Article

December 2023

An improved estimate of self-employment hours for quarterly labor productivity

In 2024, the U.S. Bureau of Labor Statistics will implement two adjustments to the self-employment hours series used for constructing productivity measures: (1) directly compositing the self-employment hours estimates as is done for national employment and unemployment statistics and (2) removing part of the estimates' irregular component, calculated during the seasonal adjustment process, from the series. These adjustments will result in a substantially smoother self-employment hours series without losing important information about changes in self-employment. In turn, this improvement will remove distortions in measured productivity.

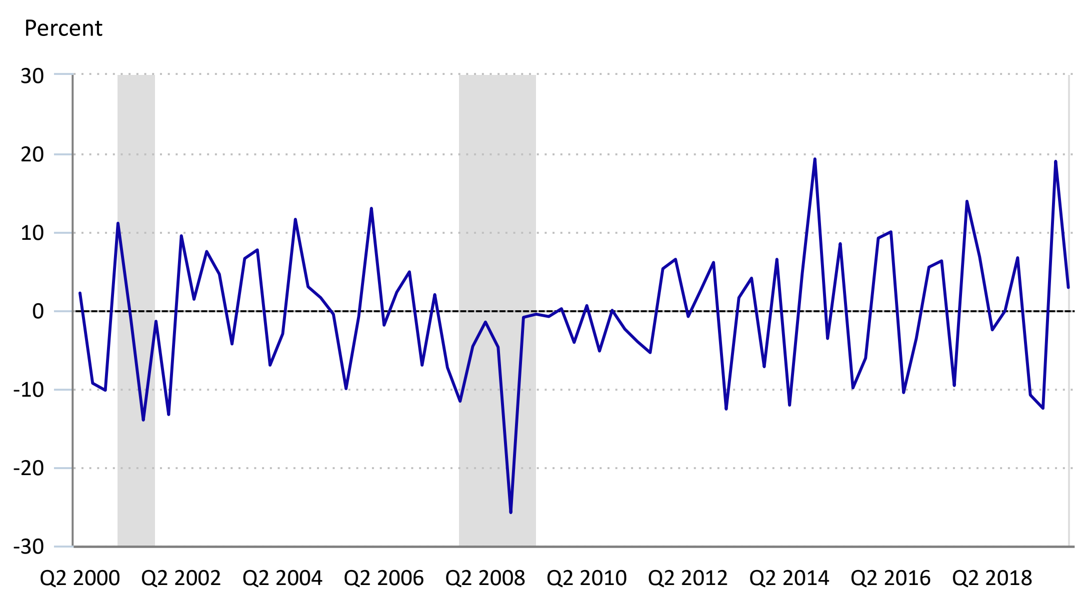
Labor productivity is a Principal Federal Economic Indicator published by the U.S. Bureau of Labor Statistics (BLS), and its correct measurement is crucial for tracking the sources of U.S. economic growth. Sometimes, however, quarterly labor productivity is unduly volatile because of large changes in measured self-employment hours. In this article, we discuss this volatility and BLS efforts to improve labor productivity measures by changing the measurement of hours worked by unincorporated self-employed and unpaid family workers.

Quarterly labor productivity is defined as the ratio of output to hours worked. Data on employee hours come from the BLS Current Employment Statistics (CES) survey, which is an establishment survey.[1] The CES sample is drawn from the longitudinal database of employer records for business establishments covered by the Unemployment Insurance program. Therefore, the sample does not cover workers who work for themselves in their own unincorporated businesses or as independent contractors (referred to as unincorporated self-employed workers or proprietors), nor does it cover those who work as unpaid family workers.[2] To include hours of work for these classes of workers in the total hours measure, the BLS productivity program supplements the CES hours with hours worked by the unincorporated self-employed and unpaid family workers from the BLS Current Population Survey (CPS), which is a household survey.[3] For simplicity, we henceforth use "self-employed" as shorthand for unincorporated self-employed and unpaid family workers. Similarly, we use "self-employment" as shorthand for unincorporated self-employment and unpaid family work.

Hours worked by the self-employed can be volatile for two broad reasons. First, these hours can increase or decrease from one period to the next, as people start businesses and shut them down or as they use self-employment as a bridge between wage-and-salary job spells.[4] Second, because the self-employed constitute such a small share of the labor force, it is harder to measure their hours by using the CPS.

Chart 1 shows the percent change in quarterly self-employment hours from 2000 to 2019.[5] Self-employment was procyclical over this period, with substantial decreases in self-employment hours during recessions.[6] In this chart, and in most of the analyses that follow, we begin the series in 2000 because productivity measures are consistently estimated back to 2000 and the current seasonal adjustment process uses data starting in 2000. We end the series in 2019 because the scale of changes in self-employment during the COVID-19 pandemic dwarfed any earlier visible volatility.[7] Although the series is considerably volatile, the source of that volatility is not obvious—no economic theory beyond business cycle theories predicts sudden quarterly fluctuations in self-employment.

Chart 1. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, seasonally adjusted, second quarter 2000 to fourth quarter 2019



Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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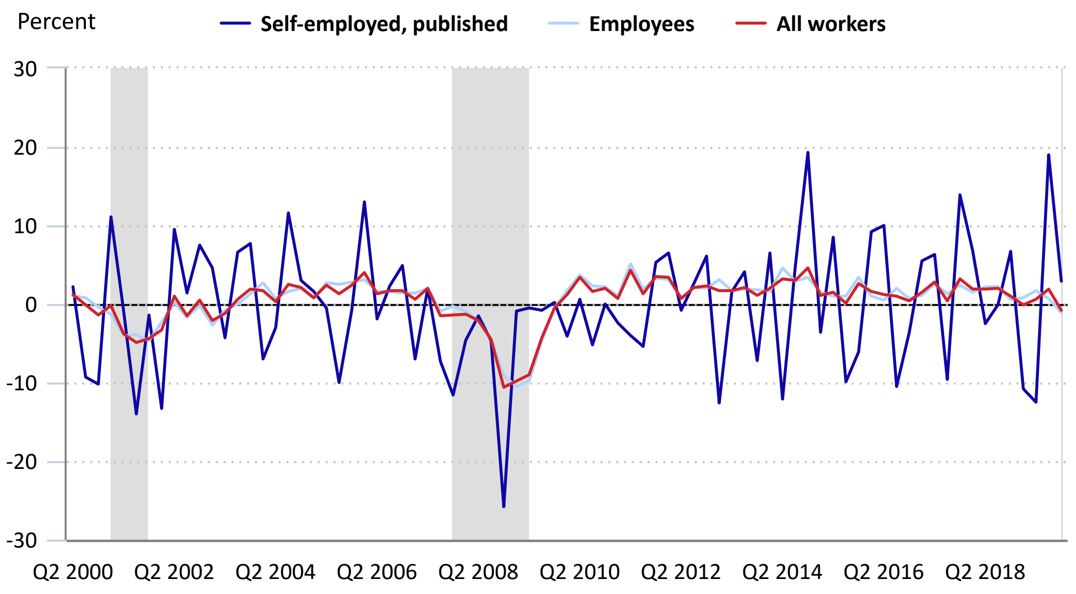
A concern with productivity measurement is that sometimes the volatility in self-employment hours is so outsized that it noticeably affects the measure of total hours, even though self-employment hours make up only a small share of total hours (about 7.3 percent in the fourth quarter of 2022). Chart 2 shows hours growth for employees, the self-employed, and all workers from the second quarter of 2000 through the fourth quarter of 2019. In several quarters, spikes in the self-employment hours series substantially affect the hours for all workers, creating a divergence between the hours growth rate for employees and all workers. For example, in the third quarter of 2005, employee hours grew by 2.5 percent, but hours for all workers grew by only 1.3 percent once a 10.0-percent fall in self-employment hours was factored in. Similarly, in the fourth quarter of 2014, employee hours grew by 3.4 percent, but hours for all workers grew by 4.6 percent because of a 19.3-percent increase in self-employment hours.

Chart 2. Annualized quarter-to-quarter percent change in hours, by class of worker in the nonfarm business sector, seasonally adjusted, second quarter 2000 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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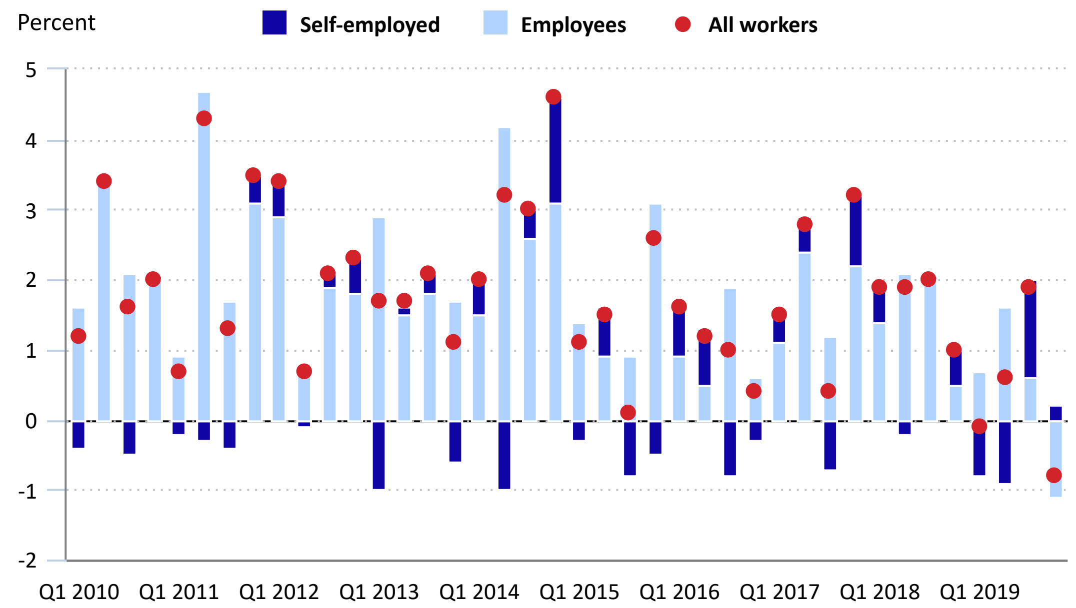
Chart 3 illustrates another way of looking at the impact of growth in self-employment hours on growth in total hours, comparing the relative percentage-point contributions of employees and the self-employed to the percent change in hours for all workers. Here, for illustrative purposes, we restrict the data to the first quarter of 2010 through the fourth quarter of 2019. Because self-employment hours account for such a small share of total hours, we would expect the dots representing hours growth for all workers to be close to the top of the bars measuring the contribution of employees, and the size of the bars measuring the contribution of the self-employed to be small relative to the bars measuring the contribution of employees. For some data points, however, the dots are quite far from the end of the employee-contribution bars. For example, there are substantial gaps in the first three quarters of 2019.

Chart 3. Contributions to annualized quarter-to-quarter percent change in hours, by class of worker in the nonfarm business sector, first quarter 2010 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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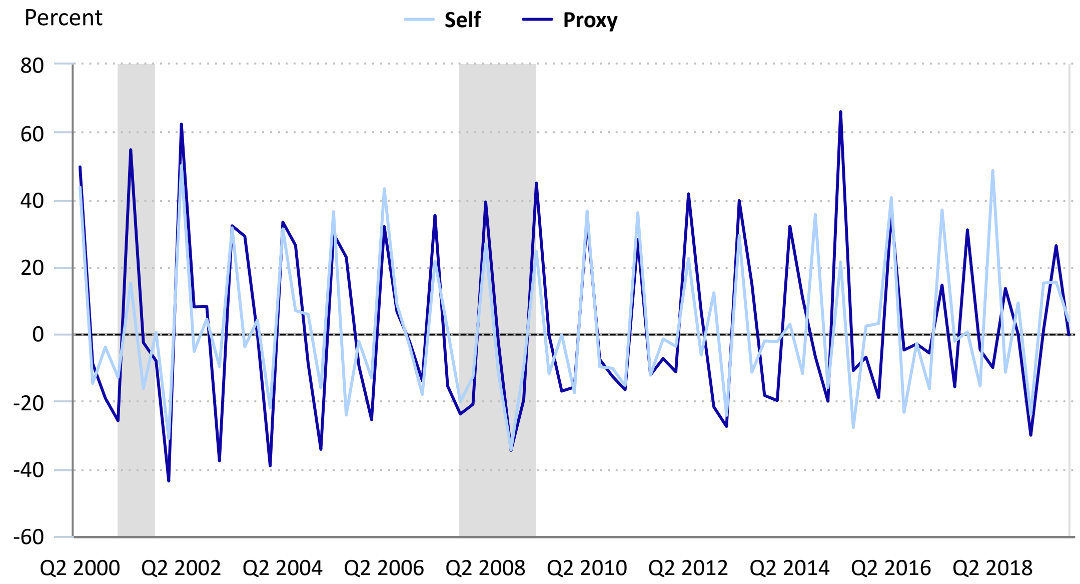
Sources of volatility

In a companion working paper (forthcoming), Cindy Michelle Cunningham and Sabrina Wulff Pabilonia investigate the sources of volatility in self-employment, focusing on sources relating to the CPS sample design that might be addressed to create a smoother series.[8] The authors identify three sources of volatility in the CPS estimate of self-employment, which is measured by a respondent's reported class of worker for the job that he or she worked at last week, for which adjustments could feasibly be made to reduce volatility. These sources of volatility include proxy responses, imputations, and sample rotation.

