. D. Warren Company was sold to Scott Paper in 1967, the close relationship between management and workers started to fade. Managers with very little experience in papermaking were brought in. Over time, the workers’ discontent with management grew because of unfair labor practices, mismanagement, and poor treatment by foremen. The newly unionized labor had contentious relationship with management and actively fought for contract protection. To illustrate these developments, Hillard dedicates a full chapter to the so-called “Madawaska Rebellion,” detailing the resistance of workers from Fraser’s paper mill in Madawaska, Maine. The workers at the mill, who were predominantly Franco-American, were discriminated against for their cultural and religious identity. These unionized workers and their families took part in the resistance, organizing a strike in 1971. While some union-led strikes, such as the 1977 strike to create mill-wise seniority, were successful, others, such as the 1975 strike organized by the newly formed Maine Woodmen Association, failed.

Chapters 6, 7, and 8 discuss the financialization of Maine’s paper companies and their subsequent decline after the 1980s. In response to competition from national companies for market share, paper companies in Maine faced pressure from Wall Street to generate higher profits. They responded by attacking traditional union contracts and made unrealistic demands to workers. When workers walked out in protest of these demands, some companies, such as Boise Cascade and the International Paper Company, fired thousands of their unionized employees in a calculated move to replace them with nonunionized workers. During this time, employers such as Scott Paper took the high road and introduced the concept of “jointness,” which, in theory, was a progressive move for the common benefit of all stakeholders, aiming at increasing cooperation between management and employees. A jointness initiative called High Performance Work Systems was successful in a few Scott Paper locations, with workers benefiting from pay raises after completing skill-improvement training.

At other locations such as Somerset and Westbrook, however, jointness was met with resistance from local unions, which viewed it as a move to undermine union power. With financialization of the paper industry, local ownership was lost, and new corporate owners gained more control. Jointness gradually came to an end as shareholders resisted investing in projects that did not generate short-run profits.

In relaying these developments, Hillard introduces the term “folk political economy” to describe a version of history of capitalism from the unique perspective of paper-mill workers, mostly passed down to generations as a community memory. Workers believed that corporate governance and labor relations were better during the Chandlerian era (roughly the first two-thirds of the 20th century), with the term “Chandlerian,” a nod to the work of business historian Alfred D. Chandler Jr., describing companies that painted management structures similar to those of Maine’s paper companies. One of the key convictions underpinning the folk political economy is that the paper companies entered a period of decline as they shifted from the Chandlerian era to the neoliberal era. Chandlerian companies guided by class-justice values and moral codes formed during the Mother Warren days could not survive the rise of neoliberal capitalist values. The author concurs with this historical interpretation and regards the theoretical underpinnings of the folk political economy to be as rational and enlightening as those of any other theory proposed by scholars.

Shredding Paper leaves us questioning whether the decline of Maine’s paper industry was a result of high costs, poor management, contentious unionized labor, digitization of the newspaper industry, or an inevitable part of globalization. The conventional wisdom has been that, in a competitive capital market, diminishing profits lead to deindustrialization. However, Maine’s paper workers disagree with this view. As revealed in the book, they blame corporate greed and internal factors (such as rapid turnover of ownership and poor management) for the decline of their state’s paper industry. We can learn many lessons from Maine’s folk political economy to prevent industries from suffering similar fate in the future. Generating profit is the goal of any company, but labor dignity and rights should be preserved in the process. Treating Maine paper companies like community assets, not just privately owned institutions steered by shareholders and equity investors, was one of the keys to their survival.
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Improving estimates of hours worked for U.S. productivity measurement

The U.S. Bureau of Labor Statistics (BLS) will introduce a new method for estimating hours worked for its major-sector productivity measures with its November 2022 Productivity and Costs news release. The new method uses the all-employee hours data from the BLS Current Employment Statistics (CES) survey and is a marked improvement over the current method, which was introduced in 2004 and uses CES production-employee hours data. In this article, we describe the current method and discuss the advantages of using the all-employee hours series. We compare the new method with the current method and find that both generate about the same long-run productivity growth for the nonfarm business sector over the 2006–21 period. However, we find notable differences in quarter-to-quarter hours growth rates, which result in the two series telling slightly different stories about the timing of productivity growth. We also compare the differences in the two hours methods for major industry groups.

Labor is an important input to the production process, and the correct measurement of hours worked is critical for estimating productivity growth. In November 2022, the U.S. Bureau of Labor Statistics (BLS) will introduce a new method for measuring hours worked by employees for its major-sector productivity data. This new method uses all-employee hours from the BLS Current Employment Statistics (CES) survey, also known as the establishment survey, as its main data source. The CES all-employee hours series was first introduced in March 2006 as a research series and became the official BLS hours series in 2010. The new method for estimating hours worked improves on the current method, which uses the CES production-employee data and relies on several assumptions that no longer hold.

The BLS productivity program uses the CES survey as its primary source of hours data rather than the Current Population Survey (CPS), also known as the household survey, because (1) output data come from establishments and thus hours data from establishments are more likely to be consistent with the output data, (2) industry coding in the establishment survey is more accurate and more consistent with that of the output data, (3) the larger sample in the establishment survey provides better industry coverage and reduces the variability of industry-level estimates, and (4) employment estimates from the establishment survey are benchmarked annually to the employment universe by industry.

A drawback of using the CES hours data is that the CES survey collects data on hours paid, whereas hours worked is the appropriate concept for measuring productivity. The CES hours-paid data include paid leave and exclude off-the-clock hours. For salaried and commission-only employees (henceforth referred to as salaried employees), the CES survey questionnaire explicitly instructs respondents to report hours based on their standard workweeks. Therefore, it is necessary to adjust the CES hours-paid data to estimate the number of hours worked by removing paid time off and adding in off-the-clock hours. The new method uses data from two other BLS surveys—the National Compensation Survey (NCS) and the CPS—to make these adjustments.

In the section that follows, we describe the current method for estimating hours worked. The next section explains why it is important to make the change to the new method. The section after that describes the new method that will be used to adjust the CES all-employee hours series to account for paid time off and off-the-clock work. The next section compares estimates of hours worked and labor productivity that were constructed using the current method with research estimates that use the new method over the 2006–21 period. The final section concludes.

Current method for estimating hours worked

The BLS productivity program last changed its method for estimating hours worked in 2004 and implemented that method beginning with data from 1979. ¹ The current method uses three sources of data to estimate hours worked by wage and salary employees. The main source is the CES survey, which is a monthly payroll survey that covers about 689,000 establishments. The CES survey collects data on employment and total hours paid for all employees and for production employees. Employment includes all employees who were paid (worked or were on paid leave) during the pay period that includes the 12th of the month. Total pay-period hours are converted to total weekly hours by using conversion factors that vary depending on the number of days in the pay period.² The CES program calculates average weekly hours paid as total weekly hours paid divided by employment.

