Slack and Cyclically Sensitive Inflation

By James H. Stock and Mark W. Watson[1]

Abstract

The low rates of price inflation in both the United States and the Euro area have been resistant to tightening economic conditions. As measured by the unemployment rate, the US economy in particular is at historically tight levels. One possibility is that the unemployment rate understates slack because of special features of the financial crisis recession and the long recovery, however we find the same puzzling quiescence of inflation in both the US and the Euro Area when we look at other slack measures. We therefore turn to the possibility that inflation *is* increasing – but only in those sectors that are historically cyclically sensitive, with prices set not in international markets but locally (such restaurants and hotels). We find that cyclically sensitive inflation has increased slightly in the US over the past two years, but has been stable in the Euro Area.

1 Introduction

Charts 1 and 2 summarize the low-inflation puzzle confronting the United States and the Euro Area. In the United States, the unemployment rate has fallen from a peak of 10% in October 2009 to a 48-year low of 3.8% in May 2018, and it has been below the Congressional Budget Office's current estimate of the natural rate of unemployment since February 2017. In Europe, the recovery from the financial crisis recession was slower to take hold, and the Euro Area (EA) harmonized unemployment rate of 8.5% still exceeds its pre-crisis trough of 7.3% in January 2008. Since mid–2013, however, the EA unemployment rate has been falling steadily and has declined by 0.9 percentage points in the past year alone.

Yet, despite this strong growth, especially over the past several years, both wage and price inflation remain stubbornly below the 2% target. In the US, core inflation as measured the personal consumption expenditure price index (PCE excluding food and energy, PCExFE) is currently 1.6% (Q1 to Q1), the same value as in the first quarter of 2013 (it has edged up in the April and May 2018 monthly data). Like prices, the rate of wage inflation, as measured by average hourly earnings (all private workers) in the United States has not increased, with its four-quarter rate of

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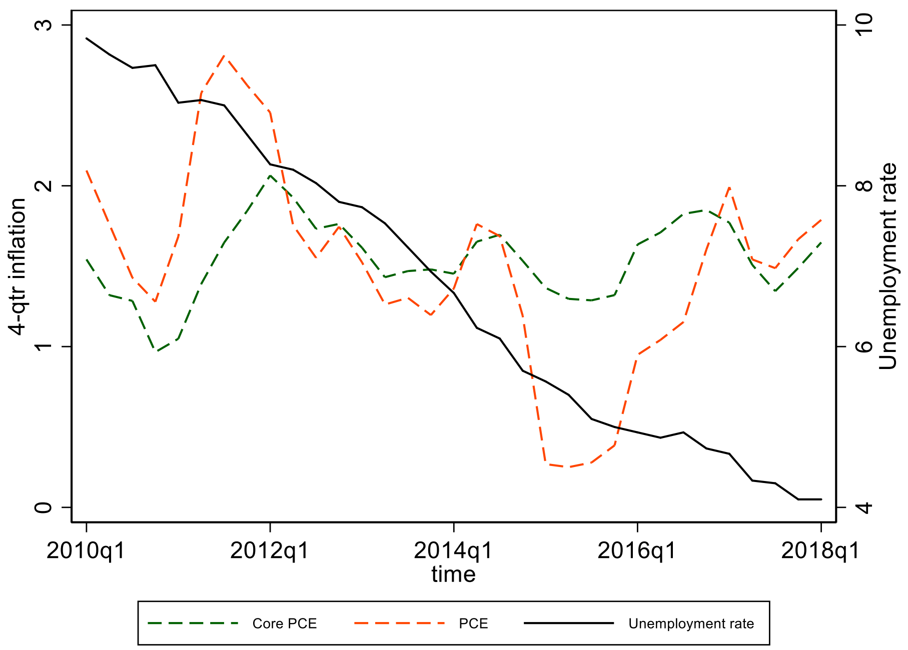
growth fluctuating in a narrow band around 2.5% since late 2015. In the Euro area, core inflation, as measured by HICP excluding energy and unprocessed food (HICPxEUF) for comparability to the US PCExFE, has increased by 0.6pp since the first quarter of 2015, yet currently is only 1.2%.

This apparent disconnect between consistent economic growth and the stable and low rates of inflation stands in sharp contrast to earlier episodes, and raises new questions for monetary policy. Is this apparent flattening of the Phillips curve a new and permanent feature of modern economies with credible monetary authorities? Or are tight economic conditions building inflationary pressures that simply have not yet been observed? Answering these questions is especially pressing in the United States, where an already-tight economy will likely become more so as a result of the additional fiscal stimulus provided by the federal tax cuts of December 2017: In its most recent economic update, the CBO projects the deficit-to-GDP ratio for FY2019 (which begins October 1, 2018) to rise to 4.6%.

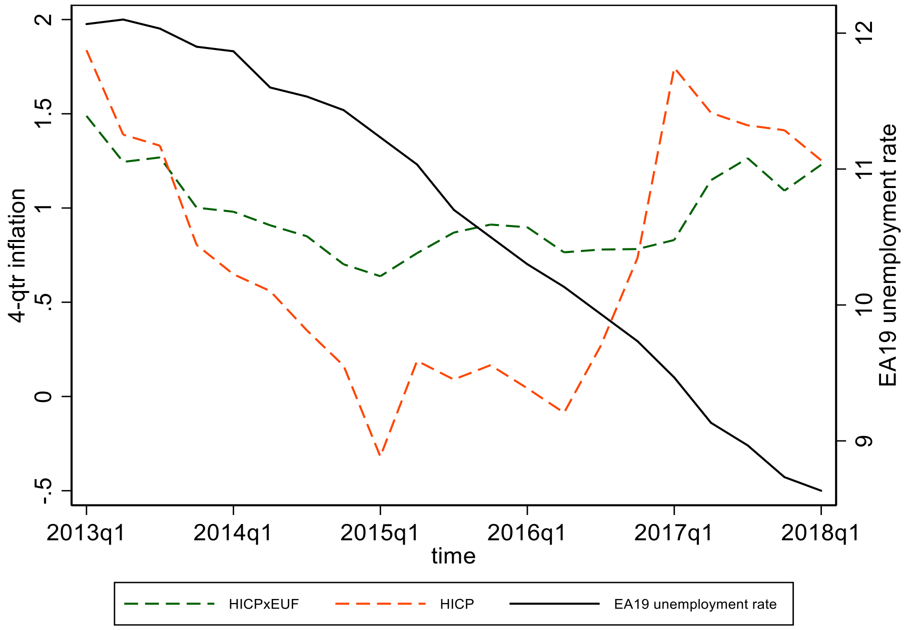
Chart 1

The unemployment rate, PCE inflation, and core PCE inflation in the US, 2010-2018q1



Source: FRED.

Chart 2
The unemployment rate, HICP inflation, and core HICP inflation in the EA, 2013-2018q1



Sources: Eurostat and ECB.

Researchers and policy makers have proposed multiple explanations for this apparent flattening of the Phillips curve. One set of explanations focuses on the role and formation of inflation expectations. A commonly proposed explanation is the success of monetary policy in anchoring expectations, however it is difficult to reconcile this theory with the US evidence without also having a reduction in the Phillips curve slope coefficient (e.g. Fuhrer (2012)) or using the short-term unemployment rate as the measure of slack (Ball and Mazumder (2014)). Coibion and Gorodnichenko (2015) suggest that firms' inflation expectations moved *countercyclically* during the recession and recovery because they are overly influenced by oil prices, which increased from 2009 to 2011 and (extending their argument) fell from 2014 through 2017. Another set of explanations focuses on special features of the financial crisis. For example, Gilchrist et. al. (2017) suggest that special features of the financial crisis affecting the pricing behaviour of liquidity-constrained firms, counteracting the expected downward pressure on inflation during the recession and early recovery. A third set of explanations focuses on structural changes that could lead to a reduction of the Phillips curve coefficient. For example, the ability to offshore jobs and increasing openness to trade restrains wages even when the labour market is tight. In addition, technological developments have made it easier to substitute capital (robots, Web sites) for labour, restraining wages and thus prices.

Other explanations, however, have to do with measurement problems. According to this second set of explanations, perhaps the apparent flattening of the Phillips Curve is, at least in part, an artefact of mismeasurement of economic slack or of the rate of price inflation, or both.

The aim of this paper is to examine the possibility that measurement issues, possibly in conjunction with an increasing share of consumption having prices strongly influenced by international markets, play a role in the recent apparent disconnect between activity and inflation. To do so, we re-examine both measures of slack and measures of price inflation, with an eye towards better measurement of cyclical sensitivity.

We begin in Section 2 by examining measures of slack in the United States. One possibility is that the depth of the recession changed labour market dynamics in ways that are not well measured by the unemployment rate alone. For example, many of the unemployed during the recession were unemployed for long periods, and the long-term unemployed have lower job-finding rates and lower search intensity than the short-term unemployed (e.g. Krueger, Cramer, and Cho (2014)); thus the short-term rate of unemployment might be a measure of slack more closely linked to inflation than the overall unemployment rate. Alternatively, many of the workers who exited the labour force in the US are now taking jobs – the labour force participation rate has been flat in the US since mid–2014, despite strong demographic trends pushing it down – so that there is more slack in the economy than the unemployment rate suggests (e.g. Bell and Blanchflower 2018). We find some evidence that, for the purpose of the Phillips relation, slack might be better measured over this recovery by the short-term unemployment rate than by the standard unemployment rate or other measures, such as the capacity utilization rate. The evidence, however, is weak, and in any event using nonstandard measures of slack does not explain the weakness in the US rate of inflation over the past two years.

We next take up the question of whether noise in the major price indexes, perhaps combined with changes in the economy, could be masking the activity-inflation relationship. This line of investigation is more novel, and our analysis draws on both detailed information about the construction of price indexes by sector and econometric methods to tease out cyclical sensitivity. Our analysis starts with sectoral data, then aggregates the sectoral data to a new price index, which we call Cyclically Sensitive Inflation (CSI).

The first step in the construction of the CSI index is to examine the construction of price indexes at the sectoral level. There is considerable heterogeneity across components in the quality of price measurement. As explained in Section 3, we exclude from our index the most poorly measured price series, which comprise 17% of consumption for the US.

Of the remaining components of PCE inflation, one would expect *a-priori* that the sectoral prices would have different degrees of cyclical sensitivity. At one extreme, the price of commodities such as oil have prices set in world markets, so the link between economic activity in any one country and the change in the oil price will be attenuated. In contrast, many services, such as recreational services or food served at restaurants, are largely nontradable and have prices that are set in local markets, so should be more subject to local and national cyclical pressures. In Section 3, we use PCE component rates of inflation and an index of real cyclical activity to estimate the weights on the individual components, and then use these estimated weights to construct our index of cyclically sensitive inflation (CSI).

Section 4 turns to the Euro area. As in the US, using different measures of slack does not explain the sluggishness of core inflation. We therefore take the same approach as we did for the US and ask whether some components of inflation are more cyclically sensitive than others. As in the US, there is in fact a very wide range of cyclical variability among components of the HICP. For example, services provided by restaurants and hotels, as well as food and non-alcoholic beverages, have inflation rates that are strongly cyclical, while other components, such as housing rents (excluding energy), communications, and health care have small or no cyclical variation. Using the methodology of Section 3, we construct a CSI index for the EA.

The HICP components and PCE components are different, with HICP components being organized along functional consumption categories (by purpose) and PCE being organized by product characteristics, broken down by durable goods, nondurable goods, and services. It is therefore not possible to compare directly the weights on components across the EA and US CSI measures. That said, there are some similarities in the measures. For example, both measures place negligible weight on energy, and place much or most of their weight on goods or services that are locally priced (as opposed to internationally priced).

We see the CSI index as providing another indicator by which to monitor the economy. Because measuring slack is difficult in real time, CSI inflation provides a real-time alternative to estimating slack measure: CSI provides a real-time index of whether cyclical pressures are causing the most sensitive components of inflation to rise or fall. Said differently, in the current regime of largely stable rates of inflation, the combination of measurement error and special factors make it particularly difficult to observe the “signal” of inflation starting to pick up as cyclical conditions tighten. The CSI index provides a new measure of this signal. This monitoring function of the CSI contrasts with two roles of inflation indexes that the CSI is *not* designed to fill: it a not measure of the overall cost of living (it cannot be, because it does not use consumption share weights), nor is it a new index for a central bank to target.

Over the past year, CSI inflation has picked up slightly in the US, but not at the pace that preceded the most recent recessions. In the EA, CSI inflation has increased at the same rate as HICPxEUF. Thus, at the moment, these CSI measures are indicating that the most cyclically sensitive components of inflation remain quiescent. Because the indexes can be computed in real time, they can be monitored going forward to provide another window on inflation as real economic conditions change.

