We use the Current Employment Statistics survey microdata for the private sector to calculate employment changes since February 2020 by employer size. We find that, for employers with 1 to 9 employees, the largest component of employment change since February is closings (either temporary or permanent) in all months. For employers with 10 or more employees, the largest component of employment change since February is within employers that have continued to report nonzero employment to the survey, rather than within those reporting zero employment or from imputed closures from nonrespondents to the survey. In percentage terms, the greatest overall employment losses shifted to larger and larger employers each month from March through July. However, the largest employers recovered employment faster than smaller employers from July to September. By September, the largest cumulative employment losses were for employers with 50 to 499 employees, with employment losses of 6.5 percent since February. Meanwhile, by September, employers with 1 to 9 employees had employment losses of 3.3 percent since February.

The U.S. Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) survey is one of the longest running and most relied-upon sources of current data on the U.S. labor market. The CES survey collects data each month on employment, hours, and earnings, and BLS publishes preliminary estimates at the national level by industry, usually on the first Friday of the following month, with revisions published in the 2 succeeding months. The survey began in 1915 for the manufacturing sector, and many CES data series are available in consistent format from BLS back to 1939. These data are among the Principal Federal Economic Indicators, and they often make headline news when they are released each month.

The CES survey is collected from a large sample of establishments covered by Unemployment Insurance (UI) programs in the United States. Reports from the UI programs are compiled in the BLS Quarterly Census of Employment and Wages (QCEW), which is the sampling frame for the CES and other BLS establishment surveys. The QCEW program also publishes estimates of employment and wages, and the QCEW data are linked to the Business Employment Dynamics (BED) program, which publishes estimates of gross job gains and losses, including by employer size. QCEW data, collected from the full universe of employers covered by UI programs in the United States, are available in much greater detail than the CES data. The QCEW data are available 5 months...
after the end of the reference quarter, while employer-size estimates from the BED are released about 7 months after that reference date. In ordinary times, employment change by employer size can easily be studied with BED data, and the time lag for these data to become available is only a minor inconvenience that is outweighed by the expanded detail not available with CES estimates. However, these are no ordinary times.

As BLS reported in the April Employment Situation news release, job losses associated with the effects of the coronavirus disease 2019 (COVID-19) pandemic on the U.S. economy in the spring of 2020 were the largest in the history of these data. Such enormous and rapid changes in labor markets have led economists to seek available data with as little time lag as possible. The economists of the Harvard University Opportunity Insights team are tracking the employment of low-wage workers by using data from the scheduling and timecard processing company Homebase and financial management application Earnin, and they are tracking the number of small businesses that have closed by using data from small business credit card processor Womply. Another group of economists is tracking labor market outcomes with data from Homebase and Kronos, another workforce management company. In this environment, we believe special tabulations based on the CES microdata are particularly valuable.

There is currently tremendous public interest in how the economic disruptions of the pandemic are affecting businesses differently, depending on the their size, especially because prepandemic trends in Economic Census data show increasing market domination by large businesses. In prepandemic work, David Autor, David Dorn, et al. showed increasing product market dominance by the largest and most productive firms in industries within the manufacturing, retail trade, wholesale trade, services, utilities and transportation, and finance sectors from 1982 to 2012; they also found a rising share of U.S. employment in firms employing more than 5,000 employees from 1987 to 2016. Chang-Tai Hsieh and Esteban Rossi-Hansberg showed that these effects are strongest within services, wholesale trade, and retail trade, as national chains in these sectors expanded into more and more local markets. Kevin Rinz showed that the five firms in each industry with the largest number of employees expanded into more and more markets over the 1976–2015 period.

Since the pandemic began, there have been few studies of employment dynamics by employer size. Those we have seen are based on surveys with much smaller sample sizes than those generally used in producing official government statistics. For example, José María Barrero et al. show that many of the 394 businesses that responded to the Survey of Business Uncertainty in April planned to implement staffing increases, and the authors...
list examples of large companies that have expanded their employment during the pandemic, even as many smaller businesses have shrunk or closed.

Most studies of employers and employment patterns during the pandemic use data only for smaller businesses. Alexander W. Bartik, Marianne Bertrand, Zoe Cullen, et al., for example, examined a survey of 5,800 small businesses and found that the likelihood of closure was highest for the smallest firms at the beginning of April. Robert W. Fairlie used Current Population Survey data to examine the effects of the pandemic on small business owners and found that the number of working business owners declined by 3.3 million, or 22 percent, between February and April 2020, and that less than half of them had returned to work by May. In another study, Alexander W. Bartik, Marianne Bertrand, Feng Lin, et al. used daily work records data from Homebase and showed how the number of hours worked plummeted in mid-March, before starting a slow recovery in late April, with much of this pattern resulting from firms shutting down. Robert P. Bartlett III and Adair Morse combined several data sources to examine outcomes for businesses with 50 workers or less located in Oakland, California, and found that businesses with 1 to 5 employees fared better than those with 6 to 49 employees or sole proprietorships. However, these studies cannot compare patterns of employment change for small and large employers.

To our knowledge, the only data (other than those from the CES survey) that are well suited for comparisons of employment change in recent months by employer size are those from the private firm Automatic Data Processing, Inc. (ADP). ADP, a human resources management software and services company that serves as the payroll processor for about 20 percent of employees in the United States, compiles these data from their own records. A group of economists (most of whom are affiliated with the Federal Reserve) has worked for several years to produce a weekly ADP employment series benchmarked to the QCEW, although this weekly employment series is not publicly available except in research papers. This past spring, Tomaz Cajner et al. used these data to show that more small businesses than large businesses paid no employees in April, but the gap in overall employment patterns by employer size narrowed by the end of May, as these small businesses reopened. By the end of May, the average employment decline in small businesses was smaller than that for large businesses.

One focus of economic research during spring 2020 has been to use changes in employment and business survival by business size to study the impact of the Paycheck Protection Program (PPP), the unprecedented federal program enacted in March 2020. This program allocated $669 billion in forgivable loans, largely to businesses with 500 or fewer employees. Raj Chetty et al. and the Opportunity Insights Team used data from Earnin, a financial management application, matched with employer names and locations in the ReferenceUSA data, to measure weekly changes in employment rates by business size and industry from February to June. They found little difference in employment changes by employer size, although their size groups do not correspond neatly to the 500-employee size cutoff of the PPP. David Autor, David Cho, et al. used the ADP data to do more precise comparisons of employment, hours, and total wages paid weekly by firm size from February to June. They found small differences in the changes in employment, total hours, and total wages paid for firms just above and below the 500-employee threshold, and these differences appear during the weeks that the PPP funds were distributed. However, none of these studies address differences in employment patterns by employment size more generally.
In contrast to the datasets described above, the CES survey offers a large, representative sample of employers. In this article, we present recent changes in CES employment for the private sector by employer size. The remainder of the article is organized as follows: the next section discusses several methodological issues in producing these estimates, the section that follows presents these estimates, and the final section provides some concluding remarks.

Methodology

Employment estimates from the CES survey are published monthly and have three components. The first and largest component is the average rate of employment change experienced by responding establishments that report positive employment in the previous and the current month. The second component is an imputation for the employment change of nonrespondents based on the rate of employment change for respondents reporting positive employment. The third component is a prediction from the net birth–death model. These methods address the following two facts: (1) establishments are less likely to report data the month they go out of business, and (2) there is about a 7-month lag between the time a new establishment opens for business and the time it appears in the sample frame. Typically, establishment births and deaths nearly cancel each other out. Instead of attempting to estimate births and deaths separately, the net birth–death model predicts net change in employment from establishment births and deaths on the basis of historical seasonal patterns. The two components are added together to produce a monthly estimate of overall employment change.