Until 2006, the CES survey collected hours data only for production and nonsupervisory employees (henceforth referred to as production employees).³ Therefore, in the current method, it is necessary to estimate hours of production and nonproduction employees separately. The first step is to convert CES production-employee hours to an hours-worked basis by using production-employee hours-worked-to-hours-paid (HWHP) ratios from the NCS, which is an establishment survey that collects data on all forms of compensation, including paid leave.⁴ The NCS HWHP ratios adjust hours paid for paid time off (annual leave earned, including paid holidays, and average annual sick leave taken). More formally, production-employee hours worked are calculated as follows:

\[
\text{Hours Worked}_{p, \text{Current}}^\text{CES} = \left[ \text{AWHP}_{p, \text{NCS}}^\text{CES} \times \text{HWHP}_{p, \text{NCS}}^\text{NCS} \right] \times \text{EMP}_{p, \text{NCS}}^\text{CES} \times 52,
\]

where AWHP_{p, \text{NCS}}^\text{CES} is quarterly average weekly hours paid for production employees from the CES survey, HWHP_{p, \text{NCS}}^\text{NCS} is the HWHP ratio for production employees from the NCS, and EMP_{p, \text{NCS}}^\text{CES} is quarterly average production-employee employment from the CES survey.⁵ Multiplying the weekly hours estimate by 52 “annualizes” the data so they are comparable with annual hours estimates. BLS applies these HWHP ratios at the three-digit industry level of the North American Industry Classification System (NAICS).⁶

To estimate nonproduction-employee hours worked, BLS uses additional data from the CPS, which is a monthly survey of about 60,000 households that collects demographic and job-related data for civilians ages 15 years and older. The CPS collects information about actual hours worked during the week that includes the 12th of the month.²
The first step is to classify employees as either production or nonproduction by using industry and occupation codes. Next, data on actual hours worked are used to calculate the ratio of nonproduction-employee average weekly hours to production-employee average weekly hours (henceforth referred to as the NPP\textsubscript{CPS} ratio).\textsuperscript{12} The NPP\textsubscript{CPS} ratio is multiplied by production-employee average weekly hours. Thus, nonproduction-employee hours are calculated as follows:

\[
(2) \text{ Hours Worked}_{\text{Current}}^{NP} = \left[ \text{AWH}_{P}^{\text{CES}} \times \text{HWH}_{P}^{\text{NCS}} \right] \times \text{NPP}_{P}^{\text{CPS}} \times \left( \text{EMP}_{\text{all}}^{\text{CES}} - \text{EMP}_{P}^{\text{CES}} \right) \times 52,
\]

where EMP\textsubscript{all} is CES employment for all employees, and (EMP\textsubscript{all}^{\text{CES}} - EMP\textsubscript{P}^{\text{CES}}) is nonproduction-employee employment from the CES survey.

The NPP\textsubscript{CPS} ratio captures some of the variation in off-the-clock hours for nonproduction employees because it uses actual hours worked. But the current method misses all the off-the-clock hours worked by salaried production employees. This is an important omission because production employees make up 80 percent of wage and salary employment, and 30 percent are salaried, which translates into about 24 percent of total wage and salary employment. In contrast, salaried nonproduction employees account for only 14 percent of wage and salary employment (about 20 percent of wage and salary employment times about 70 percent salaried).\textsuperscript{14}

Why switch to the CES all-employee hours data?

There are three compelling reasons to switch to the CES all-employee series as the main source of hours data: (1) the all-employee data are of higher quality than the production-employee data, (2) the ability to replicate the CES production-employee concept using CPS data has diminished, and (3) there is new evidence of bias in the NPP\textsubscript{CPS} ratio. We discuss the three reasons in more detail in the paragraphs that follow.

First, the CES all-employee data are more reliable than the CES production-employee data because the production-employee employment estimate is more susceptible to sampling error and nonresponse bias. Unlike total employment, production-employee employment is not estimated directly, nor is it benchmarked to the Quarterly Census of Employment and Wages (QCEW).\textsuperscript{12} CES survey respondents report the number of production employees in goods-producing industries and the number of nonsupervisory employees in service-providing industries. Within each estimating cell (defined by industry), production-employee employment is calculated as the product of total employment and the ratio of production-employee employment to total employment for establishments in that cell. Both are estimated from the sample, but only total employment is benchmarked to the QCEW. In addition, nonresponse is significantly higher for production-employee employment than for all-employee employment. Thus, estimates of production-employee employment could be biased if the production-employee ratio is different for responding and nonresponding establishments—even though all-employee employment totals are correct (after benchmarking).\textsuperscript{11} There is also evidence that some respondents have difficulty classifying employees as production or nonproduction employees.\textsuperscript{14} Although there have been no recent studies to determine whether this classification issue has gotten worse over time, it was deemed an important factor by the CES program in its move to collect all-employee hours.\textsuperscript{15}

The second reason for the method change is that the ability of the NPP\textsubscript{CPS} ratio to replicate the CES production-employee concept by using industry and occupation data has diminished. Chart 1 shows the percentage of wage and salary employees who are classified as nonproduction employees in both the CES survey and the CPS. From 1994 through the mid-2000s, the two series track each other closely. In both series, the percentage of nonproduction-employees ranged from 18.2 to 20.4 percent. The largest differences were in the 1.7- to 1.9-percent range, and there was no apparent trend. However, beginning around 2006, the two series began to diverge. The CES series reached its peak of 19.2 percent in early 2004, but then it declined by 1.7 percentage points, to 17.5 percent in the fourth quarter of 2007, with little movement the ratio since then. In contrast, the percentage of nonproduction employees in the CPS started increasing in 2006—from about 18.5 percent to about 21.0 percent by the end of 2019. Thus, the two series went from being within 2 percentage points of each other in the pre-2006 period and tracking each other fairly closely to diverging and differing by more than 3 percentage points in the post-2006 period.
U.S. Census Bureau occupational classification system that included additional “first-line supervisor” codes. There is no way to determine whether either of these changes is responsible for the divergence, but it is clear that the two series no longer track each other closely.

The third reason for adopting the CES all-employee hours data is that there is new evidence of bias in the NPP ratio. The current method’s reliance on the NPP ratio implicitly assumes that any CPS reporting bias in average weekly hours worked is the same for both groups.

After the NPP ratio method was developed, BLS introduced the American Time Use Survey (ATUS), which provides an avenue for testing bias in hours reports in the CPS. In several different studies, Harley Frazis and Jay Stewart compared CPS hours data with hours data from the ATUS and found that reported hours in the CPS data were accurate, on average. However, in their 2004 study, Frazis and Stewart also found variation in reporting accuracy across demographic groups. In particular, they found that workers with more education overstated their hours, while those with less education understated their hours. This suggests that the NPP ratio could be biased upward because, on average, production employees have less formal education than nonproduction employees. In addition, Lucy P. Eldridge and Sabrina Wulff Pabilonia found that nonproduction employees are more likely to bring work home from their workplaces, which could make it more difficult for them to recall their hours worked.