In the CPS, one household member age 15 years and older often provides labor force information on behalf of other household members. This member is a proxy reporter for other household members. For example, a mother may answer for her college-age children, one spouse for another, and so on. Cunningham and Pabilonia look at how proxy responses in the CPS might affect the volatility of self-employment hours—whether differences between how a worker describes their class of worker and the way another member of the household responding on their behalf does might cause self-employment measures to change over time. In general, the authors find that while the self-employment trends are similar whether measured by proxy reporters or self-reporters, in all periods proxy reporters report less self-employment (for the respondents on whose behalf they are answering) than do self-reporters. In chart 4, we find somewhat more volatility in the annualized quarter-to-quarter growth of self-employment hours when that information is collected by a proxy.[9]

Chart 4. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, by type of reporter, not seasonally adjusted, second quarter 2000 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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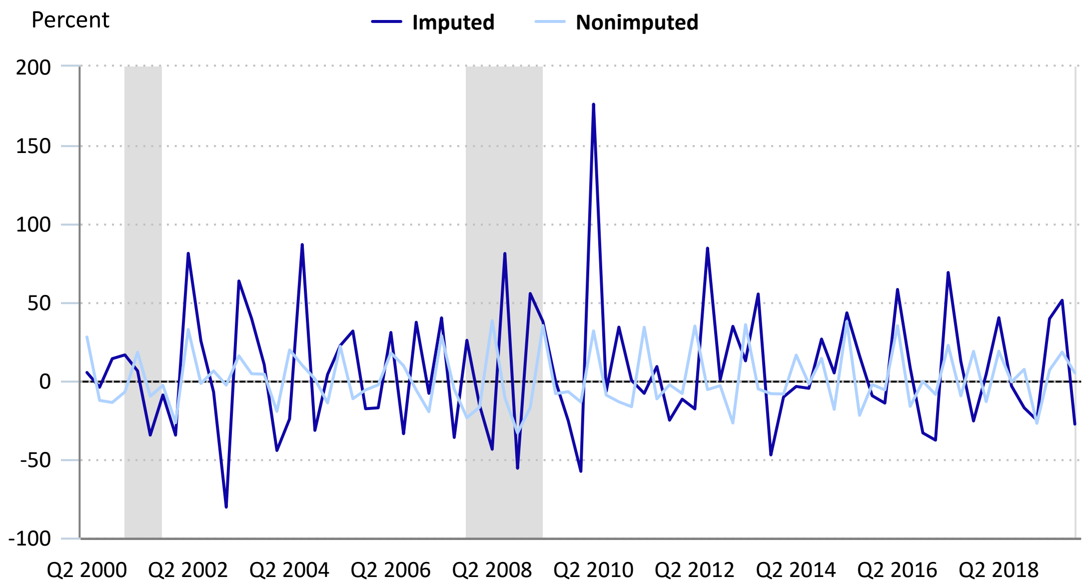
A second source of volatility examined by Cunningham and Pabilonia results from the imputation of class of worker when it is missing in the data because the respondent answered "don't know" or "refused" to the class-of-worker question (in other words, a case of item nonresponse as opposed to survey nonresponse). The number of imputed instances of self-employment in the CPS has been rising slowly since 2000, although the weighted count of the imputed self-employed is still less than a tenth of the weighted count of the nonimputed self-employed.[10] Chart 5 compares the volatility of self-employment hours from imputed responses with that from nonimputed responses. The effect of imputed responses is occasionally large enough to exacerbate an already large change in the nonimputed responses. For example, in the second quarter of 2010, hours grew by 31.7 percent for the nonimputed self-employed and by 176.1 percent for the imputed self-employed, resulting in an overall growth in self-employment hours of 34.9 percent; in the second quarter of 2017, hours grew by 22.5 percent for the nonimputed self-employed and by 68.9 percent for the imputed self-employed, resulting in an overall growth in self-employment hours of 30.0 percent. And in a few quarters, the growth rate of the imputed values moves in the opposite direction of the nonimputed values and is large enough to slightly offset what would otherwise be a large increase in self-employment hours. For example, in the third quarter of 2006, hours grew by 9.5 percent for the nonimputed self-employed but fell by 33.8 percent for the imputed self-employed, resulting in an overall growth of 5.4 percent in self-employment hours.

Chart 5. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, by imputation status, not seasonally adjusted, second quarter 2000 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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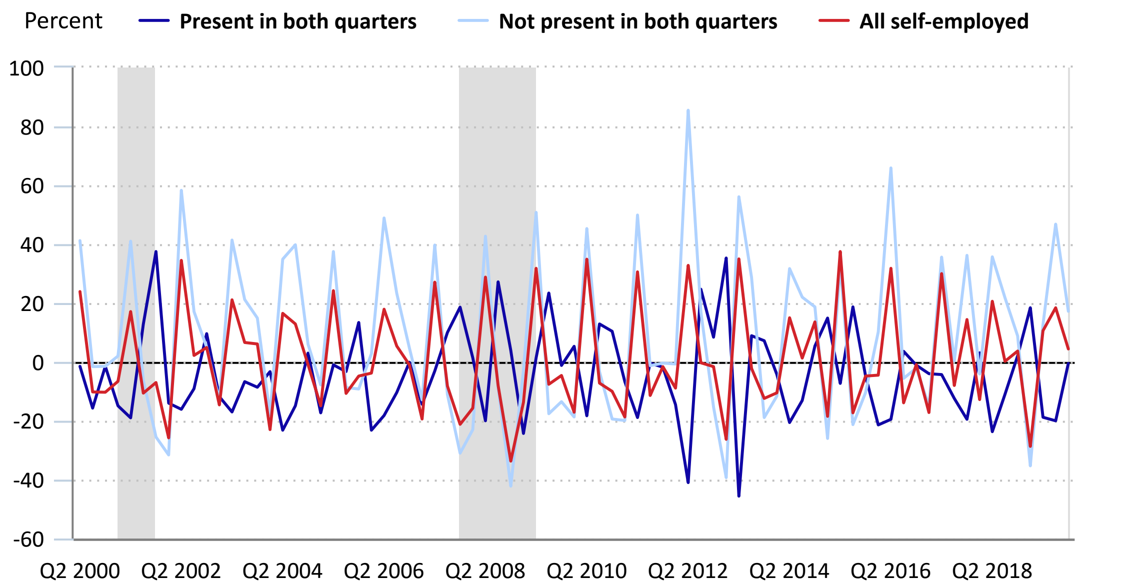
Following CPS respondents across consecutive months, Cunningham and Pabilonia examine respondents' transitions into and out of self-employment that coincide with changes both between self- and proxy responses and between imputed and nonimputed responses. They find that these transitions from one month to the next occur at lower rates when the reporter type stays the same (either a self-reporter in both months or a proxy reporter in both months) than when the reporter type changes from self to proxy, as well as when the responses are nonimputed in both consecutive months compared with imputed in both months or changes in imputed status. In particular, the likelihood of transitioning is largest between self- and proxy responses for those switching between unincorporated self-employed and not employed, suggesting that household respondents do not always know about the self-employment work another household member does.

Cunningham and Pabilonia investigate methods to correct for this source of volatility by directly editing the underlying CPS data. For example, they replace one month's proxy response with an adjoining month's self-response. This smoothing strategy requires subjective decision making regarding which response is more likely to be accurate, how many months forward or backward to look for edits, and whether observed transitions might be genuine. Ultimately, the authors conclude that the edits to the underlying CPS data have minimal impact on the volatility of self-employment hours. Given the subjective nature of these edits and the complexity of implementing them into official statistics, we do not pursue this smoothing strategy. However, researchers interested in studying the dynamics of self-employment may choose to test whether making such edits affects their results.

Finally, Cunningham and Pabilonia investigate how the CPS sample rotation design—respondents moving into and out of the sample—might lead to increased volatility in measures of self-employment. In the CPS, respondents answer questions for 4 consecutive months (months in sample (MIS) 1–4), then are out of the sample for the next 8 consecutive months, and finally return to the sample for another 4 consecutive months (MIS 5–8). Thus, from one calendar month to the next, one-quarter of respondents exit the sample and are replaced with entering (or, in the case of MIS 5, reentering) respondents. This sample rotation creates the potential for two sources of volatility. First, the fraction of individuals who are self-employed may differ between entering and exiting rotations. This difference can arise by chance because of sampling error.[11] The second source, known as rotation-group bias, is due to systematic differences by MIS in how respondents report self-employment status, with workers in earlier MIS being more likely to report self-employment.[12] For the 2000–22 period, the average percentage of self-employed workers is about 7.0 percent in MIS 1, 6.8 percent in MIS 2–4, 6.7 percent in MIS 5, and 6.6 percent in MIS 6–8. These differences can arise for various reasons, including respondent fatigue, differences in unit nonresponse by class of worker, and in-person versus telephone interviewing.

Chart 6 shows the hours growth in self-employment, in total and broken into two sources—the growth that comes from the difference between those who entered the sample in a quarter and those who exited it in the previous quarter and the growth that comes from those who were surveyed in both quarters (continuers). We find evidence of both sample rotation effects and rotation-group bias. Sample rotation effects are evident in the considerably greater volatility in the quarterly growth rates for respondents who were not present in both quarters relative to continuers. The average growth rate is 8.8 percent for those who were not present in both quarters and −4.1 percent for continuers.[13] The impact of rotation-group bias can be seen in chart 6 by looking at the self-employment growth rate for respondents present in both quarters. Because respondents are more likely to report self-employment in MIS 1 than in subsequent months, the quarter-to-quarter changes in the number of self-employed workers in the sample tend to be negative. These fluctuations, together with rotation-group sampling errors that affect the relative distribution of self-employment in incoming and outgoing rotation groups, suggest that the sample rotation design plays an important role in the volatility of self-employment hours.

Chart 6. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, by whether present in both quarters, not seasonally adjusted, second quarter 2000 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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Given these findings, we describe below how we apply two adjustments to the self-employment hours series to reduce excess volatility. The first adjustment involves directly compositing self-employment hours as is done for national employment and unemployment statistics also calculated from the CPS. The second adjustment involves removing a component of seasonal adjustment—the final irregular component adjusted for extreme values—which we show is primarily picking up sampling error.

Directly compositing self-employment hours

In 1954, BLS began using a composite estimate for reporting employment and unemployment measures. Morris H. Hansen, William N. Hurwitz, Harold Nisselson, and Joseph Steinberg describe the composite estimate as a weighted average of two different level estimates: one based solely on the current month and one that accounts for information from the previous month for the three-quarters of the sample that is surveyed in both months.[14] The composite estimates reduce the variance of estimates of levels and changes, with the largest reductions occurring for estimates of changes.

Expanding on Hansen et al.'s description of the two weighted components of the composite estimate, Margaret Gurney and Joseph F. Daly, as well as Elizabeth T. Huang and Lawrence R. Ernst, show that this estimate can be improved by adding a bias-correction term that gives slightly more weight to data from respondents in MIS 1 and 5—months when unemployment responses have been found to be much higher.[15] BLS uses these adjusted composite estimates, referred to as AK-composite estimates, for reporting national employment, unemployment, and those not in labor force, but not for reporting self-employment hours. We use this method to directly composite self-employment hours for the quarterly labor productivity series.