The sudden and enormous impact of the COVID-19 pandemic beginning this past spring required revisiting some of the assumptions underlying the birth–death model used in producing the official CES estimates. As noted previously, before the pandemic, establishment reports of zero employment were not explicitly included in the estimates; instead, they were handled implicitly through the net birth–death model. Beginning in April, if the number of reports of zero employment was greater than what normally would be expected, they were explicitly included in the employment-change estimates. Excess returns of employment from zero—which became more prominent beginning in May—were also explicitly included in these employment-change estimates. In addition, growth rates for the portion of the sample reporting positive employment were included in the net birth–death model to capture the cyclical component of business openings and closing.

This article takes a somewhat different approach to addressing the estimation issues raised by the pandemic. We focus on establishments that responded to the February survey and disregard births since then, on the assumption that openings have been negligible during this period of uncertainty and record-high unemployment. Similar to the published CES estimates, the major component in our estimates of employment change is the average sample growth rate of February establishments that continued to report positive employment in subsequent months. Unlike with the published CES estimates, our approach explicitly includes all reports of zero employment in our estimates of employment change. In addition, we explicitly impute the employment of nonrespondents, by using employment change for respondents in the same month and the proportion of CES nonrespondents who permanently closed in previous years of QCEW data. Because we disregard openings and estimate the fraction of nonrespondents that have zero employment, we do not use the net birth–death model at all. This method prevents us from including the public sector in these estimates, because reporting units in the public sector can differ substantially between the CES survey and the QCEW. One additional difference between our estimates and the official CES
estimates is that we include all establishments that responded in February and are still in the CES sample in later months, while the official CES estimates are based only on establishments responding in consecutive months.

We categorize employer size by total employment across all establishments that use the same Internal Revenue Service employer identification number (EIN) when they file reports with state UI programs, assigning size groups from annual average employment for fourth quarter 2019 in QCEW data, with no reclassification of size groups as employer sizes change over time.[23] Readers should be cautioned that the EINs reported to the UI system are nonrandom pieces of information about firms; there are many instances in our data in which a large firm acquires an establishment, but the payroll department of that establishment does not switch to the new firm’s EIN in reporting employment to its state UI program.

As noted previously, our methods explicitly distinguish between nonrespondents and respondents with zero employment. Because a substantial number of establishments that do not respond in time for the first or second preliminary estimates do respond in time to be included in final estimates, we use CES estimates based on final data wherever possible. Thus, as of October 2020, the most recent final data were those for July 2020, with second-preliminary data available for August 2020 and first-preliminary data available for September 2020.

Continuing employers

Let \( \text{emp}_{i,M,S,J} \) denote the employment of establishment \( i \) in month \( M \), size class \( S \), and industry \( J \), and let \( \text{emp}_{i,Feb,S,J} \) denote the employment of the same establishment in February 2020. The change in employment between month \( M \) and February for all establishments that respond in month \( M \), report positive employment in month \( M \), are in size class \( S \), and are in industry \( J \) is given by

\[
\Delta \text{EMP}_{R,M,C,S,J} = \sum_{i \in R} (\text{emp}_{i,M,S,J} - \text{emp}_{i,Feb,S,J})
\]

where \( R \) is the set of responding establishments and \( C \) is the set of continuing establishments with positive employment in month \( M \). Then the percent change in employment for these continuing establishments is given by

\[
\% \Delta \text{EMP}_{R,M,C,S,J} = \frac{\sum_{i \in R} \text{emp}_{i,M,S,J} - \text{emp}_{i,Feb,S,J}}{\sum_{i \in C} \text{emp}_{i,Feb,S,J}}.
\]

Figure 1 shows the percent change in employment in each month from March to September 2020, for each employer size category, relative to February 2020 employment for these establishments. We calculated these estimates by using equation (1) and weighted employment in February for each establishment in size class \( S \) across all industries.\(^24\) Establishments in all size groups had employment below February levels from March to September. In percentage terms, the greatest employment losses were shifting to larger and larger employers for each subsequent month through July, but then the very largest employers had the fastest employment recovery between July and August, and in preliminary figures for September, it appears that employers with 100 or more employees had the fastest employment recovery from August to September. The employment trough was in April
for all size groups except 500 or more employees, which had lower employment in May, June, and July than in April.

**Employers reporting zero employment**

The change in employment between month $M$ and February for establishments that report zero employment in month $M$, in size class $S$, and industry $J$ is given by

(3) $\Delta EMP_{R,C',S,J} = - \sum_{i \in R,C'} emp_{i,Feb,S,J}$

where $C'$ is the set of establishments reporting positive employment in February and zero employment in month $M$. The reduction in employment at closing establishments in month $M$ relative to the average employment of respondents in February is given by

(4)
Figure 2 shows the percentage of establishments that reported zero employment in each month from March to September 2020, relative to the number of establishments that existed in February 2020, by employer size. In every month, the employer size category with the largest fraction of employers having no employment is the smallest size category: employers with 1 to 9 employees.

Patterns of establishment closure over time have been different for employers of different sizes. Among employers with 49 or fewer employees, the percentage of establishments that were closed was greatest in April and has been declining since then. Among employers with 500 or more employees, the percentage of establishments that were closed was highest in May. The percentage of establishments with zero employment increased from June through September among employers with 50 to 499 employees.

Figure 3 shows the percentage of employment lost since February 2020 in the establishments reporting zero employment in each month from March to September 2020. The patterns are very similar to those shown in figure 2. However, except for the smallest two size categories in April, the percentage of employers reporting zero employment is always greater than the percentage of employment lost as a result of employers reporting zero
employment. This suggests that, within each category, smaller employers are more likely to have zero employment.

![Figure 3. Percentage of employment lost since February 2020 in establishments reporting zero employment in each month from March 2020 to September 2020, by employer size](image)

**Employers that did not respond to the CES survey**

Finally, we estimate the change in employment for establishments that responded to the CES survey in February but did not respond in month $M$. Similar to the birth–death model used in standard CES estimates, our approach assumes nonrespondents with positive employment in month $M$ experienced the same changes in employment as similarly sized responding establishments in the same industry.\(^{25}\) Additionally, using prior years’ data from the QCEW to estimate the probability that a nonresponding establishment in the CES survey is closed, we include this probability of an establishment being closed in the imputed employment for each nonresponding establishment in month $M$.

To estimate the proportion of nonrespondents with zero employment, we use QCEW data from 2007 to 2018 to model the probabilities that responding and nonresponding establishments subsequently shut down permanently. For each month $M$, employer size class $S$, and industry $J$, we calculate the proportion of CES nonrespondents that last had positive employment in the QCEW in the same calendar year, $P'_{R_{SMJ}}$. Similarly, we denote the proportion of CES month $M$ respondents in size class $S$ and industry $J$ that last had positive employment in the QCEW in the
same calendar year as \( R \). Let \( \frac{R}{M,S,J} \) denote the ratio of these two proportions, and let \( b_{M,S,J} \) denote the fraction of responding establishments in size class \( S \) and industry \( J \) that reported zero employment to the CES survey in month \( M \) in 2020, as shown in figure 2. We assume the fraction of nonrespondents with zero employment is equal to the product of \( b_{M,S,J} \) and \( c_{M,S,J} \). For example, if nonrespondents and respondents in size class \( S \) and industry \( J \) closed with the same frequency in the 2007–18 period, we assume the fraction of nonrespondents in month \( M \) that had zero employment is exactly the same as the proportion of respondents that reported zero employment. If the nonrespondents in size class \( S \) and industry \( J \) in the 2007–18 period closed with a 20-percent higher probability than similar respondents, then our specification implies that the fraction of nonrespondents in month \( M \) that had zero employment is 20 percent higher than the proportion of respondents that reported zero employment in month \( M \).

Given these assumptions, our estimate of the percent change in employment from February 2020 to month \( M \) for nonresponding establishments in size class \( S \) and industry \( J \) is given by

\[
\% \Delta \text{EMP}_{R',M,S,J} = \% \Delta \text{EMP}_{R,M,C,S,J} - (b_{M,S,J} \cdot c_{M,S,J}).
\]

We estimate the percent change in the employment of nonrespondents as the percent change in the employment of respondents with positive employment minus the estimated probability that a respondent reports zero employment.