To examine the bias in the NPP ratio, we compare hours ratios calculated from CPS and ATUS data. We consider the ATUS estimates to be the more accurate hours measure, given that responses are less likely to be subject to recall bias and aggregation bias.

Table 1 shows that there is an upward bias in the NPP ratio in most years and, more importantly, that the bias varies over time and over the business cycle. The new method, which uses the CES all-employee hours data and therefore does not need the NPP adjustment, addresses these three issues.

Table 1. Bias in the ratio of nonproduction-employee average weekly hours to production-employee average weekly hours, 2003–19

<table>
<thead>
<tr>
<th>Year</th>
<th>Current Population Survey NPP ratio</th>
<th>American Time Use Survey NPP ratio</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>1.14</td>
<td>1.09</td>
<td>0.05</td>
</tr>
<tr>
<td>2004</td>
<td>1.14</td>
<td>1.10</td>
<td>0.04</td>
</tr>
<tr>
<td>2005</td>
<td>1.14</td>
<td>1.10</td>
<td>0.04</td>
</tr>
<tr>
<td>2006</td>
<td>1.13</td>
<td>1.12</td>
<td>0.01</td>
</tr>
<tr>
<td>2007</td>
<td>1.13</td>
<td>1.03</td>
<td>0.10</td>
</tr>
<tr>
<td>2008</td>
<td>1.14</td>
<td>1.09</td>
<td>0.05</td>
</tr>
<tr>
<td>2009</td>
<td>1.15</td>
<td>1.06</td>
<td>0.09</td>
</tr>
<tr>
<td>2010</td>
<td>1.16</td>
<td>1.24</td>
<td>-0.08</td>
</tr>
<tr>
<td>2011</td>
<td>1.15</td>
<td>1.10</td>
<td>0.05</td>
</tr>
<tr>
<td>2012</td>
<td>1.15</td>
<td>1.15</td>
<td>0.00</td>
</tr>
<tr>
<td>2013</td>
<td>1.14</td>
<td>1.16</td>
<td>-0.02</td>
</tr>
<tr>
<td>2014</td>
<td>1.14</td>
<td>1.13</td>
<td>0.01</td>
</tr>
<tr>
<td>2015</td>
<td>1.14</td>
<td>1.17</td>
<td>-0.03</td>
</tr>
<tr>
<td>2016</td>
<td>1.13</td>
<td>1.06</td>
<td>0.07</td>
</tr>
<tr>
<td>2017</td>
<td>1.13</td>
<td>1.13</td>
<td>0.00</td>
</tr>
<tr>
<td>2018</td>
<td>1.12</td>
<td>1.17</td>
<td>-0.05</td>
</tr>
<tr>
<td>2019</td>
<td>1.12</td>
<td>1.12</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Note: Ratios of nonproduction-employee average weekly hours to production-employee average weekly hours (NPP) compare average weekly hours of nonproduction employees to production employees. The CPS-based NPP ratios were calculated by using the basic monthly CPS. The ATUS-based NPP ratios were calculated by using diary days that fell within CPS reference weeks and are corrected for sample composition and rotation-group bias. All ratios are calculated using the main job only. The calculations of hours for the ratios follow the method used by Harley Frazis and Jay Stewart in “Comparing hours worked per job in the CPS and the ATUS,” Social Indicators Research, vol. 93, no. 1 (August 2009), pp. 191–95; and “Why do BLS hours series tell different stories about trends in hours worked?” in Katharine G. Abraham, James R. Spletzer, and Michael J. Harper, eds., Labor in the New Economy, National Bureau of Economic Research: Studies in Income and Wealth, vol. 71 (Chicago, IL: University of Chicago Press, 2010), pp. 343–72. CPS = Current Population Survey; ATUS = American Time Use Survey.


New method for estimating hours worked

The new method uses the CES all-employee hours data and therefore eliminates the need to separately estimate hours worked by production and nonproduction employees. However, like the current method, the new method requires the adjustment of CES hours-paid data to an hours-worked concept. The new method can be expressed as follows:

$$4 \quad \text{Hours Worked}_{\text{New}} = \left[ \frac{\text{Hours Paid}_{\text{CES}} \times \text{HWHP}_{\text{New}}}{\text{Hours Paid}_{\text{all}}} \right] \times 52.$$  

The ideal hours-worked-to-hours-paid adjustment ratio, HWHP*, compares hours worked to hours paid, where hours worked include paid hours worked and hours of off-the-clock (OTC) work, and hours paid include paid hours worked and hours of paid time off (PTO). The ratio can be written as

$$5 \quad \text{HWHP}^* = \frac{\text{Hours Worked}}{\text{Hours Paid}}.$$  

Equation (5) can be decomposed into separate PTO and OTC adjustment ratios:

$$6 \quad \text{HWHP}^* = \left( \frac{\text{Paid Hours Worked}}{\text{Hours Paid}} \right) \times \left( \frac{\text{Hours Worked}}{\text{Paid Hours Worked}} \right).$$
The first term is the PTO adjustment, or PTO ratio. It is a ratio of paid hours worked to hours paid and is conceptually the same as the NCS HWHP ratio used in the current method. The NCS calculates paid hours worked as hours paid minus hours of PTO. The second term is the OTC adjustment, or OTC ratio, which is a ratio of hours worked (paid hours worked plus OTC hours) to paid hours worked.

In the new method, the PTO ratio is constructed from NCS data as is currently done, except that it is calculated for all employees rather than for production employees. Because the NCS PTO ratio is calculated from establishment data, we assume that estimates of the level of PTO hours are more accurate than those that would be obtained from CPS data. And because the NCS PTO data are based on annual leave earned and average sick leave taken, the NCS PTO ratio is free of seasonal variation.25

The OTC ratio is constructed from CPS data. Note that, even though we estimate the PTO ratio from the NCS and the OTC ratio from the CPS, the ratios are constructed to be consistent with each other. That is, the denominator in the OTC ratio is the same (at least conceptually) as the numerator in the PTO ratio. This gives us:

\[
\text{HWHP}_{\text{New}} = \left( \frac{\text{Paid Hours Worked}}{\text{Hours Paid}} \right)_{\text{NCS}} \times \left( \frac{\text{Hours Worked}}{\text{Paid Hours Worked}} \right)_{\text{CPS}}.
\]

To estimate the new HWHP ratio for all employees, the new method focuses on the estimation of the OTC ratio using CPS data.