This paper is related to several lines of research within the vast literature on the relation between inflation and output. The papers most closely related to this one also focus on sectoral inflation. Peach, Rich, and Lindner (2013) propose different price-setting mechanisms for goods and services inflation (the former being more trade-sensitive) and use goods and services separately to forecast inflation. Tallman and Zaman (2017) use inflation components to forecast aggregate inflation. Drawing on early presentations of the material in this paper (Stock and Watson, 2016a), at least two groups have developed experimental cyclically sensitive indexes, the Federal Reserve Bank of San Francisco (Mahedy and Shapiro, 2017) and Goldman Sachs economic research (Struyven, 2017). Dées and Güntner (2017) find improvements to Euro Area inflation forecasts by disaggregating to four sectors (industry, services, construction, and agriculture). The ECB also has investigated the cyclical properties of HICP components as described in a box in the ECB Monthly Bulletin (ECB (2014)).

This paper is also related to work on core inflation, which uses inflation components to construct a less noisy measure of trend inflation. Research on core and on the use of inflation components to measure trend inflation includes the early papers of Gordon (1975) and Eckstein (1981), and more recently Cristadoro, Forni, Reichlin, Veronese (2005) Boivin, Giannoni, and Mihov (2009), and Amstad, Potter, and Rich (2017); see Stock and Watson (2016b) for additional references and discussion of this literature. Papers on the apparent flattening of the Phillips curve in the 2000s, and especially since the financial crisis recession includes (among others) Stock and Watson (2010), Ball and Mazumder (2011, 2014), Stock (2011), Gordon (2013), Watson (2014), Kiley (2015), Blanchard (2016), and Bell and Blanchflower (2018). This literature focuses on the United States. Mazumder (2018) finds a stable Phillips curve for the Euro area using short-term professional survey expectations data, and he attributes the weakening of EA inflation to a decline in expected inflation.

2 Measures of Slack in the US

Is the puzzling absence of a Phillips relation in the recent US data simply an artefact of mismeasuring slack? In this section, we examine Phillips correlations, Phillips slopes, and inflation forecasting relations using multiple measures of slack. We find that the results for these additional slack measures mirror those for the unemployment gap: for all these slack measures, the Phillips correlation has fallen over time, the Phillips slope has flattened, and inflation forecasts using the candidate slack measure are unstable.

2.1 Slack and gaps

Slack is an economic construct that is not measured directly. Slack is commonly estimated using an activity gap computed as the difference between an activity variable measured in real time and an unobserved level of that variable that represents full utilization of productive resources. These full-utilization levels are unobserved but can be estimated. For example, the unemployment gap is the difference between the observed unemployment rate and an estimate of the NAIRU, which can be estimated econometrically using an empirical Phillips relation.

We refer to gap measures in which the full-utilization value is estimated using retrospective (full-sample) data as *ex-post* gap measures, in contrast to gap measures that are available in real time (real time gaps). As new data become available, the *ex-post* estimates of the full-utilization value at any given date, and thus of the gap, are revised. These revisions tend to be largest towards the end of the sample, where the newly available data have the greatest influence. As a result, *ex-post* gaps can be useful for understanding historical relationships and developments, but are noisy – and potentially misleading – indicators of real-time economic conditions (Orphanides and Norden [2002]).

In this section, we consider seven ex-post gaps. The first two are from the Congressional Budget Office (CBO): the unemployment gap, which is the difference between the unemployment rate and the CBO long-term NAIRU, and the output gap, which is the log difference between GDP and CBO's estimate of potential GDP.

The remaining five gap measures are constructed using time series estimates of the full-utilization value. The premise of the time series approach is that, over a period of a decade or longer, a given activity measure fluctuates around a long-term value that tracks the full-utilization value. Thus the long-term mean, or more precisely the estimated mean constructed using a low-frequency filter, of the activity measure can serve as a proxy for the full-utilization value, and deviations from this long-term mean provide estimates of the gap. Concretely, we estimate the low-frequency mean using a two-sided biweight filter with a bandwidth of 60 quarters, and the gap is the deviation of the activity measure from this low-frequency mean.[2]

The five activity gaps estimated using the time series approach are the unemployment rate, the short-term unemployment rate (those unemployed 26 weeks or less as a fraction of the labour force), the employment-population ratio (household survey), the employment-population ratio for ages 25-54, and the capacity utilization rate.[3] To facilitate comparisons, we transform each gap to have the same mean and standard deviation as, and to be positively correlated with, the CBO unemployment gap.

The seven standardized gaps and the slack index are plotted for the period 1984-2018 in Chart 3. Most of the seven measures are highly correlated, with 12 of the 21 correlations exceeding 0.85 and the smallest correlation being 0.48.

In addition to these seven measures, Chart 3 plots a slack index, computed as the first principal component of these seven standardized gap measures. The slack index explains 83% of the total variation in the seven gap measures (trace R-

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2 For the unemployment rate, we can compare the CBO estimate of the gap to our time series estimate. Over 1984-2018q1, the two unemployment gap measures have a correlation is 0.95. The two measures differ the most at the end of the sample (where the low-frequency filter must be mainly one-sided, and the CBO NAIRU estimate lacks future inflation); over 1990-2005, the correlation between the two unemployment gaps rises to 0.98.

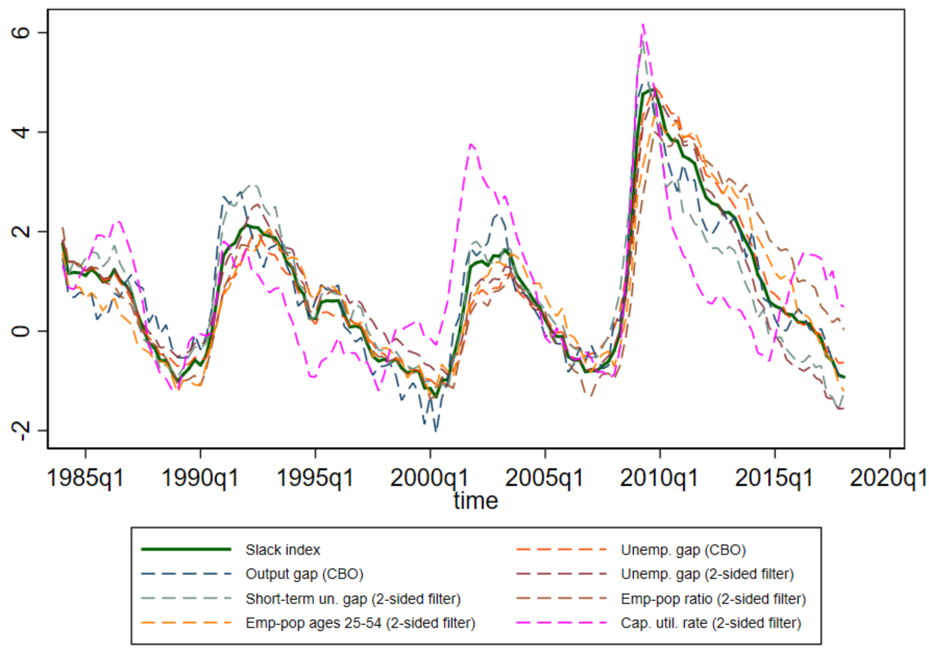
3 Stock (2011), Gordon (2013), Ball and Mazumder (2014), Krueger, Cramer, and Cho (2014), and Watson (2014) generally find that the short-term unemployment rate is a more stable activity variable in empirical Phillips curves than the long-term unemployment rate, using aggregate time series data for the US, however Kiley (2015) finds no advantage to short-term over the standard unemployment rate using state data. The capacity utilization rate received attention as a possible slack measure in Phillips curve research in the 1990s (e.g. Garner (1994) and Franz and Gordon (1993). The employment-population ratio is a less commonly used slack measure, but can be thought of as a broad unemployment rate because it incorporates those not in the labour force, including those who might have dropped out of the labour force because of absence of work but would want to work if a job were on offer.

squared). We treat this slack index as an eighth *ex-post* gap measure. The gap index evidently is a central estimate of slack at any given date and is somewhat smoother than the individual measures.

As can be seen in the chart, as of early 2018 nearly all the gaps, including the slack index, stand at historically low levels. This said, the greatest dispersion among the gaps is towards the end of the sample. As of the first quarter of 2018, the capacity utilization gap and the employment-population gap indicate more slack than the unemployment gap, but the short-term unemployment gap indicates even less slack. This dispersion in part reflects the difficulty of estimating full-utilization values, and thus gaps, at the end of the sample.

Chart 3

Ex-post gaps and slack index for the U.S



Source: Authors' calculations.
Notes: Variables are transformed to have same mean, standard deviation, and sign as the unemployment gap.

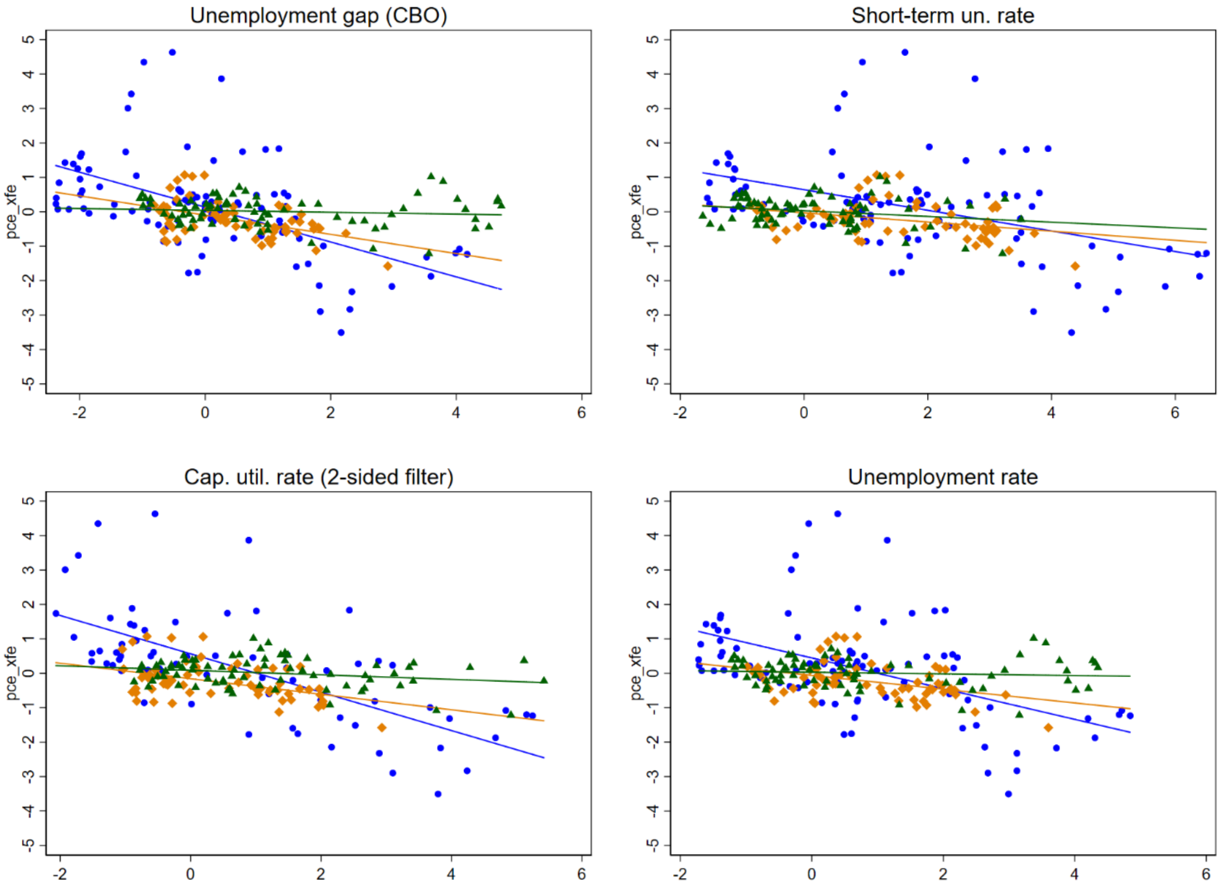
2.2 The changing Phillips correlation

Monetary authorities are interested in achieving inflation targets over medium-term horizons. In addition, rates of inflation have high-frequency variation arising from survey measurement error and from transient special factors. For these reasons, it is conventional to focus on rates of inflation over the past year, and we adopt this convention. Specifically, we focus on the four-quarter inflation rate, which we define using the log approximation, $\pi_t^4 = 100\ln(P_t/P_{t-4}) = (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})/4$, where P_t is the quarterly price index and π_t is the quarterly rate of inflation at an annual rate.[4]

Chart 4

Evolution of the US Phillips correlation: 4-quarter change in 4-quarter core PCE inflation vs. four standardized gap measures

(1960-83 (blue dots); 1984-99 (orange diamonds); 2000-2018q1 (green triangles))



Source: Authors' calculations.
Notes: The inflation measure is the 4-quarter change from date *t*–4 to *t* in the 4-quarter rate of PCE-xFE inflation. The slack measures are the standardized average value of the quarterly slack variable in the four quarters from date *t*–3 to date *t*; normalized to be positively correlated with the unemployment gap.