Figure 4 shows the percentage of sampled establishments that did not respond to the CES survey over the March–September 2020 period, conditional on responding in February 2020, by employer size categories. For March to July, these are the percentages as of the point when BLS compiled figures for the final estimate (10 to 11 weeks after the survey reference week), but for August the second preliminary estimates are based on data collected only 6 to 7 weeks after the survey reference week, and for September the preliminary estimates are based on data collected only 2 weeks after the reference week. These percentages show some increases over time, even before the preliminary data for August and September. A possible explanation is that as time goes on, establishments that are permanently shutting down are dropping out of the survey.
Overall employment results

We now examine the contributions of these three separate components to the overall change in employment since February 2020. Note that the estimated change in employment of nonrespondents in size class $S$ and industry $J$ in month $M$ is given by

\[ \Delta\text{EMP}_{R',M,S,J} = \left( \frac{N_{M,R',S,J}}{N_{M,S,J}} \right) \times \frac{\text{emp}_{M,S,J}}{\text{emp}_{R',S,J}} \times \left( \%\Delta\text{EMP}_{R,M,S,J} - b_{M,S,J} \times c_{M,S,J} \right), \]

where $N_{M,R',S,J}$ is the number of nonrespondents in month $M$, size class $S$, and industry $J$; $N_{M,S,J}$ is the number of sampled respondents in month $M$, size class $S$, and industry $J$; $\frac{N_{M,R',S,J}}{N_{M,S,J}}$ is the nonresponse rate for month $M$, size class $S$, and industry $J$; $\frac{\text{emp}_{M,S,J}}{\text{emp}_{R',S,J}}$ is the average establishment employment in February for the set of nonrespondents $R'$ in month $M$, size class $S$, and industry $J$. Total February employment is the product of the number of eligible respondents in month, $M$, size class $S$, and industry $J$, and the average February employment, denoted by

\[ N_{M,S,J} \times \text{emp}_{Feb,S,J} \]
Dividing (1) by (7) yields the percent change in overall employment of establishments in size class $S$ and industry $J$ that is due to the change in employment at continuing establishments. Dividing (3) by (7) yields the percent change in overall employment resulting from the change in employment at closing establishments. Dividing (6) by (7) yields the percent change in overall employment of establishments in size class $S$ and industry $J$ that is due to the decline in employment for nonrespondents. For August and September, in order to correct for a higher nonresponse rate resulting from using preliminary data, we assign the nonresponse rate for July to August and September's numbers. So,

$$\frac{N_{August,R',S,J} \times \frac{\text{emp}_{Feb,R',S,J} \times (\%\Delta\text{EMP}_{R,August,C,S,J} - b_{August,S,J} * c_{August,S,J})}{\text{emp}_{Feb,S,J}}}{N_{August,S,J}}$$

becomes

$$\frac{N_{July,R',S,J} \times \frac{\text{emp}_{Feb,R',S,J} \times (\%\Delta\text{EMP}_{R,August,C,S,J} - b_{August,S,J} * c_{August,S,J})}{\text{emp}_{Feb,S,J}}}{N_{July,S,J}}$$

and

$$\frac{N_{September,R',S,J} \times \frac{\text{emp}_{Feb,R',S,J} \times (\%\Delta\text{EMP}_{R,September,C,S,J} - b_{September,S,J} * c_{September,S,J})}{\text{emp}_{Feb,S,J}}}{N_{September,S,J}}$$

becomes

$$\frac{N_{July,R',S,J} \times \frac{\text{emp}_{Feb,R',S,J} \times (\%\Delta\text{EMP}_{R,September,C,S,J} - b_{September,S,J} * c_{September,S,J})}{\text{emp}_{Feb,S,J}}}{N_{July,S,J}}$$

where $\frac{N_{July,R',S,J}}{N_{July,S,J}}$ is the nonresponse rate for July for size class $S$ and industry $J$.

Each of the three components of change is for a specific industry group. To obtain percent changes for the economy as a whole, we sum the components across all industries. The results are depicted in figure 5. The dotted line for nonresponding establishments in this figure represents their excess employment reduction beyond that accounted for by the employment losses at responding establishments because of their imputed excess closures (as represented by the fact that $c_{M,S,J} > 1$). The employment losses in nonresponding establishments that are imputed not to have closed match the solid line shown for continuing establishments. We see in figure 5 that the massive employment changes of the last few months were driven by employment losses in continuing establishments in every employer size category except for the very smallest. For employers with 1 to 9 employees, job losses (and gains) were driven by employer closures and reopenings.
Overall employment changes are the sum of the changes in the three components. Figure 6 shows overall employment changes since February by employer size. The largest declines in employment were in April for employers with fewer than 100 employees. Overall employment recovery in the first few months since then was much faster for smaller employers. Between April and June, employment levels largely recovered for employers with fewer than 100 employees, they recovered less for larger employers, and employment losses converged across employer sizes. Between June and August, employment levels continued to recover for employers with fewer than 50 employees, but there was less recovery for larger employers. However, from August to September, employment levels recovered fastest among employers with more than 100 employees. Since July, employers with at least 500 employees have had the biggest improvement. As of September, employers with fewer than 10 employees in February had the smallest losses in employment, followed by employers with more than 500 employees in February, and employers with 50-499 employees in February had the largest losses in employment.
Conclusion

In this article, we have discussed the rationale for producing estimates of recent employment changes by employer size using a large representative survey sample, we have explained our method of producing these estimates, and we have shown the results. Our methods for producing these special estimates rely on disregarding the net-birth–death modeling of the official CES publications and instead examining only the set of private sector establishments that responded to the CES survey this past February. These procedures will only be appropriate as long as employer births remain negligible and this group of establishments does not rotate out of the CES sample.

We find that the massive employment changes of the past few months were driven by employment losses in continuing establishments in every employer size category except for the very smallest employers. For employers with 1 to 9 employees, job losses (and gains) were driven by employer closures and reopenings. The largest employment impacts of the pandemic were for employers with 1 to 99 employees in April, but as the pandemic-induced economic crisis continued this summer, its employment impacts shifted to larger employers. By June and July, the largest impacts were for employers with 100 to 499 employees. Employment recovery of employers with 500 or more employees appeared to be slower than for that of smaller employers through July; but employers with
500 or more employees had the fastest employment growth from July to August, and preliminary employment figures for September suggest that this was also true from August to September.

These overall patterns of employment losses since February—whereby losses varied much less by employer size in September than in April and, by July, were greater for employers with 50 or more employees than for employers with 1 to 49 employees—may surprise some readers. However, the patterns are similar to those shown for February through May in figure 3 of Cajner et al., which are based on ADP data. These researchers also report that, for smaller employers, employment fell more in late March and April and recovered faster in May, leading to to convergence in cumulative employment patterns for employers of different sizes by the end of May.

We have no overall explanation for the patterns we find, but we note that employment changes from July to September may coincide with the end of Paycheck Protection Program (PPP) support for many employers. This program, which began approving loans on April 3 and provided forgivable loans to cover 2.5 months of payroll costs, was intended primarily for businesses with fewer than 500 employees.[28] The forgiveness of loans dispersed before June 5 was tied to employee retention for an 8-week period beginning on the disbursement date.[29] Published data from the program show that 85 percent of the 4.3 million disbursed loans were approved by May 15, and two and a half months after May 15 is the end of July. To the extent that PPP funds helped smaller businesses retain or rehire their employees—or that the requirements for PPP loan forgiveness gave smaller businesses an incentive not to lay off employees until 8 weeks after receiving these funds—the timing of the PPP program may explain why improvements in employment were slowing for smaller employers relative to the largest employers from mid-July to mid-September. Recent research by Steven J. Davis and John C. Haltiwanger show that improvements in the liquidity available to young and, to a lesser extent, small firms directly affect employment decisions.[30] Since the PPP offered a large single injection of liquidity for smaller firms, it is likely that it had at least a temporary effect on employment, which would be attenuated once the liquidity injection runs out and that may explain the slowdown in improvement for smaller firms relative to larger firms as of September 2020. This remains an open empirical question for future research.


