NO. 11–2021 SEPTEMBER 2021
FEDERAL RESERVE BANK OF ATLANTA'S *POLICY HUB*

The Phillips Curve during the Pandemic: Bringing Regional Data to Bear

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Summary:

The Phillips curve appears to have held up well at the regional level during the COVID-19 era. Areas of the country that took relatively large hits to their unemployment rate and employment-population ratio during the pandemic have had lower inflation, on average, than areas that took relatively small hits. And, just as prior to the pandemic, the inverse relationship between inflation and unemployment continues to be statistically stronger for the prices of services than of goods.

Key Findings:

1. During the pandemic, there has been a significant inverse relationship between unemployment and inflation at the city size by census region level.
2. We cannot reject the hypothesis that, for services and other expenditure categories, the strength of the relationship is unchanged from prior to the pandemic.
3. At the census division level, there has been an inverse relationship between inflation and the unemployment rate in recent years, and a positive relationship between inflation and the employment-population rate. The latter relationship has been somewhat stronger.

Center affiliation: Center for Quantitative Economic Research

JEL classification: C23, E31, E32

Key words: inflation, unemployment, labor markets, Phillips curve, regional data, panel data

https://doi.org/10.29338/ph2021-11

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Summary:

The Phillips curve appears to have held up well at the regional level during the COVID-19 era. Areas of the country that took relatively large hits to their unemployment rate and employment-population ratio during the pandemic have had lower inflation, on average, than areas that took relatively small hits. And, just as prior to the pandemic, the inverse relationship between inflation and unemployment continues to be statistically stronger for the prices of services than of goods.

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Acknowledgments: The author thanks Anton Braun and John Robertson. The views expressed here are the author's and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. Any remaining errors are the author's responsibility.

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Introduction

In its August 2020 statement on longer-run goals and monetary policy strategy, which it reaffirmed in January 2021, the Federal Open Market Committee (FOMC) stated that it "seeks to achieve inflation that averages 2 percent over time" and that it "seeks over time to mitigate shortfalls of employment from the Committee's assessment of its maximum level and deviations of inflation from its longer-run goal." The statement also notes that "[t]he Committee's employment and inflation objectives are generally complementary." Underpinning this latter notion is the Phillips curve, named after economist A.W. Phillips who, in a 1958 study, discovered an inverse relationship between nominal wage growth and the unemployment rate in the United Kingdom over the 1861–1957 period. The Phillips relationship was subsequently extended to unemployment and prices.[1] This article looks at the stability, or lack thereof, of "price Phillips curves" during the pandemic. Although the pandemic has only been widely felt in the United States for about one and a half years, there has been an unusually large degree of variation in labor utilization during such a short period. Our analysis will incorporate data by Census Bureau regions and divisions to further increase statistical power. Powell (2021) noted that "rising durables prices are a principal factor lifting inflation," so estimating Phillips curves for these and other categories of prices will enhance our ability to determine to what degree the improving labor market is responsible for rising inflation.

Monetary policymakers often refer to variants of the Phillips "curve," in which price inflation is a linear function of a measure of "labor market slack" and other determinants. In speeches presenting empirical estimates of this type of Phillips curve for core personal consumption expenditures (PCE) inflation,[2] former and current Fed chairs Yellen (2015) and Powell (2018) used the term "labor market slack" and proxied it as the difference between the official unemployment rate and a Congressional Budget Office (CBO) estimate of the natural rate of unemployment. Here, I show the Phillips curve equation presented in Powell (2018) and originally used in Erceg et al. (2018) to provide analytical clarity:

$$(1)\ INFLATION_t = -B * SLACK_t + C * INFLATION_{t-1} + OTHER_t,$$

where the "other" term is the sum of a constant and residual. Equation (1) in Powell (2018) was estimated with rolling 20-year samples and annual data.[3] When *C* is close to 1.0, as was the case in the 20-year samples in Powell (2018) ending before 2002 that included at least part of the so-called Great Inflation,[4] then labor market slack is more closely related to the change in inflation than it is to inflation. When *C* is 0, then inflation is directly related to slack and the coefficient *B* measures the short-run trade-off between inflation and labor market slack even when slack persists for more than one period. (In the case of Erceg et al. (2018) and Powell (2018), a period is one year, but the same principle applies to either a monthly or quarterly specification.) In Powell (2018), *C* was about 0.25 in the terminal 1998–2017 rolling sample.

[1] See, for example, figure 2 of Samuelson and Solow (1960).

[2] More formally known as inflation for the price index for personal consumption expenditures excluding food and energy prices.

[3] When monthly or quarterly data are used, higher-order inflation lags are often used.

[4] See Bryan (2013), for example, who dated the Great Inflation as the period between 1965 and 1982.