Chart 4 shows a Phillips scatterplot of the four-quarter change in four-quarter PCE-xFE inflation ($\Delta_4\pi_t^4 = \pi_t^4 - \pi_{t-4}^4$) vs. the contemporaneous standardized four-quarter moving average of various slack measure ($x_t^4 = (x_t + x_{t-1} + x_{t-2} + x_{t-3})/4$), along with regression lines for three periods, 1960-1983, 1984-1999, and 2000-2018q1. These scatterplot and the regression lines correspond to a benchmark Phillips curve specification $\Delta_4\pi_t^4 = \beta_0 + \beta_1 x_t^4 + u_t^4$. The slack measures shown are the CBO

4 The PCE price index and its components are available monthly, as are HICP and its components, however some of the activity variables, such as GDP, are only available quarterly. This paper uses quarterly data exclusively, where monthly data are aggregated to quarterly using the average value of the variable (i.e. the index value for prices, or of the unemployment rate) over the months in the quarter. For prices, this yields a quarterly price index. Throughout we use the logarithmic approximation to percentage changes. Four-quarter rates of inflation have the additional useful feature that they are a form of seasonal adjustment, which is useful in our analysis in Section 4 of Euro area inflation, which is not seasonally adjusted.

unemployment gap, the short-term unemployment rate (not gapped), the *ex-post* capacity utilization gap, and the unemployment rate (not gapped).

Table 1

Phillips correlations and slopes for PCE-xFE inflation and various slack measures for the US

(Phillips relation: $\Delta_4\pi_t^4 = \beta_0 + \beta_1 x_t^4 + u_t$, where $\Delta_4\pi_t^4 = \pi_t^4 - \pi_{t-4}^4$, $\pi_t^4 = (\pi_t + \pi_{t-1} + \pi_{t-2} + \pi_{t-3})/4$ and $x_t^4 = (x_t + x_{t-1} + x_{t-2} + x_{t-3})/4$, where x_t is a slack measure)

	Correlation			Slope (SE)		
	1960-1983	1984-1999	2000-2018q1	1960-1983	1984-1999	2000-2018q1
Ex-post slack						
Unemployment gap (CBO)	-0.52	-0.48	-0.11	-0.47 (0.11)	-0.28 (0.09)	-0.03 (0.04)
GDP gap (CBO)	-0.51	-0.35	-0.24	-0.31 (0.05)	-0.18 (0.07)	-0.06 (0.04)
Unemployment gap (two-sided filtered)	-0.57	-0.49	-0.07	-0.60 (0.13)	-0.29 (0.10)	-0.02 (0.04)
Short-term unemployment gap (two-sided filtered)	-0.53	-0.49	-0.25	-0.38 (0.08)	-0.22 (0.08)	-0.07 (0.05)
Employment-population ratio (two-sided filtered)	-0.56	-0.44	-0.02	-0.73 (0.17)	-0.24 (0.09)	-0.01 (0.04)
Employment-population ratio ages 25-54 (two-sided filtered)	-0.49	-0.44	-0.03	-0.74 (0.13)	-0.25 (0.10)	-0.01 (0.04)
Capacity utlilization rate (two-sided filtered)	-0.64	-0.45	-0.24	-0.52 (0.10)	-0.23 (0.08)	-0.07 (0.03)
Gap index	-0.57	-0.47	-0.14	-0.53 (0.10)	-0.25 (0.09)	-0.04 (0.04)
Real-time slack						
Unemployment rate	-0.49	-0.40	-0.09	-0.43 (0.09)	-0.20 (0.07)	-0.02 (0.04)
Short-term unemployment rate	-0.44	-0.35	-0.24	-0.30 (0.07)	-0.14 (0.06)	-0.08 (0.06)

Source: Authors' calculations.
Notes: All slack measures have been standardized to have the same mean and standard deviation as the CBO unemployment gap, and inverted when needed to be positively correlated with the unemployment gap; thus the slope coefficients have the same units so their magnitudes are comparable. Results for 2000-2018 go through the first quarter of 2018. Standard errors (in parentheses in the final three columns) are Newey-West with 8 lags.

Table 1 provides the correlation between $\Delta_4\pi_t^4$ and x_t^4, along with the Phillips slopes, over these three periods for all seven ex-post gaps and for the slack index. In addition, results are shown for the (not gapped) unemployment rate and the short-term unemployment rate. For these two measures, the variation in the estimated full-utilization values is fairly small relative to the variation in the activity measure, so that most of the variation in the activity measure is variation in the gap.

By each of these slack measures, the US Phillips correlation has been getting weaker and its slope has been getting flatter. This conclusion is robust to using shorter or longer temporal aggregation and to deviating π_t^4 from a *t*–4 – dated univariate forecast.

2.3 Inflation forecasts using slack over the recession and recovery

Our primary focus is on the contemporaneous Phillips relation, especially at business cycle frequencies. In this section, however, we digress to examine the possibility that alternative slack measures might produce stable and informative inflation forecasting models.

The slack measures considered so far are ex-post and thus are not suitable for a forecasting exercise. We therefore introduce some real-time gaps, where the full-utilization values are computed as a one-sided exponentially-weighted moving average, with a weight with half-life of 15 years.[5] These real-time gaps were computed for the unemployment rate, the short-term unemployment rate, the capacity utilization rate, and the two employment-population ratios. In addition, we used two non-gapped variables, the unemployment rate and the short-term unemployment rate. As an illustration, we examined the performance of these seven real-time gap measures, along with an index of these measures computed as their first principal component, in a prototypical Phillips curve forecasting model, $\Delta_4\pi_t^4 = \beta_0 + \beta_1 x_{t-4} + \beta_2\pi_{t-4}^4 + e_t^4$, where x_t is the candidate real-time gap.

Table 2 summarizes results for two illustrative forecasting exercises. The first column summarizes the results of a pseudo out-of-sample forecasting exercise, in which the forecasting model was estimated using pre-recession data (from 1984q1-2007q1) and used to forecast inflation during the recession and recovery (from 2008q1-2018q1; 2008q1 is the first fully out-of-sample date for the four-quarter ahead forecast). The table reports the root mean square forecasting error (RMSFE) in the out-of-sample period from the model including slack, relative to the RMSFE of the model with the slack measure excluded, so a relative RMSFE less than one indicates that the slack measure improved inflation forecasts over the final 17 quarters of the data. The second column reports the sup-Wald test of the hypothesis that the coefficients in this forecasting regression are stable over the 1984q1-2018q1 period.

[5] The exponential moving average filter yields real time gaps with correlations with the two-sided biweight smoothing gaps between 0.88 and 0.96 for the two unemployment rates and the capacity utilization rate; these correlations are lower (.72 and .79) for the employment-population ratio gaps, which have large nonstationary components. Similar results obtain using one-sided 15-year equal-weighted moving averages to construct the gaps, although those gaps generally have a lower correlation with the two-sided biweight gaps.

Table 2

Forecasting annual changes in PCE-xFE inflation using slack variables for the US

(four-quarter ahead direct forecasting regression: $\Delta_4\pi_t^4 = \beta_0 + \beta_1 x_{t-4} + \beta_2 \Delta_4 \pi_{t-4}^4 + e_t^4$)

Predictor slack variable	Sup-Wald test	Pseudo out-of-sample RMSFE ratio, 2008q1-2018q1
Unemployment rate	12.62**	1.517
Short-term unemployment rate	8.51**	1.052
unemployment rate (real time gap)	13.71**	1.480
short-term unemployment rate (real time gap)	9.27**	1.067
employment-population ratio (real time gap)	29.31**	1.338
employment-population ratio ages 25-54 (real time gap)	20.64**	0.989
Capacity utilization rate (real time gap)	23.05**	1.023
Real-time slack index	13.93**	1.362

Source: Authors' calculations.
Notes: The first column reports the Sup-Wald statistic (15% trimming) testing the null hypothesis that all three coefficients in the forecasting regression are stable, when estimated over the period 1984q1-2018q4. The second column is the ratio of the pseudo out-of-sample root mean squared forecast errors of the direct forecasting regression in the table header, to the RMSFE for the restricted version without the slack variable, where all regressions are estimated over 1983q1-2007q1 and the RMSFEs are computed over 2008q1-2018q1. **Rejects the null of constant coefficients at the 1% significance level.

The results in Table 2 are striking. For all but one of the real-time gap measures, using a gap *worsens* out-of-sample performance; for the sole real-time gap that improves the forecast (the employment-population ratio, ages 25-54), the improvement is negligible. For all the gap measures, the hypothesis of coefficient stability is rejected at the 1% significance level. This finding of instability, illustrated here for simple forecasting models, is in line with the literature on inflation forecasting, which stresses the prevalence of time-variation in forecasting relations using activity variables (e.g. Groen, Paap, and Ravazzolo (2013)).

The conjecture that motivated this investigation of alternative gap measures was that perhaps the apparent flattening of the Phillips curve was an artefact of focusing on a gap measure, the unemployment gap, that currently has less value than other gap measures, and that the apparent flattening would be resolved if we found the "right" gap measure. The evidence, however, does not support this conjecture. Thus, if measurement is to be the explanation, we must look not to alternative measures of slack, but rather to inflation itself.

2.4 Earnings and slack

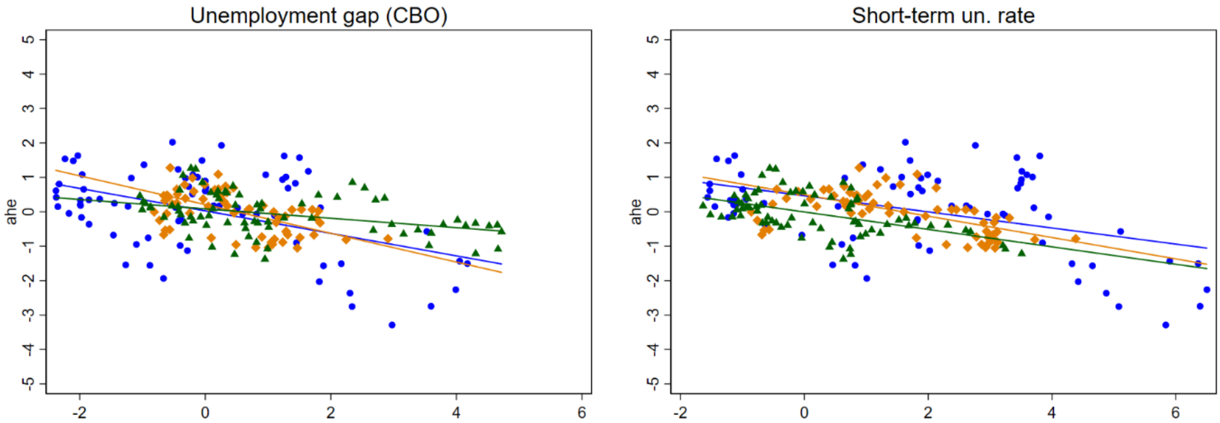
Although our focus is price inflation, we briefly digress to examine stability of the relation between wage inflation and slack measures in the US The wage measure we use is average hourly earnings of production and nonsupervisory workers (total private sector). The relationship between wage inflation and slack, especially as measured by the short-term unemployment rate, has been more stable than the corresponding price inflation-slack relationship.

Chart 5 provides two wage inflation scatterplots similar to those in Chart 4 for price inflation; the slack measures in Chart 5 are the CBO unemployment gap and the short-term unemployment rate. Tables 2.3 and 2.4 provide the results in Tables 2.1 and 2.2, but for wage inflation instead of core PCE inflation.

Chart 5

Evolution of the US wage Phillips correlation: 4-quarter change in 4-quarter average hourly earnings inflation vs. the CBO unemployment gap and the short-term unemployment rate

(1960-83 (blue dots), 1984-99 (orange diamonds), 2000-2018q1 (green triangles))



Source: Authors' calculations.
Notes: The inflation measure is the 4-quarter change from date *t*–4 to *t* in the 4-quarter rate of AHE inflation. The slack measure plots the standardized average value of the quarterly slack variable in the four quarters from date *t*–3 to date *t*.

Unlike core PCE inflation, the correlation between wage inflation and contemporaneous slack measures falls only slightly, and for some slack measures does not fall at all, from the pre–2000 period to the post–2000 period. This is consistent with the good fit found by Galí (2011) for a new Keynesian wage Phillips curve using data through 2007. For the short-term unemployment rate in particular, the relation between slack and the change in wage inflation appears to be quite stable, although there is an intercept shift consistent with a decline in the wage NAIRU in the post–2000 period.