### Estimating the OTC ratio

Before turning to the details of the calculations, we describe the data issues and provide a brief outline of our approach.26 The numerator of the OTC ratio is hours worked. The CPS collects data on actual hours worked directly, but it does not collect information on paid hours worked, the variable in the denominator of equation (7). This variable can be estimated by combining other information from the CPS with a few reasonable assumptions.

First, we assume that hourly paid workers are paid for all of the hours they work (i.e., they do not work off the clock).26 Because the CPS collects data on hourly status only for main jobs, our second assumption is that workers on their second jobs are paid on an hourly basis (i.e., no OTC work).26 Thus, for hourly employees, paid hours worked are assumed to be equal to actual hours worked.26 The CPS collects hourly status data as part of its earner-study questions, which are asked only in the outgoing rotations (months in sample 4 and 8). Thus, it is necessary to impute hourly status for the other six rotation groups.26

For main jobs in which the employee is both full time and salaried, we estimate paid hours worked as paid hours minus hours of PTO, which is consistent with the NCS concept.25 The CPS collects information about usual hours worked on each job, but this may not correspond to hours paid for salaried employees. For example, a person may usually work 45 hours per week even though he or she is paid for 40 hours. We calculate time off relative to hours paid. If this employee worked 36 hours, time off would be 4 hours rather than 9. As to whether the employee was paid for the time off, the CPS collects this information only if the employee did not work during the reference week. Thus, in situations in which the employee both worked and took time off, there is no information about whether the time off was paid.

The new method addresses these shortcomings by using variables from the CPS to impute the missing data. We start by assuming in most cases that employees who are full time and salaried on their main job are not paid for more than 40 hours per week, a standard workweek.25 Next, we compare actual hours worked with usual hours paid (usual hours worked topcoded at 40) to determine whether the person took time off. We then estimate the probability that time off was paid and use these predicted probabilities, prob(PTO), to adjust time off to PTO. Once we have estimates of hours paid and hours of PTO, calculating paid hours worked and the OTC ratio is a straightforward process. In the subsections that follow, we describe the method for imputing hourly-paid status and estimating paid hours worked (hours paid minus hours of PTO) for full-time, salaried employees.

### Imputing hourly-paid status

Given our assumption about hourly employees, we need to know whether each CPS respondent is paid hourly.26 Because this variable is available only in the outgoing rotation groups of the CPS (one-fourth of the sample and only for main jobs), we must estimate the probability that the worker is paid hourly (prob(hourly)) for the rest of the sample.

To estimate prob(hourly), we use a random-forest algorithm.26 This algorithm is applied to a “training dataset” that has no missing values for the dependent variable. We used the outgoing-rotation-group data, which has information about hourly/salaried status, as the training dataset to generate the predicted probabilities. Once the algorithm has been trained, the results are used to generate predicted values in the target dataset (the six rotation groups for which data on hourly/salaried status are not collected).

The random forest is composed of repeated decision trees that use random subsets of data generated by the algorithm. Each node of a given tree uses one predictor of a random subset of the predictor variables (known as “features” in machine learning language).25 For each observation, each decision tree will make a prediction. The algorithm then combines these individual decision trees into a “forest.” A key feature of the random-forest algorithm is that, although the predictions from individual trees tend to be poor, the prediction from the forest is quite accurate.

The final prediction for each observation in our training dataset is the average of these predicted probabilities. Predicted probabilities (prob(hourly)) for observations in the target dataset are generated from similar observations in the training dataset. The simplest way to interpret prob(hourly) is that it is equal to the fraction of people represented by the observation that were paid on an hourly basis. To illustrate, an observation that has a sample weight of 2,400 represents 2,400 workers. If prob(hourly) = 0.75, 1,800 of the people represented by the observation were paid hourly, and the other 600 were not.

### Estimating paid hours worked (hours paid minus hours of PTO)

For full-time, salaried employees, we estimate paid hours worked and hours of PTO, which are needed to calculate the denominator of the OTC ratio (paid hours worked). To estimate hours paid, we start by topcoding usual hours at 40, which is the standard workweek in most industries.25 For respondents who report “hours vary” on their main job, we assume usual hours worked and paid are equal to 40 if the respondents report that they usually work full time.23 We then assume that hours paid are equal to the topcoded values of usual hours worked. Next, for each job, we calculate time off as the difference between usual hours paid and actual hours worked:

\[
\text{Time Off} = \max(0, \text{Usual Hours Paid} - \text{Actual Hours Worked})
\]

If actual hours worked are greater than usual hours paid, then time off is set to zero. Determining whether the respondent was paid for the time off is more complicated. If respondents report that they were employed but not at work, the CPS asks if they were paid for the time off. If the respondents took time off but worked for part of the week, they are not asked if they were paid for their time off. For these observations, we must estimate the proportion of time off that was paid. As was done for prob(hourly), we use the random-forest algorithm to generate predicted probabilities. The algorithm is trained on the subset of CPS respondents who are asked if their absence from work was paid. Thus, hours of PTO for an observation are equal to

\[
\text{Hours of PTO} = \text{Time Off} \times \text{prob(PTO)},
\]
where \( \text{prob}(\text{PTO}) \) is estimated for those not asked about paid absences and is equal to either 0 or 1 for those who were asked. As was done for \( \text{prob}(\text{hourly}) \), \( \text{prob}(\text{PTO}) \) is estimated using the random-forest algorithm and is equal to the fraction of people represented by the observation that was paid for time off.

The denominator of the OTC ratio is paid hours worked. By assumption, paid hours worked are equal to actual hours worked for all part-time employees and full-time employees who are paid hourly. For full-time employees who are paid a salary, paid hours worked equals hours paid minus hours of PTO. Thus, for all full-time employees, paid hours worked can be written as

\[
\text{Paid Hours Worked}_{\text{full-time}} = \text{prob}(\text{hourly}) \times (\text{Actual Hours Worked}) + (1 - \text{prob}(\text{hourly})) \times (\text{Hours Paid} - \text{Hours of PTO}).
\]

The OTC ratio is calculated by (1) summing actual hours worked over all observations, where each observation is a job; (2) summing paid hours worked over all observations; and (3) dividing (1) by (2):

\[
\text{OTC ratio} = \left( \frac{\text{Actual Hours Worked}}{\text{Paid Hours Worked}} \right)_{\text{CPS}}.
\]

This OTC ratio is seasonally adjusted and then multiplied by the NCS PTO ratio to give us the new HWHP ratio for all employees.

The final step is to multiply the new HWHP ratios by the CES all-employee hours paid data as in equation (4). Hours worked for employees are calculated at the three-digit NAICS level at a quarterly frequency. Because the CPS sample size varies from month to month, we tested whether constructing OTC ratios from 3 months of data produces reliable results. To do this, we estimated the sample mean percent margin of error corresponding to a 90-percent confidence interval by resampling the microdata underlying both the ratio’s numerator and its denominator with a nonparametric bootstrapping algorithm and verified that this value fell below 10 percent in both cases. Thus, we are confident in the reliability of the quarterly estimates.