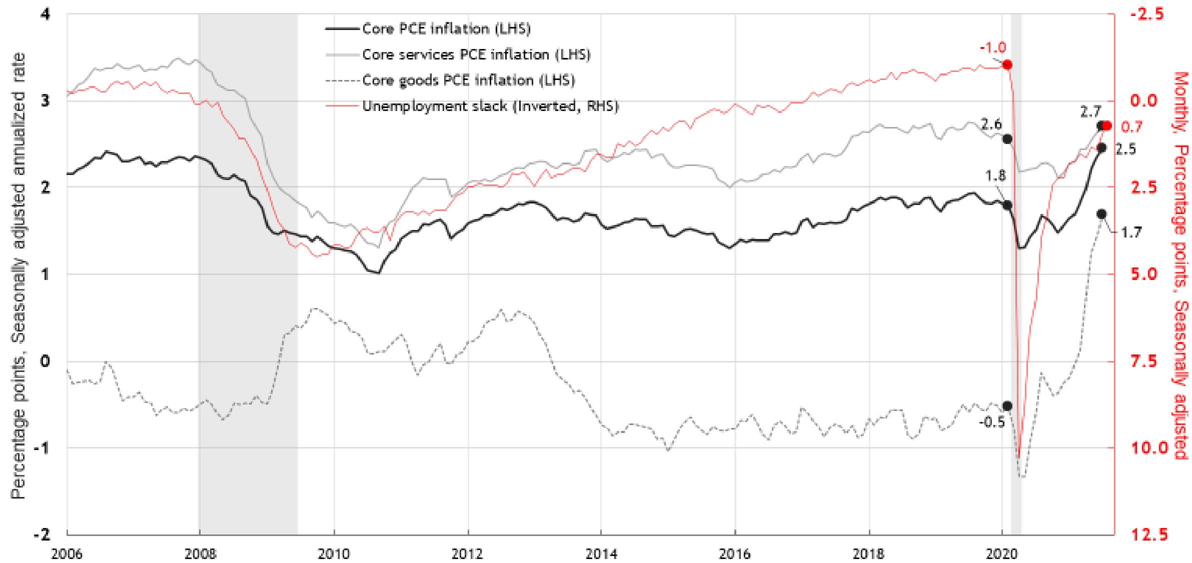
Powell (2018), and Yellen (2015) in a similar specification using quarterly data, noted that $-B < 0$, consistent with the inverse relationship found in Phillips (1958).[5] A version of the measure of labor market slack used in Yellen (2015) and Powell (2018)—which I call “unemployment slack”[6] for reasons discussed near the end of this article—is inverted and plotted in figure 1 alongside annualized 24-month inflation rates for the core PCE price index and its goods and services subcomponents. The 24-month window for inflation, also used by Federal Reserve governor Lael Brainard in a recent speech, avoids the distortion to the 12-month inflation rate induced by the unusually short and severe 2020 recession rolling outside of the calculation window.[7]

[5] This is consistent with Phillips (1958) since CBO estimates of the natural unemployment rate change slowly over time so that nontrivial changes in the unemployment rate generally have the same sign as changes in this measure of labor market slack.

[6] In the files accompanying the February 2021 *Budget and Economic Outlook* publication, the CBO included both a “natural rate of unemployment” and an “underlying long-term rate of unemployment”. See https://www.cbo.gov/system/files/2021-02/55022-2021-02-historicaleconomicdata.zip or https://fred.stlouisfed.org/series/NROUST. I use the former series for figure 1 and in all of our analyses below. The two series are identical after the fourth quarter of 2018. The CBO has also referred to these series as the “short-term” and “long-term” natural rates of unemployment. In its July 2021 update, CBO only released a “noncyclical rate of unemployment.” The July 2021 reported the “noncyclical rate of unemployment” was previously termed the “underlying long-term rate of unemployment.” Indeed, the July 2021 time series was identically equal to the February 2021 time series (see https://www.cbo.gov/publication/57263). I use the “short-term” natural unemployment rate series because that is what the CBO has used historically for its inflation projections (see the note to https://fred.stlouisfed.org/series/NROUST). The quarterly CBO natural rate of unemployment never changes by more than 0.15 percent between consecutive quarters. So for each quarter, I assign the quarterly CBO value to three months within the quarter to get a monthly natural rate.

[7] From the February 2020 business peak to the April 2020 business cycle peak, as dated by the National Bureau of Economic Research’s Business Cycle Dating Committee, the core PCE price index declined by 0.5 percentage points (not annualized). This decline in prices is inside the 12-month calculation window for February 2021 inflation (1.5 percent) and outside the calculation window for April 2021 inflation (3.1 percent).

Figure 1: Annualized 24-month inflation rates and inverted unemployment slack



Sources: U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, Federal Reserve Bank of Atlanta and Haver Analytics.

We can see that this 24-month core inflation rate increased from 1.8 percent in February 2020 to 2.5 percent in July 2021 while “unemployment slack” increased 1.7 percentage points, on balance, over the February 2020 to August 2021 period (as did the unemployment rate), illustrating that the Phillips relationship between unemployment or labor market slack and inflation is not ironclad. Further, we can see it was also violated in the middle of the last decade when core PCE inflation was trending down in spite of the continued improvement of the labor market. One advantage of a Phillips curve framework is that it can provide a historical decomposition—or less formally, an historical narrative—for the observed movements of inflation. The Phillips curve presented in Yellen (2015) implied that relative imported goods prices were pushing down total PCE inflation in 2015 by just over 0.5 percentage points.[8] This movement is consistent with the decline in core PCE goods inflation in the middle of last decade that we see in figure 1.

We can also see in figure 1 that, in an accounting sense, goods have been responsible for most of the increase in core inflation during the pandemic as core PCE services inflation has only inched up 0.1 percentage point to 2.7 percent. Of course, the current 24-month inflation rate also incorporates inflation over the seven-month period leading up to the pandemic. Atkinson, Dolmas, and Giannoni (2021) and Clarida (2021) calculate annualized cumulative inflation since February 2020 and, following their lead, we find annualized core PCE over the first 17 months of the pandemic is 2.8 percent, up from the 1.9 percent 12-month rate in February 2020. Compared to a counterfactual with observed spending shares and annualized inflation rates for both core PCE goods and core PCE services running at their trailing 12-month February 2020 rates in every month of the pandemic, we find that core goods are responsible for about 80 percent of the rise in core PCE inflation.

[8] The import measure excluded petroleum, natural gas, computers, and semiconductors, and the estimated impact on total PCE inflation implied core PCE inflation was depressed by about 0.6 percentage point.

A number of studies using prepandemic data, including Peach et al. (2013) and Stock and Watson (2020), have found that since the mid-1980s, there was little or no relationship between goods inflation and unemployment slack (or a related measure of resource utilization used in the latter study). Using 1988–2007 data, Shapiro (2020) disaggregated the core PCE price basket into 124 items, estimated a collection of this number of monthly Phillips curve equations similar to (1) with each of the item-level monthly inflation rates individually, and assigned them one-by-one to a cyclical group whenever $-B$ was sufficiently below 0[9] and to an acyclical group whenever it was not. In terms of nominal February 2020 expenditure shares, 94 percent of the share-weighted PCE core goods items were assigned to the acyclical group. Even though this atheoretical assignment used only data prior to the Great Recession, a look at figure 1 suggests that the acyclicality of core goods held up well during the 2007–09 recession and the subsequent expansion.