Also unlike core PCE inflation, for which none of the forecasting relations were stable or provided improvements over the 2008-2018 period, some slack measures provide substantial improvements in the pseudo out-of-sample forecasting exercise. All the real-time slack measures except for the employment-population ratios improve upon using only lagged inflation in the out-of-sample period, especially the short-term unemployment rate, the capacity utilization rate (both real-time gaps), and the real-time slack index. This said, the hypothesis of coefficient stability is rejected for all slack measures.

Table 3

Phillips correlations and slopes for average hourly earnings inflation and various slack measures for the US

(four-quarter inflation and four-quarter moving average of slack measures)

	Correlation			Slope (SE)		
	1960-1983	1984-1999	2000-2018q1	1960-1983	1984-1999	2000-2018q1
Ex-post slack						
Unemployment gap (CBO)	-0.47	-0.52	-0.39	-0.32	-0.36	-0.14
				(0.11)	(0.12)	(0.05)
GDP gap (CBO)	-0.41	-0.42	-0.50	-0.20	-0.25	-0.19
				(0.10)	(0.11)	(0.05)
Unemployment gap (two-sided filtered)	-0.45	-0.49	-0.42	-0.39	-0.33	-0.15
				(0.14)	(0.12)	(0.04)
Short-term unemployment gap (two-sided filtered)	-0.47	-0.58	-0.51	-0.27	-0.31	-0.20
				(0.10)	(0.10)	(0.04)
Employment-population ratio (two-sided filtered)	-0.39	-0.46	-0.29	-0.41	-0.29	-0.10
				(0.21)	(0.10)	(0.06)
Employment-population ratio ages 25-54 (two-sided filtered)	-0.33	-0.40	-0.33	-0.39	-0.26	-0.12
				(0.20)	(0.12)	(0.05)
Capacity utlilization rate (two-sided filtered)	-0.41	-0.72	-0.62	-0.26	-0.43	-0.24
				(0.13)	(0.05)	(0.05)
Gap index	-0.46	-0.54	-0.46	-0.33	-0.33	-0.17
				(0.12)	(0.11)	(0.04)
Real-time slack						
Unemployment rate	-0.45	-0.51	-0.38	-0.31	-0.30	-0.14
				(0.11)	(0.11)	(0.05)
Short-term unemployment rate	-0.46	-0.54	-0.51	-0.24	-0.25	-0.25
				(0.09)	(0.10)	(0.05)

Source: Authors' calculations.
Note: See the notes to Table 1.

Table 4

Forecasting annual changes in wage inflation (average hourly earnings) using slack variables for the US

(four-quarter ahead direct forecasting regression: $\Delta_4\pi_t^4 = \beta_0 + \beta_1 x_{t-4} + \beta_2 \Delta_4 \pi_{t-4}^4 + e_t^4$)

Predictor slack variable	Sup-Wald test	Pseudo out-of-sample RMSFE ratio, 2008q1-2018q1
Unemployment rate	24.29**	0.967
Short-term unemployment rate	20.00**	0.970
unemployment rate (real time gap)	24.14**	0.947
short-term unemployment rate (real time gap)	19.89**	0.915
employment-population ratio (real time gap)	23.49**	1.046
employment-population ratio ages 25-54 (real time gap)	19.59**	1.200
Capacity utilization rate (real time gap)	11.23**	0.872
Real-time slack index	21.87**	0.925

Source: Authors' calculations.
Note: See the notes to Table 2.

3 Cyclically Sensitive Inflation in the US

We now turn to the possibility that, although the overall cyclical sensitivity of price inflation has been declining, certain goods and services remain cyclically sensitive, and thus could serve as indicators of price pressure. This section continues our focus on the US; we turn to the Euro Area in the next section.

We begin by reviewing the components, or sectors, that comprise PCE inflation. Recently there has been increasing attention to the possibility of mismeasuring prices and, as a result, inflation and productivity growth. Our interest here is in whether measurement problems could be obscuring the cyclical movements in inflation. We therefore briefly review some price measurement challenges and how they differentially affect the components of inflation. We then take up cyclical measures of slack, the cyclical properties of the inflation components, and finally the construction of the CSI index.

3.1 Components of PCE inflation

Personal consumption expenditures are expenditures on final purchases of goods and services consumed by persons, and PCE inflation measures the rate of price inflation of those goods, weighted by their share in final consumption. The US Bureau of Economic Analysis (BEA) uses 16 third-tier components of consumption (four components of durable goods, four of nondurable goods, seven of household services expenditures, and final consumption expenditures by nonprofit institutions serving households (NPISH) that pay for services then provide them to households without charge. We further decompose housing services into two components, housing excluding energy and housing energy services, for a total of 17 components.

These 17 components are listed in the first column of Table 5. The second column gives the component expenditure shares in total PCE (average over 2000s). The components with the largest shares (16% each) are housing ex utilities and health care; the percentage share weights of all other components are in the single digits. The quarterly rates of inflation for the 17 components are plotted in Chart 6.

The PCE price concept is the price paid for final consumption of a good or service. This price could be paid by the final consumer directly, or on behalf of the consumer by a company or institution (e.g. an insurance company or a nonprofit serving individuals). Price measurement confronts a number of well-known challenges, of which we focus on two: the estimation of prices when market prices are not available, and the challenge of rolling in prices on new or improved goods or services. Additional challenges include substitution bias, incomplete historical revisions for some sectors when methods change[6], updating sampling procedures (e.g. incorporating new outlets), and (perhaps) introducing prices for non-priced

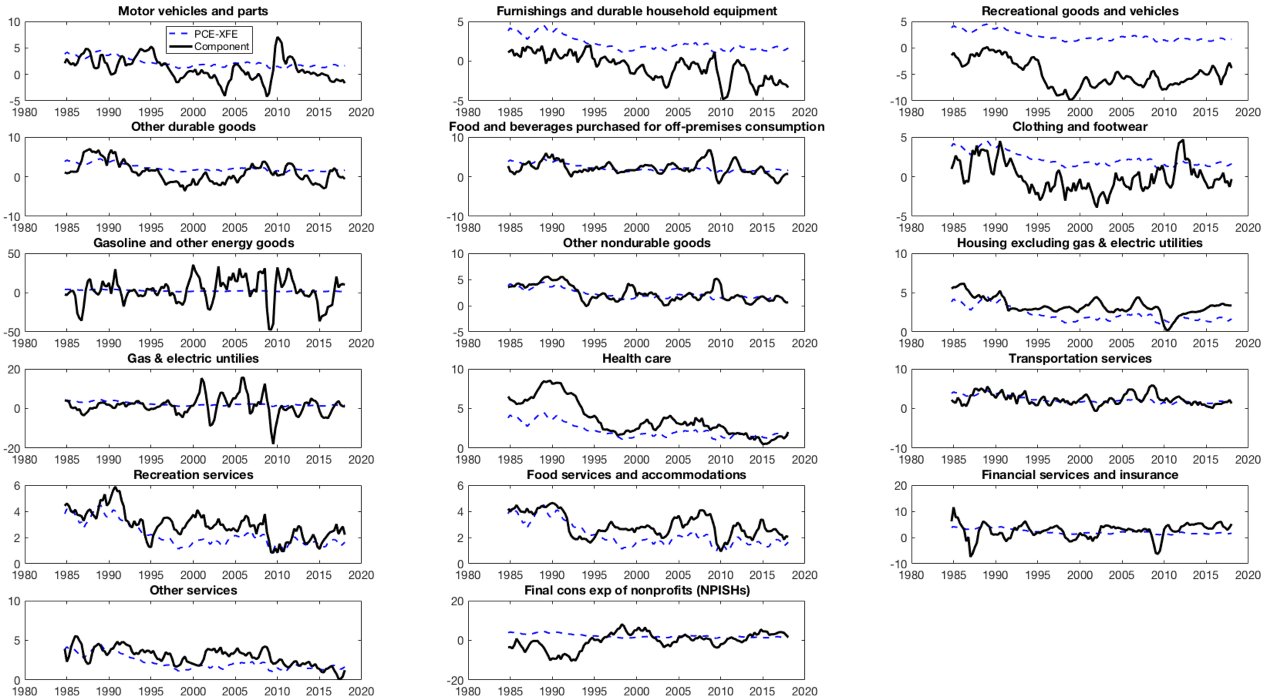
[6] For example, the 2013 PCE revision introduced a number of changes to the imputation of prices for financial services, including the use of a less volatile interest rates to measure foregone interest in accounts at commercial banks that provided unpriced conveniences. The BEA revised the series using the new methodology back to 1985, but before 1985 the series is unrevised. The large break in volatility evident in this component of inflation in 1985 in Chart A.1 is due to this partial revision (Hood (2013)).

goods provided for free to consumers by businesses (e.g. Google searches). We keep the discussion here brief and refer the reader to Moulton (2018) and US BEA (2017) for details and references.

Chart 6

The 17 PCE inflation components in the US, 1984-2018q1

(each figure plots a different inflation component and, for comparison, PCExFE inflation. All inflation rates are 4-quarter (π_{it}^{4}))



Sources: FRED and authors' calculations.

When available, posted market prices are used. Posted market prices are typically available for goods, but not for many services. For example, in the US, health care prices typically are negotiated prices not posted market prices (negotiated between health care provider organizations and insurance companies), in which case BEA and BLS attempt to estimate prices for specific packages of health services. In other cases, such as some legal services sold as final consumption (wills, real estate closings, personal legal defence fees, etc.), prices are in part estimated based on a cost approach using billable hourly rates and estimated numbers of hours for a service. An extreme example of this is the price index for unpriced services provided to the public by nonprofits, such as religious institutions, where the price for religious services (say) is estimated based on the cost of providing those services. Another example of imputation of prices where none exist (either negotiated or market) is many financial services. For example, the price of convenience services provided by a bank for checking accounts is imputed using the interest income forgone by holding a balance in a checking account instead of a non-checkable asset with a higher rate of interest; implementing this concept requires estimating the interest rate on the foregone (counterfactual) investment.

Table 5

Third-tier components of PCE inflation and their shares

Component	Share (2000s)	Subtotals
A. Well-measured		
Housing ex utilities	0.16	**0.34**
Recreation services	0.04	
Food and beverages for off-premises consumption	0.08	
Food services and accommodations	0.06	
Housing - energy utilities component	0.02	**0.05**
Gasoline and other energy goods	0.03	
B. Some information content		
Other services	0.09	**0.29**
Other nondurable goods	0.08	
Transportation services	0.03	
Motor vehicles and parts	0.04	
Other durable goods	0.02	
Furnishings and durable household equipment	0.03	
Health care	0.16	**0.16**
C. Poorly measured		
Recreational goods and vehicles	0.03	**0.17**
Clothing and footwear	0.03	
Financial services and insurance	0.08	
NPISH	0.03	

Sources: US BEA and FRED for the data, and author's judgement for the A, B, and C categories.

Another challenge for price measurement concerns new goods and quality improvements. The problem with quality improvements arises when a good reaches the end of its life cycle and is replaced by a similar, but improved, good. The new goods problem is an extreme version that arises when a new type of good becomes available, such as the introduction of smart phones. BEA has a number of strategies for addressing the new/improved goods problem. In some cases, the value of the quality improvements can be estimated using hedonic methods. In other cases, the quality improvements are estimated based on changes in production costs, however this method conflates efficiencies in production with quality improvements. In yet other cases, new goods are chained in without an attempt to quality-adjust. The challenges posed by new/improved goods problem is often raised in the context of IT goods, but it includes low-tech as well as high-tech goods. For example, clothing typically has a short life cycle stemming from changing fashions, and prices for a given good (say, a specific shirt) decline over time as it gets marked down; at some point, the good disappears as new goods (new shirts) are introduced.[7]

[7] A third challenge, which has been the subject of considerable attention recently, is the free goods problem. This issue is frequently raised in the context of IT services provided for free, such as services provided by free apps or Google searches. The free goods problem also is not new: television provides free goods too. Whether to address the free goods problem raises basic questions about whether NIPA accounting measures welfare (if so, they should be included) or market-based economic activity (if so, they should not). Here we stick to the standard concept of market-based activity so do not venture into the realm of free goods.

Based on these and related considerations, and on discussions with experts on price measurement in the US government and elsewhere, we categorized the 17 PCE components into three working categories, A, B, and C, and grouped the components in Table 5 accordingly.

Category A consists of components that have relatively well measured prices. Prices in these categories tend to be market prices, and the new goods problem (while present) is relatively less pronounced than in other categories. For example, rents (the basis for the housing inflation index) are measured using a rotating survey of a panel of housing rental units with low turnover, and are adjusted for improvements in the units.[8]

Category B contains components which in our judgement have some information content, but for which either the new goods or non-market price problems are potentially substantial. For example, health care prices are measured using (typically negotiated) prices actually paid for specific representative health care goods, but are not adjusted for quality based on outcomes so arguably understate quality improvements.