NOTES


18 This is not the first effort to use the CES data to estimate changes in employment by employer size. In 2012, the U.S. Bureau of Labor Statistics (BLS) released experimental estimates from the CES survey by firm size for April 1990 through March 2011. (For details of this estimation program, see Nicholas Fett and Brenda Loya. “Current Employment Statistics by size class using base-size definitions,” Statistical Survey Paper [U.S. Bureau of Labor Statistics, October 2015], https://www.bls.gov/osmr/research-papers/2015/st150130.htm.) However, user comments and internal analysis showed that these estimates required further work in benchmarking employment totals to the Quarterly Census of Employment and Wages (QCEW) and accounting for new employer births. As efforts to release QCEW data more and more quickly succeeded, there was less reason for BLS to devote additional resources to the improvement of CES estimates by employer size, and the experimental estimates were removed from the BLS web pages in early 2020. (For more information, see “Current Employment Statistics—CES [national]: experimental size class employment, hours, and
earnings series from the Current Employment Statistics survey” [U.S. Bureau of Labor Statistics, January 2020] https://www.bls.gov/ces/notices/2017/size-class-discontinuation.htm.) However, the scale of employment changes in recent months has given us new reason to produce more timely estimates of changes in employment by employer size. Furthermore, benchmarking is not an issue for our short-run analysis and there have likely been few new employer births during the pandemic.


21 For more information on BLS unemployment estimates, see “Labor force statistics from the Current Population Survey: help finding the unemployment rate over time” (U.S. Bureau of Labor Statistics, May 2020), https://www.bls.gov/cps/prev_yrs.htm. During the 2007–09 Great Recession, firm openings fell by 27 percent from their high during the 2005–10 period. The current economic contraction is more severe than that of the Great Recession, and it is reasonable to expect that openings have declined by a greater amount. Consistent with this, new business applications of likely employers, as tabulated by the Census Bureau's Business Formation Statistics series, fell sharply from March 2020 through the first week of June. However, these applications increased beginning in June. We are not sure what to make of this, but note that to the extent that this increase reflects potential births of new establishments, there is still often a lag between the application and the actual opening. For more information on the Business Formation Statistics, see https://www.census.gov/econ/bfs/index.html.

22 As noted above, the CES also imputes the employment of nonrespondents using the average employment change for respondents in the same month. However, the CES also imputes this employment change to establishments that report zero employment and subsequently corrects for this with the net birth–death model.

23 The establishment is our unit of analysis because the CES survey receives reports from establishments rather than from entire UI accounts. However, we classify these establishments by the size of their EINs in the QECW in order to obtain estimates by employer size. The Business Employment Dynamics data refer to estimates of employment by EIN size as “firm size estimates,” but our previous work that attempted to link true firm-reported data to the QCEW show many examples in which firms use multiple EINs in reporting to the QCEW. Thus, we refer to our estimates by using the more general term “employers” rather than “firms.” See “Linking firms with establishments,” *Monthly Labor Review*, June 2013, https://www.bls.gov/opub/mlr/2013/06/art2full.pdf.

24 Weighted employment takes the sample weight multiplied by the reported employment.

25 This assumption is probably conservative in the present context because establishments with greater disruptions in employment may well be less likely to respond to the CES survey.

26 Of course, this is an approximation since shutting down permanently is not the same as having no employment in a given month, but $c_{MSJ}$ should capture the fact that establishments with no employment are more likely to be nonrespondents than establishments that are operating.

27 More precisely, we estimate the employment change components separately for each size and industry group, and then weight them by the share of employment in each group. The industry groups we use are agriculture, mining, utilities, construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, financial and insurance, real estate, professional services, management services, educational services, healthcare services, leisure and hospitality, and other services.


29 See “Paycheck Protection Program: frequently asked questions (FAQs) on PPP loan forgiveness” (Small Business Administration, August 4, 2020), https://www.sba.gov/sites/default/files/2020-08/PPP%20Loan%20Forgiveness%20FAQs%208-4-20-508.pdf.

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How have lost market hours from the partial economic shutdown affected Americans?

Lisa N. Huynh

Using data from the American Time Use Survey (ATUS), Leukhina and Yu break down how many total market hours, on average, are lost and how the extra hours of home production and leisure are spent. ATUS classifies individuals’ use of time into 17 categories. Of these 17, this study focuses on 7 categories of primary time use: market work, other income-generating activities, job search, childcare, nonmarket work, leisure, and other time use. The authors use market work and leisure categories and combine childcare and nonmarket work to formulate the home-production category that they address, in particular.

Between February and April, average market weekly hours were reduced by 6.25 hours—households with less education and with children were affected the most. Approximately 90 percent of lost work hours have been reallocated to leisure or home-production activities. Lost market hours that go into home-production activities range from 11 percent to 49 percent, with single women without a college degree and without children at the lowest percentage.

In turn, overall, home-production hours increased more for households with children and married individuals. Weekly home-production hours increased by 2.1 between February and April after the additional effects of remote work were added. To evaluate the cost of the shutdown, the authors calculate the value of home production as an average wage earned by workers of that industry (e.g., cooks, cleaners, or childcare workers). The value of monthly home production increased by $25.09 billion. In contrast, monthly gross domestic product, or GDP, decreased $292.61 billion during this period.

While home-production hours have increased because of the need for childcare and other nonmarket work, leisure hours have also increased because 35 percent of commuting workers have switched to telecommuting. Although the shutdown has decreased the options for leisure activities, the authors find that leisure hours consist mostly of sleeping, watching TV, socializing, and exercising. Married men with less education, nonworking spouses, and children lost the most market work hours (10.6 hours) and had the largest change between work and leisure (65.4 percent).

The overall effect of hours of work lost from the pandemic depends on the type of household experiencing it. The authors found that married men with children, stay-at-home wives, and less education (nearly 11 hours lost) and single households with children and with no college degree were most affected. Meanwhile, college-educated men with no children and with working spouses were least affected by the changes caused by the partial shutdown.
What can search frictions tell us about the labor market?


An important issue with macroeconomic models is accounting for observed labor market volatility, such as the one seen in the 2006 U.S. housing bubble and the 2007–09 recession. In *Labor, Credit, and Goods Markets: The Macroeconomics of Search and Unemployment*, Nicolas Petrosky-Nadeau and Etienne Wasmer address this issue by proposing a three-market model—a credit–labor–goods (CLG) model—to describe how search frictions in the financial (credit), labor, and goods markets explain labor market volatility. Search frictions are impediments to a match, or agreement, between two parties for a partnership or transaction. In credit markets, the parties include a firm evaluating an investment project and a creditor that could finance it. In labor markets, the parties are the employer and the person seeking employment. Finally, when a project is financed and workers are able to produce a good, the good is not sold until a consumer is matched with it. In the book, Petrosky-Nadeau and Wasmer develop a theory to explain volatility over time and extend labor market search theory, while also being upfront about the advantages and disadvantages of their approach.

The authors’ central variable for gauging labor market behavior is labor market tightness, which is measured as the ratio of job vacancies to unemployment level. When the labor market is tight—that is, when the ratio of vacancies to unemployment is high—jobseekers quickly find jobs while firms put more effort into filling vacancies. According to the authors, standard labor models designed to account for the
business cycle fail to predict fluctuations in labor market tightness. In particular, unemployment volatility and its persistence after a shock are lower in such models than what is observed in the data. Persistence, which reflects how far the effect of an initial economic shock propagates into the future, is of special importance. For example, the U.S. unemployment rate peaked nearly 2 years after the onset of the 2007–09 recession. In a standard labor model, the response curve measuring labor market volatility would be concurrent with the initial economic shock. In the recent literature, however, many authors have used search frictions to model labor markets.