The aforementioned Peach et al. (2013) and Stock and Watson (2020) studies—as well as Clark (2004), Tallman and Zaman (2017), and Forbes (2018)—note that increasingly important global factors might have reduced the link between goods inflation and slack over time. The Stock and Watson (2020) so-called cyclically sensitive inflation (CSI) measure—constructed as a weighted average of PCE subcomponent inflation rates with the weights optimized to maximize its 1984-2019Q1 correlation with a cyclical activity index (CAI) that the authors construct—allocates only 9 percent of its total weight to core goods items.[10] Motor vehicles and parts (MVP) get a weight of 0 in the Stock and Watson (2020) CSI measure, and Shapiro (2020) only assigns "accessories and parts,"[11] within the larger MVP category to his cyclical grouping. A number of policymakers have noted that autos, whose supply has been affected by the global semiconductor shortage, have played a major role in the recent run-up of U.S. inflation (see Brainard 2021 and Williams 2021, for instance), and a Tornqvist index calculation finds that MVP has contributed 0.6 percentage point to annualized core PCE inflation during the pandemic compared to virtually no contribution during the 12 months leading up to it. However, Hill (2021) finds that the recent run-up in used auto prices has been much larger in the United States than in a number of developed countries that collect comparable data, thereby suggesting that domestic factors, such as fiscal stimulus, might be playing some role in the rise in U.S. auto prices.

Figure 1 shows that core services inflation was inversely related to unemployment slack during the Great Recession and subsequent expansion. But the correlation is not perfect, and we see a modest downward shift in services inflation in the mid-2010s in spite of the improving labor market. Mahedy and Shapiro (2017) argued that cuts to Medicare payment growth rates were responsible for much of this disinflation in health care and core PCE prices in general, and the Shapiro (2020) study assigns most of PCE health care to the acyclical group.[12] Within core PCE services, the categories Shapiro (2020) assigns to his cyclical group accounts for 45 percent of February 2020 nominal spending on core PCE services. Of note within this cyclical group is housing, virtually all of which is deemed cyclical by Shapiro

[9] At least 2.32 standard errors.

[10] By comparison, core goods spending accounted for just under 25 percent of total PCE spending over the same period. The Stock and Watson (2020) CAI is procyclical; that is, it correlates positively with the CBO's output gap. Therefore, we should expect it to correlate positively with inflation whenever a Phillips relation holds.

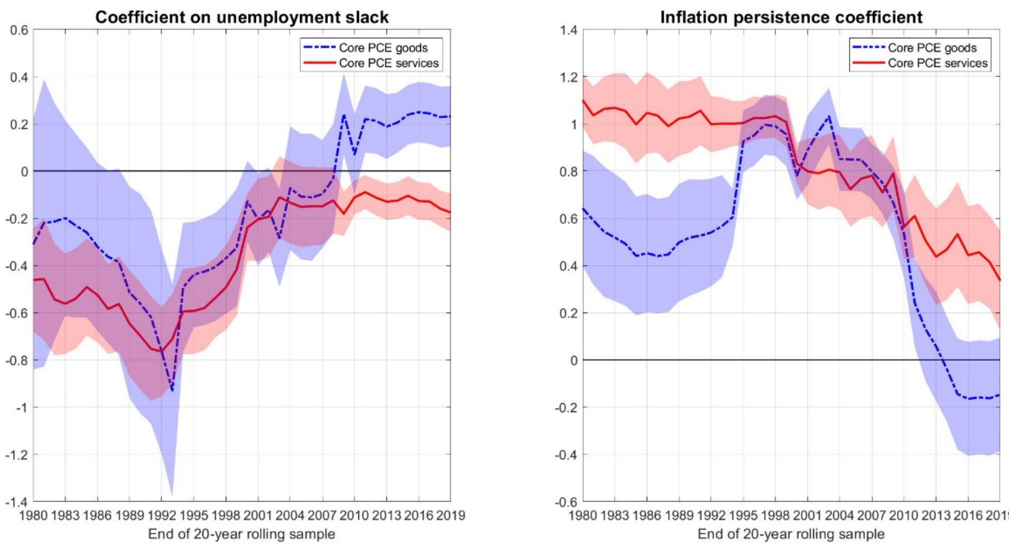
[11] This accounted for only 9 percent of MVP spending in February 2020.

[12] Nursing home care, which was only 8 percent of PCE health care spending in February 2020, is the only health care component classified by Shapiro 2020 as cyclical.

(2020).[13] In the Stock and Watson (2020) CSI measure, housing gets a weight of nearly 50 percent, about three times its average share of nominal PCE spending since the mid-1980s.

In figure 2, I plot the unemployment slack and inflation persistence coefficients estimated separately for core PCE goods and core PCE services with the Phillips curve in equation (1) above using 20-year rolling samples as Powell (2018) and Erceg et al. (2018) did for overall core PCE inflation. In these estimations, current and one-year lagged values of fourth-quarter over fourth-quarter inflation rates are used as is the annual measure of "unemployment slack" plotted in figure 1. The shaded regions in the charts denote the points within one standard error of the rolling coefficients.

Figure 2: Evolution of Phillips curve parameters



Note: The lines denote OLS regression estimates for the 20-year period ending in the fourth quarter of the year shown on the horizontal axis. The shaded regions denote +/- 1-standard errors, or approximately 70 percent confidence intervals.
Sources: U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, Congressional Budget Office, Haver Analytics, and author calculations.