Category C components are ones that in our judgement have very significant measurement issues, including new/improved goods problems (IT equipment, which falls under recreational goods and vehicles, and clothing) and/or rely mainly on imputed nonmarket prices (like the price index for services provided for free by nonprofit institutions serving households [NPISH]).

3.2 Cyclical activity measures

As discussed in Section 2, a basic challenge of measuring slack in real time is that slack, as measured by a gap, represents a departure of the actual value of an activity variable from a full-capacity value of that variable, such as the departure of the unemployment rate from the NAIRU. However, the full-capacity value is never observed, so the gap also is unobserved. In addition, at shorter horizons, gaps can be noisy because of measurement error or transitory disturbances. Thus, gap measures of slack have the twin challenges of requiring a low-frequency full-utilization rate and smoothing over higher frequency noise.

For the construction of cyclically sensitive inflation, we handle these twin challenges by using a time series filter to extract the movements of activity variables that are of the primary economic interest, those that occur over time horizons typical of the business cycle. Specifically, for an activity measure x_t we filter x_t using a band-pass filter with pass band of 6-32 quarters (the filter is described in the Appendix). The band-bass filtered version of x_t, which we denote x_t^{BP}, eliminates low-frequency trends so in this sense is like a gap measure, where the “trend” consists of

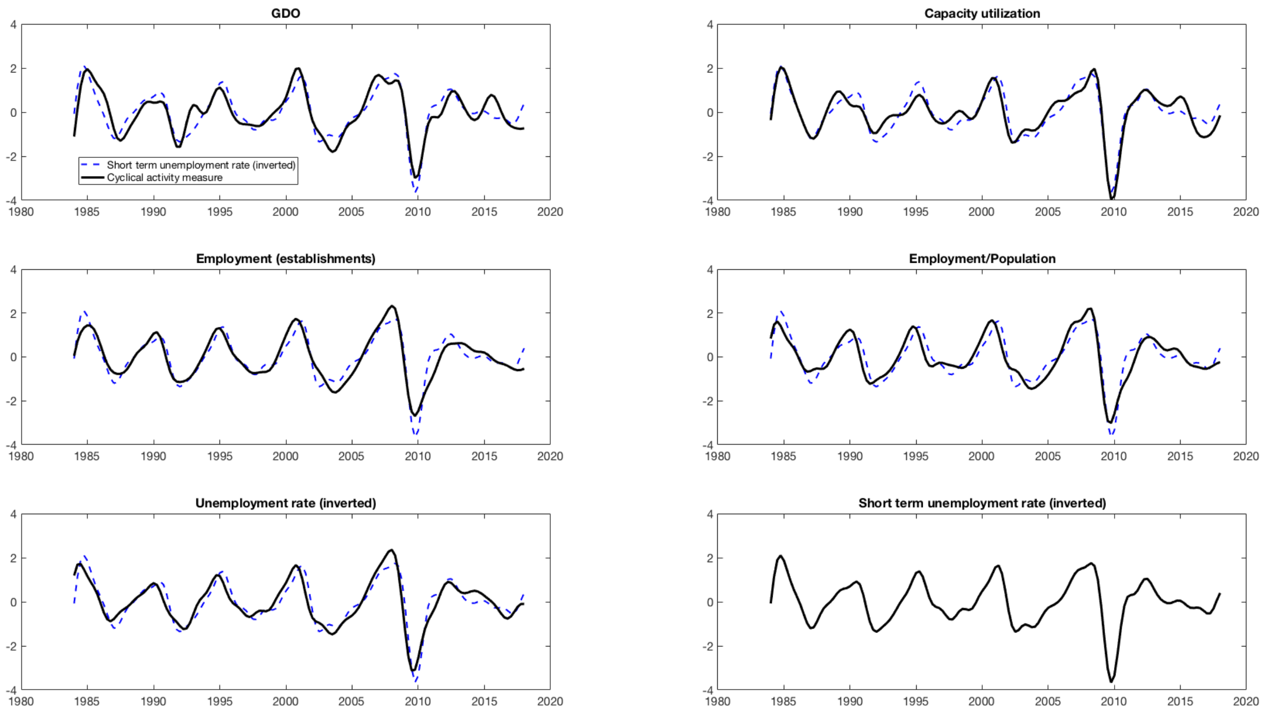
8 For owner-occupied housing, the housing services component treats the price the owner pays as the rents the owner would pay to herself, where those rents are imputed based on rents for comparable homes in the local market. This imputation introduces imputation error, especially for more expensive homes for which the rental market is thin. Nevertheless, the imputation is based on actual rental prices so the imputation simply places greater weight on some rental units than others.

fluctuations with a period of longer than 32 quarters. In addition, it smooths over high-frequency fluctuations including noise from survey measurement error. Loosely, this band-pass filtered version of x_t is like a gap measure, where the full-capacity value is computed using a two-sided filter and it is smoothed to eliminate noise. Like the *ex-post* gap measures of Section 2, x_t^{BP} is a full-sample measure (a two-sided filter), and thus is least reliable at the end of the sample (where the filter is necessarily one-sided).

Chart 7

Cyclical activity measures for the US

(each figure plots a different cyclical activity measure (black) and the short-term unemployment rate cyclical activity measure (blue))



Sources: FRED and authors' calculations.
Notes: The cyclical activity measures are band-pass filtered of the various activity variables, using a pass band of 6-32 quarters as explained in the Appendix. The band-pass filtered series are standardized to have mean zero and unit variance. The unemployment rates are multiplied by -1 so that they co-vary positively with the output gap.

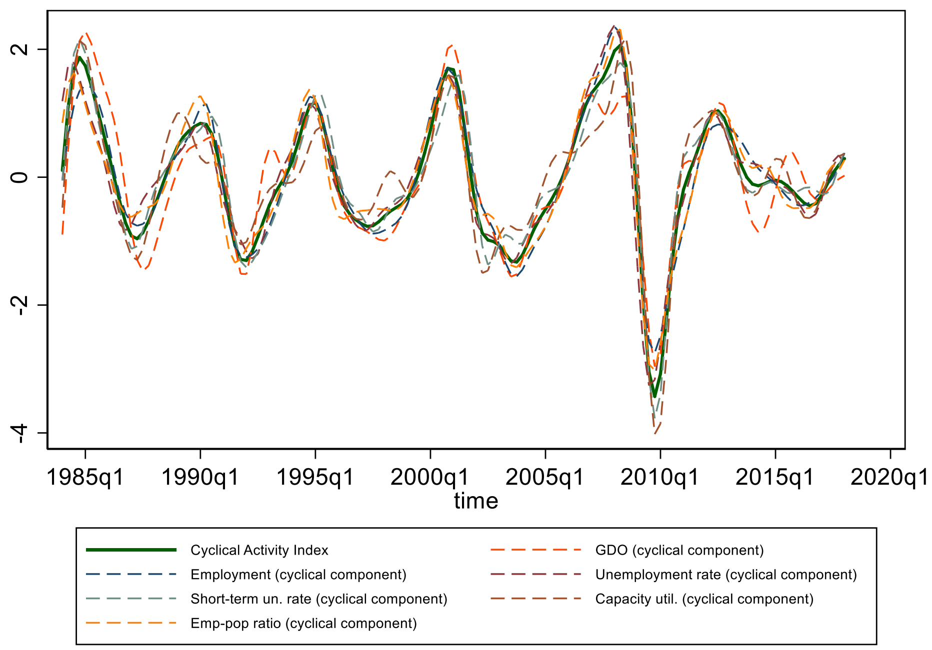
We consider six activity variables: Gross Domestic Output (GDO, the geometric average of GDP and Gross Domestic Income, see Nalewaik, 2010), the capacity utilization rate, establishment employment, the employment-to-population ratio (household survey), the unemployment rate, and the short-term unemployment rate. The band-pass filtered cyclical measures computed from these six variables are plotted in Chart 7. To facilitate subsequent visual comparisons with inflation, the cyclical activity variables are standardized to have the same mean and standard deviation, and the unemployment rate activity variables are multiplied by -1 to co-vary positively with output. (Note that this "output gap" sign convention is the opposite of the "unemployment gap" sign convention in the previous section.)

The six cyclical activity measures are evidently very similar, however they exhibit different timing, as can be seen by comparing each measure to the cyclical component of the short-term unemployment rate (shown for reference in each panel). The cyclical components of the short-term unemployment rate, GDO, and capacity utilization are approximately contemporaneous, however establishment employment, the employment-population ratio, and the unemployment rate each lag the short-term unemployment rate by 2 quarters.

We use these six series to construct a composite index of cyclical activity, computed as the first principal of the second lag of the short-term unemployment rate, GDO, and capacity utilization, and the unlagged value of the other three cyclical measures. This composite activity index (CAI) is plotted in Chart 8, along with the six constituent cyclical activity measures (in three cases, lagged two quarters). The composite index explains 92% of the variation (trace R2) of its six constituent cyclical activity measures.

Chart 8

Cyclical activity measures for the US and the cyclical activity index



Source: Authors' calculations.
Notes: The six cyclical activity measures are the band-passed filtered activity variables listed in the legend. The cyclical activity index is the first principal component of the six cyclical activity measures. The capacity utilization rate is lagged two quarters, and the unemployment rate and short-term unemployment rate are lagged two quarters and normalized to co-vary positively with the output gap.

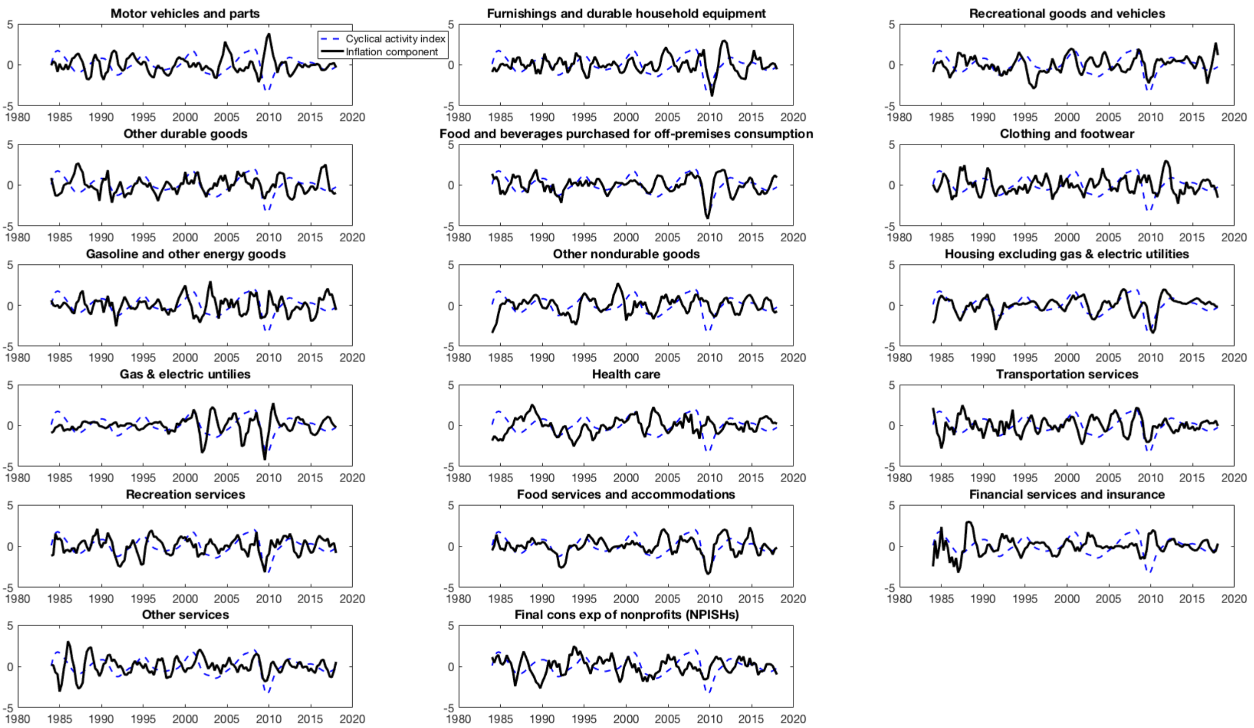
3.3 Cyclical properties of inflation components

We begin our examination of the variation in cyclical properties of sectoral inflation by comparing movements in the four-quarter change of four-quarter inflation to the composite index of cyclical activity (the CAI). These series are plotted in Chart 9 for the 17 components. The correlations between the inflation components and the cyclical index are given in Table 6 for band-pass filtered inflation (first column) and the four-quarter change of four-quarter inflation (second column). Recall that the CAI sign convention is the “output gap” sign convention, so positive comovement (procyclical inflation) corresponds to a downward-sloping Phillips relation.