The composite estimate of self-employment hours in calendar month t, $\hat{Y}_t^C$, is measured by

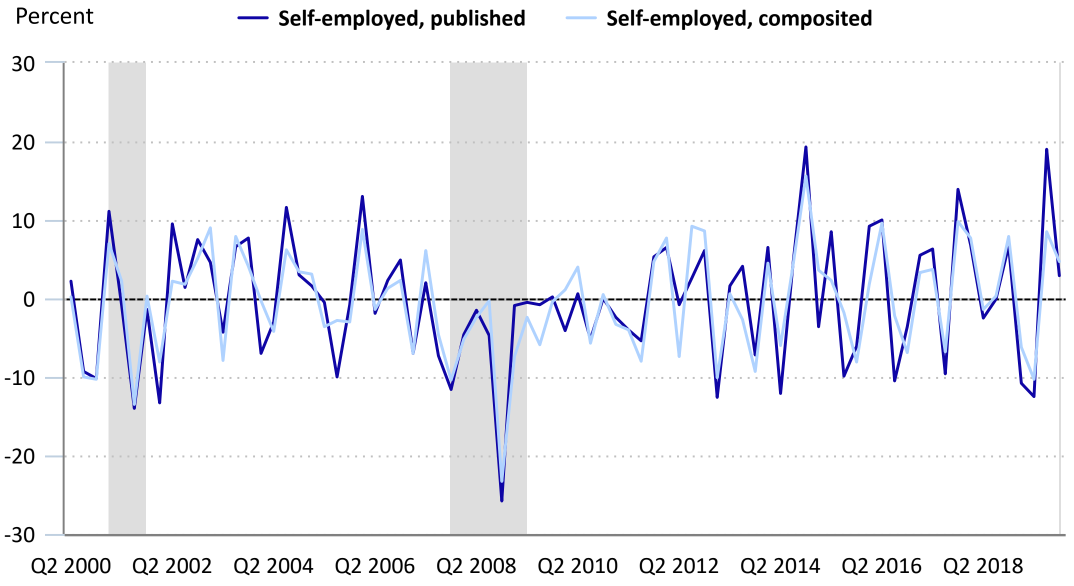
$$\hat{Y}_t^C = (1-K)\left[\frac{1}{8}\sum_{i=1}^{8}\hat{Y}_{i,t}\right] + K\left[\hat{Y}_{t-1}^C + \frac{1}{6}\sum_{i\in S}\left(\hat{Y}_{i,t} - \hat{Y}_{i-1,t-1}\right)\right] + A\left[\frac{1}{8}\left(\sum_{i\notin S}\hat{Y}_{i,t} - \frac{1}{3}\sum_{i\in S}\hat{Y}_{i,t}\right)\right],$$

where $\hat{Y}_{i,t}$ is an estimate of self-employment hours for the population in month t using only responses in rotation group i, and A and K are parameters. The first bracketed term is the direct estimate of self-employment, an average of the estimate over all eight rotation groups i, ignoring any possible differences in responses across rotation groups. The second bracketed term adds to the previous month's composite estimate, $\hat{Y}_{t-1}{}^C$, the change in estimated self-employment among those continuing in the survey from the previous month ($i \in S$ (= 2, 3, 4, 6, 7, 8)). The final bracketed term is the bias correction that reweights the estimates from the incoming ($i \notin S$) and continuing ($i \in S$) parts of the current month's sample.

In an AK-composite estimate, the parameters A and K are selected to minimize the variance of the AK estimator relative to the direct estimate. How closely a set of parameters approximates the best linear unbiased estimate for a labor force characteristic depends both on the pattern of responses across rotation groups and on the correlation over time in the labor force estimates. This means that the optimal values for estimating the level of employment may not be optimal for estimating the level of unemployment, or the month-to-month change in unemployment. Janice Lent, Stephen Miller, and Patrick Cantwell find that $A = 0.3$ and $K = 0.4$ are optimal values for estimating unemployment levels and close to optimal for month-to-month changes, whereas $A = 0.4$ and $K = 0.7$ perform the best for estimating employment levels and changes.[16] For our composite estimate of self-employment hours, we use $A = 0.4$ and $K = 0.7$, assuming that self-employment most closely resembles employment in terms of the correlation over time. We directly composite only self-employment on main jobs because class-of-worker information for second jobs is only collected in MIS 4 and 8. To the directly composited estimates, we add hours on secondary jobs, which have been weighted with CPS outgoing rotation weights.

Chart 7 compares the quarterly growth rate for the composited self-employment hours series with the growth rate for the published series from the second quarter of 2000 to the fourth quarter of 2019. Compositing reduces the size of most spikes in the growth rate. For example, in the second quarter of 2014, the growth rate of self-employment hours was −12.1 percent without compositing and only −6.0 percent with compositing. In the third quarter of 2019, the rate was 19.0 percent without compositing and 8.5 percent with compositing. Thus, it appears that compositing substantially reduces volatility in self-employment hours.

Chart 7. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, published versus composited, seasonally adjusted, second quarter 2000 to fourth quarter 2019



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Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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Seasonal adjustment and removing irregulars

To obtain quarterly self-employment hours for productivity measures, BLS seasonally adjusts the basic monthly CPS self-employment hours series and then averages these monthly data to obtain a quarterly series. Although the primary purpose of seasonal adjustment is to provide a clearer picture of underlying trends and cyclical movements distinct from regular seasonal movements, this adjustment can also be used to dampen unusual movements in the data. The X-13 ARIMA-SEATS program first models the time-series properties of the data, then uses that model to adjust and extrapolate forward the series, and finally decomposes the adjusted series into a trend-cycle component, a seasonal component, and an irregular component.[17] Removing the seasonal component leaves the seasonally adjusted series, which consists of the trend-cycle component plus the irregular component.

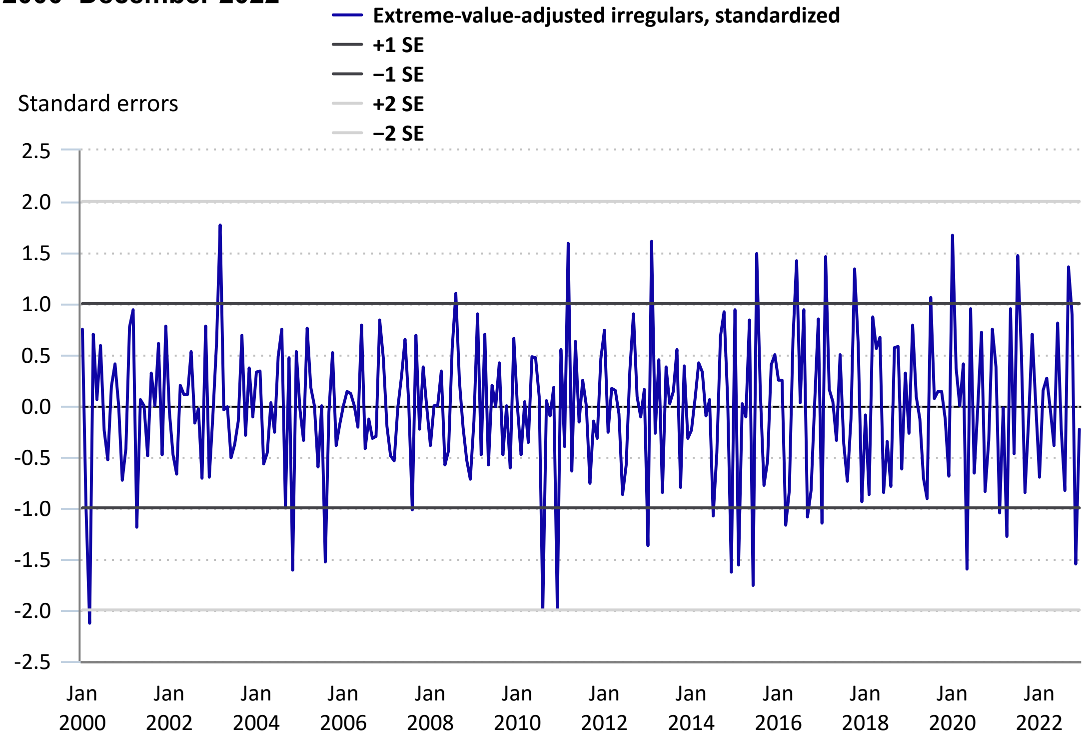
The irregular component consists of ordinary noise in the series that can be due to both sampling and nonsampling error, as well as extreme abnormal events such as unseasonable weather, natural disasters, pandemics, or strikes. Outliers in the original data series are typically identified in the time-series model—either a priori or by the program's automatic outlier-detection feature. In this way, the seasonal component can be estimated without being distorted by the outliers, but the seasonally adjusted data series will continue to include their impact.

We might expect greater sampling error in estimates of self-employment hours compared with estimates of hours for all workers, mainly because the sample sizes for the self-employed are relatively smaller. Response error also can arise because differences between self-employment and contract work and between incorporated and unincorporated self-employment are subtle and may be subject to greater differences in responses between the worker and a proxy respondent, and even from one interview to the next. Because our objective is to reduce the volatility in our estimate of self-employment hours, we want to remove the part of the irregular component that may be due to sampling error. The X-13 ARIMA-SEATS program used for seasonal adjustment produces a final irregular component series that excludes the impact of extreme values—which in most cases are due to abnormal events. Thus, we can remove this irregular component (hereafter referred to as the extreme-value-adjusted (EVA) irregular), along with the seasonal component, from the original series in order to obtain a smoother seasonally adjusted self-employment hours series.

To check whether the EVA irregular series is a reasonable estimate of the sampling error, we compare the size of the series' irregulars with the standard errors of our estimates of self-employment obtained from generalized variance functions (GVF).[18] Because the CPS publishes GVF model parameters for employment only, we restrict our analysis to the number of self-employed workers. We assume that the conclusions we draw from this analysis can be applied to self-employment hours.

Chart 8 shows the EVA irregular series obtained from a seasonal adjustment decomposition, standardized by dividing the EVA irregulars by the estimated standard errors of our composited self-employment estimates.[19] Nearly all the values of the irregular component fall within 2 standard errors of our self-employment estimate, suggesting that the EVA irregular is due to sampling error and not economic outliers. This implies that removing this irregular component from the self-employment series can potentially further smooth the series without removing real movements in self-employment hours.

Chart 8. Extreme-value-adjusted irregulars, standardized by dividing by the estimated standard error (SE) of composited self-employment, January 2000–December 2022



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

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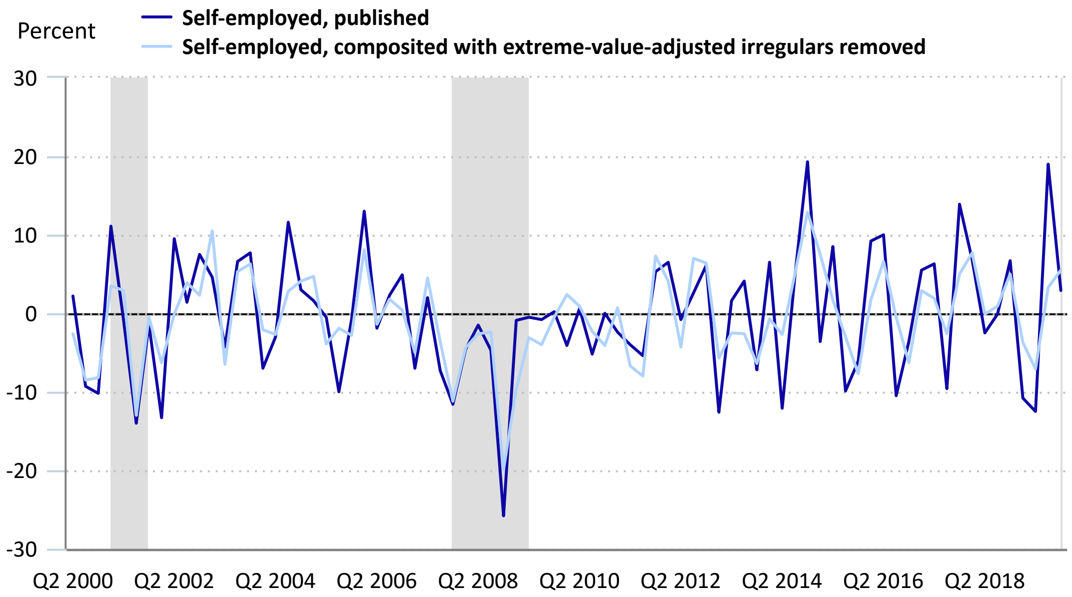
Charts 9a and 9b show the combined effects of compositing as well as removing the EVA irregular on the quarterly growth in self-employment hours. While chart 9a focuses on the second quarter 2000 through the fourth quarter of 2019, chart 9b extends the series through the fourth quarter of 2022 to show that the new method of calculating self-employment hours does not diminish the effects of the COVID-19 pandemic on the series. Removing the EVA irregular further reduces the volatility of the series beyond the reductions obtained from compositing the series alone (chart 7), without oversmoothing and distorting important economic outliers. If we were to instead remove the entire irregular series, we would remove most of the effects of the pandemic and potentially oversmooth the series during the 2000–01 recession and the 2007–09 Great Recession. (See chart 10.)