To link market frictions and economic volatility, Petrosky-Nadeau and Wasmer argue that transaction costs arising from search frictions in credit, labor, and goods markets make the macroeconomy more sensitive to shocks. This argument informs a search model that can successfully incorporate interacting search frictions from various markets and then describe the observed volatility and persistence of labor market tightness in the data. The authors state that their generalizations and applications of search frictions are permitted by supplier and demander idiosyncratic preferences that mirror a search-and-match function. In systematically analyzing and integrating the various markets, the authors develop new tools and concepts, providing rich interpretations of the results obtained from the search model. For example, in incorporating the goods market into the model, Petrosky-Nadeau and Wasmer calculate an added persistence in the mismatch between transacting parties. They attribute this added persistence to many competing firms entering the goods market during an economic boom. Under such conditions, the rate at which a product finds a consumer decreases, and rising product supply lowers prices, causing a decline in firm profits. This decline moderates the rate at which firms create job vacancies during a boom. In addition, as incomes rise and prices are bargained over, consumers increase their search efforts in the goods market. As demand increases, firms are more likely to find a consumer at a higher price point, and this potential match provides incentives for firms to create more vacancies after the initial shock. Therefore, the authors conclude that incorporating goods and financial market frictions generates volatility and persistence in the search model.

To systematically lay out their arguments and analyses, Petrosky-Nadeau and Wasmer divide the book into two sections. The first section derives the main labor market model, which is based on a matching function between vacancies and unemployment. The model’s initial labor market parameters are the job separation rate, the matching rate, vacancy costs, bargaining weights, and the value of nonemployment. Later in the section, unemployment, the wage-bargaining equilibrium, and the job creation condition are also introduced. Then, the labor market model is solved, and potential policy implications are discussed. In the labor market model, the authors explore two model improvements by introducing wage and fixed job creation costs, both of which reduce the amount of surplus to firms entering the labor market and increase wage rigidity. Because of the reduction in labor surplus, a firm’s hiring decision is more sensitive to potential shocks. While these model improvements sufficiently amplify unemployment volatility, the persistence estimated by the labor market model does not match the persistence observed in the data.

The second section of the book extends the model to the credit and goods markets. The credit market parameters are the separation rate, bargaining weights, project search costs, creditor search costs, the matching curvature, and the risk-free rate. The goods market parameters are the goods matching separation rate, the matching curvature, the cost function level, the cost function elasticity, bargaining weights, and the marginal utility of matched consumers. In this expanded model, potential shocks can be accounted for by incorporating search frictions in the credit market, such as those that arise when firms share rents from a created job with creditors, diminishing firm surplus. These credit frictions amplify volatility. Finally, the CLG model introduces a new stage in
the life cycle of a firm. In this stage, firms face the opportunity cost of searching for a consumer while paying wages, thus incurring loses without making revenue.

In my view, the three-market search frictions model builds on standard labor market search theory. According to the authors, the main novelty of their work is the inclusion of goods market frictions in the search frictions model. For this model, estimated volatility matches the observed volatility in the data when a firm’s profit share from a labor match is small either because of large worker surplus or because of high job vacancy search costs. Another consideration is that nonwork benefits provide a floor for wages. One may extend the authors’ approach by revising existing or introducing new parameters in the CLG model.

*Labor, Credit, and Goods Markets: The Macroeconomics of Search and Unemployment* is an excellent blend between a survey of the search and matching literature and a methodological extension that adopts a multimarket frictional approach. The book is well suited for graduate students and anyone with a background in economics, providing a starting point into understanding the effects of market interactions on the business cycle, the impacts of frictions in various markets, and the role of search market frictions in explaining these dynamics. The writing is cogent and well organized.
From the barrel to the pump: the impact of the COVID-19 pandemic on prices for petroleum products

This article details price movements for petroleum products in the context of the coronavirus disease 2019 (COVID-19) pandemic. The pandemic affected energy prices for products ranging from crude oil to various refined petroleum products, such as heating oil, jet fuel, diesel fuel, retail gasoline, and gasoline at the pump. The onset of the pandemic led to an initial drop in prices for petroleum-based products, and then, just as abruptly, prices rose sharply as producers limited production and demand increased.

On January 7, 2020, officials in China announced that they had identified a new virus in the Hubei region. By the end of the month, the virus, designated coronavirus disease 2019 (COVID-19), had spread to other countries in Asia. In February, cases were reported throughout Europe and the United States, prompting the World Health Organization to declare a global emergency. On March 3, the United States followed suit by declaring a national emergency, a move that resulted in lockdowns across the country.

As economic activity slowed sharply across the globe, demand for petroleum and petroleum products plummeted. The drop in demand, coupled with an unexpected increase in supply, led to a collapse in crude oil prices and subsequent impacts on prices for refined petroleum products and other downstream items, notably gasoline. As economies reopened, the initial price downturn gave way to reduced oil production and some renewed demand. As a result, prices for oil products partially recovered.

Crude petroleum prices

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This section discusses how the U.S. Bureau of Labor Statistics (BLS) measures crude oil prices and how these prices have changed over the course of the COVID-19 pandemic.

**BLS measures of crude oil prices**
The Producer Price Index (PPI) measures the average monthly change in selling prices received by domestic producers of goods and services. The Import Price Index measures the average monthly change in prices of foreign goods purchased by domestic consumers and producers.

For crude oil, the Producer Price Index measures the change in prices that U.S. crude oil producers receive from purchasers, and the Import Price Index measures the change in prices that U.S. purchasers pay for crude oil imported into the United States. The calculation of the PPI for crude petroleum is based on monthly price data from a sample of petroleum producers in the United States and uses a midmonth reference period. BLS revises the producer price data 4 months after their initial publication. Unlike the PPI for crude petroleum, which is calculated with data for domestic prices, the Import Price Index for crude petroleum is calculated with data from two U.S. Energy Information Administration (EIA) sources. The first source is the EIA Monthly Foreign Crude Oil Acquisition Report (EIA-856), which is a listing of the price and quantity of crude oil involved in nearly all import transactions in a given month. BLS uses these data to calculate a weighted average of import prices throughout the month, and this average is then compared with the average for the previous month. For the month of initial data publication and the previous month, BLS calculates a preliminary import index measure, because not all import transactions data are available. BLS supplements the data by estimating regression models, which use information from the preliminary EIA-856 report and EIA weekly crude oil average contract values weighted by estimated import volumes. BLS revises import prices in each of the first 3 months after initial publication.²

**The sharp drop in prices: COVID-19 and a price war**
In January 2020, after seeing a customary decline due to business shutdowns for the Chinese New Year celebration, oil demand from China continued to fall because of economy-wide pandemic-related closures. Demand for oil decreased by 3 million barrels per day, which represents approximately 20 percent of the country’s overall oil consumption.³ In February, China’s Purchasing Managers’ Index fell nearly 49 percent, reaching its lowest level since it was first measured in 2005. Given that China overtook the United States as the world’s top oil importer in 2016, the sudden decrease was the largest demand-side shock to the market since the 2008–09 global recession.⁴ In January, BLS producer and import oil price measures declined modestly, by 2.5 and 0.3 percent, respectively. Price declines continued in February, with producer prices for crude petroleum falling 14.3 percent and import prices declining 10.9 percent.