Chart 9

Seventeen inflation components and the composite index of cyclical activity

(four-quarter change of four-quarter inflation ($\Delta_4\pi_{it}^4$), standardized to have mean zero and unit standard deviation)



Sources: FRED and authors’ calculations

The variation across components in the cyclical comovements of inflation and activity is striking. For some components, cyclical inflation (i.e. band-pass filtered) is very highly correlated with the cyclical activity index; these sectors include food services and accommodations (correlation = 0.67) and housing excluding energy (also 0.67), Other components, however, either exhibit little cyclical variability or vary countercyclically. These noncyclical components include other nondurable goods, transportation services, health care, gasoline and other energy goods, clothing and footwear, and financial services and insurance. Motor vehicles and parts is countercyclical, a feature that is largely driven by the price jump in used cars in October 2009 following the end of the “cash for clunkers” program. For most components, correlations for four-quarter changes of four-quarter inflation are lower than for band-passed inflation, however they show the same pattern across components as do the band-pass inflation correlations.

These correlations and plots are consistent both with cyclical sensitivity varying across sectors and with the quality of measurement varying across sectors. The sectors with the highest cyclical correlations tend to be dominated by services that have prices determined in local (non-tradable) markets and which are relatively well-measured: housing services, recreational services, and food services and accommodations. Food and beverages off-premises is relatively well-measured and although raw commodity prices are set internationally, there is a substantial local (non-tradeable) component of food prices.

Table 6

Correlations between inflation components and the cyclical activity index, and CSI weights, 1984-2018q1

Component	Correlation between cyclical activity index and:		CSI weight
	Band-pass inflation	4-qtr change in 4-qtr inflation	(w_i)
Motor vehicles and parts	-0.24	-0.37	0.000
Furnishings & durable household equipment	0.28	0.10	0.000
Recreational goods and vehicles	0.34	0.25	*excluded*
Other durable goods	0.24	0.10	0.000
Food and beverages purchased for off-premises consumption	0.56	0.43	0.159
Clothing & footwear	-0.03	-0.08	*excluded*
Gasoline & other energy goods	-0.01	-0.04	0.000
Other nondurable goods	0.08	0.06	0.000
Housing excluding gas & electric utilities	0.67	0.48	0.629
Gas & electric utilities	0.23	0.13	0.022
Health care	-0.03	-0.11	0.000
Transportation services	0.04	0.02	0.000
Recreation services	0.41	0.28	0.086
Food services & accommodations	0.67	0.46	0.036
Financial services & insurance	-0.04	-0.12	*excluded*
Other services	0.09	0.15	0.069
NPISH	0.27	0.14	*excluded*

Source: FRED
Notes: CSI weights are estimated by nonlinear least squares estimation of the regression in Equation (1), using the 13 Category A and B components of PCE inflation.

The sectors with the smallest cyclical correlations tend to be internationally traded goods (e.g. gasoline); sectors with prices that are heavily influenced by internationally traded goods (e.g. transport services, for which a cost is energy prices); sectors with managed or negotiated prices (health care and transportation services); and/or sectors with prices that are poorly measured (financial services and insurance and clothing & footwear). The components of other services prices are in many cases estimated using costs (e.g. attorneys' hourly costs), and the low correlation of that sector might be a consequence of the cost-based imputation missing cyclical variation in markups. One surprising finding is the procyclicality of NPISH inflation, which might stem from procyclicality of the costs used to impute NPISH prices rather than actual procyclicality of those prices (recall that those prices in fact do not exist because these services are provided without charge).

3.4 Cyclically Sensitive Inflation

We now turn to the construction of the Cyclically Sensitive Inflation (CSI) index. We exclude on a-priori grounds the four Category C components in Table 5 (the most poorly measured components), so we use only the thirteen components in Category A and B.

Our benchmark CSI index is a weighted average of the thirteen component rates of inflation, where the weights maximize the correlation between the composite index of cyclical activity and the four-quarter change in the four-quarter moving average of the index, subject to the constraint that the weights are positive and add to one. These weights are estimated by nonlinear least squares estimation of the regression,

$CAI_t = \beta_0 + \beta_1 \sum_{i=1}^{13} w_i \Delta\pi_{it}^4 + u_t$, subject to $0 \leq w_i \leq 1$ and, $\sum_{i=1}^{13} w_i = 1$ (1)

where *CAI* is the composite index of cyclical activity. The quarterly CSI rate of inflation is $\pi_t^{CSI} = \sum_{i=1}^{13} \hat{w}_i \pi_{it}$.

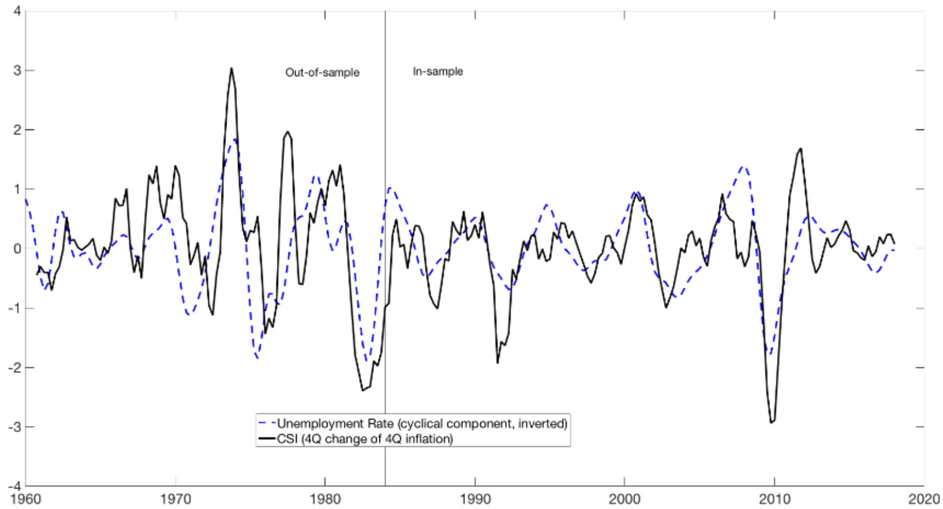
The CSI weights on sectoral inflation, estimated over the 1984-2018q1 sample, are reported in the final column of Table 6. The estimates place nonzero weight on only a few sectors: two-thirds of the weight is placed on housing ex energy, 16% is placed on food and beverages off-premises, with the remaining weight spread over recreation services, other services food services & accommodations, and the energy component of housing services. The only goods component that enters the CSI index is food and beverages off-premises. Notably, 93% of the weight in the CSI index is on the relatively well-measured Category A series, even though those components comprise only 39% of consumption.

Chart 10 plots the four-quarter change in the resulting four-quarter CSI inflation index, along with the normalized standardized band-passed unemployment rate, over the period 1960-2018 (we use the band-passed unemployment rate here because the cyclical activity index starts in 1967, when the capacity utilization rate becomes available). The vertical line in the chart marks the start of the 1984-2018 sample over which the weights were estimated; for the 1984-2018 sample, the CSI index in Chart 10 is the in-sample predicted value from estimation of regression (1). In the 1960-1983 period, the CSI was computed by applying the 1984-2018 weights in Table 6 to the historical values of the PCE components.

Chart 10

Four-quarter change in four-quarter CSI inflation ($\Delta_4\pi_t^{CSI,4}$) and the normalized cyclical component of the unemployment rate, 1960-2018

(CSI inflation is computed using weights estimated over 1984-2018 (after the vertical line))



Sources: FRED and authors' calculations.

Because the CSI weights were estimated over the 1984-2018 sample, the 1960-1983 sample provides an opportunity to assess the cyclical stability of CSI inflation. Inspection of Chart 10 suggests that the cyclical properties of CSI inflation are stable in the pre-estimation sample. The correlation between the two series in Chart 10 is 0.57 in both the estimation (1984-2018) and pre-estimation (1960-1983) samples. A regression test of the stability of this relationship in and out of sample does not reject stability at the 10% significance level. Similar stability results are found for the other band-pass filtered activity variables.

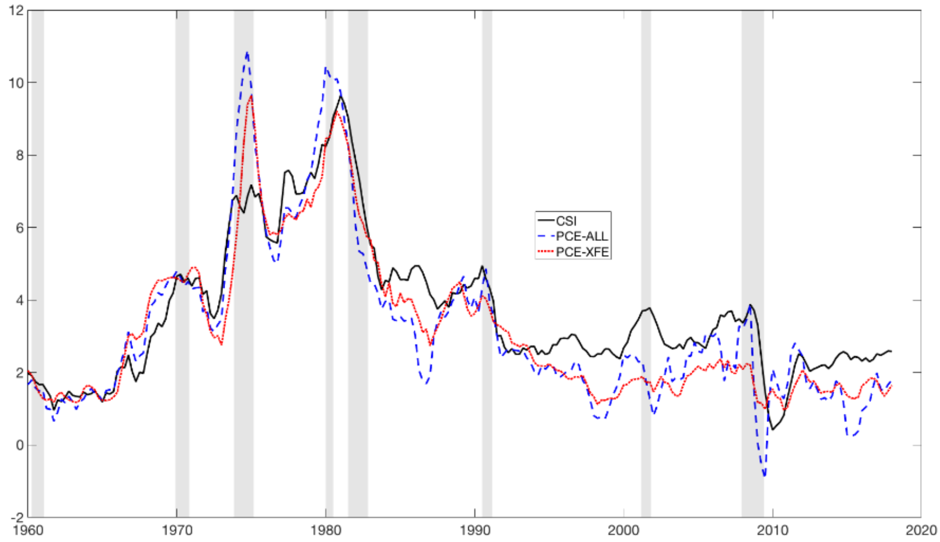
There are a number of reasons why these correlations might be smaller in the 1960-1983 out-of-sample period than in the estimation period, including the supply-side sources of the inflation shocks of the 1970s, differences in monetary policy regimes, and changes in the relative quality of measurement of the components. In this light, this stability of the cyclical behaviour of the CSI index in the pre-estimation period suggests that its cyclical behaviour could be stable in the post-estimation period as well.

Chart 11 plots CSI inflation (in levels) along with headline PCE and PCE-xFE inflation. We note three features of Chart 11.

First, CSI has more pronounced cyclical movements than the other measures, especially towards the end of the last three expansions: CSI rises as the cyclical peak approaches and subsequently falls during the recession and the early recovery. This pattern is evident in every recession since 1960, except for the brief first recession of the twin recessions of the 1980s.

Chart 11

US four-quarter inflation rates for the US: PCE, PCExFE, and CSI



Sources: FRED and Authors' calculations.
Note: Shading denote NBER recessions.

Second, the relationship between CSI inflation and the two other inflation series changes over time. During the 1960s and early 1970s, the three inflation measures moved together. Starting in the early 1980s, however, CSI inflation frequently diverged from the headline and core. For example, the during the 1990s core and headline declined while CSI inflation remained constant, then CSI inflation rose substantially towards the end of the 1990s expansion. CSI inflation also shows stronger cyclical behaviour than core around the financial crisis recession. These changing patterns are summarized in Table 7, which reports correlations between the band-passed unemployment rate and four-quarter changes in four-quarter inflation for CSI, headline, and core. Both core and headline were strongly cyclical in the 1970s, but much less so since 1984, in contrast to CSI inflation which is cyclical in all three periods.

Table 7

Correlations between the band-passed unemployment rate and various inflation measures

(four-quarter difference of four-quarter inflation)

Inflation measure	1960-1983	1984-1999	2000-2018q1
PCE-all	0.69	0.18	0.27
PCE-xFE	0.46	-0.03	0.27
CSI	0.57	0.41	0.64

Source: Authors' calculations.

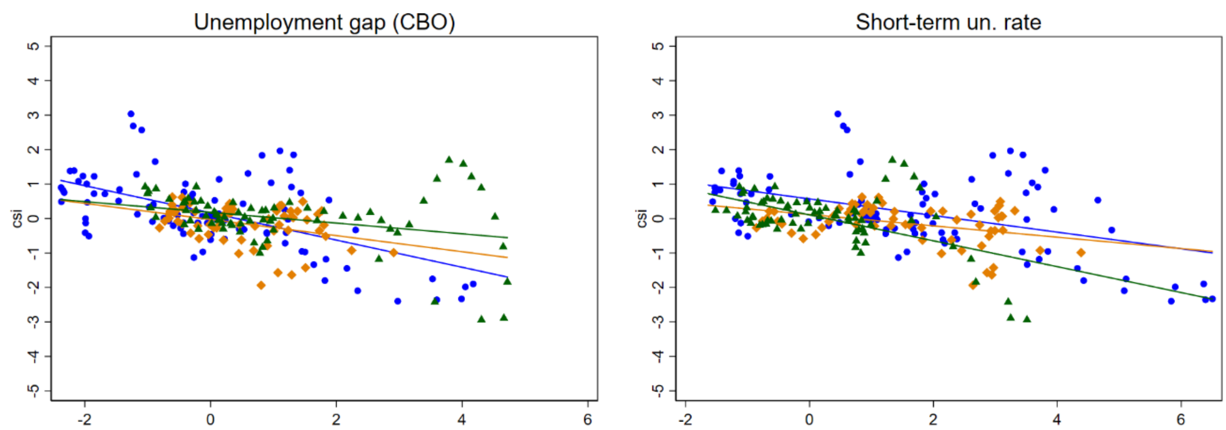
Third, the CSI index seems to be less sensitive to energy prices than headline or even core inflation. For example, CSI inflation did not move appreciably during the oil price jump of 1973, although both headline and core spiked, nor did it fall by as much as headline or core during the oil price collapse of 1986. Neither CSI nor core PCE inflation fell during the oil price decline of 2014-15.