Notably, we see that the slack coefficient on core services for the 20-year samples starting after the Great Inflation are closer to 0 than the slack coefficient for periods including this period. This relationship was observed by Powell (2018) and Erceg et al. (2018) for overall core PCE inflation. Powell (2020) referred to it as "the flattening of the Phillips curve." For the 20-year samples ending in 2009 and after, the slack coefficient for core goods inflation has the "wrong" sign. In samples including the Great Inflation, the slack coefficient for both services and goods always has the "right" sign and fall inside one or both of the error bands (though the goods coefficient is closer to 0 in most cases). I have not included relative import prices for the goods Phillips curve, and long-run inflation expectations for the services curve, as Peach et al. (2013) did in their Phillips specifications. These authors and Tallman and Zaman (2017) found that modeling services and goods inflation separately, with the former dependent on the cyclical state of the economy and the latter not, leads to improved *overall* forecasting relative to models

[13] The only acyclical housing category in Shapiro (2020) is the rental value of farm dwellings.

not disaggregating goods and services inflation after 1994. I can summarize my discussion from the literature I've cited above and my own findings with the following stylized facts:

- Most of the rise in core inflation during the pandemic is attributable to goods (around 80 percent). However, core PCE services inflation has inched up modestly in contrast to the Great Recession, when it fell by more than 2.0 percentage points.
- In the 35 years or so prior to the pandemic, core goods inflation was largely acyclical, including in motor vehicles and parts, where much of the rise in core inflation has been concentrated. During the same period, aggregate core services inflation has been inversely related to slack, though the relationship has been stronger in some categories (housing) than others (medical care).
- In the Great Inflation, the Phillips curve coefficients for both core goods and core services had the "right sign" and were further away from 0—that is, less flat—than they were in the period beginning in the mid-1980s or after.

These facts suggest that *if* the Phillips curve has not changed from the 20 years prior to the pandemic, then much of the rise in US inflation is probably not attributable to labor market developments since it has been concentrated in goods. Over the April 2020–July 2021 period, the simple correlation between one-month core PCE goods inflation and the unemployment rate is –0.48.[14] Of course, this observation is not strong prima facie evidence that a robust Phillips relationship has reemerged for goods inflation. For that, I examine evidence using regional CPI inflation and employment data.

A number of studies have used regional CPI data to show the Phillips curve relationship between labor market utilization and inflation has continued to hold-up even in recent years in spite of its flattening noted by Powell (2020) and others. Some of these studies—including Babb and Detmeister (2017), Kiley (2015), Hooper et al. (2020), and Fitzgerald et al. (2020)—use metropolitan statistical area (MSA)-level CPI data. A disadvantage of the MSA-level CPI data for an analysis that focuses on the COVID-19 era is that apart from Chicago, Los Angeles, and New York, the US Bureau of Labor Statistics (BLS) only collects and reports most MSA-level prices, other than food and energy, on a bimonthly basis. Roughly half these MSAs have missing (noncore) CPI data in odd-numbered months, and the other half have missing data in the even-numbered months. For these MSAs, CPI data is published on a bimonthly and semiannual basis. Given the unusually high volatility and, in recent months, unusually high levels of core inflation, I use the BLS's regional CPI data, both for the eight groupings of Census regions by city-size class areas as well as by the nine Census divisions. Both sets of data are published, without any missing values, every month. However, the division-level data are only available starting in 2018 [15].

[14] I don't include March 2020 because the Current Population Survey used to calculate the unemployment occurred in the first half of the month before the closures of nonessential businesses went into effect for many states. Including March 2020, the correlation is –0.35.

[15] The BLS does impute "off-cycle" MSA-level CPI data, but it does not publish it directly. Prior to 2015, imputation for month *t* data at the MSA level was done internally using the geometric mean of the published month *t*–1 and month *t*+1 data, allowing an analyst to exactly reproduce the published semiannual data with the data published bimonthly. Starting in January 2015, the BLS began using its so-called new estimation system—also known as NewEst—to internally impute uncollected bimonthly data in month *t* using only collected data through month *t.* This system allows for publication of MSA-level data at the end of each half-year even for "odd-month" reporters, but it means that the published semiannual MSA CPI levels can no longer be reproduced using the published bimonthly MSA data. BLS economist Jonathan Church provided very helpful information about imputation of

As documented in Williams (1996) and Paben et al. (2016), the BLS collects at least bimonthly prices for all of the largest MSAs called "class A," or self-representing, areas or primary sampling units (PSUs) and bimonthly prices for a probabilistically determined subset of medium and smaller population core-based statistical areas (CBSAs) called "class B/C" or non-self-representing, PSUs.[16] The BLS publishes monthly CPI data each month for various aggregates—"All items," "All items excluding food and energy," etc.—and expenditure categories for all 8 = 4 x 2 combinations of census region and class size. Williams (1996) and Paben et al. (2016) report the MSAs, counties, and in the latter report, the CBSAs included for the eight regions by class size groupings, so I am able to construct unemployment rates for the MSAs in these eight groups both before and after the change from the 1998 to 2018 sampling frame using data reported in the BLS's Local Area Unemployment Statistics (LAUS) program.[17] Importantly, I include all MSAs outside of the class A PSUs when constructing the B/C size class unemployment rate.[18] Figure 3 shows the evolution of the unemployment rate and cumulative core CPI inflation by census region and class size. Through May 2020, Cho et al. (2020) found that large MSAs had bigger increases in unemployment during the early months of the pandemic than smaller MSAs. Figure 3 shows that this gap remained through July 2021. It shows a similar difference for cumulative inflation. Smaller MSAs have had higher cumulative core inflation than large MSAs. The Northeast and West regions have had larger increases in unemployment than the Midwest and South. The Northeast has had the lowest rate of cumulative core CPI inflation, while the South has had the highest. The West and Midwest have had similar rates of core inflation despite the latter region's lower unemployment rate.

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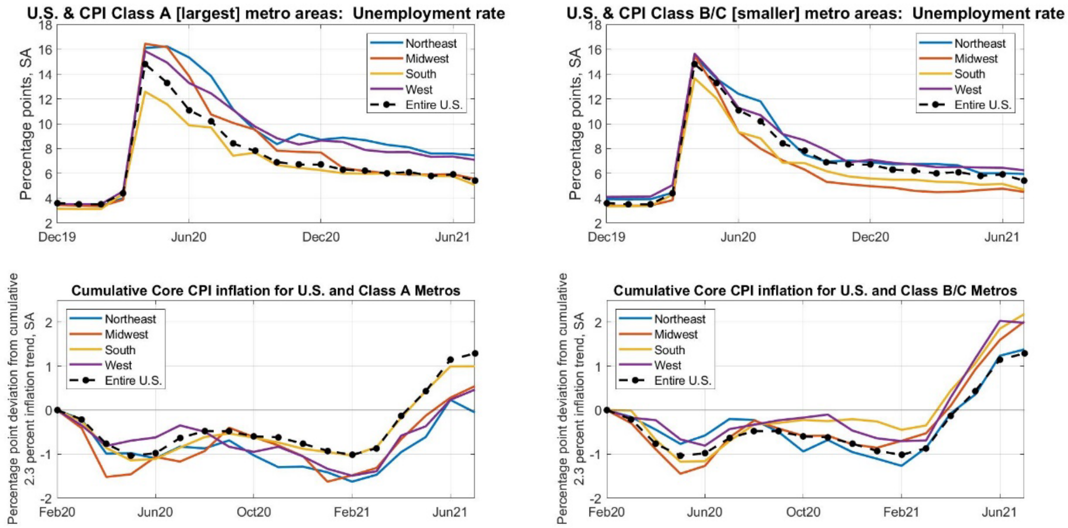
regional CPI data. Further references and details regarding NewEst are provided in BLS (2015), Friedman (2016), and Sheidu (2019).