As the COVID-19 pandemic continued to spread across the world, Saudi Arabia, the world’s second-largest oil producer behind the United States, urged fellow Organization of the Petroleum Exporting Countries (OPEC) members and Russia to cut production.⁵ Having formed a 2016 alliance with OPEC to control the price of oil through production cuts, Russia, the world’s third-largest oil producer, now resisted the call for further reductions in...
response to the pandemic. Russia sought to gain market share in anticipation that the U.S. shale industry’s profitability and output would fall in the face of lower prices.\(^6\)

On March 5 and 6, 2020, OPEC and Russia met in Vienna in an effort to iron out their differences. On the OPEC side, Saudi Arabia was upset that Russia had not previously met production cut agreements, causing the Kingdom to assume a disproportionate share of the cuts.\(^7\) At the meeting, OPEC members threatened to cancel cuts altogether unless Russia agreed to reduce production by a further 1.5 million barrels per day. Despite ending on a hopeful note, the meeting did not produce results; Saudi Arabia and fellow OPEC members Iraq and the United Arab Emirates began reversing production cuts.

By the beginning of April, OPEC had raised output by 1.7 million barrels per day, up to a level of 30.4 million barrels per day, the largest production jump since September 1990. According to Bloomberg, Saudi Arabia alone reached a record production of 12.3 million barrels per day on April 1, an output exceeding the pre-pandemic consumption levels of Japan, Germany, France, the United Kingdom, Italy, and Spain combined.\(^8\) The production boom coincided with an International Energy Agency (IEA) estimate that global demand for oil was down by almost 30 million barrels per day because of the shutdowns in response to the COVID-19 pandemic.\(^9\) With demand down, the addition of petroleum to an already saturated market led to a near-record level of 535.2 million barrels of crude petroleum stockpiles in the United States on May 1.\(^10\)

Prices dropped precipitously in March and April 2020. The combination of falling demand, rising supply, and diminishing storage space caused such a pronounced crude petroleum price plunge that, on April 20, crude petroleum traded at a negative price in the intraday futures market. Producer prices for crude petroleum declined 34.0 percent in March and 48.8 percent in April. In all, the PPI for crude petroleum fell 71.0 percent from January to April. The March and April decreases were the two largest monthly declines since the index was first published in July 1991. The trend was similar for U.S. import prices. The Import Price Index for crude petroleum declined 34.1 percent in March and 36.6 percent in April. In all, prices for crude petroleum imports fell 62.8 percent from January to April. As was the case with producer prices, the March and April declines in the Import Price Index were the largest 1-month decreases since the index was first published on a monthly basis in September 1992.

The rebound: partial recovery and production cuts

After falling sharply during the early months of the pandemic, crude petroleum prices began advancing at the end of April 2020. Producer prices for crude petroleum partially recovered from April to June, and import prices recorded a similar recovery from April to July. The price upturn began with a supply decrease, with a positive shock to demand eventually contributing as well.

Facing pressure from the United States and having no place to store any further petroleum surplus, Saudi Arabia called an emergency meeting of OPEC+ from April 9 to 12, 2020.\(^11\) During the meeting, OPEC+ members agreed to record production cuts and, this time, Russia complied as well.\(^12\) The agreement called for a composite cut of 9.7 million barrels per day through the end of June, the largest production cut ever.\(^13\) (At a followup meeting, the cuts were extended through the end of July.) Following the agreement, OPEC production fell to its lowest level since May 1991. In the end, Saudi Arabia, Kuwait, and the United Arab Emirates cut production beyond the amounts that were negotiated, and production cuts were also adopted by non-OPEC+ countries. From January to
May, the United States and Canada—the first- and fourth-largest global oil producers, respectively—reduced output by a combined 3 million barrels per day.

By May 2020, amid partial business reopenings in the United States and abroad, petroleum demand was showing signs of a rebound. The IEA estimated that the number of people under some form of lockdown peaked at around four billion in late April, even as restrictions in some countries began to ease.\textsuperscript{14} The first to emerge from the demand slump was China, where petroleum demand in April was almost back to levels seen 12 months prior.\textsuperscript{15} In May, crude petroleum inventories in the United States fell for the first time since January, indicating that demand was starting to outpace reduced supply.

Crude petroleum prices responded quickly. Producer prices for crude petroleum rose 35.9 percent in May 2020, before jumping 74.0 percent in June. Prices for import crude petroleum also advanced in both months, although low import demand kept these advances below those for producer prices. The Import Price Index for crude petroleum increased 18.9 percent in May and 33.3 percent in June. Just as April saw record monthly declines in both the producer and import price indexes for crude petroleum, June recorded the largest 1-month increases in the indexes since either of them was first published on a monthly basis.

World petroleum supplies recovered somewhat after July, as the OPEC+ cuts were reduced from 9.7 million to 7.7 million barrels per day. In addition, the countries that had previously cut production beyond agreed amounts reversed those cuts. With prices up in May and June, U.S. and Canadian production increased as well.

The recurrence of COVID-19 cases in the United States and other countries, as well as travel restrictions, led to a slower-than-expected recovery. Both the IEA and OPEC made downward revisions to their earlier demand forecasts for 2020. For both 2020 and 2021, world petroleum demand is projected to decline from 2019 levels.\textsuperscript{16} One factor bolstering demand expectations is the commitment by China to increase imports of petroleum from the United States as part of a trade agreement—a signal for continued demand recovery in the Asian country.

Table 1 shows the V-shaped price movements of crude petroleum for both domestic producers and importers. In both cases, prices fell sharply in February, March, and April 2020, before increasing in May and June. Movements in the producer and import price indexes for crude petroleum diverged in July. Producer prices for crude petroleum, which had risen by a greater percentage than import prices in May and June, declined 13.7 percent in July. The Import Price Index for crude petroleum continued to rise, increasing 21.2 percent. In August, producer crude petroleum prices rose 11.4 percent and import crude petroleum prices advanced 3.1 percent. Producer prices fell 71.0 percent from January to April, before rising 104.2 percent from April to July. The Import Price Index for crude petroleum declined 62.8 percent in the 3 months ended in April, before rising 92.0 percent in the following 3 months.

Table 1. Producer and import price indexes for crude petroleum, monthly percent changes, January–August 2020

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<tbody>
<tr>
<td>PPI for crude petroleum</td>
<td>-2.5</td>
<td>-14.3</td>
<td>-34.0</td>
<td>-48.8</td>
<td>35.9</td>
<td>74.0</td>
<td>-13.7</td>
<td>11.4</td>
<td>-71.0</td>
<td>104.2</td>
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See footnotes at end of table.
Figure 1 shows the producer and import price indexes for crude petroleum from December 2019 to August 2020. Despite the partial recovery in crude petroleum prices, both indexes remained below their January 2020 levels. The volatile movement in crude petroleum prices affected prices for items down the supply chain.

Table 1. Producer and import price indexes for crude petroleum, monthly percent changes, January–August 2020

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<tr>
<td>MPI for crude petroleum</td>
<td>-0.3</td>
<td>-10.9</td>
<td>-34.1</td>
<td>-36.6</td>
<td>18.9</td>
<td>33.3</td>
<td>21.2</td>
<td>3.1</td>
<td>-62.8</td>
<td>92.0</td>
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Note: PPI = Producer Price Index; MPI = Import Price Index.