One of the motivations for this investigation was the flattening of the Phillips curve and the declining Phillips correlation using conventional measures of inflation and a variety of slack measures, so it is of interest to examine whether this phenomenon is also true for CSI inflation. Chart 12 provides two Phillips scatterplots, which can be compared directly to their PCExFE counterparts in the first row of Chart 4. Table 8 computes Table 1 using CSI inflation instead of PCExFE. For all the slack measures except the employment-population ratio, the Phillips correlation and slope is stable across the 1984-1999 to 2000-2018 samples (although the slopes are imprecisely estimated), and the correlations are substantially larger with CSI than with PCExFE.

Finally, we note that the behaviour of CSI and core PCE inflation has differed since 2014: From 2013q4 through 2018q1, four-quarter core PCE inflation was unchanged at 1.5%, but CSI inflation increased from 2.1% to 2.6%.

Chart 12

Evolution of the US CSI inflation Phillips correlation: 4-quarter change in 4-quarter CSI inflation vs. the CBO unemployment gap and the short-term unemployment rate



Source: Authors' calculations.
Notes: The inflation measure is the 4-quarter change from date *t*–4 to *t* in the 4-quarter rate of CSI inflation. The slack measure plots the standardized average value of the quarterly slack variable in the four quarters from date *t*–3 to date *t*.

Table 8

Phillips correlations and slopes for average hourly earnings inflation and various slack measures for the US

(four-quarter inflation and four-quarter moving average of slack measures)

	Correlation			Slope (SE)		
	1960-1983	1984-1999	2000-2018q1	1960-1983	1984-1999	2000-2018q1
Ex-post slack						
Unemployment gap (CBO)	-0.61	-0.34	-0.32	-0.42	-0.21	-0.15
				(0.10)	(0.10)	(0.15)
GDP gap (CBO)	-0.62	-0.54	-0.49	-0.29	-0.29	-0.25
				(0.08)	(0.13)	(0.14)
Unemployment gap (two-sided filtered)	-0.64	-0.36	-0.31	-0.52	-0.23	-0.15
				(0.12)	(0.10)	(0.15)
Short-term unemployment gap (two-sided filtered)	-0.61	-0.46	-0.54	-0.34	-0.22	-0.29
				(0.09)	(0.10)	(0.13)
Employment-population ratio (two-sided filtered)	-0.59	-0.32	-0.19	-0.59	-0.18	-0.09
				(0.15)	(0.10)	(0.12)
Employment-population ratio ages 25-54 (two-sided filtered)	-0.50	-0.28	-0.24	-0.57	-0.17	-0.12
				(0.15)	(0.11)	(0.14)
Capacity utilization rate (two-sided filtered)	-0.70	-0.47	-0.64	-0.43	-0.25	-0.35
				(0.08)	(0.12)	(0.11)
Gap index	-0.65	-0.42	-0.41	-0.46	-0.23	-0.20
				(0.11)	(0.10)	(0.15)
Real-time slack						
Unemployment rate	-0.56	-0.32	-0.30	-0.38	-0.17	-0.15
				(0.11)	(0.09)	(0.15)
Short-term unemployment rate	-0.52	-0.34	-0.53	-0.27	-0.14	-0.36
				(0.09)	(0.09)	(0.17)

Source: Authors' calculations.
Notes: See the notes to Table 1.

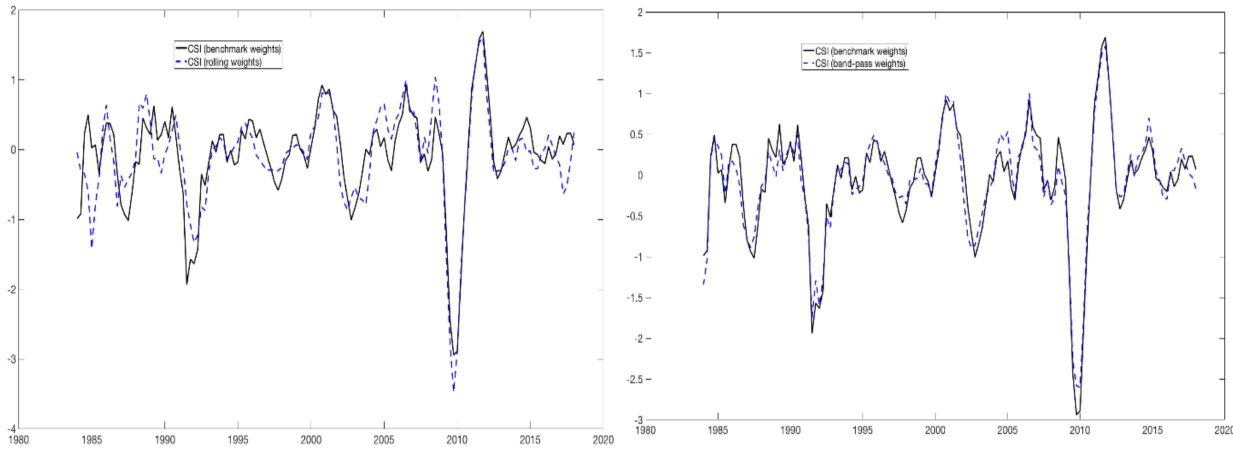
3.5 Sensitivity analysis

We summarize five sets of sensitivity checks.

First, the estimates reported above were computed using the full 1984-2018q1 sample, and it is of interest to whether and how the weights and the resulting CSI inflation have been stable over time. We therefore recomputed the CSI measure by estimating Equation (1) using rolling regressions with a 60-quarter window. The resulting rolling CSI inflation is compared with the full-sample CSI index in the left panel of Chart 13, which plots both series as 4-quarter changes in 4-quarter inflation. Although there is substantial time variation in the rolling weights themselves, the components that receive weights do not differ substantially over time (most weight is put on housing, food & accommodation services, food & beverages off-premises, and recreation services), and the predicted changes in CSI inflation differ little between the full- and rolling-sample estimates. This finding that the weights are unstable, but the CSI inflation estimate is not, seems to be a consequence of the relatively high correlation among those components that receive weight.

Chart 13

Sensitivity checks: 4-quarter changes in 4-quarter CSI inflation using rolling (left) and band-pass (right) estimates of weights



Sources: FRED and authors' calculations.
Notes: For the left figure, the weights were estimated using rolling regressions with a 60-quarter window. For the right figure, the weights were estimated using the 13 band-passed components of inflation as the regressors, instead of four-quarter changes of four-quarter inflation.

Second, the benchmark CSI computed using Equation (1) uses four-quarter changes of 4-quarter sectoral inflation. An alternative approach is to estimate the weights using band-passed sectoral inflation instead, then using those weights to compute CSI from the component quarterly inflation series. The resulting CSI, using band-pass weights, is plotted in the right panel of Chart 13, also in 4-quarter changes of 4-quarter inflation. Evidently using band-pass inflation instead of 4-quarter changes of 4-quarter inflation to estimate the weights makes little difference.

Third, we excluded the four Category C components on *a-priori* grounds because they are poorly measured. As a check, we re-estimated the CSI using all 17 components. Of the four poorly-measured components, only recreational goods and vehicles entered with non-negligible weight (0.07), otherwise the 13- and 17-component CSI index weights are similar, with housing ex energy, food & beverages off-premises, and food services & accommodations getting the most weight (in that order). As can be seen in the left panel of Chart 14, this change has negligible effect. The correlation between the 13- and 17-component indexes (four-quarter differences of four-quarter inflation) is 0.98 on the 1984-2017 estimation sample. We prefer the 13-component index on *a-priori* measurement grounds but take these results as indicating that estimated CSI is insensitive to these judgements about measurement quality.

Fourth, the band-passed activity measures are one measure of slack that complements more familiar *ex-post* gap measures such as the CBO unemployment gap. To see whether the CSI is sensitive to using a traditional definition of slack, we re-estimated the CSI index using the slack index from Section 2.1 (the first principal component of the seven standardized ex-post gap measures, see Chart 3) as the dependent variable instead of the band-pass filtered CAI. As seen in the right panel of Chart 14, the resulting CSI index differs from the CSI index estimated using the CAI as the dependent variable. To inform the choice of which slack measure to use, we considered an index consisting of the CIA and the CBO unemployment and GDP gaps, and estimated the weights of that index simultaneously with the CSI weights. The results placed 80% of the weight on the CAI and yielded a CSI very nearly the same as the CSI using the CAI alone. These results merit additional discussion. Because they are similar to ones for the EA, we defer that discussion to Section 4.

Chart 14

Sensitivity checks: 4-quarter changes in 4-quarter CSI inflation using all 17 components (left) and the gap index as the dependent variable (right)

Sources: FRED and authors' calculations
Notes: 17-component CSI inflation weights are estimated using all 17 components in Table 9. The gap CSI (right) is estimated using the gap index as the dependent variable, using the 13 better-measured components.

Fifth, the single cyclical activity index imposes either no or second lags (only) of the component cyclical activity variables. As an alternative, we estimated the CSI weights to maximize the correlation between the 13 component inflation series (4-quarter changes of 4-quarter inflation, and alternatively band-passed) and the 6 real activity variables including 0-3 lags each for a total of 24 activity indicators. The weights were restricted to be between 0 and 1 and each set of weights (on inflation, and on activity) were restricted to sum to one, so this method corresponds to maximizing the restricted canonical correlation. The resulting activity index is numerically very close to the composite cyclical activity index used in our benchmark estimation, as is the resulting CSI (results not shown).

4 CSI for the Euro Area

Our analysis of inflation components in the Euro Area (EA) parallels that in Section 3 for the US. Although the methods are the same, there are two important differences in the data. First, as discussed in Section 3.1, the HICP components are different than the US PCE components, most importantly the purpose-based tier-two HICP components mix goods and services and do not break out energy goods separately as is done in the product-based PCE. This has implications for the construction and interpretation of CSI. Second, the quarterly HICP data begin in 1996q1 so the data span is shorter, with fewer cyclical movements, resulting in less precise estimation.

4.1 HICP components

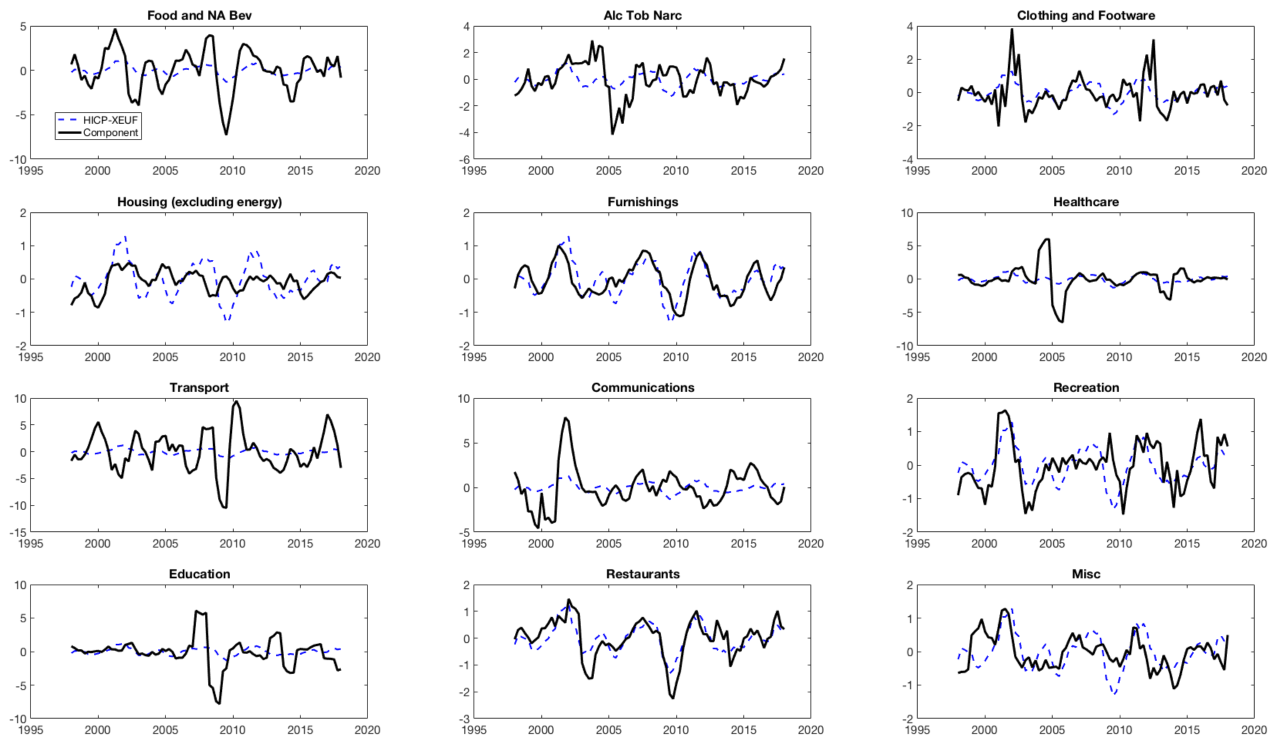
We use the 12 tier-two HICP components with a modification for housing, where we use housing excluding energy.