The impact of using the new all-employee hours method

In this section, we examine how the research hours series constructed using the new all-employee method compares with the series constructed using the current method. We first compare hours worked for all employees in the private nonfarm sector to show the impact of adjusting CES all-employee hours paid for PTO and OTC hours. Next, we discuss the impact on measures of hours worked by employees in 14 major industries. Finally, we show the impact of the new hours method on measured productivity in the nonfarm business sector.

Chart 2 shows the impact of the different adjustments on total hours worked for employees in the private nonfarm sector. All series have the same general trend, which is not surprising because changes in hours are driven primarily by changes in employment and all series use the same CES employment data. However, the series differ in levels. The hours-worked levels for the new series are about 3.3 percent higher than those calculated with the current method over the 2006–21 period. This difference declines from about 3.3 percent in 2006 to about 2.7 percent in 2021, although there is quarter-to-quarter variation around that downward trend.
and the second quarter of 2020, it fell from 1.040 to 1.031. The ratio remained in the range of 1.034 to 1.037 through the end of 2021. The sharp decline in the OTC ratio coincided with the coronavirus disease 2019 (COVID-19)-related shutdowns, which we would expect to decrease the need to work extra hours.

The average OTC ratio of 1.043 may be higher than one would expect given that salaried employees are only 39 percent of all employees and would seem to imply that salaried employees work a lot of OTC hours. But it is important to recognize that the ratio is calculated relative to paid hours worked—not paid hours. A simple numerical example will provide some intuition. Suppose that full-time salaried employees are paid for 40 hours per week, that they work 41 hours on average, and that they represent 39 percent of wage and salary employees. If OTC hours are calculated relative to the standard 40-hour workweek, then the aggregate OTC ratio would be about \(1.01 \approx (1 + ((41 - 40)/40) \times 0.39)\). However, the OTC ratio we construct is calculated relative to paid hours worked to be conceptually consistent with the PTO ratio calculated by using NCS data. Under the same assumptions, but using paid hours worked \((37.1 = 40 \times 0.928)\) in the denominator, the aggregate OTC ratio is \(1.041 \approx (1 + ((41 - 37.1)/37.1) \times 0.39)\).

Next, we consider differences in growth rates. Chart 3 shows the long-term growth in aggregate hours worked for employees, as measured by the current series and the new series. Both series are expressed as indexes with a base period of second quarter 2006. The two series are nearly identical over the 2006–19 period, indicating that long-run growth rates are similar. For the business cycle spanning from the fourth quarter of 2007 to the fourth quarter of 2019, the current hours series had an annual average growth rate of 0.8 percent, while the comparable rate for the new series was 0.7 percent. (See the first line of table 3, below.) Since the trough of the COVID-19 recession in the second quarter of 2020, hours worked calculated with the new method have grown slightly slower than hours worked calculated with the old method, which reflects the impact of the new OTC ratio.

### Chart 3. Index of aggregate hours worked for employees in the private nonfarm sector, new and old calculation methods, second quarter 2006 to fourth quarter 2021

The chart shows the growth in aggregate hours worked for employees in the private nonfarm sector calculated using two different methods: the current series and the new series. The two series are nearly identical over the 2006–19 period, indicating that long-run growth rates are similar. For the business cycle spanning from the fourth quarter of 2007 to the fourth quarter of 2019, the current hours series had an annual average growth rate of 0.8 percent, while the comparable rate for the new series was 0.7 percent. Since the trough of the COVID-19 recession in the second quarter of 2020, hours worked calculated with the new method have grown slightly slower than hours worked calculated with the old method, which reflects the impact of the new OTC ratio.
Thus far, our comparison has focused on the aggregate private nonfarm sector. However, examining industry detail is also important for two reasons: (1) BLS builds its aggregate hours estimates from industry data, and (2) BLS publishes productivity estimates at the industry level. Charts 6a and 6b show the OTC ratios for major industries in the goods-producing and service-providing sectors, respectively. In all major industries, the ratios are either falling slightly or steady over the period. Except for nonfarm natural resources, OTC ratios are in the 1.04–1.05 range in 2006. They fall slightly to the 1.03–1.04 range by 2021, although the range widens during and after the Great Recession. The OTC ratio for nonfarm natural resources is substantially higher, falling from 1.11 in 2006 to 1.08 in 2021. In the service-providing industries, wholesale trade and transportation and warehousing have the highest OTC ratios for most of the period, while retail trade, education and health services, and leisure and hospitality have the lowest OTC ratios.
In charts 7a to 7n, we compare the different employee hours series for the 14 major industries. To make it easier to compare the differences across industries and determine which industries contribute the most to the aggregate difference in levels, the range of the scales shown on the vertical axes in these charts are scaled so that the difference between the maximum and minimum values equals 14. We see that the hours worked levels calculated with the new method are noticeably higher than those calculated with the old method in most of the service industries. The two hours measures are about the same in durable and nondurable goods manufacturing, as well as in utilities. The new measure is only slightly higher in natural resources, information, and construction. These differences show the substantial number of off-the-clock hours that were previously unaccounted for.

Select an industry (or show all industries):  

Nonfarm natural resources
Table 2 shows the percent difference between the two series for the fourth quarter of 2021 and reveals stark differences across industries. The smallest differences occurred in durable and nondurable goods manufacturing, both of which were less than 0.5 percent in absolute value. By contrast, the differences in wholesale trade, transportation and warehousing, utilities, information, and other private services (excluding households) were all 4 percent or more. The new hours series is 1.3 percent higher than the old hours series in construction, in which approximately 42 percent of employees are nonhourly workers.

Table 2. Percent difference in hours worked for all employees between the new and old calculation methods, fourth quarter 2021

<table>
<thead>
<tr>
<th>Industry sector</th>
<th>Percent difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private nonfarm</td>
<td>2.7</td>
</tr>
<tr>
<td>Nonfarm natural resources</td>
<td>3.8</td>
</tr>
<tr>
<td>Construction</td>
<td>1.3</td>
</tr>
<tr>
<td>Durable goods manufacturing</td>
<td>0.4</td>
</tr>
<tr>
<td>Nondurable goods manufacturing</td>
<td>-0.2</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>4.3</td>
</tr>
<tr>
<td>Retail trade</td>
<td>1.4</td>
</tr>
<tr>
<td>Transportation and warehousing</td>
<td>4.7</td>
</tr>
<tr>
<td>Utilities</td>
<td>5.1</td>
</tr>
<tr>
<td>Information</td>
<td>4.2</td>
</tr>
<tr>
<td>Financial activities</td>
<td>3.3</td>
</tr>
<tr>
<td>Professional and business services</td>
<td>3.2</td>
</tr>
<tr>
<td>Education and health services</td>
<td>3.7</td>
</tr>
<tr>
<td>Leisure and hospitality</td>
<td>2.2</td>
</tr>
<tr>
<td>Other private services (excluding households)</td>
<td>4.5</td>
</tr>
</tbody>
</table>