Chart 9a. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, published versus composited with extreme-value-adjusted irregulars removed, seasonally adjusted, second quarter 2000 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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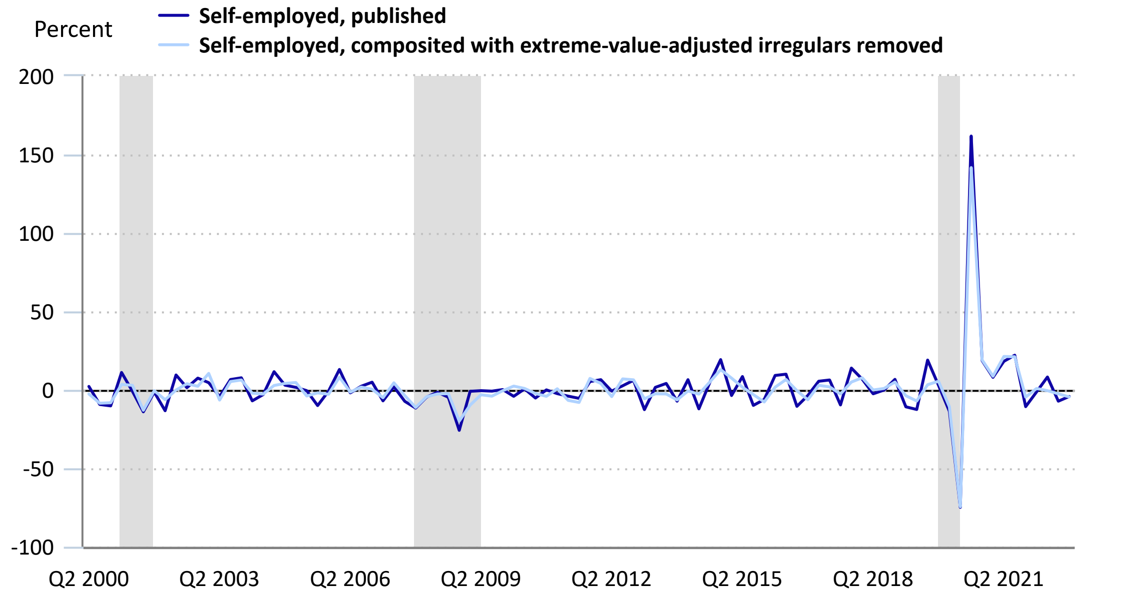
Chart 9b. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, published versus composited with extreme-value-adjusted irregulars removed, seasonally adjusted, second quarter 2000 to fourth quarter 2022



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Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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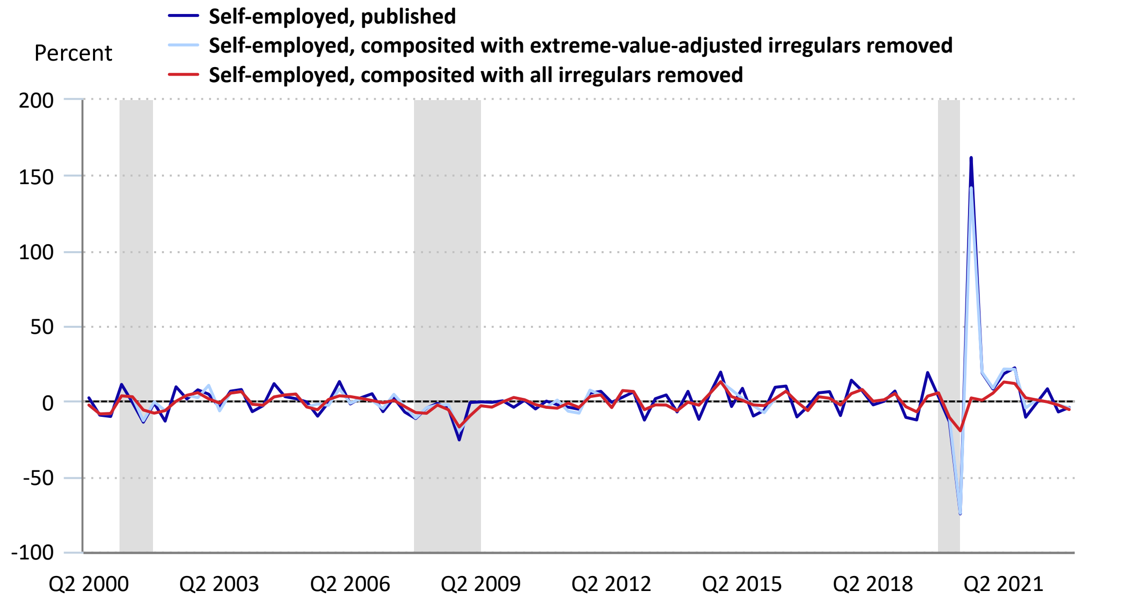
Chart 10. Annualized quarter-to-quarter percent change in hours for the self-employed in the nonfarm business sector, published, composited with extreme-value-adjusted irregulars removed, and composited with all irregulars removed, seasonally adjusted, second quarter 2000 to fourth quarter 2022



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Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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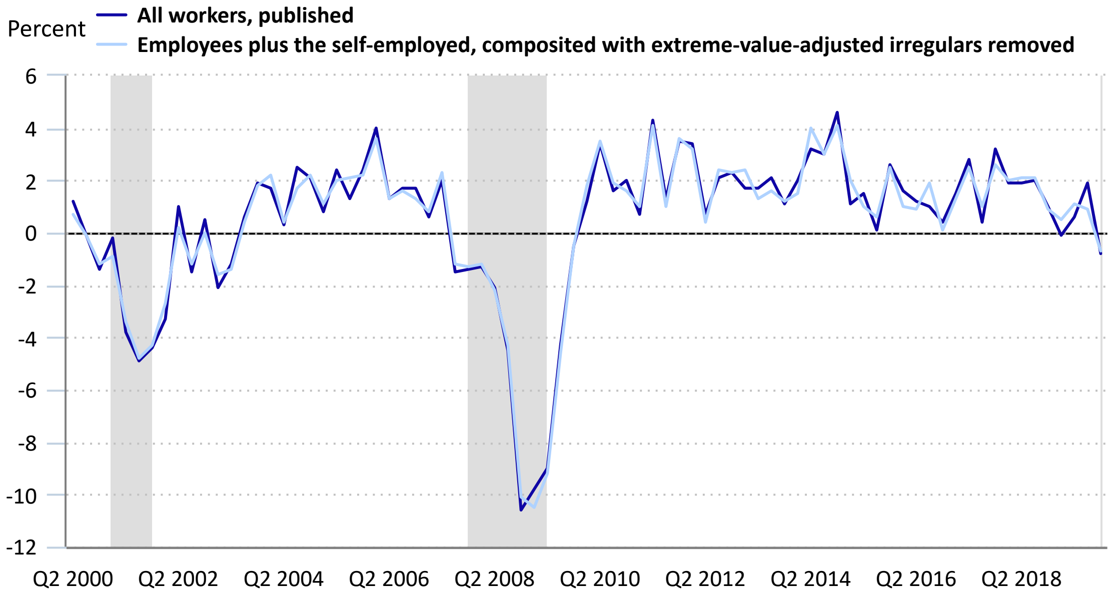
Effects of adjustments to self-employment hours

The outsized effect of self-employment hours volatility on total hours growth is the primary motivation behind Cunningham and Pabilonia's working paper and the new method implemented here. An important check, then, is to see how this method of estimating self-employment hours affects the volatility in total hours growth. Chart 11 shows the published quarterly total hours growth and our estimate of quarterly total hours growth that uses the adjusted self-employment hours series. For most of the large spikes in the series, the adjustment reduces the volatility of total hours growth, especially toward the end of the series. In two noticeable instances, however, the adjusted series has larger spikes than the published series—in the second quarter of 2014 and in the third quarter of 2016. Looking back to those data points in chart 9a, we see that, in the second quarter of 2014, self-employment hours growth was −12.1 percent before the adjustments and −2.7 percent after; in the third quarter of 2016, that growth was −10.5 percent before the adjustments and −0.5 percent after. These large negative spikes in the unadjusted self-employment hours series were distorting underlying positive spikes in employee hours growth that now are evident after the self-employment hours series has been smoothed.

Chart 11. Annualized quarter-to-quarter percent change in hours for all workers in the nonfarm business sector, published versus including hours for the self-employed that are composited with extreme-value-adjusted irregulars removed, seasonally adjusted, second quarter 2000 to fourth quarter 2019



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Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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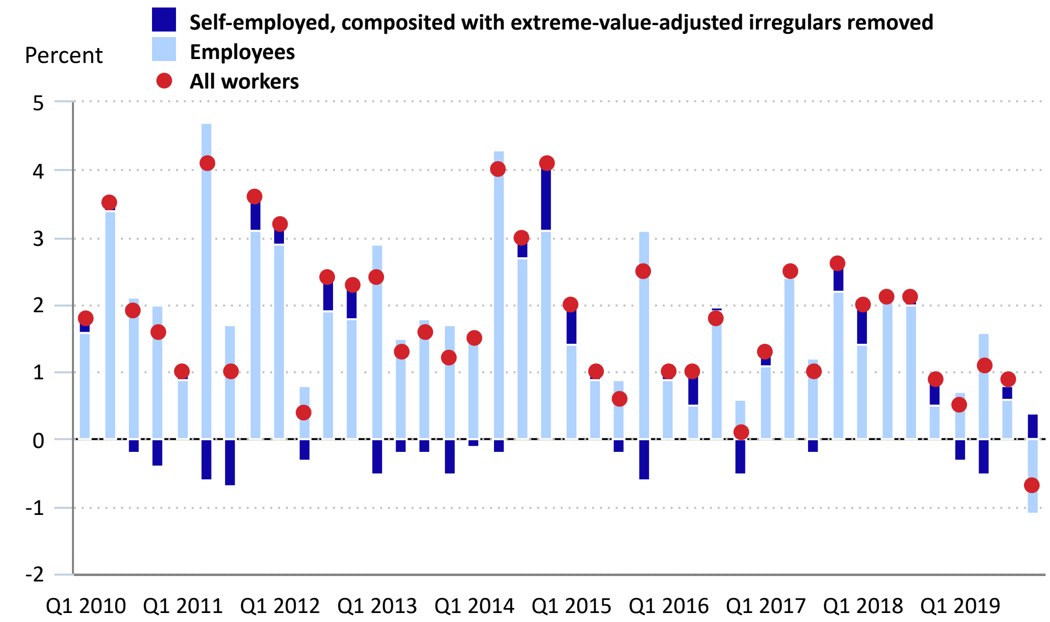
To see the reduction in volatility better, in chart 12, we reexamine the contributions to total hours growth that we presented in chart 3. The bars showing the contribution of the self-employed to hours growth are much smaller than they were in chart 3. For example, the contribution of the self-employed is substantially reduced in the third quarter of 2019. Under this new method of estimating self-employment hours, the self-employed contributed 0.2 percentage point to a 0.9-percent growth in total hours, whereas before the adjustments they contributed 1.4 percentage points to a 1.9-percent growth in total hours. Similarly, in the second quarter of 2016, the self-employed contributed 0.8 percentage point to a 1.2-percent growth in total hours under the old method, but they contributed 0.5 percentage point to a 1.0-percent growth in total hours under the new method.