[16] With the exception of Anchorage, AK, and Honolulu, HI, which are treated as class A areas because of their geographic distinctions, the population threshold for class A PSUs was increased from a 1990 population of at least 1.5 million persons for the geographic sampling frame used beginning in January 1998 to a 2010 population of at least 2.5 million persons for the geographic sampling frame used beginning in January 2018. Thus, the number of "class A" PSUs decreased from 31 in 1998 sampling frame to 23 in the 2018 sampling frames, as midsized cities such as Pittsburgh and Cincinnati fell out of the "class A" areas. CBSAs were first defined in 2003. The 1998 CPI sampling frame covered the urban portion of nonmetropolitan areas. A change in the sampling frame in 2008 based on the 2000 decennial census did not take place because of resource constraints.

[17] See https://www.bls.gov/lau/. Seasonally adjusted MSA-level unemployment and labor force data are taken from https://www.bls.gov/lau/metrossa.htm, while nonseasonally adjusted county level data are taken from https://download.bls.gov/pub/time.series/la/. When the county-level geographic boundaries for the class A PSUs necessitates using county-level labor data, I seasonally adjust the county's unemployment rate and labor force level before combining with (or subtracting) the MSA-level labor data.

[18] An alternative would be to include only those MSAs that were probabilistically chosen for the CPI sampling frame. This would be challenging to do in practice because some of the new 2018 class B/C PSUs were rotated in for some of the old 1998 B/C PSUs in a series of four waves over a four-year period as described by Paben et al. (2016).

Figure 3: Unemployment rate and Core CPI inflation by region and class size



Note: The lines in the charts' bottom panels show the percentage point difference between cumulative core CPI inflation and a price index growing at a constant 2.3 percent annualized rate since February 2020. Thus, the horizontal line at 0 is consistent with a constant 2.3 percent annualized rate of inflation. I use 2.3 percent rather than 2.0 percent to account for the average difference between CPI and PCE inflation over longer periods of time. The BLS seasonal factors for the US core CPI have been used to "seasonally adjust" the regional prices.
Source: U.S. Bureau of Labor Statistics, Haver Analytics, and author calculations

I estimate the following region by class size Phillips curve that allows for a change in the Phillips curve slope during the pandemic:

$$(2)\ 1200\Delta\log(CPI_t^i) = \alpha_i + \theta_t + \beta^{Covid} I_t \widetilde{UR}_{t-1}^i + \beta^{PreCovid}(1 - I_t)\widetilde{UR}_{t-1}^i + \varepsilon_t^i,$$

where *i* denotes a census region by class size group, CPI_t^i denotes the monthly consumer price index for a particular area and expenditure category or aggregate price measure,[19] $\widetilde{UR}_{t-1}^i$ is the lagged difference between the seasonally adjusted unemployment rate for the region by class and the CBO's estimate of the national (short-term) natural unemployment rate,[20] θ_t and α_i are time and region by class fixed effects, I_t is an indicator variable that is 0 before March 2020 and 1 thereafter, and ε_t^i an error term. The regression is estimated over the January 1998 to July 2021 period.[21] The time-fixed effects will account

[19] The CPI measures reported by the BLS are not seasonally adjusted. I use the national seasonal factors in place of the regional seasonal factors as a crude way to seasonally adjust prices. Because of the time-fixed effect, however, this adjustment is not necessary. However, our approach won't be able to account for regional and/or class size differences in seasonal factors. The 1200Δlog(*) notation denotes 1,200 times the difference of the natural logarithm of the CPI index, an approximation for an annualized monthly inflation rate used in the literature for econometric reasons. For example, unlike standard percent changes, regression results using log differences are invariant to the choice of whether to use annualized units or not.
[20] The region by class-fixed effect will account for any constant difference in the natural unemployment rate by region and class-size as well as any mean differences in inflation. Results using contemporaneous, rather than lagged, unemployment are very similar, and the lag allows for the immediate inclusion of the latest CPI data on the day of its release in the regression.
[21] Our reasons for choosing to start the sample in January 1998 are largely pragmatic, as that was the month that the 1998 sampling frame for the CPI was first used. Using data before this would require constructing labor market measures consistent with the 1987 CPI sampling frame. However, there were a number of important

for relative import prices, longer-run inflation expectations, and other national measures often included in national-level Phillips curves. Unlike in equation (1), I do not put a negative sign in front of the β coefficient to be clear that we should expect to see a negative slope coefficient in table 1 whenever an inverse Phillips relationship holds (as expected for services, core, and overall inflation). I also estimate a second specification where the Phillips curve slope does not change during the pandemic:

$$(3)\ 1200\Delta\log(CPI_t^i) = \alpha_i + \theta_t + \beta\widetilde{UR}_{t-1}^i + \varepsilon_t^i.$$

methodological adjustments to the CPI made prior to 1998. The CPI is not methodologically consistent, but the BLS constructs a “research series” that is. Since 1999, the absolute difference between 12-month core CPI inflation and its “research series” counterpart is never more than 0.1 percentage point. From 1991 to 1999, the difference between the published and research 12-month rates narrowed fairly steadily from 0.7 percentage point to 0. Thus, omitting data prior to 1998 largely avoids issues related to the methodological changes to the CPI.