As can be seen in table 3, the growth rates over the 2007–19 period show that, in all major industry sectors, the difference in the long-run growth in hours between the old and new estimation methods was less than 0.9 percentage point in absolute value.
### Table 3. Growth in hours worked by employees over the 2007–19 business cycle, old and new calculation methods (average annual percent change)

<table>
<thead>
<tr>
<th>Industry sector</th>
<th>Business cycle, fourth quarter 2007 to fourth quarter 2019</th>
<th>Recession period, fourth quarter 2007 to second quarter 2009</th>
<th>Post-recession period, second quarter 2009 to fourth quarter 2019</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Old</td>
<td>New</td>
<td>Old</td>
</tr>
<tr>
<td>Private nonfarm</td>
<td>0.8</td>
<td>0.7</td>
<td>-5.3</td>
</tr>
<tr>
<td>Nonfarm natural resources</td>
<td>-0.1</td>
<td>0.7</td>
<td>-7.5</td>
</tr>
<tr>
<td>Construction</td>
<td>0.0</td>
<td>0.2</td>
<td>-14.7</td>
</tr>
<tr>
<td>Durable goods manufacturing</td>
<td>-0.7</td>
<td>-0.7</td>
<td>-13.1</td>
</tr>
<tr>
<td>Nondurable goods manufacturing</td>
<td>-0.4</td>
<td>-0.5</td>
<td>-8.0</td>
</tr>
<tr>
<td>Wholesale trade</td>
<td>-0.1</td>
<td>-0.1</td>
<td>-5.4</td>
</tr>
<tr>
<td>Retail trade</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
</tr>
<tr>
<td>Transportation and warehousing</td>
<td>2.1</td>
<td>1.8</td>
<td>-6.3</td>
</tr>
<tr>
<td>Utilities</td>
<td>0.0</td>
<td>0.0</td>
<td>0.2</td>
</tr>
<tr>
<td>Information</td>
<td>-0.7</td>
<td>-0.4</td>
<td>-4.7</td>
</tr>
<tr>
<td>Financial activities</td>
<td>0.7</td>
<td>0.6</td>
<td>-3.4</td>
</tr>
<tr>
<td>Professional and business services</td>
<td>1.4</td>
<td>1.4</td>
<td>6.0</td>
</tr>
<tr>
<td>Education and health services</td>
<td>2.0</td>
<td>2.1</td>
<td>1.9</td>
</tr>
<tr>
<td>Leisure and hospitality</td>
<td>1.5</td>
<td>1.7</td>
<td>3.2</td>
</tr>
<tr>
<td>Other private services (excluding households)</td>
<td>0.5</td>
<td>0.5</td>
<td>-1.8</td>
</tr>
</tbody>
</table>

Note: The National Bureau of Economic Research determined that a peak in economic activity occurred in the fourth quarter of 2007, a trough occurred in the fourth quarter of 2009, and a peak occurred in the fourth quarter of 2019, representing a full peak-to-peak business cycle.


Finally, we look at the impact of using the new hours method on labor productivity in the nonfarm business sector. (See chart 8a.) Again, long-run growth is similar for the two series over the 2006–21 period. However, during the COVID-19 recession, productivity grew at a faster pace when calculated with the new hours method. Charts 8b and 8c show the impact of the new method for durable and nondurable goods manufacturing. Long-run productivity growth is similar, with the lines representing the new and old methods being nearly identical throughout the period, although we again observe some differences in quarter-to-quarter growth.

![Chart 8a. Index of productivity in the nonfarm business sector, new and old hours calculation methods, seasonally adjusted, second quarter 2006 to fourth quarter 2021](chart_url)

Click legend items to change data display. Hover over chart to view data.

Note: “Productivity, new” uses all-employee hours paid with a paid-time-off and off-the-clock hours adjustment; “Productivity, old” uses employee hours calculated with the old (2004) method. Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter. Shaded areas represent recessions as determined by the National Bureau of Economic Research.

In November 2022, the BLS productivity program will introduce a new method for estimating hours worked that uses the CES all-employee hours data, which were first published in March 2006. A key advantage to using the all-employee data is that it is no longer necessary to estimate the hours of production or nonproduction workers separately. In addition, the new method does a better job of adjusting CES hours-paid data to an hours-worked concept. The new method still uses NCS data to adjust for paid time off, but it uses CPS data to make an additional adjustment for off-the-clock hours. This latter adjustment accounts for hours worked by full-time, salaried employees beyond their paid work hours.

The new method for measuring hours is a notable improvement over the current method, especially in its incorporation of off-the-clock hours, but it does not result in substantial revisions to productivity estimates. The new method produces results that are similar, but not identical, to those produced with the current method. Both series have nearly identical long-run growth rates, but total hours are about 3.3 percent higher, on average, with the new method. The main difference between the new and old data series is that they tell somewhat different stories about quarter-to-quarter growth of hours worked.

**Conclusion**

In November 2022, the BLS productivity program will introduce a new method for estimating hours worked that uses the CES all-employee hours data, which were first published in March 2006. A key advantage to using the all-employee data is that it is no longer necessary to estimate the hours of production or nonproduction workers separately. In addition, the new method does a better job of adjusting CES hours-paid data to an hours-worked concept. The new method still uses NCS data to adjust for paid time off, but it uses CPS data to make an additional adjustment for off-the-clock hours. This latter adjustment accounts for hours worked by full-time, salaried employees beyond their paid work hours. The new method for measuring hours is a notable improvement over the current method, especially in its incorporation of off-the-clock hours, but it does not result in substantial revisions to productivity estimates. The new method produces results that are similar, but not identical, to those produced with the current method. Both series have nearly identical long-run growth rates, but total hours are about 3.3 percent higher, on average, with the new method. The main difference between the new and old data series is that they tell somewhat different stories about quarter-to-quarter growth of hours worked.

**Notes**

1. There will be no change to the measurement of hours worked by the self-employed and unpaid family workers.

**SUGGESTED CITATION:**
The Current Employment Statistics (CES) survey sample is 6 times larger than the Current Population Survey (CPS) sample and is stratified by industry; the CPS sample is not stratified by industry. CPS sample weights are benchmarked to match the annual census population controls, which are based on the most recent decennial census population count supplemented with birth and death data and estimates of net international migration.

This method is linked to historical data. Prior to 2004, the U.S. Bureau of Labor Statistics (BLS) adjusted the hours of production employees in the manufacturing sector by using the ratio of office to nonoffice worker hours extrapolated from a survey that was last conducted in 1978. In the nonmanufacturing sector, OPT assumed that supervisory employees worked the same hours as nonsupervisory employees. For details, see Lucy P. Eldridge, Marilyn E. Manser, and Phyllis F. Otto, “Alternative measures of supervisory employee hours and productivity growth,” Monthly Labor Review, April 2004, pp. 9–28, https://www.bls.gov/opub/mlr/2004/04/art2full.pdf.