Chart 12. Contributions to annualized quarter-to-quarter percent change in hours, by class of worker in the nonfarm business sector, where the hours of the self-employed are composited with extreme-value-adjusted irregulars removed, seasonally adjusted, first quarter 2010 to fourth quarter 2019



Click legend items to change data display. Hover over chart to view data.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

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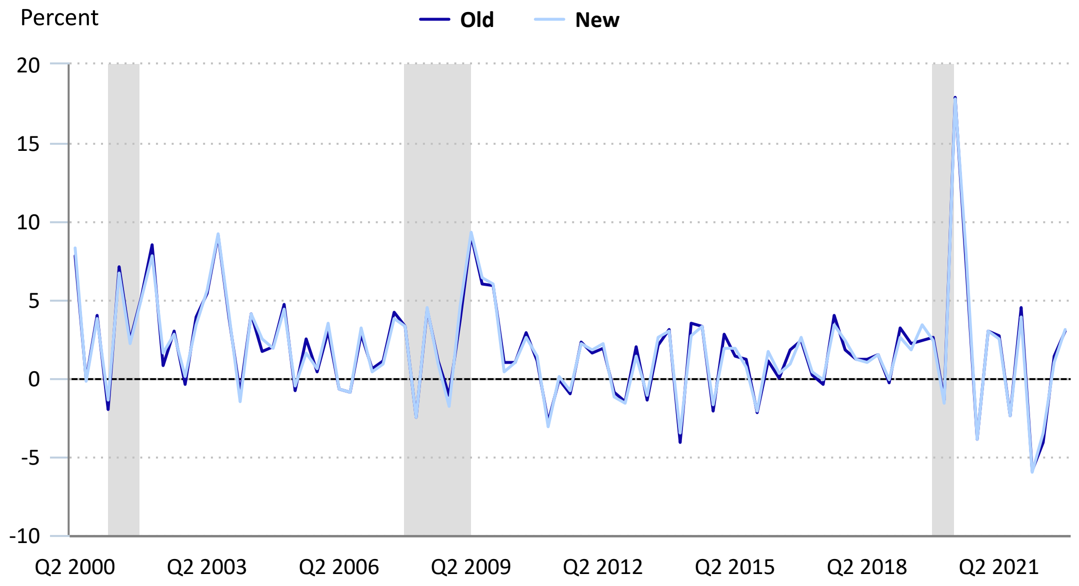
Finally, in chart 13, we examine the effects of smoothing the self-employment hours series on annualized quarter-to-quarter growth in labor productivity. Over the 2000–22 period, the absolute change in productivity was greater than 0.5 percentage point in 21 of the period's 91 quarters. In 8 of the 21 quarters, the productivity rate under the new method was larger in magnitude than the rate under the old method. This difference occurred in quarters that, prior to adjustment, had unusually large spikes in self-employment hours relative to employee hours. For example, in the third quarter of 2019, productivity grew at a 2.4-percent annual rate under the old method, but at a 3.4-percent rate under the new method. In two instances (the fourth quarter of 2002 and the second quarter of 2011), productivity growth changed direction from a small decrease to a small increase. Although we see changes in measured productivity using the new method, adopting the method does not affect long-run productivity growth, which averaged 1.9 percent annually over the 2000–22 period.

Chart 13. Annualized quarter-to-quarter percent change in labor productivity in the nonfarm business sector, old versus new method, seasonally adjusted, second quarter 2000 to fourth quarter 2022



Click legend items to change data display. Hover over chart to view data.
Shaded areas represent recessions as determined by the National Bureau of Economic Research.
Note: Q1 = first quarter, Q2 = second quarter, Q3 = third quarter, and Q4 = fourth quarter.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Conclusion

We find that self-employment hours are volatile because of survey-error-related volatility, which sometimes has outsized impacts on quarterly labor productivity. In 2024, to improve its measure of productivity, BLS will implement two adjustments to self-employment hours estimates: (1) directly compositing the estimates and (2) removing the EVA irregular component from the series. Because these adjustments will reduce survey-related volatility without oversmoothing the data, we will still be able to capture cyclical changes in self-employment. Consequently, the adjustments will improve our measure of labor productivity.

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Notes

1 For general information on the Current Employment Statistics (CES) survey, see "CES overview" (U.S. Bureau of Labor Statistics), https://www.bls.gov/web/empsit/cesprog.htm.

2 The concept of self-employment is often elusive. Audrey Light and Robert Munk find that 68 percent of jobs classified as self-employment are not also reported as self-owned businesses in the 1979 National Longitudinal Survey of Youth. Instead, these jobs involve contract work or home-based, single-person pursuits, such as babysitting. See Light and Munk, "Business ownership versus self-employment," *Industrial Relation*s, vol. 57, no. 3, 2018, https://doi.org/10.1111/irel.12213.

3 For general information on the Current Population Survey (CPS), see "Labor force statistics from the Current Population Survey overview" (U.S. Bureau of Labor Statistics), https://www.bls.gov/cps/cps_over.htm.

4 See Kevin E. Cahill, Michael D. Giandrea, and Joseph F. Quinn, "New evidence on self-employment transitions among older Americans with career jobs," Working Paper 463 (U.S. Bureau of Labor Statistics, March 2013), https://www.bls.gov/osmr/research-papers/2013/pdf/ec130030.pdf; and Robert W. Fairlie and Frank M. Fossen, "Defining opportunity versus necessity entrepreneurship: two components of business creation," in Solomon W. Polachek and Konstantinos Tatsiramos, eds., *Change at Home, in the Labor Market, and On the Job* (*Research in Labor Economics*, vol. 48) (Emerald Publishing Limited, Bingley, November 2020), pp. 253–289, https://doi.org/10.1108/S0147-912120200000048008.

5 Official data used in this article are based on data released in *Productivity and Costs: Fourth Quarter and Annual Averages 2022, Preliminary*, USDL 23-0150 (U.S. Department of Labor, February 2, 2023), https://www.bls.gov/news.release/archives/prod2_02022023.htm.

6 Using the CPS panel, Fairlie and Fossen ("Defining opportunity versus necessity entrepreneurship") find that the number of new business owners increases with the national unemployment rate. They further examine opportunity versus necessity entrepreneurship over the business cycle and find that necessity entrepreneurship, defined as moving from unemployment to self-employment between CPS matched months, is strongly countercyclical.

7 Charlene Marie Kalenkoski and Sabrina Wulff Pabilonia find that self-employment fell precipitously in the second quarter of 2020 relative to the decline in wage and salary employment. See Kalenkoski and Pabilonia, "Impacts of COVID-19 on the self-employed," *Small Business Economics*, vol. 58, 2022, pp. 741–768, https://doi.org/10.1007/s11187-021-00522-4.

8 Cindy Michelle Cunningham and Sabrina Wulff Pabilonia, "Why are measures of aggregate hours worked by the unincorporated self-employed so volatile?," Working Paper 567 (U.S. Bureau of Labor Statistics, forthcoming December 2023).

9 The charts in this section are replications based on Cunningham and Pabilonia (see ibid.), but here they measure hours instead of employment and include hours for unpaid family workers. The measures are not seasonally adjusted.

10 Jonathan Eggleston, Mark A. Klee, and Robert Munk find that imputed self-employment rates are rising in other household surveys. In addition, using the Survey of Income and Program Participation (SIPP), they find that the self-employed are not missing at random conditional on observables. This latter finding is likely also true for the CPS, which uses hot-deck imputation to impute self-employment and incorporation status. Hot-deck imputation is limited in the number of respondent characteristics that are used to match nonrespondents to respondent donors. Eggleston, Klee, and Munk use sequential regression multiple imputation and administrative data from the Social Security Administration Detailed Earnings Record and the Internal Revenue Service Information Returns Master File to substantially improve imputation in the SIPP. See Eggleston, Klee, and Munk, "Self-employment status: imputations, implications, and

improvements," SIPP Working Paper 303 (U.S. Census Bureau, March 2022), https://www.census.gov/content/dam/Census/library/working-papers/2022/demo/sehsd-wp2022-06.pdf.

[11] In quarter-to-quarter comparisons, of the respondents in 24 of the month-in-sample (MIS)–month pairs (3 months in a quarter times 8 MIS groups in each) in the second quarter, those in 12 of the pairs were also observed at least once in the previous quarter, and those in the other 12 pairs were entirely new to the CPS sample.

[12] Rotation-group bias was first recognized by researchers attempting to construct estimates of gross flows between labor force states with the use of CPS data. These researchers found that people responding to the CPS for the first time are more likely to report being unemployed than in the average month in sample, while those in the final rotation group are less likely to report being unemployed. See Barbara A. Bailar, "The effects of rotation group bias on estimates from panel surveys," *Journal of the American Statistical Association*, vol. 70, no. 349, 1975, pp. 23–30, https://doi.org/10.2307/2285370; Hie Joo Ahn and James D. Hamilton, "Measuring labor-force participation and the incidence and duration of unemployment, "*Review of Economic Dynamics*, vol. 44, April 2022, pp. 1–32, https://doi.org/10.1016/j.red.2021.04.005; and Andrew Halpern-Manners and John Robert Warren, "Panel conditioning longitudinal studies: evidence from labor force items in the Current Population Survey," *Demography*, vol. 49, no. 4, November 2012, pp. 1499–1519, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3648659/.

[13] Given that the sample rotation effects are present every month, one would expect them to be even over time. However, in chart 6, the upward spikes are much larger than the downward spikes. This is because quarterly growth rates are affected by the change in levels. For example, an increase in one quarter would require a smaller decrease in the subsequent quarter to return to the initial level.

[14] See Morris H. Hansen, William N. Hurwitz, Harold Nisselson, and Joseph Steinberg, "The redesign of the Census Current Population Survey," *Journal of the American Statistical Association*, vol. 50, no. 271, September 1955, pp. 701–719, https://www.jstor.org/stable/2281161?typeAccessWorkflow=login.

[15] See Margaret Gurney and Joseph F. Daly, "A multivariate approach to estimation in periodic sample surveys," *Proceedings of the Social Statistics Section*, vol. 242 (American Statistical Association, 1965), pp. 242–257, http://www.asasrms.org/Proceedings/y1965/A%20Multivariate%20Approach%20To%20Estimation%20In%20Periodic%20Sample%20Surveys.pdf; and Elizabeth T. Huang and Lawrence R. Ernst, "Comparison of an alternate estimator to the current composite estimator in CPS," *Proceedings of the Survey Research Methods Section* (American Statistical Association, 1980), pp. 303–308, http://www.asasrms.org/Proceedings/papers/1981_063.pdf.

[16] Janice Lent, Stephen Miller, and Patrick Cantwell, "Composite weights for the Current Population Survey," *Proceedings of the Survey Research Methods Section* (American Statistical Association, 1994), https://www.bls.gov/osmr/research-papers/1994/pdf/cp940060.pdf.

[17] The regARIMA model, which combines regression with autoregressive integrated moving average (ARIMA) modeling, includes controls for fixed seasonal effects, trading-day effects, holidays, and various types of outliers that have been identified either a priori or by the program's outlier-detection feature. The time-series model is also used to forecast data in order to extend the series so that series endpoints are not estimated with asymmetrical information.

[18] See "Calculating approximate standard errors and confidence intervals for Current Population Survey estimates," technical documentation (U.S. Bureau of Labor Statistics, November 2018), https://www.bls.gov/cps/calculating-standard-errors-and-confidence-intervals.pdf.

[19] Before dividing, we multiply the standard errors computed with generalized variance functions (GVF) by 0.8. This is necessary because the GVF was generated with nonseasonally adjusted data, while our series is seasonally adjusted. It is well known that the standard errors of seasonally adjusted data are lower than those of nonseasonally adjusted data. See, for example, Danny Pfeffermann and Michail Sverchkov, "Estimation of mean squared error of X-11-ARIMA and other estimators of time series components," *Journal of Official Statistics*, vol. 30, no. 4, 2014, pp. 811–838, https://sciendo.com/article/10.2478/jos-2014-0049.

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Book Review

December 2023

Reflections on introductory economics education and its consequences

Economism: Bad Economics and the Rise of Inequality. By James Kwak. New York City, NY: Pantheon Books, 2017, 237 pp., $25.95 hardcover.

While economics courses can take many approaches to pedagogy, one guarantee is a graph—a graph with price on one axis, quantity on the other. Contained therein are two lines, one indicating demand, and the other, supply. What some users of this ubiquitous model often forget is that this graph is meant to introduce ideas about the behavior of perfectly competitive markets, and these ideas come with many assumptions that do not fully reflect reality. This overuse of the model is what leads James Kwak, the author of *Economism: Bad Economics and the Rise of Inequality*, to assert that a blind adherence to the simplest of the laws of supply and demand has done a great deal of economic harm, both in terms of allocation of resources and with respect to the welfare of many poor, working people.

Kwak defines the book's titular term, economism, as "what you are left with if you learn the first-year models, forget that there are assumptions involved, and never get your hands dirty with real-world data." Throughout the nine chapters of the book, the author introduces readers to the problems plaguing the introductory model of supply and demand, illustrating them with real-world accounts of market failure in fields such as healthcare, finance, and trade. He begins with a "crash course" in introductory economic theory, providing readers with the information necessary for interpreting the perfectly competitive market model. He then dissects the effects of supply and demand shifts on perfectly competitive markets and introduces the ideas of market equilibrium and dead-weight loss. This discussion is followed by a history of how such models gained prevalence, as well as an account of the key actors involved in that process, including Friedrich Hayek, Milton Friedman, and Ludwig von Mises. Kwak is not only foreshadowing the consequences of economism but also exposing how a full contextualization of the theory is what is sorely missing from introductory economics education.