Table 1: Region by Class Size Phillips Curves

	Consumer Price Index Expenditure Category					
	All-times	Core	Services	Durable goods	Nondurable goods	Housing
Regression estimates for specification (3) [no change in Phillips curve slope]						
Phillips curve slope	–0.39***	–0.40***	–0.39***	–0.09	–0.29	–0.46***
	(0.11)	(0.09)	(0.12)	(0.17)	(0.24)	(0.16)
Regression estimates for specification (2) [change in Phillips curve slope]						
Pandemic-era Phillips curve slope	–0.50***	–0.47***	–0.43**	–0.39	–0.14	–0.47*
	(0.17)	(0.14)	(0.18)	(0.27)	(0.38)	(0.25)
Prepandemic Phillips curve slope	–0.33***	–0.36***	–0.37***	0.06	–0.36	–0.46**
	(0.12)	(0.11)	(0.14)	(0.20)	(0.29)	(0.19)
Impact of slack on inflation measure during pandemic (seasonally adjusted annual rate, percentage points)						
Equation (3): Unchanged slope	–1.2	–1.3	–1.2	–0.3	–0.9	–1.5
Equation (2): New slope	–1.6	–1.5	–1.4	–1.2	–0.5	–1.5
CPI inflation rate (seasonally adjusted annual rate, percentage points)						
February 2020/February 2015	1.9	2.1	2.7	-0.9	1.0	2.7
July 2021/February 2020	3.6	3.2	2.5	10.6	3.9	2.8

Note: Seasonal factors for each region/class size assumed to be same as national seasonal factors published by the BLS. Each regression uses monthly inflation data from January 1998 to July 2021 and includes 2264 = 8*283 observations. Standard errors are in parentheses. * denotes significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.
Source: Author calculations using data from U.S. Bureau of Labor Statistics, Congressional Budget Office, and Haver Analytics

Data availability is the primary reason I do not report "core goods" and "core services" instead of the overall "goods" and "services" measures.[22]

Table 1 above displays the Phillips curve slope regression coefficients from specifications (2) and (3). In every specification, we cannot reject the hypothesis that the Phillips curve slope has *not* changed during the pandemic at even the 10 percent significance level. In specification (2), the slope coefficient for durable goods is similar in magnitude to services, but it is not significantly different from 0 given the large volatility in durables inflation. Overall, the estimates in table 1 suggest that the Phillips curves have not changed dramatically during the pandemic. Although the inclusion of time-fixed effects means we cannot distinguish a level shift in the natural unemployment rate from a sequence of supply shocks, the estimates suggest that if the natural rate of unemployment coincides with the CBO estimate, then labor market slack has depressed annualized inflation during the pandemic by about 0.5 to 1.5 percentage points for most of the CPI measures shown above. That said, the results suggest we should not be surprised that annualized, month-over-month CPI inflation for services has been higher after January 2021 (4.9 percent, on average), when the lagged unemployment rate has been 6.1 percent on average, than it was during May through August 2020 (3.2 percent, on average), when the lagged unemployment rate was 12.4 percent on average. And, unlike during the Great Recession, CPI housing services inflation

[22] For example, the BLS reports a "services less energy" CPI measure for each of the four census regions but not for the Class A and Class B/C groups within them. Food services are included in the core PCE services, so its closest CPI analog is probably "services less energy."

has not changed much on average from prior to the pandemic,[23] which perhaps suggests an increase in the short-term natural unemployment rate. But such an increase would not account for the dramatic increase in durables goods inflation.

For the purposes of this article, there are several shortcomings with using the census region by class size inflation data, as I have in the above analysis. I have not included micropolitan areas in the construction of the unemployment rate class B/C areas.[24] Beyond this, a change in the geographical boundaries occurred within the eight area groupings with the transition to the 2018 frame, as some MSAs moved from class A areas to class B/C areas. Though I can largely control for this switch in the aggregation of the unemployment rate and labor force data for these groupings, I cannot do the same for the price data. Therefore, the area specific fixed effects estimated in the above regressions may have a level shift in 2018 that cannot be controlled for.

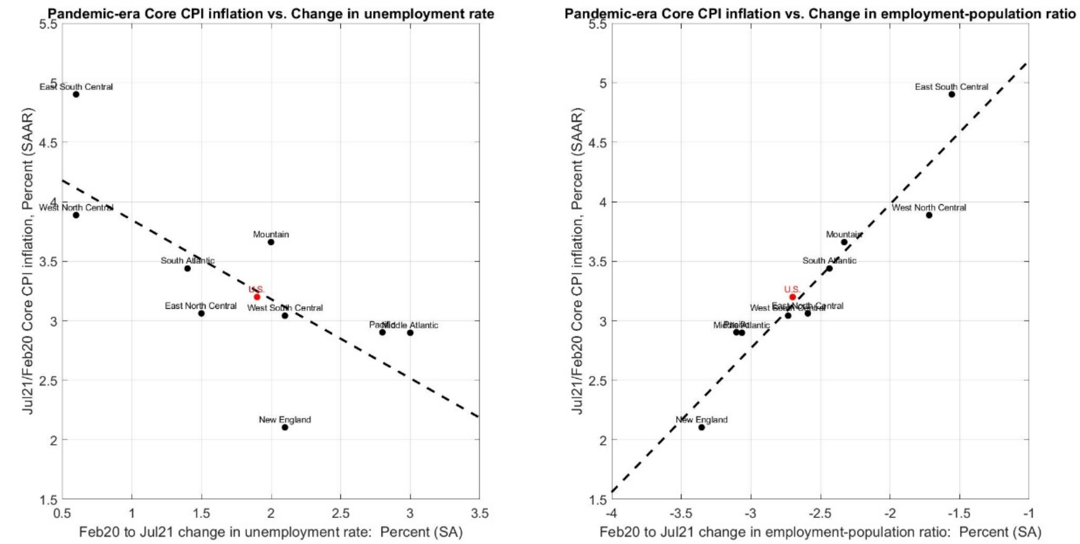
Moreover, though the BLS publishes comprehensive MSA-level data on nonfarm payroll employment, unemployment, the unemployment rate, and the size of the labor force, it does not publish analogous data on the labor force participation rate (LFPR) or the employment-population ratio. Given the outsize role the decline in LFPR has played in the net decline in employment over the pandemic,[25] a relevant consideration is whether the employment-population ratio has had an impact on inflation during the pandemic distinct from that of the unemployment rate. Figure 4, which shows scatterplots of census division annualized core CPI inflation rates during the pandemic against February 2020 to July 2021 changes in unemployment rates (left panel) and employment-population ratios (right panel), suggests that it might. We can see that core CPI inflation has been more highly correlated with changes in the employment-population ratio than inverted changes in the unemployment rate (0.94 versus 0.72) and that the slope of the fitted-regression line is steeper in the employment-population ratio plot.