For monthly and semimonthly pay periods, this will depend on the number of days in the month.

The CES survey instructs respondents to classify employees as production or nonproduction employees in goods-producing industries and as nonsupervisory or supervisory employees in service-providing industries. This results in inconsistencies in how some employees are classified. For example, an accountant who does not supervise other employees would be classified as a nonproduction employee if employed in a goods-producing industry but as a nonsupervisory employee in a service-providing industry. Moreover, a record analysis survey conducted in 1981 showed that respondents do not always follow CES instructions when classifying their employees. See Employer Records Analysis Survey of 1981: Final Report (U.S. Bureau of Labor Statistics, 1983).

One of the primary uses of the National Compensation Survey (NCS) data is to construct the Employment Cost Index. Prior to 2000, the hours-worked-to-hours-paid (HWHP) ratio was estimated using data from the now-discontinued Hours at Work Survey. For more information, see the NCS page at https://www.bls.gov/ncc/home.htm.

The seasonally adjusted CES data are published monthly. The quarterly average weekly hours estimate is constructed by averaging total hours for the 3 months of the quarter and dividing that by the corresponding average number of employed production employees. Quarterly employment is an average of the 3 months of the quarter. The CES HWHP ratio is a 3-year moving average of annual ratios. Quarterly values of the NCS HWHP ratios are interpolated using the Denton procedure.

For a few industries that have data gaps, BLS uses a higher aggregate HWHP ratio for a three-digit NAICS industry level in the North American Industry Classification System (NAICS). Because leave policies do not change quickly over time, a 3-year moving average is used to limit the volatility of the series.

Reference weeks in November and December are sometimes moved up to avoid conflicts with the Thanksgiving and Christmas holidays. The CPS goes to great length to collect data on the number of actual hours worked. CPS respondents are asked to report their usual hours on their main jobs as well as other jobs they may hold. For their main job, they are then asked if they took time off or worked extra hours during the previous week; they are then asked to report their actual hours worked. For other jobs, respondents are only asked to report their actual hours worked during the previous week.

Hours from the CPS are not used to directly estimate nonproduction-employee hours because the CPS sample is not stratified by industry, and therefore employment totals will not necessarily match CES totals by industry.

The nonhourly group includes those who receive a salary, work for commission, or are paid in kind from a private employer. Throughout this article, we refer to these employees as salaried.


It is worth noting that the response rate for both production-hourly and nonhourly employees is substantially lower than the response rate for total employment. The response rate for reporting all-employee counts is about 53 percent, on average, but it varies by establishment size. Conditional on reporting an all-employee count, the response rate for hours is about 57 percent, which translates to an unconditional response rate of about 30 percent. BLS has studied the impact of nonresponse on CES earnings using data from the OCEW and found a downward bias resulting from nonresponse. See Jeffrey Groen, Kerrie Leslie, Julie Gershunyka, Patrick Hu, Tran Kratzke, Michael McCali, Edward Park, and Anne Polivka, “An investigation into nonresponse bias in CES hours and earnings,” internal report (U.S. Bureau of Labor Statistics, 2013). The OCEW does not collect data on hours, so the Groen et al. study compared CES and CPS hours data. See also Harley Frazis and Jay Stewart, “Why do BLS hours series tell different stories about trends in hours worked?” in Katharine G. Abraham, James R. Spletzer, and Robert F. duplication.

The CES program has attempted to address this issue, but employers tend to report data they use for their business, which may not conform to the CES concepts. See Employer Records Analysis Survey of 1981: Final Report.


Misreporting in the CPS was a concern at the time of implementation because research by John P. Robinson and Ann Bostrom cast doubt on the accuracy of hours-worked data from household surveys. Comparing responses to retrospective questions to time-diary data, which are generally considered to be more accurate, the authors found that respondents answering retrospective questions tend to report longer work hours and that the difference between responses to retrospective and time-diary estimates had increased over time. The method for the ratio of nonproduction-employee average weekly hours to production-employee average weekly hours (NPP ratio) assumes that any bias would be similar for production and nonproduction employees. However, there are a number of issues with the Robinson-Bostrom study. In particular, the time-diary surveys that they used collected hours data, but the questions differed across surveys and time periods. In a 2004 study, Harley Frazis and Jay Stewart showed that responses to “usual hours” and “actual hours” questions differ significantly. The exact question wording also matters. In addition, it is not clear what sample weights were used in the Robinson-Bostrom study; nor is it clear how work was defined in the time-diary data. Still, the main finding in the 2004 Frazis-Stewart study (and confirmed in subsequent Frazis-Stewart studies) is that average weekly hours calculated from the CPS data are accurate, on average, although some groups overreport hours while others underreport hours. For more information, see Robinson and Bostrom, “The overestimated workweek? What time diary measures suggest,” Monthly Labor Review, August 1994, pp. 11–23, 1994, https://www.bls.gov/opub/mlr/1994/08/art2full.pdf; see also Frazis and Stewart, “What can time-use data tell us about hours of work?” Monthly Labor Review, December 2004, pp. 3–9, https://www.bls.gov/opub/mlr/2004/12/art1full.pdf; Frazis and Stewart, “Where does the time go? Concepts and measurement in the American Time-Use Survey”; Ernst Berndt and Charles Hulten, eds., Hard to Measure Goods and Services: Essays in Memory of Zvi Griliches, National Bureau of Economic Research: Studies in Income and Wealth, vol. 67 (Chicago, IL: University of Chicago Press, 2007), pp. 73–97, https://www.nber.org/system/files/chapters/c0037/d0874/d0874.pdf; Frazis and Stewart, “Comparing hours worked per job in the CPS and the ATUS,” Social Indicators Research, vol. 93, no. 1 (August 2009), pp. 191–98, doi:10.1007/s11205-008-9380-7; and Frazis and Stewart, “Why do BLS hours series tell different stories about trends in hours worked?”

See Frazis and Stewart, “What can time-use data tell us about hours of work?”, Frazis and Stewart, “Where does the time go? Concepts and measurement in the American Time-Use Survey”; Frazis and Stewart, “Comparing hours worked per job in the CPS and the ATUS”; and Frazis and Stewart, “Why do BLS hours series tell different stories about trends in hours worked?”


See Frazis and Stewart, “What can time-use data tell us about hours of work?”; Frazis and Stewart, “Where does the time go? Concepts and measurement in the American Time-Use Survey”; Frazis and Stewart, “Comparing hours worked per job in the CPS and the ATUS”; and Frazis and Stewart, “Why do BLS hours series tell different stories about trends in hours worked?”