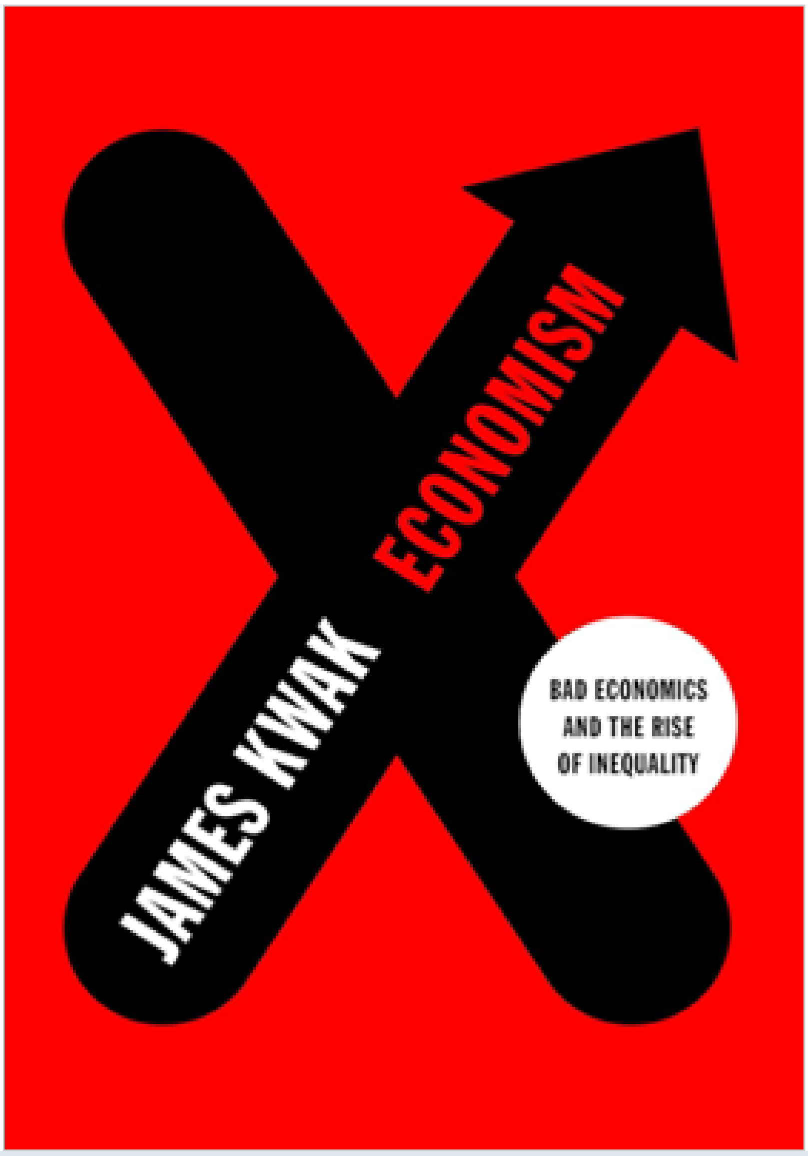
Early in the book, Kwak uses history to begin to unwind the model of perfectly competitive markets, but it is in subsequent chapters that he solidifies his thesis. These chapters begin by looking into the minimum wage, salaries and benefits given to corporate executives, and the disparity between wages and productivity. The discussion on the minimum wage starts by introducing various views on the concept of a price floor, including those of economists such as Mises and Hayek. These views—portrayed as representing economism—are then contrasted with economic research that studies how the minimum wage affects employment. Arguments of this variety are then assessed with respect to chief executive officer compensation packages, as well as the incentives, or lack thereof, such packages create. The section on wages concludes with a discussion of how worker wages have failed to keep pace with the accompanying steady rise in productivity over the previous few decades.

Economism is then discussed in the context of healthcare in the United States, with Kwak explaining how arguments based on the model of perfectly competitive markets fail to accurately describe that domain. The author attributes this failure to two main causes: the existence of an insurance apparatus that ensures that medical services are seldom paid for directly by those receiving healthcare and the fact that most people do not need healthcare on an ongoing basis. Distortions are then amplified, Kwak claims, by a series of policy choices over the years that have failed to reflect best practices gleaned from either research or the experiences of other countries within the Organisation for Economic Co-operation and Development. As always, the topic of healthcare is complex, but Kwak weaves through it with an appropriately critical lens.

Kwak's best is revealed in a chapter concerning economism in the financial sector. The author's expertise in banking and financial regulation helps inform his discussion of the effects of markets in finance. Special attention is paid to developing arguments against economism and expanding upon the 2008 financial crisis. Although the crisis was a complicated affair, Kwak dissects it efficiently, adding the history of how it came to pass. He spends considerable time describing how the logic of economism was used to deregulate the banking sector in order to create new risky financial products and how these products then began to be traded among and within banks. He identifies the products and describes how they worked, what led the banks to create them, and, ultimately, how they were the catalyst for the financial crisis itself. This much-needed history could greatly benefit anyone seeking to know more about financial economics.

Moving on from the financial sector, Kwak then looks at trade, getting to the core of an issue that, while uniting nearly all economists, still calls into question the axioms of economism. Although free trade does create wealth, it does not come without costs. Kwak begins this discussion with the simple two-country model of trade covered in introductory economics classes, describing the value of trade when two entities each have a comparative advantage. However, as seen repeatedly in the book, the real-world data do not necessarily reflect introductory theory. Using research on the results of the North American Free Trade Agreement, Kwak argues that while trade has contributed to U.S. economic growth, that contribution has been very small and countered by the loss of many U.S. manufacturing jobs that have been allowed to flow out of the country.

Overall, Kwak makes valid points and backs them up with excellent data and evidence from existing research. Helped by his solid understanding of economics, he is able to dismantle models demanding that everything be decided in a market. These models are useful for the introduction of core concepts, but they rarely hold when one is exposed to further economics education. In introductory courses, buyers and sellers are price takers. In advanced courses, the attention shifts to how firms can decide both prices and output. In introductory trade theory, the two-country model is excellent for illustrating trade's benefits. However, advanced trade theory considers many countries, goods, and distance costs simultaneously. Although introductory models are excellent for simplifying a dynamic, complex world, Kwak's argument that dogmatic adherence to them has dire consequences cannot be denied.



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Article

December 2023

Effects of the PPI weight update on final-demand relative-importance values

In January 2023, the U.S. Bureau of Labor Statistics introduced its latest update of value weights used to calculate producer price indexes (PPIs). This update, based on 2017 value-of-shipments data, resulted in shifting PPI relative-importance values. This article analyzes the update's effects on the relative-importance values of selected indexes for goods, services, and construction products within PPI's headline final-demand index.

The U.S. Bureau of Labor Statistics regularly updates the value weights used to calculate producer price indexes (PPIs). The purpose of these updates is to reflect recent production and marketing patterns more accurately. The most recent weight update was introduced with the release of January 2023 PPI data and is based on 2017 value-of-shipments data collected from the census of manufactures, the census of mining, the census of services, and the census of agriculture. From January 2018 through December 2022, PPI weights were based on 2012 shipment values.

The most recent weight update affected all PPIs, including industry net-output indexes, traditional commodity-group indexes, Final Demand–Intermediate Demand (FD–ID) indexes, special commodity-group indexes, and inputs-to-industry indexes. Although the update did not change the basic classification structures of the PPI commodity and FD–ID indexes, it did result in shifting relative-importance values, which indicate the portion of an aggregate index that is accounted for by a component index at a given point in time. This article analyzes shifts in relative-importance values within PPI's headline final-demand index, focusing on shifts resulting from weight updates based on 2012 and 2017 value-of-shipments data.

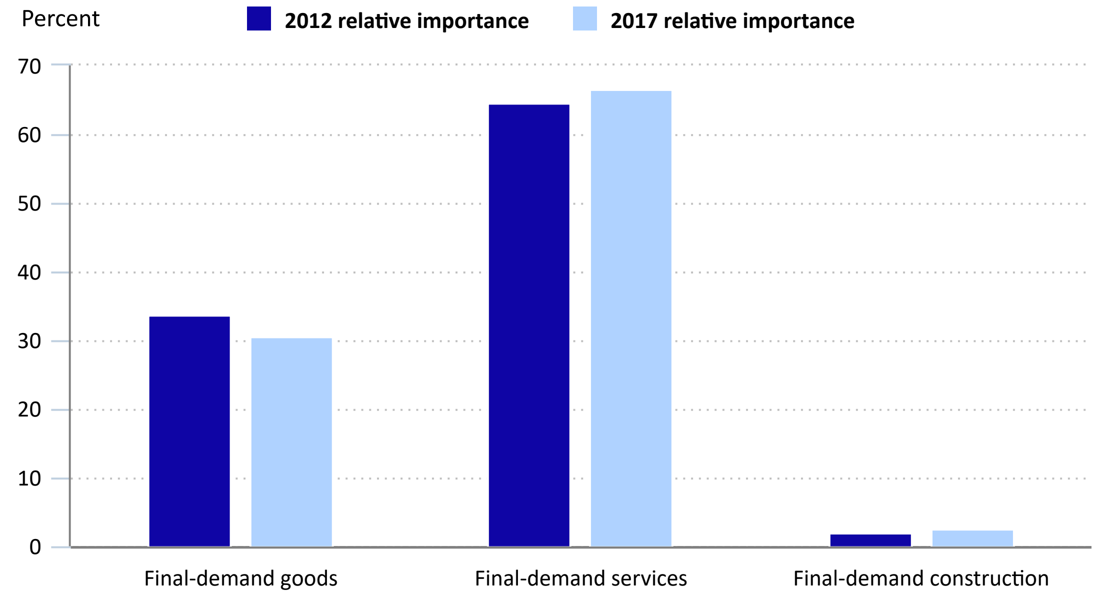
The relative-importance tables available from the PPI program compare values from December 2021 and December 2022.[1] These values changed because of updated value-of-shipments data and price movements from 2021 to 2022. To isolate the effects of the most recent weight update on PPI relative-importance values, this article compares December 2022 relative-importance values based on 2012 value-of-shipments data with December 2022 relative-importance values based on 2017 value-of-shipments data. By comparing relative-importance values for the same period, the analysis removes the effect of shifts in relative prices and isolates the effect of weight changes on relative-importance values.

Final demand

The PPI for final demand measures price change for goods, services, and construction products sold for personal consumption, as capital investment, to government, and as exports. As noted previously, the weight revision based on 2017 value-of-shipments data did not change the basic structure of the PPI for final demand, but it did shift the relative-importance values of component indexes for various products within the overall index.

Within final demand, the update to 2017 weights resulted in positive relative-importance shifts for services and construction, and a negative shift for goods production. The shift away from goods reflects the continuing trend of U.S. economic activity moving from manufacturing to services.[2] With the shift from 2012 to 2017 weights, the relative importance of the index for final-demand services increased from 64.5 to 66.7 percent, and the relative importance of the index for final-demand construction increased from 1.9 to 2.7 percent. In contrast, the relative importance of the index for final-demand goods fell from 33.6 to 30.7 percent.[3] (See chart 1.)

Chart 1. Relative importance of major component indexes within the Producer Price Index for final demand, calculated with 2012 and 2017 value weights, December 2022



Click legend items to change data display. Hover over chart to view data.
Note: Values may not add to 100 because of rounding.
Source: U.S. Bureau of Labor Statistics.

View Chart Data

Final-demand services

The index for final-demand services comprises three main component indexes for the following service categories: transportation and warehousing services; trade services; and services less trade, transportation, and warehousing. Contributing most to the increase in the relative importance of the index for final-demand services, the relative importance of the index for final-demand services less trade, transportation, and warehousing grew from 38.9 percent (based on 2012 value-of-shipments data) to 41.8 percent (based on 2017 value-of-shipments data). In addition, with the shift from 2012 to 2017 value weights, the relative importance of the index for final-demand transportation and warehousing services increased from 4.6 to 5.2 percent. Conversely, the relative importance of the index for final-demand trade services declined from 21.0 to 19.7 percent. (See table 1.)

Table 1. Relative importance of selected component indexes within the Producer Price Index for final demand, calculated with 2012 and 2017 value weights, December 2022

Index	2012 relative importance (percent)	2017 relative importance (percent)	Change (percentage points)
Final demand	100.0	100.0	[1]
Final-demand services	64.5	66.7	2.2
Final-demand services less trade, transportation, and warehousing	38.9	41.8	2.9
Final-demand transportation and warehousing services	4.6	5.2	0.6
Final-demand trade services	21.0	19.7	-1.3
Final-demand construction	1.9	2.7	0.8
Final-demand goods	33.6	30.7	-2.9
Final-demand foods	6.2	5.9	-0.3
Final-demand energy	6.1	5.9	-0.2
Final-demand goods less foods and energy	21.3	18.9	-2.4

[1] Not applicable.
Source: U.S. Bureau of Labor Statistics.

The remainder of this section discusses selected component indexes for detailed final-demand services with notable shifts in relative importance. The discussion examines the underlying drivers of those shifts, highlighting the importance of technological advancements and monetary policy.