[23] July 2021/February 2020 annualized seasonalized adjusted CPI housing services is 2.8 percent, little changed from the 2.7 percent rate in the 12 months prior to the pandemic. Twelve-month CPI housing services inflation fell from 3.0 percent in the December 2007 business cycle peak to 0.0 percent in the June 2009 business cycle trough.

[24] In the 1998 sampling frame, only the urban portion of micropolitan/non-MSA counties were included in the urban portion of the United States covered by the CPI-U. In the 2018 frame, the entirety of micropolitan counties was considered urban. According to Paben et al. (2016), the share of the US population covered by CPI-U went from 87 percent to 94 percent with the transition to the 2018 sampling frame. In the latter sampling frame, MSAs accounted for 85 percent of the US population and micropolitan areas 9 percent.

[25] The decline in the LFPR accounted for 27 percent of the decline in the employment-population ratio (EPOP) from February 2020 to April 2020 and 56 percent of the decline from February 2020 to July 2021. By comparison, the LFPR accounted for 10 percent of the decline in the EPOP during the Great Recession and 29 percent of its decline from December 2007 to its trough in June 2011.

Figure 4: Census Division Core CPI inflation vs. Change in labor market ratios



Note: “Seasonally adjusted” division-level core CPI inflation was obtained by using the US seasonal factors for every census division. This method has virtually no impact on the correlations cited in the text as it moves the division-level inflation rates about 0.1 percentage point.
Source: U.S. Bureau of Labor Statistics, Haver Analytics, and author calculations

To investigate this more formally, I estimate specification (3) given above using various measures of CPI inflation for each of the nine census divisions that are available starting in January 2018.[26] I also estimate a specification similar to (3) using the employment-population gap in place of the unemployment gap

$$(4)\ 1200\Delta \log(CPI_t^i) = \alpha_i + \theta_t + \beta \widehat{EPOP}_{t-1}^i + \varepsilon_t^i,$$

where $\widehat{EPOP}_{t-1}^i$ is the lagged difference between the CBO’s “estimate” of the national short-term employment-population ratio and the actual employment-population ratio in census division i[27] and perhaps the measure most conceptually consistent with the “employment shortfall” that I quoted at the beginning of this article, from the FOMC’s longer-run goals and strategy statement.[28] The census division labor measures cover the rural population, and the inflation measures do not, but this distinction also holds true in national-level specifications.

Because divisional-level CPI inflation data have only been available for the last three and a half years, it might be difficult to estimate the geographic-level fixed effects when using divisional data gathered over this short a period. Therefore, I estimate an additional specification where I remove the

[26] Paben et al. (2016) details why census division CPI data could be estimated after the transition from the 1998 CPI geographic sampling frame to the 2018 sampling frame.
[27] The CBO EPOP measure is constructed by multiplying 1 minus the natural short-term unemployment rate with the CBO’s estimate of the potential labor force participation rate available at https://www.cbo.gov/system/files/2021-07/55022-2021-07-historicaleconomicdata.zip.
[28] This specification is why I’ve used the term “unemployment slack” instead of “labor market slack” whenever I refer to the slack measure denoting the difference between the actual and natural rates of unemployment.

division-level fixed effects and account for secular differences in divisional-level inflation and (un)employment:

$$(5)\ 1200\Delta \log(CPI_t^i) - \bar{\pi}^i = \theta_t + \beta \tilde{X}_{t-1}^i + \varepsilon_t^i,$$

where $\bar{\pi}^i$ accounts for the average difference between division-level and national-level inflation prior to the pandemic, and $\tilde{X}_{t-1}^i$ is the lagged estimate of the census division–specific unemployment rate or employment-population ratio gap. As I describe in the brief appendix to this article, I use state-level CPI inflation data prior to 2018 from Hazell et al. (2021) to estimate $\bar{\pi}^i$ for all CPI items (excluding rent of primary residence and owners' equivalent rent). As the unemployment rate was 3.6 percent in the final quarter of 2019 and the US economy was near the end of its longest business cycle on record, according to the National Bureau of Economic Research, I assume that all regions of the country were at full employment[29] at the end of last decade when constructing $\tilde{X}_{t-1}^i$.[30] I also estimate a version of specification (5) with 3-lags of the dependent variable included as regressors to partially offset the omission of a division-level fixed effect.

Table 2: Census Division Phillips Curves

	Consumer Price Index Expenditure Category							
	All times	**Core**	**Services**	**Durables**	**Nondurables**	**CPI ex primary residential rent/OER**		
UR based for specifications (2) and (4)								
Phillips curve slope	–0.44**	–0.36**	–0.37**	–0.24	–0.28	–0.40	–0.31	–0.38*
	(0.18)	(0.16)	(0.19)	(0.39)	(0.41)	(0.24)	(0.21)	(0.21)
EPOP based for specifications (3) and (4)								
Phillips curve slope	–0.71***	–0.59***	–0.61**	–0.18	–0.75	–0.80**	–0.62**	–0.80***
	(0.22)	(0.20)	(0.24)	(0.50)	(0.52)	(0.31)	(0.27)	(0.28)
No. of autoregression lags	0	0	0	0	0	0	0	3
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Impact of slack on inflation measures during the pandemic (seasonally adjusted annual rate)								
Using the unemp. rate	–1.4	–1.1	–1.2	–0.8	–0.9	–1.3	–1.0	
Using EPOP	–2.2	–1.8	–1.9	–0.6	–2.3	–2.4	–1.9	
Annualized inflation rate (seasonally adjusted)								
Feb. 20/Feb. 15	1.9	2.1	2.7	–0.9	1.0	1.2	1.2	1.2
July 21/Feb. 20	3.6	3.2	2.5	10.6	3.9	4.3	4.3	4.3
Regression sample size	387	387	387	387	387	387	387	360

Note: Seasonal factors for each division assumed to be same as national seasonal factors published by the BLS. Each regression uses monthly inflation data from January 2018 to July 2021. UR denotes the unemployment rate, EPOP employment-population ratio. * denotes statistical significance at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level. OER indicates owner's equivalent rent.