For quarterly series prior to the second quarter of 2006 and annual series prior to 2007, the new hours-worked time series is constructed by linking the level of the new hours-worked series to the movements of the previous series. This approach prevents a break in the series.

The importance of off-the-clock (OTC) hours has been recognized in previous research. For example, Stephanie Aaronson and Andrew Figura examine the cyclicality of OTC hours in their article, "How biased are measures of cyclical movements in productivity and hours?", Review of Income and Wealth, vol. 56, no. 3 (September 2010), pp. 539–58. In addition, Harley Frazis and Jay Stewart consider whether the difference in concepts (worked versus paid) can explain the divergent trends in CES and CPS hours measures in their article "Why do BLS hours series tell different stories about trends in hours worked?" and Lucy P. Eldridge and Sabrina Wulf Pabilonia examine whether increasing amounts of unpaid overtime work brought home from the office may bias estimates of productivity growth in their article "Bringing work home: implications for BLS productivity measures."

The subscript denoting all employees is dropped from this point forward.

Because the CPS does a better job of capturing variation in actual leave taken, we experimented with constructing a hybrid paid-time-off (PTO) ratio that combines estimates of variation in PTO around the trend using CPS data and with NCS levels. However, because nearly all of the variation in actual leave taken is seasonal, the gain to using actual variation was minimal. A notable exception occurred during the coronavirus disease 2019 (COVID-19) pandemic. Research in progress will use a hybrid PTO adjustment to examine the impact of quarterly variation in paid leave during the pandemic on hours of work.

This measure of OTC hours differs from definitions used by previous researchers who analyzed OTC work. Both Aaronson and Figura (2010) and Frazis and Stewart (2010) calculated OTC hours as the difference between hours worked and (simulated) hours paid directly from the CPS, without adjusting hours paid for PTO. See Aaronson and Figura, "How biased are measures of cyclical movements in productivity and hours?" and Frazis and Stewart, "Why do BLS hours series tell different stories about trends in hours worked?"

Our approach is similar to that of Frazis and Stewart in their 2010 article "Why do BLS hours series tell different stories about trends in hours worked?", except that we focus on all employees rather than on production employees. Our approach improves on the treatment of PTO and uses data-science tools to perform imputations.

Unlike full-time, salaried work, for which the standard workweek is usually 40 hours, there is no standard workweek for part-time, salaried work. Because only 3 to 4 percent of wage and salary workers are both part time and salaried, this assumption should have a minimal impact on estimates of aggregate hours.

We think that this is a reasonable assumption because usual hours worked on second jobs are, on average, about 14 hours per week, and those who work part time are more likely to be paid hourly. In addition, only about 5.5 percent of employed people in the CPS hold more than one job; thus, the impact of these assumptions is relatively minor.

Note that the CPS data are on a person basis, whereas the CES data are on a job basis. People who work at two jobs are counted once in the CPS but twice in the CES survey. Because the CPS OTC ratio will be applied to the CES data, we converted the CPS data to a job basis by creating separate observations for second jobs.

Sampled households are in the CPS for 4 consecutive months, out of the sample for 8 months, and back in the sample for another 4 months. The questions on earnings, which include whether the worker is paid hourly, and the additional questions on second jobs are asked in months in sample 4 and 8—the outgoing rotations.

Between 37 and 42 percent of employees worked full time and were salaried on their main job from 2006 to 2021.

In some industries, where CES average weekly hours paid for all-employees exceed 40 hours and it is possible that some employees regularly receive overtime pay, we assign the topcode as the 3-year moving average in that industry.

Hourly/nonhourly status is collected as part of the CPS earner-study questions. Respondents are asked about the easiest way to report their earnings. If respondents indicate "hourly," they are classified as hourly. If they indicate that it is easier to report their earnings at some other periodicity (weekly, biweekly, etc.), they are asked if they are paid hourly.

Another variation of the random-forest model is to assign integer values (0 or 1) to each observation rather than computing probabilities. The two approaches generate similar results.

The variables (features) used to train the algorithm for prob(hourly) are age, sex, education, marital status, family income, weekly earnings, major industry, major occupation, and usual hours worked.

Usual hours paid is available for a subset of workers, and we use that measure when it is available. The value of the cap on weekly hours has virtually no effect on the growth rate of hours and labor productivity. It does, however, have a small impact on hours levels.

We also topcode total actual and usual hours worked per worker at 84 hours per week (7 days per week × 12 hours per day).

We use information from the subset of CPS respondents who are asked if their absence from work was paid as the training dataset to generate the predicted probabilities. The variables (features) used to train the algorithm for prob(PTO) are age, sex, education, marital status, number of children, family income, major industry, major occupation, class of worker, and usual hours worked. Because there was a large increase in unpaid absences due to "other reasons" reported by CPS respondents during the early stages of the pandemic that BLS believes should have been mostly classified as unreported on temporary layoff and this should not be relevant to partial week workers, we use monthly data from March through August 2019 as the training datasets for monthly PTO predicted probabilities in the same months of 2020 as in 2019. For more information on this, see The Employment Situation: March 2020, USDL-20-0521 (U.S. Department of Labor, April 3, 2020), p. 5. https://www.bls.gov/news.release/archives/empsit_04032020.htm.

In a small number of cases, CPS respondents report their usual hours worked are zero. In these cases, we set paid hours worked for full-time salaried employees equal to actual hours worked topcoded at 40.

Under the old method, it was not possible to apply the NPP(CPS) ratio to three-digit NAICS industries, because the ratio was calculated by using 20 percent of the sample (nonproduction employees only) in the numerator and 80 percent of the sample (production employees only) in the denominator. The new method uses all observations in both the numerator and the denominator.

We also tested OTC ratios constructed from a single month of data and found that the results for some industries were not reliable.

The official series will track the research series closely, but there may be slight differences.

This sector corresponds to data collected in the CES survey and includes government enterprises and nonprofit institutions but excludes general government. This differs from the definition of the private nonfarm sector used in the BLS total factor productivity data, which also removes government enterprises.

The nonfarm business sector includes private nonfarm industries and government enterprises and excludes nonprofits and general government. The nonfarm business productivity estimates are calculated for all workers, not just employees, including hours worked by the self-employed and unpaid family workers.

The data in charts 2 through 8c are consistent with official BLS productivity data released on August 9, 2022.

This is approximately correct, as the vast majority of salaried employees work full time.

Approximately 42 percent of employees in durable goods manufacturing and 40 percent of employees in nondurable goods manufacturing were paid on a nonhourly basis in 2021.
Approximately 51 percent of employees in wholesale trade, 40 percent of employees in transportation and warehousing, 48 percent of employees in utilities, 62 percent of employees in professional and business services, 41 percent of employees in education and health services, and 50 percent of employees in other services were nonhourly employees in 2021.

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