Automobile retailing

With the shift from 2012 to 2017 weights, the index for automobile retailing experienced one of the largest relative-importance changes—an increase from 0.8 to 1.5 percent—among commodity indexes included in final demand.[4] (See appendix table A-1.) A combination of factors, including low interest rates, greater availability of subprime autoloans, pent-up demand, and declining fuel prices, helped boost automotive sales for 7 consecutive years after the end of the 2007–09 Great Recession. Consumers who delayed car purchases because of the recession took advantage of the postrecessionary environment of low interest rates and replaced older vehicles with brand-new ones.[5] Many of these consumers were approved for autoloans despite having low credit scores.[6] Additionally, lower fuel prices further boosted demand, with gasoline prices falling from $3.44 per gallon in January 2012 to $2.60 per gallon in December 2017.[7]

Brokerage fees and commissions from residential property sales and rentals

With the shift from 2012 to 2017 weights, the relative importance of the index for residential property sales and rental (brokerage fees and commissions) increased from 1.1 to 1.7 percent. (See appendix table A-1.) This increase was driven by consistent growth in housing sales. Between 2012 and 2017, the number of new homes sold grew from 368,000 to 613,000,[8] and existing-home sales rose from 4.66 to 5.51 million units.[9] More Americans also became renters, with the total number of renters jumping from 99.4 million in 2010 to 108.5 million in 2018.[10] The rising demand for rentals is also evident in the number of rental units constructed between 2012 and 2017. In 2017, there were 331,800 rental units built, up from 152,100 in 2012.[11] Home and rental prices moved in step with the rise in sales. Over the 2012–17 period, the average home price increased from $244,400 to $322,425,[12] and the median monthly rental price increased from $904 to $1,037.[13] Although commission rates during this period declined, rising home and rental prices helped offset potential losses in brokerage revenue. As homes became easier to sell during the recovery from the Great Recession, fewer agents were needed to aid homeowners in selling their homes, which put downward pressure on commission rates.[14] The boost in housing prices was facilitated by low interest rates and by demand outpacing the available supply of housing.[15]

Residential internet access services

Since the weight revision based on 2012 value-of-shipments data, the internet has become accessible to more Americans. The percentage of U.S households with internet access rose from 74.8 percent in 2012 to 78.0 percent in 2017.[16] As a result, the relative importance of the index for residential internet access services increased from 0.1 to 0.3 percent. (See appendix table A-1.) Although the trend of growing internet access had existed since the 1990s, it was further bolstered in the 2010s, with the telecommunications industry and the federal government increasing investment (a total investment of $795 billion between 2009 and 2017) for expanded access to broadband internet in the United States.[17] Between 2015 and 2017, the Federal Communications Commission expanded internet service to approximately 2.3 million residential and small-business locations.[18] This expansion was especially pronounced in rural areas, which typically face significant barriers to obtaining high-speed internet. Other potential factors that may have contributed to the increase in internet access include a rise in online education, an expansion of telehealth services, and an increase in video on-demand streaming.[19]

Home health and hospice care

Because of multiple factors, including a rise in the U.S. elderly population and an increase in demand for home-based healthcare services, the home health and hospice care sector grew consistently between 2012 and 2017. With the shift from 2012 to 2017 weights, the relative importance of the index for home health and hospice care increased from 0.7 to 0.9 percent. (See appendix table A-1.) Population growth among the elderly during the 2012–17 period was due mostly to the aging of the baby-boom generation, which started reaching age 65 in 2011.[20] Many providers of home health and hospice care services recognized this demographic shift, as well as the growing patients' preference for receiving care at home instead of at long-term care facilities. As a result, the number of home health agencies rose from 7,528 in 2000 to 11,300 in 2019.[21] A similar rising trend occurred in total expenditures on home health and hospice care, with those expenditures increasing from roughly $70 billion in 2012 to just under $100 billion in 2017.[22] The growing demand for home health and hospice care was also driven by cost avoidance on the part of patients, insurance companies, and the government, because such care could be used as a more affordable substitute for services at expensive facilities and could prevent costly emergency-room visits by closely monitoring chronic health conditions. The industry has provided relief for long-term care facilities, many of which are faced with limited capacity to house additional patients.[23]

Hospital care: outpatient and inpatient

The relative importance of the index for hospital outpatient care rose with the shift from 2012 to 2017 weights, increasing from 3.9 to 4.3 percent. (See appendix table A-1.) Consumer demand and technological advances were among the main factors that drove the growth of outpatient care services in hospitals.[24] Over the years, patients have been increasingly drawn to the convenience and low cost of receiving outpatient care as an alternative to hospital admissions. Technological innovations have made clinical procedures less invasive and thus more accessible to patients in outpatient facilities. Some surgical operations can now be performed more precisely with the aid of robotics, and outpatient surgeons can use high-definition cameras for surgical procedures that require smaller incisions. As a result, patient recovery times have become shorter, limiting the need for inpatient care and reducing costs for both patients and providers.[25] In contrast, with the update to 2017 weights, the relative importance of the index for hospital inpatient care decreased from 4.9 to 4.5 percent, providing further evidence of the shift from inpatient to outpatient services.

Furniture retailing

Margin revenue for furniture retailing rose as the U.S. housing market recovered during the 2012–17 period, boosting the relative importance of the index for furniture retailing from 0.3 to 0.5 percent. (See appendix table A-1.) Furniture and bedding sales rose from $82.7 billion in 2012 to $105.2 billion in 2017, an increase of 27 percent.[26] Besides the improving overall economy and housing market, other major sources of growth in furniture retailing were e-commerce and millennial consumers. From 2009 to 2017, e-commerce furniture sales grew at an annual rate of 22.2 percent, while sales at brick-and-mortar retail establishments grew at an annual rate of 3.0 percent.[27] In 2014, millennials became the largest consumer group in the U.S. furniture and bedding market, with a market share of 37 percent, compared with just 14 percent in 2012. This group is also credited for the rise in e-commerce, especially purchases made via smartphones, as retailers experienced substantial growth in mobile traffic and mobile commerce transactions.[28]

Cable and satellite subscriber services

With the shift from 2012 to 2017 weights, the relative importance of the index for cable and satellite subscriber services declined from 0.7 to 0.4 percent. (See appendix table A-1.) Much of this decrease was due to the growing popularity of television streaming services. Increasingly expensive cable and satellite packages—as well as the convenience of watching content on mobile devices such as laptops, cell phones, and tablets—drove the transition. Many consumers either opted for less expensive cable and satellite packages with fewer channels or canceled their subscriptions entirely.[29] The loss of subscriptions began in 2013 and intensified in subsequent years. In those years, existing companies that offered internet-based programming grew in influence and competing companies entered the market, some providing exclusively on-demand content and others also providing live television.[30] This development, coupled with lower consumer demand, reduced advertising revenue for cable and satellite companies, further contributing to the downward shift in the relative importance of the index for this category.[31]

Truck transportation of freight

The indexes for local and long-distance motor carrying both increased in relative importance with the shift from 2012 to 2017 weights. The relative importance of the index for local motor carrying rose from 0.6 to 0.7 percent, and the relative importance of the index for long-distance motor carrying rose from 1.9 to 2.2 percent. (See appendix table A-1.) These shifts reflect an upward trend in trucking revenues, which increased from just under $60 billion in the first quarter of 2013 to almost $70 billion in the fourth quarter of 2017.[32] The rise in e-commerce during this period can partly account for this growth, as consumers increasingly made purchases online. Online shoppers could also return merchandise more freely, propping up the trucking sector. Additionally, to minimize the distance between product storage facilities and consumers' homes, e-commerce companies increased investments in urban warehousing, reducing delivery times.[33] These investments likely contributed to the increase in the relative importance of the index for local motor carrying. Other contributors to the rise in trucking revenue included an improving economy, greater operational efficiencies, and an aging workforce that reduced the supply of truckers.[34]

Final-demand construction

With the shift from 2012 to 2017 weights, the relative importance of the index for final-demand construction increased from 1.9 to 2.7 percent. (See table 1.) This increase can be traced primarily to an advance in new warehouse building construction.[35]

The relative importance of the index for new warehouse building construction rose from 0.2 to 0.5 percent. (See appendix table A-1.) This increase was driven mostly by growth in online shopping, which forced e-commerce companies to acquire additional space to store inventory. Companies also sought out more warehousing facilities in urban locations in order to reduce delivery times and cut transportation costs. The connection between e-commerce sales and demand for warehousing can be seen in the progression of their growth rates, both of which accelerated between 2012 and 2017 relative to the prior 5-year period. E-commerce sales rose 11 percent annually from 2007 to 2012, and 14 percent annually from 2012 to 2017. Mirroring this trend, demand for warehouse space grew 0.7 percent annually from 2007 to 2012, and 1.1 percent annually from 2012 to 2017.[36] Additionally, available warehouse space became scarce, with vacancies reaching a 16-year low in 2016, intensifying the need for new warehouse construction.[37]

Final-demand goods

The index for final-demand goods comprises three main component indexes for the following commodity categories: foods, energy, and goods less foods and energy. With the update to 2017 weights, the decline in the relative importance of the index for final-demand goods was due mostly to a drop, from 21.3 to 18.9 percent, in the relative importance of the index for final-demand goods less foods and energy. The relative-importance values of the indexes for final-demand foods and final-demand energy also declined, with the former falling from 6.2 to 5.9 percent and the latter from 6.1 to 5.9 percent. (See table 1.)

The remainder of this section discusses selected component indexes for detailed final-demand goods with notable shifts in relative importance. Again, the discussion highlights important economic trends that underpin those shifts.

Passenger cars and light motor trucks

Between 2012 and 2017, consumer preferences shifted from passenger cars to light trucks such as minivans, pickup trucks, and sport utility vehicles. Over this period, sales of new light trucks increased more than 38 percent, from 6.2 to 8.6 million units, while sales of new passenger cars decreased 21 percent, from 5.7 to 4.5 million units.[38] This trend is reflected in changes in the relative importance of the indexes for both commodities. With the shift from 2012 to 2017 weights, the relative importance of the index for light trucks rose from 1.3 to 1.6 percent, while the relative importance of the index for passenger cars fell from 0.9 to 0.4 percent. (See appendix table A-1.) In addition to low interest rates and lax lending practices, low gas prices and greater consumer demand for more vehicle space contributed to the preference shift from cars to light trucks.[39]

Nonelectronic cigarettes

With the shift from 2012 to 2017 weights, the relative importance of the index for cigarettes (excluding electronic) declined from 0.5 to 0.4 percent. (See appendix table A-1.) Cigarette consumption continued a decades-long decline beginning in 1965, when the Center for Disease Control National Health Interview Survey began tracking cigarette usage among adults. The adult usage rate was 42.4 percent in 1965, 18.1 percent in 2012, and 13.9 percent in 2017.[40] This downward trend can be attributed to rising cigarette prices, antismoking campaigns, smoke-free laws, and smoking-cessation programs.[41] Additionally, between 2010 and 2020, government policies were put in place to reduce usage rates. The Children’s Health Insurance Program Reauthorization Act of 2009 increased federal taxes on cigarettes to $1.01 per pack, and the Patient Protection and Affordable Care Act of 2010 mandated most health insurance plans to cover smoking-cessation programs. Cigarette consumption declined 16.7 percent between 2012 and 2017, as 14 million cigarette packs were sold in 2012, compared with 12 million in 2017.[42] Although e-cigarettes likely contributed to lower usage rates, it remains unclear if they played a significant role in the decline.[43]

Residential electric power

The use of electricity by U.S. households declined during the 2010s. As a result, the relative importance of the index for residential electric power decreased from 2.0 to 1.9 percent. (See appendix table A-1.) Advances in technology were the main drivers of this decline, with both electronic devices and appliances becoming smaller and more energy efficient. The transition from traditional incandescent lightbulbs to bulbs with light-emitting diodes (LEDs) played the largest role in reducing electricity use.[44] Consuming 85 percent less electricity than incandescent lightbulbs, LEDs became more popular as their prices declined. Between 2008 and 2016, LED prices fell 94 percent, and the number of LED installations rose from less than 500,000 to over 450 million.[45] Additional factors that reduced household electricity use were the increasing prevalence of more-energy-efficient flat-screen television sets and the replacement of larger and less-energy-efficient desktop computers with laptops and tablets. Americans also spent less time watching television and more time using the internet, further contributing to the decline.[46]

Pharmaceutical preparations

With the shift from 2012 to 2017 weights, the relative importance of the index for pharmaceutical preparations declined from 1.4 to 1.1 percent. (See appendix table A-1.) Driving this trend was a consistent shift from domestic to foreign production of pharmaceuticals. This shift, which started in the mid-2000s and continued through the 2010s,[47] resulted mostly from cost-cutting initiatives prompted by the rising trend of generic drugs hitting the market.[48] Drug companies were drawn to lower labor and production costs afforded by countries such as China and India, and they faced fewer environmental regulations in China around the buying, handling, and disposing of chemicals used in the pharmaceutical manufacturing process.[49]

Conclusion

The result of the 2023 PPI weight update, which involved a transition from 2012 to 2017 value-of-shipments data, reveals an underlying theme in some of the largest shifts in relative-importance values. Many of those shifts were driven by either technological advancements or monetary policy, which helped boost the economy after the 2007–09 Great Recession. Technological advancements, such as simplified medical procedures, television streaming services, and energy-efficient LEDs, played a major role in reducing the relative importance of the indexes for hospital care, cable and satellite subscriber services, and residential electric power. Monetary policy affected the relative importance of the indexes for real estate brokerages and automobile retailing, as both sectors realized growth in revenue, largely because of the Federal Reserve’s lowering of interest rates.[50] Additionally, lower borrowing costs incentivized discretionary spending, shifting consumer purchases from passenger cars to more expensive light trucks. Consumers also shopped online more frequently, which in turn increased demand for trucking services and new warehouse building construction, boosting the relative importance of the indexes for these categories.