Source: Author calculations using data from U.S. Bureau of Labor Statistics, Congressional Budget Office, and Haver Analytics, and Hazell et al. (2021).

[29] This assumption is not innocuous. Howard et al. (2021), for example, calculate the employment-population ratio in February 2020 was about 2.5 percentage points above its full employment level.

[30] Specifically, for each census division, I add the difference between the division-level actual (seasonally adjusted) and US-level natural unemployment rate in month *t* to the difference between the US and region-level unemployment rate in 2019:Q4 to get the estimated region-specific unemployment gap in month *t*. I use the same adjustment for the employment-population ratio, and multiply by –1, to get the region-specific employment-population gap. Similar results are obtained when 2017:Q4 is taken as the full employment level.

Table 2 shows the results for Phillips curves estimated with panel data by census divisions after 2017. The size of the unemployment-based Phillips curve slopes are fairly consistent with table 1, suggesting that changes in geographical boundaries introduced with the transition to the 2018 CPI sampling frame are not overly distorting the region by class-size results. Though the coefficients on durable and nondurable goods inflation have the “right sign,” they still are not statistically different from 0. If the CBO estimates of the natural unemployment rate and potential LFPR are correct, then table 2 implies that the employment-population gap has had between a 55 and 95 percent larger downward impact on inflation than the unemployment rate gap has during the pandemic. It could also be the case that structural factors are accounting for a larger share of the decline in labor force participation during the pandemic than CBO estimates imply.

Conclusion

Regional data do not suggest that the Phillips curve has become “broken” during the pandemic. If anything, they suggest the relationship between labor market utilization and inflation is as strong—or stronger—than it was during the prior two decades. During the first 18 months of the pandemic, the unemployment rate has averaged 7.6 percent, which could suggest some rise in the natural unemployment rate given the lack of disinflation in housing services. As it is not evident that a Phillips curve for goods has reemerged during the pandemic—following the approximately 35-year period when goods prices were largely acyclical—nothing in my evidence contradicts the notion that the spike in goods prices, which has been responsible for much of the rise in inflation in an accounting sense, is largely unrelated to US labor market slack. However, one should not overstate what can be concluded from this analysis. I have used fairly parsimonious Phillips curve specifications, and the timed fixed effects—θ_t in equations (2) through (4)—might include factors related to overall US-level or lagged region-level labor market utilization that these specifications cannot separately identify.

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Appendix: Construction of Pre-2018 CPI Inflation by Census Division

Quarterly averages of 12-month inflation rates for most US states where the BLS sampling frame has a sufficiently large coverage area have been estimated for much of the 1978–2017 period by Hazell et al. (2021).[31] This study uses their 1999 to 2017 data for Washington, DC and the 35 states—primarily those with medium or large populations—included in that subsample of the authors' database. For each state, the authors' database includes an overall measure of CPI inflation excluding rent of primary residence and owners' equivalent rent (OER) of residences.[32] I construct equivalent measures of quarterly averaged 12-month inflation rates for each of the four census regions using published regional CPI data and published relative importance weights for housing both within the regions and, where data gaps remain, within the United States. For the less populous states not included in the Hazell et al. (2021) database, I assume that the state inflation rate is identical to its census region inflation rate constructed with the published CPI data. I then use the US Bureau of Economic Analysis's (BEA) concordance of Consumer Expenditure Survey and PCE categories by year,[33] as well as BEA estimates of annual state-level nominal spending by PCE subcomponent[34] to construct state-level CPI weights for the Hazell et al. (2021) CPI measure. I use these weights to construct first-stage census region CPI inflation measures that are highly, but not perfectly, correlated with the constructed BLS measures.[35] For each region and year, using only fourth-quarter values, I add an adjustment factor to each of the state-specific inflation rates[36] so that the adjusted regional inflation rate coincides exactly with the measure constructed using published BLS data. The adjusted state-level inflation rates are then aggregated to the census division level for the fourth quarters of 1999 through 2017 and extended to 2018 and 2019 with published BLS data. The average 1999–2019 difference between US and census division inflation rates for CPI excluding rent/OER, and the average difference between US total CPI and CPI excluding rent/OER inflation rates during the same period, are used to construct $\bar{\pi}^i$ in equation (5).[37]

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[31]The state CPI data are available at https://eml.berkeley.edu/~enakamura/papers.html.

[32] The authors also split this inflation measure into tradeable and nontradeable sectors, but the regional CPI expenditure categories data available to the public are not granular enough to construct analogs by census region using published BLS data.

[33] Available from https://www.bls.gov/cex/cepceconcordance.htm.

[34] Available from https://www.bea.gov/data/gdp/gdp-state and taken from the Haver Analytics database.

[35] The correlation is 0.85 for the West region of the census and between 0.91 and 0.94 for the other three census regions. The lower correlation for the West might be the result of the absence of Arizona data in the Hazell et al. (2021) due to data anomalies in the BLS microdata for that state, which the authors had not yet resolved.

[36] In the calculations involving weights, I convert to log-based inflation rates to mimic a Tornqvist index calculation.

[37] A 2.3 percent inflation rate is also added to the fixed effects, approximately consistent with 2.0 percent PCE inflation. Prior to the adjustments, average US CPI ex rent/OER inflation is 1.90 percent on average for the fourth quarters of 1999 through 2019, and the divisional level averages range from 1.74 percent in the West North Central Division to 2.02 percent in the Pacific Division.