The producer perspective: refined petroleum products

The COVID-19 pandemic contributed to large fluctuations in the prices for all refined petroleum products during the first half of 2020. However, changes in demand and refiners’ reactions aiming to reduce output and shift toward more profitable fuels resulted in differences in the timing and severity of the pandemic’s impacts on specific petroleum products, such as jet fuel, diesel fuel, and gasoline. Decreased fuel demand due to voluntary consumer choices, state-mandated stay-at-home orders, and international travel restrictions—combined with crude oil
oversupply resulting from the OPEC–Russia price war—produced record declines in the PPIs for jet fuel and gasoline in April 2020. Then, three factors caused prices to rebound: OPEC+ agreeing to limit crude production (as described previously); refiners reducing production capacity utilization rates to near-minimum viable levels and shuttering some plants; and demand rising as travel and business restrictions were lifted. These factors resulted in record 1-month increases in the PPI for gasoline in May and the PPI for jet fuel in June.17

Jet fuel was the first refined petroleum product affected by the COVID-19 pandemic. At the onset of 2020, continued growth in air travel demand led to optimistic long-term forecasts for jet fuel prices. However, as news of the pandemic spread, global jet fuel prices began falling in January.18 Travel demand in Asia quickly declined, leading to more pessimistic forecasts and prompting Asian airlines to cut flight capacity. In turn, Asian refiners began shipping unneeded jet fuel to the United States.19 As the virus spread, bleaker forecasts for air travel demand spread beyond Asia. The United States announced travel restrictions from China on January 31 and extended restrictions to dozens of countries, including most of Europe, soon thereafter.20

Table 2 shows that jet fuel prices declined 18.9 percent in February. As more flights were canceled, global jet fuel storage capacity continued to fill up.21 Prices continued to fall in March, decreasing 14.5 percent. By April, jet fuel demand was down by nearly 1 million barrels per day, or 62 percent, from the 2019 average.22 The U.S. Transportation Security Administration reported that, in April 2020, passenger checkpoint throughput was 95 percent lower than it was in 2019.23 Demand for air travel was so low that some airlines experimented by filling unused passenger jets with cargo, and the PPI for jet fuel fell a record 48.6 percent in April.24 Refiners also reacted to the record low demand, reducing domestic production of jet fuel to record lows in the first week of May.25 By June, some travel demand returned, and the combination of rising crude oil prices and declining supply contributed to jet fuel prices rising 51.7 percent in June and 15.0 percent in July.26 Prices leveled off in August, but remained 41.3 percent below January 2020 levels.

Table 2. Producer price indexes for selected petroleum products, monthly percent changes, not seasonally adjusted, January–August 2020

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<tr>
<td>Gasoline</td>
<td>2.3</td>
<td>-6.4</td>
<td>-20.2</td>
<td>-53.0</td>
<td>45.0</td>
<td>37.1</td>
<td>9.7</td>
<td>-2.7</td>
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<tr>
<td>No. 2 diesel fuel</td>
<td>-7.2</td>
<td>-9.9</td>
<td>-12.2</td>
<td>-27.2</td>
<td>-12.4</td>
<td>27.3</td>
<td>31.5</td>
<td>5.9</td>
</tr>
<tr>
<td>Jet fuel</td>
<td>4.6</td>
<td>-18.9</td>
<td>-14.5</td>
<td>-48.6</td>
<td>-6.8</td>
<td>51.7</td>
<td>15.0</td>
<td>1.5</td>
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The pandemic affected not only demand and prices for jet fuel, but also demand and prices for diesel fuel—although to a lesser extent. Diesel maintained more stability because of its industrial and commercial uses.27 On April 23, 2020, EIA stated the following: “The decline in distillate fuel oil consumption so far has been less severe than the changes in motor gasoline and jet fuel. Distillate fuel oil is primarily consumed as diesel fuel, the predominant fuel of the trucking, locomotive, and agricultural sectors. Continued demand for distribution of necessities such as food and medical supplies and increased home deliveries for goods likely contributed to relatively stable demand for distillate fuel in the initial weeks following the shutdown.”28 The American Trucking Associations reported that its For-Hire Truck Tonnage Index rose 1.8 percent in February and 1.2 percent in March, attributing those increases mainly to trucks hauling consumer staples.29 Chasing better margins, refiners
shifted output toward diesel.\textsuperscript{30} This led to a glut of diesel fuel, with inventories reaching their highest levels since 1982.\textsuperscript{31} Still, because of comparatively stable demand for diesel fuel, diesel prices declined less than other fuel prices: the PPI for diesel fuel decreased 42.4 percent from January to April 2020, compared with 64.4 percent for the PPI for jet fuel and 64.9 percent for the PPI for gasoline. Recording increases in June, July, and August, the PPI for diesel fuel surpassed its March 2020 level.

In absolute terms, COVID-19 affected demand and prices for gasoline more than demand and prices for other refined petroleum products. In April 2020, when 90 percent of the U.S. population was under some type of stay-at-home orders, demand for gasoline (measured by EIA as “product supplied”) fell by 3.5 million barrels per day, or 37 percent, below its April 2019 level.\textsuperscript{32} This low demand, the lowest in over 50 years, led to a 53.0-percent decline in the PPI for gasoline—the largest 1-month decline since the series began in February 1947.\textsuperscript{33} Meanwhile, gasoline stocks reached record highs, and the U.S. Environmental Protection Agency extended deadlines for the switch to summer-grade gasoline as storage tanks were still full of winter-grade gasoline.\textsuperscript{34} Refiners hoped to take advantage of low crude petroleum prices to supply diesel, but meanwhile they continued to produce unwanted gasoline. As a result, producers occasionally resorted to selling a barrel of gasoline for less than the cost of a barrel of crude petroleum.\textsuperscript{35} However, low gasoline prices, the Memorial Day holiday, and loosened lockdowns put more drivers on the roads in May, reviving demand for gasoline. This brought attention to some novel real-time proxies for rising gasoline demand, such as an uptick in the relative number of cellphone navigation app requests.\textsuperscript{36} EIA statistics also indicated that demand in May reached pre-pandemic levels. Still, according to EIA, demand for the summer driving season remained about one-fifth below its historical average.\textsuperscript{37} As crude oil prices and demand rebounded, the PPI for gasoline jumped 45.0 percent in May, a record 1-month increase. Some U.S. regions recorded gasoline blendstock spot price increases of more than 100 percent from the previous month.\textsuperscript{38} Producer gasoline prices continued their advance, rising 37.1 percent in June and 9.7 percent in July, before leveling off in August at 25.5 percent below their January 2020 level. (See figure 2.)
Margins for gasoline stations: a response to energy market shocks

A portion of refined oil products flows to retailers, a group facing related but distinct impacts from the pandemic. The PPI for automotive fuels and lubricants retailing measures the average change in margins that fuel retailers receive for the sale of automotive fuel. These margins are measured as the difference between the average selling and acquisition prices for fuel products. For U.S. fuel retailers, early 2020 was just as volatile as it was for many other businesses. Fuel retailer costs depend heavily on global crude oil prices, and retail firms generally use a “sticky price method” to set prices. As oil prices decrease, retailers hesitate to adopt commensurately lower selling prices because of future market uncertainty. The result is higher margins when crude oil prices fall, as the gap between acquisition and sales prices widens. Likewise, as crude oil prices increase, fuel retailers often are slower to raise selling prices. This dynamic is generally driven by local competition: if a retail price increase is not matched locally, customers will go to competing gas stations. As a result, fuel retailers often post lower margins when oil prices rise.39

With the small decrease in crude oil prices reported in January 2020, retail margins increased as costs fell. Over the month, the PPI for automotive fuels and lubricants retailing increased 2.1 percent. The crude oil price decrease extended into February, driving fuel retailer input costs further downward. As a result, the margins for automotive fuel and lubricant retailers increased an additional 2.7 percent in February.

In March 2020, rising COVID-19 cases, particularly in the United States, coupled with the OPEC–Russia price war, further disrupted crude petroleum markets. Several European countries and some areas in the United States
imposed mandatory lockdowns, substantially decreasing demand for crude oil. The large demand drop allowed automotive fuel and lubricant retailers to expand margins, which increased 24.0 percent in March.

In April, widespread stay-at-home orders and business closures in the United States continued to drive down refined fuel demand and crude oil prices. Fuel retailers took advantage of input price decreases by further expanding margins. In April, the PPI for automotive fuels and lubricants retailing increased an additional 33.4 percent.