Appendix

Table A-1. Relative importance of selected Producer Price Index detailed component indexes, calculated with 2012 and 2017 value weights, December 2022

Index	Commodity	2012 relative importance (percent)	2017 relative importance (percent)	Change (percentage points)
054121	Residential electric power	2.0	1.9	-0.1
057103	Unleaded premium gasoline	0.2	0.4	0.2
0638	Pharmaceutical preparations	1.4	1.1	-0.3
063801	Pharmaceuticals affecting neoplasms, the endocrine system, and metabolic diseases	0.4	0.2	-0.2
063802	Pharmaceuticals acting on the central nervous system and the sense organs	0.4	0.3	-0.1
063803	Pharmaceuticals acting on the cardiovascular system	0.1	0.1	0.0
063804	Pharmaceuticals acting on the respiratory system	0.2	0.1	-0.1
063805	Pharmaceuticals acting on the digestive or the genito-urinary systems	0.1	0.0	-0.1
063806	Pharmaceuticals acting on the skin	0.0	0.1	0.1
063807	Vitamin, nutrient, and hematinic preparations	0.1	0.1	0.0
063808	Pharmaceuticals affecting parasitic and infective diseases	0.1	0.1	0.0
141101	Passenger cars and chassis	0.9	0.4	-0.5
141105	Trucks, truck tractors, and bus chassis 14,000 lb or less, including minivans and SUVs	1.3	1.6	0.3
152101	Cigarettes, excluding electronic	0.5	0.4	-0.1
301201	Local motor carrying	0.6	0.7	0.1
301202	Long-distance motor carrying	1.9	2.2	0.3
341101	System software publishing	0.3	0.9	0.6
351101	Affiliate agreements, programming sales, and retransmission fees for cable and broadcast TV	0.3	0.1	-0.2
372101	Cellular phone and other wireless telecommunication services	0.7	1.0	0.3
373101	Cable and satellite subscriber services	0.7	0.4	-0.3
374102	Residential internet access services	0.1	0.3	0.2
381101	Hosting, ASP, and other IT infrastructure provisioning	0.3	0.4	0.1
401101	Securities brokerage, dealing, and investment advice	0.6	1.0	0.4
402101	Portfolio management	2.0	1.6	-0.4
411101	Life insurance	0.4	0.9	0.5
412101	Annuities	0.5	0.2	-0.3
431201	Nonresidential property sales and leases including land, brokerage fees and commissions	0.3	0.4	0.1
432101	Residential property sales and rental, brokerage fees and commissions	1.1	1.7	0.6
454101	Administrative and general management consulting services	0.3	0.2	-0.1
511101	Physician care	3.6	4.0	0.4
511103	Home health and hospice care	0.7	0.9	0.2
511104	Hospital outpatient care	3.9	4.3	0.4
512101	Hospital inpatient care	4.9	4.5	-0.4
552101	Motor vehicle repair and maintenance (partial)	0.5	0.4	-0.1
571102	Parts and supplies for machinery and equipment	1.3	0.7	-0.6
571104	Professional and commercial equipment wholesaling	0.9	0.7	-0.2
577101	Apparel wholesaling	0.5	0.3	-0.2
578101	Food wholesaling	0.9	1.1	0.2
579101	Other commodities wholesaling	1.9	2.4	0.5
581102	Food retailing	2.1	1.7	-0.4
583101	Apparel, footwear, and accessories retailing	1.2	1.0	-0.2
586101	Automobile retailing (partial)	0.8	1.5	0.7
58B101	Furniture retailing	0.3	0.5	0.2
58D101	Hardware and building materials and supplies retailing	0.3	0.2	-0.1
58F101	Automotive fuels and lubricants retailing	0.8	0.5	-0.3
601104	Support activities for oil and gas operations	0.7	0.5	-0.2
801101	New warehouse building construction	0.2	0.5	0.3
801102	New school building construction	0.4	0.6	0.2
801103	New office building construction	0.5	0.7	0.2

Note: ASP = active server pages; IT = information technology.
Source: U.S. Bureau of Labor Statistics.

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Beyond BLS

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

December 2023

The unequal responses to pandemic-induced schooling shocks

Summary written by: Jelena H. Goldstein

Education is meant to benefit all students. The COVID-19 pandemic, however, changed this notion. The pandemic emphasized discrepancies in support and resources for school children of different socioeconomic backgrounds, and the aftermath of the pandemic may be seen beyond the short-term differences. In their article "The unequal responses to pandemic-induced schooling shocks" (Federal Reserve Bank of St. Louis *Review*, first quarter 2023), Andrea Flores and George-Levi Gayle look at what effects the pandemic has had on school-age children. They suggest, similar to natural disasters, that COVID-19 limited schooling of children on the basis of their background. Limitations included canceled classes, no access to online schooling, and general school resources. Flores and Gayle state that "non-White respondents were more likely to have had their classes cancelled at the onset of the pandemic." This group of students was also less likely to have computer access if their classes continued online. Overall, school disruptions affected both short-term learning and their continued education.

To determine how the pandemic altered children's learning, the authors use a dataset that they first introduced in an earlier article that they coauthored. They use this dataset, which they developed from the U.S. Census Bureau's Household Pulse Survey data, to compare demographics from April 2020 through March 2021. The study covers 2 academic years, including the initial pause to in-person meetings and return to the classroom with distancing. Flores and Gayle use Census data to measure three "changes in learning format," identified as "switch to remote learning," "class suspension," and "schools remaining open." They also focused on computer access.

Flores and Gayle find that "children in households in the bottom quintile of the income distribution and children in non-White and non-college-educated respondents' households" faced more class cancellations and less computer access when classes were switched online. These students' long-term education was disrupted substantially more than their peers who could better continue learning during COVID-19. School is seen as an equalizer, allowing students to learn and grow. Students with access to computers at home were able to continue learning, while those who did not have resources did not continue the same level of learning at home. Findings show that educational benefits can no longer be equal when they are taken away from or disrupted for only some groups.

Beyond BLS

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

December 2023

What caused the high inflation during the COVID-19 period?

Summary written by: Lawrence H. Leith

The COVID-19 pandemic profoundly affected the world economy. The U.S. economy lost 23 million jobs at the start of the pandemic, leading to a recession in early 2020. The federal government responded with sharp increases in fiscal spending, and the Federal Reserve lowered interest rates to near zero and kept them there for almost 2 years. The economy began to recover, but inflation rose to its highest level in decades. This led to debates among economists about what caused the high inflation rates and how best to lower them. In a recent conference paper, "What caused the U.S pandemic-era inflation?" (presented at the Brookings Institution, Washington, DC, May 23, 2023), Ben Bernanke and Olivier Blanchard analyze the complex set of factors that led to the highest inflation rates in more than 40 years.

In their literature review, Bernanke and Blanchard divide policy analysts into two groups: the "inflation optimists" and "the critics" (counting themselves among the latter). As the authors explain, standard economic theory suggests that easing fiscal and monetary policy can increase inflation if labor markets overheat and output exceeds the economy's potential. The inflation optimists argued that even if the new policies caused the unemployment rate to decline more than is optimal (i.e., below 4.0 percent), any resulting rise in inflation would probably be minimal and temporary. By contrast, the critics argued that the large fiscal transfers and easing of monetary policy risked increasing aggregate demand to the point of overheating the labor market and thus increasing inflation.

Bernanke and Blanchard introduce an analytical model that focuses on the behavior of wages, prices, and short- and long-term inflation expectations, with labor market slack and shocks to prices taken as given. The authors use empirical data on wages and prices to test their "model of wage-price determination." They examine data from two periods: first quarter 1990 to fourth quarter 2019 (the pre-COVID period) and first quarter 2020 to first quarter 2023 (the COVID period). The model allows the authors to "decompose" price and wage inflation and determine its sources at a more specific level. In particular, they examine demand issues, such as food and energy prices, and supply issues, such as the shortages caused by production shutdowns and other supply-chain disruptions during the pandemic. In addition, Bernanke and Blanchard use the ratio of job vacancies to unemployed workers in their analysis, arguing that it measures labor market tightness more accurately. The ratio increased from less than 1.0 in April 2021 to 1.9 a year later, the highest level on record.

From their analysis, the authors present three main findings:

1. The shocks to food and energy prices contributed substantially to the sharp rise in inflation during the COVID-19 period. Energy price shocks were the primary cause of the high inflation rates from late 2021 to the middle of 2022. Lower energy prices in the second half of 2022 contributed to the inflation decline during that period.

2. The combined effects of increased demand for durables and shortages caused by supply-chain disruptions were the main source of inflation in the second quarter of 2021. Both the direct and indirect effects of those supply-chain problems remained substantial through the end of 2022.

3. Tight labor-market conditions, one of the main concerns of the early critics of U.S fiscal and monetary policy, contributed only slightly to inflation. In fact, the tight labor market affected the economy negatively in 2020 and early 2021. Since then, however, the traditional Phillips-curve effect has begun to reemerge, with the high vacancy-to-unemployment ratio becoming an increasingly important factor in the high inflation rates.

Bernanke and Blanchard argue that the critics' concerns of higher inflation were correct. But the sources of the high inflation differed from those the critics had anticipated. The authors conclude that price shocks in product markets were the leading cause of the initial rise in inflation. However, as labor markets began to overheat in 2022, with unsustainable employment increases, a high ratio of job openings to unemployed workers, and low levels of quits, labor market tightness increasingly became the main cause of the persistently high inflation rates.

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December 2023

What are the impacts of graduates receiving a college degree later in life?

Summary written by: Richard Hernandez

The path for most students who obtain a college education is thought to be straightforward. After students receive their high school diploma, they then enroll in a postsecondary educational institution to earn their college degree in their 20s—they are known as *early college graduates*. However, what share of college graduates finish their college education after turning 30? These college graduates are known as *late bloomers*. So, does the age of a person matter when obtaining a college degree? In a recent working paper, “Late bloomers: the aggregate implications of getting education later in life” (National Bureau of Economic Research, Working Paper 31874, November 2023), authors Zsófia L. Bárány, Moshe Buchinsky, and Pauline Corblet investigate the percentage of the population who earn their degree after turning 30, the returns of a college education, and the resulting implications for the skilled workforce of obtaining a college degree later in life.

Using data from the U.S. Census Bureau and U.S. Bureau of Labor Statistics, Bárány and colleagues find that of people born between 1930 and 1970, around 20 percent have earned their college degree after turning 30. Furthermore, women tend to earn their degree later in life than men. The authors also discover that when they further break down the data by race, Black and Hispanic individuals are more likely to be late bloomers compared with their White counterparts. Late bloomers have contributed to shrinking the gap between the gender and racial college share. After graduating, late bloomers receive a college wage premium (the difference in pay between a bachelor’s degree holder and a high school graduate). However, wages of late bloomers are less than those of early college graduates who followed the traditional college path. But when comparing late bloomers with those without a college degree, the authors find that late bloomers substantially outearn them.

In their working paper, the authors also explore how late bloomers affect the college share of overall workers. They find that since 1960, late bloomers have increased the aggregate supply of the skilled workforce, and their share is increasing with each cohort group. The authors point out that to understand the varying returns of earning a college degree at different ages, researchers should further investigate the reason people return to college at various ages later in life. They suggest that learning and comparing the different forces that drive early college graduates and late bloomers would benefit policymakers who implement educational public policies.