By May, several countries had started to reopen their economies, increasing global demand for fuel. The resulting crude oil price increase raised the cost of fuel for U.S. fuel retailers. The retailers increased selling prices to compensate for the rising cost, but they did so slowly because of the higher-than-average margins received over the previous few months. As summer began, fuel retailers continued to report lower margins amid a continued recovery in oil prices. The PPI for automotive fuels and lubricants retailing declined 9.1 percent in May, 12.8 percent in June, and 5.2 percent in July. (See table 3.)

### Table 3. Producer price indexes for automotive fuels and lubricants retailing, monthly percent changes, not seasonally adjusted, January–August 2020

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<tr>
<td>Automotive fuels and lubricants retailing</td>
<td>2.1</td>
<td>2.7</td>
<td>24.0</td>
<td>33.4</td>
<td>-9.1</td>
<td>-12.8</td>
<td>-5.2</td>
<td>-3.5</td>
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### Consumer gasoline prices

This section discusses how BLS measures consumer gasoline prices and how these prices have changed over the course of the COVID-19 pandemic.

### BLS measures of consumer gasoline prices

The Consumer Price Index (CPI) measures the average monthly change in prices that U.S. consumers pay for a representative market basket of goods and services. To calculate the CPI for gasoline, BLS samples gasoline prices in 75 metropolitan areas across the country, collecting about 3,800 prices each month. At all gas stations sampled, BLS collects prices for regular, midgrade, and premium gasoline, publishing price indexes for each category. In addition, BLS publishes a gasoline (all types) price index, which is based on prices for all three grades, and a price index for other motor fuels, which includes sampled prices for diesel and alternative motor fuels.

The average prices captured by the consumer price indexes reflect what consumers pay at the pump per gallon, including all sales and excise taxes. Besides taking into account the specific grade or octane level of the fuel purchased, gasoline prices in the CPI reflect specific levels of service (full service or self-service) and brand name.

Normally, BLS economic assistants collect gasoline prices in person across the country. Since March 16, 2020, when COVID-19 concerns prompted the suspension of in-person data collection, BLS has transitioned to alternative methods for collecting all gasoline price data. After encountering problems during initial attempts at
collection by telephone, economic assistants shifted to collecting data from websites, supplementing them with a third-party source. However, the outlets and specific prices in the sample remained unchanged; only the method of collection varied.

For gasoline, as with most CPI items, BLS collects any given price during one of three specified pricing periods within a calendar month: roughly the first 10 days, the second 10 days, and the final 10 days of the month. Because the process involves collecting a similar number of prices during each period, the gasoline index represents an average of prices over the course of the month.

In addition to publishing the CPI for gasoline, BLS publishes average price data for gasoline. These data include average prices for gasoline (all types), the three individual grades of gasoline, and diesel fuel.

**Consumer gasoline prices in 2020: supply and demand factors push gasoline prices to their lowest level since 2009**

In December 2019, the average price for gasoline (all types) was $2.65, the highest December level since 2013. (See figure 3.) Historically, gasoline prices have typically risen through the early part of the year, peaking in the summer, but in the first 4 months of 2020, they declined sharply, bottoming out at $1.95 in April and May, the lowest level since January 2009, near the trough of the Great Recession. (In Dallas, prices fell to $1.41 in May, the lowest level across all metro areas for which prices were published.) Prices increased in June and July, but the July figure of $2.24 remained 15.4 percent lower than the December 2019 level and stayed virtually unchanged in August.

![Figure 3. CPI average gasoline prices, December 2019–August 2020](image)
The gasoline price index tells a story similar to that of average price values. (See table 4.) On a seasonally adjusted basis, the gasoline price index fell 34.8 percent from December 2019 to the May 2020 trough. The index rose in June, July, and August, but remained 21.2 percent below its December 2019 level. (The index decline is larger than the average price decline because, for seasonal reasons, gasoline prices are generally higher in December than in July.)

Table 4. CPI for gasoline (all types), monthly percent changes, January–August 2020

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</tr>
</thead>
<tbody>
<tr>
<td>Gasoline, all types</td>
<td>-1.6</td>
<td>-3.4</td>
<td>-10.5</td>
<td>-20.6</td>
<td>-3.5</td>
<td>12.3</td>
<td>5.6</td>
<td>2.0</td>
<td>-31.4</td>
<td>14.4</td>
</tr>
</tbody>
</table>

Note: CPI = Consumer Price Index.

Examining the series month by month reveals modest initial declines: in January 2020, the CPI for gasoline fell 1.6 percent on a seasonally adjusted basis and the average gasoline price dropped by just over 2 cents. These declines were similar to those in crude oil prices in January. The declines accelerated in February, as the seasonally adjusted gasoline price index dropped 3.4 percent and the average price fell by about 10 cents. However, the February declines were outpaced substantially by the sharp decline in crude oil prices during the month. This pattern is common, because consumer gasoline prices tend to be less volatile than crude petroleum prices, recording similar but more muted movements. While global demand fell in February, economic conditions within the United States remained fairly normal; the brunt of the pandemic-related contraction began in March.

As global crude oil prices continued falling and COVID-19 spread in the United States, gasoline prices at the pump fell sharply in March 2020. The seasonally adjusted CPI for gasoline declined 10.5 percent, and the average price for gasoline fell by nearly 20 cents. The decline accelerated in April. With lockdowns throughout much of the United States reducing driving, and with crude oil prices falling sharply, the average price for gasoline fell by almost 40 cents and the gasoline price index fell 20.6 percent, the largest monthly decline since November 2008.

Despite increases in the producer and import price indexes for crude petroleum in May 2020, the CPI for gasoline declined. The gasoline index fell 3.5 percent, while the average price remained stable, at $1.95. As crude oil prices continued to recover and the economy partially reopened, the CPI for gasoline started to rebound in June and July. The index rose 18.6 percent over the 2 months, and the average price recovered about 30 cents of its 70-cent decline per gallon. A smaller increase of 2.0 percent followed in August. Like the producer and import price indexes for crude petroleum, the CPI and average prices for gasoline remained well below their December 2019 levels.

Conclusion

In early 2020, BLS price indexes for petroleum products reflected the dramatic shift in economic activity caused by the onset of the COVID-19 pandemic. Shocks to demand and then supply pushed prices for petroleum products downward. From January to April, BLS reported substantial decreases in the Import Price Index for crude petroleum; the PPIs for crude petroleum, gasoline, diesel, and jet fuel; and the CPI and average consumer prices for gasoline. PPI margins for automotive fuel and lubricant retailers were driven sharply upward by the decrease in
petroleum prices over the same period. Although pronounced, the market forces driving BLS energy price indexes during the first quarter of 2020 did not persist. The end of the OPEC–Russia price war, coupled with economic reopenings in the United States and abroad, pushed petroleum prices upward from April to July. Notwithstanding the rebound, BLS price indexes for petroleum products recorded lower levels than those prior to the pandemic. In all, the story of the first 8 months of 2020 was one of petroleum price fluctuations starting from the barrel for importers and refiners and extending all the way to the pump for end consumers.

The COVID-19 pandemic affected the collection of BLS price data, although the impact for price indexes in the energy sector was less pronounced than that in other sectors. Despite the constraints associated with the pandemic, price data collection has continued at a sufficient level, allowing BLS to publish dependable, high-quality price indexes.


NOTES


6 Ibid.


8 Ibid.


10 The record was eventually broken on June 26, despite production levels falling after mid-April.

11 OPEC+ is made up of the OPEC member countries and Azerbaijan, Bahrain, Brunei, Kazakhstan, Malaysia, Mexico, Oman, Russia, South Sudan, and Sudan.

12 Blas, “Trump’s oil deal.”
Initially, Mexico was reluctant to agree to the entire cut, but it did so after the United States agreed to cut production to cover the remainder of Mexico’s obligation.


In this article, Producer Price Index (PPI) data for June–September 2020 are preliminary. To reflect late reporting by survey respondents, all PPIs are recalculated 4 months after original publication.


Barnett, “COVID-19 mitigation efforts result in the lowest U.S. petroleum consumption in decades.”


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