The organization of sectoral HICP is different than for US PCE: the tier-two HICP components are organized by purpose of expenditure rather than by product type (goods and services). The key implication for our analysis is that the HICP components generally contain both goods and services. For example, HICP transport includes transportation services (air, train, bus), fuel purchased by households (diesel and gasoline for cars), and purchases of automobiles. In addition, the coverage concept is also different: the consumption concept for PCE is all final consumption by households, whereas the HICP concept is household final monetary consumption expenditure (Eurostat (2018)). Thus, among other things, the HICP concept (like the US CPI) excludes consumption provided for free to consumers by nonprofit institutions (NPISH in the US).

Chart 15

The 12 second-tier HICP components: four-quarter inflation for the Euro 19 countries

(component inflation (black) and HICPxEUF inflation (blue), 4-quarter moving average)



Sources: Eurostat and authors' calculations

Another difference is that the Eurostat component data are provided only in non-seasonally adjusted form. We handle the seasonality by using 4-quarter changes and/or 4-quarter moving averages of the quarterly data. This amounts to assuming constant multiplicative seasonal factors in the levels of the indexes.

The tier-two quarterly HICP component series are available starting 1996q1.[9] The 1997q1-2018q1 quarterly component rates of four-quarter inflation are plotted in Chart 15, along with HICPxEUF (HICP excluding energy and unprocessed food).

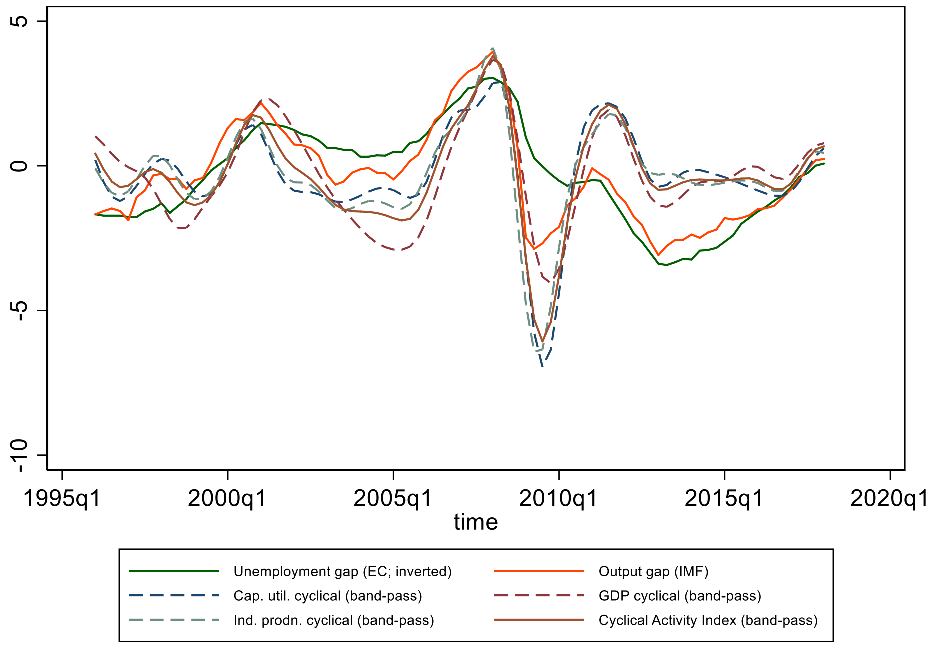
4.2 Euro Area measures of cyclical activity

We construct three cyclical activity variables for the EA using EA GDP, the EA harmonized unemployment rate (inverted), and EA capacity utilization, all band-pass filtered as described in Section 3.2. We standardize these three series and compute an EA index of cyclical activity as the simple average of these three cyclical measures. The three constituent series and the index are plotted in Chart 16. Evidently, the three activity variables all co-move strongly at business cycle frequencies, and their co-movements are generally well captured by the single index.

Chart 16

Cyclical activity variables, the Cyclical Activity Index, and ex-post gaps for the Euro Area

(all variables are transformed to have the same mean and standard deviation as the IMF percentage output gap, and the cyclical activity index is the equal-weighted average of the three band-passed cyclical activity variables)



Sources: EUROSTAT and authors' calculations.
Notes: The cyclical activity measures are band-passed versions of the indicted series, with a pass band of 6 to 32 quarters, as described in the Appendix.

As a comparison, Chart 16 also plots the EA unemployment gap (using the European Commission NAWRU) and the EA output gap (computed using the IMF

9 Some of the lower level components from which the tier-two components are constructed are initially missing, and not all sub-components are available until 2001q1. As a result, the coverage of some of the tier-two inflation rates changes over the first few years of the sample.

potential output series).[10] The gap series and band-pass series broadly move together but with several differences that are important for interpreting the results. Most importantly, the swings in the band-pass series are higher frequency than the *ex-post* gap series. Thus the cyclical series have been roughly neutral since 2013, whereas the gaps have only become roughly neutral in the past year. Mechanically, this is a consequence of the gaps being deviated from a very slowly-moving potential series, whereas the band-pass filter in effect subtracts off a more volatile trend. All the variables – gaps and band-pass – suggest that EA conditions are currently neutral to tight.

4.3 Cyclical sensitivity of EA inflation components

The 12 inflation components are plotted in Chart 17, along with the EA cyclical activity index. The correlations between these components and the activity index is given in the first column (for band-passed inflation) and second column (for 4-quarter changes of 4-quarter inflation) of Table 9.

Although there is less heterogeneity of the cyclical comovements of sectoral inflation with the cyclical activity index, some components are more cyclically sensitive than others. Restaurants & hotels and food & non-alcoholic beverages and show strong procyclical movements, as does furnishings & household items. Some components show little cyclicality, notably health care and communications (which includes postal and telephone services, and telephone equipment).

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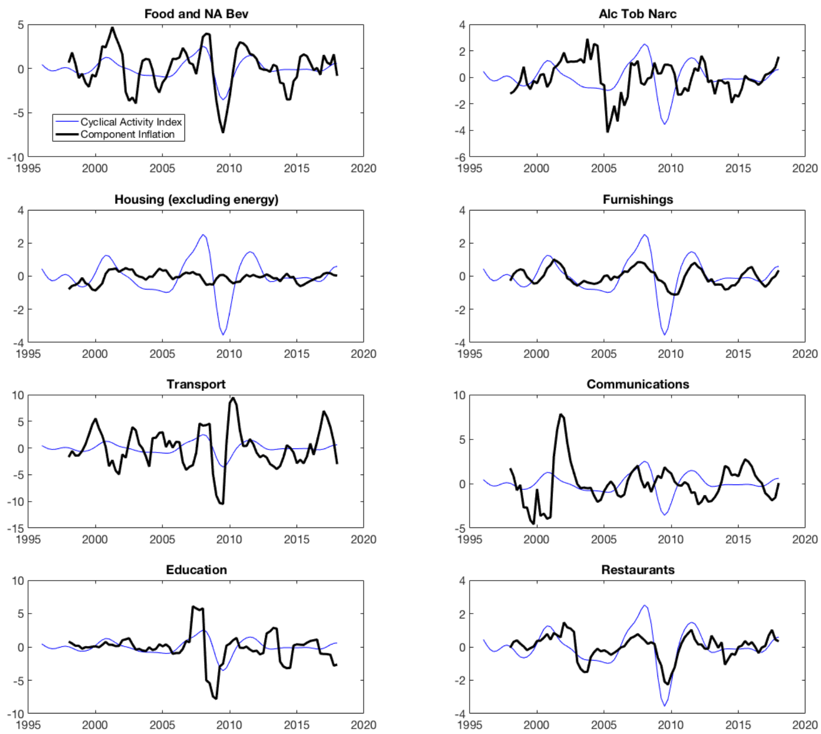
[10] Both the EC NAWRU and IMF potential output are annual series. We used linear interpolation and distribution, respectively, to obtain quarterly values, and the quarterly gaps were computed as deviations of the seasonally adjusted series from their respective potential values.

Chart 17

Components of HICP inflation and the EA cyclical activity index

(component inflation is 4-quarter difference of 4-quarter inflation)



Sources: Eurostat and authors' calculations.

Table 9

Components of HICP for the Euro area: correlations with the cyclical activity index and CSI weights, 1997-2018q1

Component and HICP code	Consumption share (2018)	Correlation between cyclical activity index and 4-qtr change in 4-qtr inflation	CSI weight (w_i)
Food & non-alcoholic beverages (01)	0.155	0.73	0.125
Alcohol, tobacco, & narcotics (02)	0.040	-0.05	0.000
Clothing & footwear (03)	0.059	0.16	0.000
Housing excluding energy (04x)	0.064	0.02	0.000
Furnishings, household items, & routine maintenance (05)	0.062	0.63	0.440
Health (06)	0.048	0.12	0.042
Transport goods & services (07)	0.154	0.21	0.043
Communications (08)	0.032	-0.06	0.000
Recreation & culture (09)	0.092	0.24	0.000
Education (10)	0.010	0.27	0.011
Restaurants & hotels (11)	0.098	0.72	0.338
Misc. goods & services (12)	0.092	0.35	0.000

Sources: EUROSTAT and authors' calculations.
Notes: CSI weights are estimated by nonlinear least squares estimation of the regression in Equation (1), using the 11 non-housing HICP second tier components and housing excluding energy (which we refer to as (HCIP–04x).

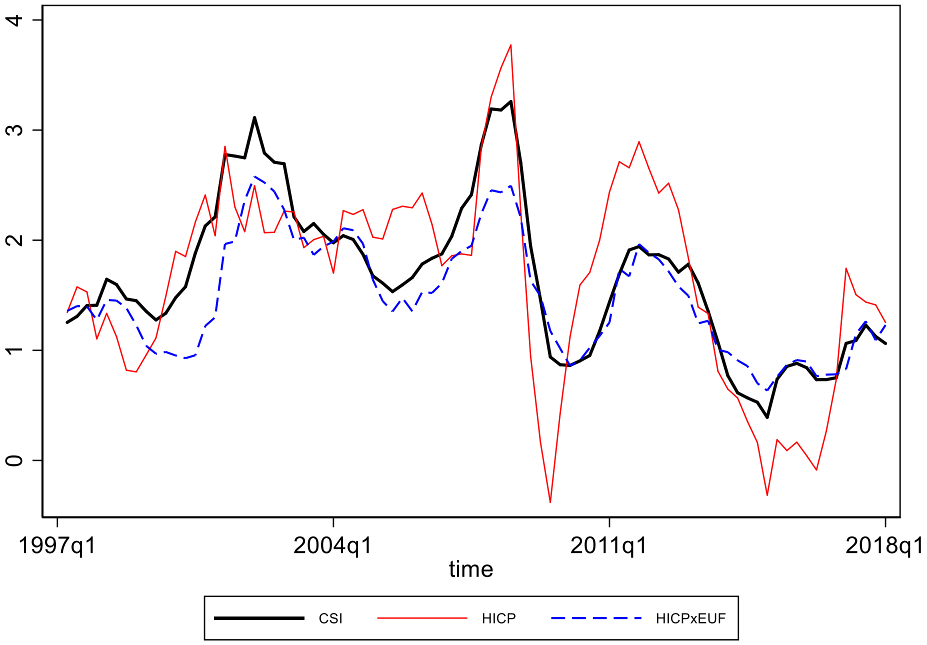
Despite the many differences between the EA and US categories, it is noteworthy that there are some similarities in the cyclical behavior. In particular, in both the EA and US, food & beverages off-premises and food services & accommodations are cyclically sensitive, whereas health care prices are not.

4.4 Euro Area CSI

The final column of Table 9 provides the CSI weights obtained by estimating regression (1); the dependent variable is the EA cyclical activity index, and the regressors are the 12 HICP components, in four-quarter changes of four-quarter inflation. The resulting CSI inflation index is plotted in Chart 18, along with overall HICP and HICPxEUF.

Chart 18

CSI inflation, HICP, and HICPxEUF for the Euro Area, 1997q4-2018q1



Sources: EUROSTAT and authors' calculations.

The EA CSI places more than three-quarters of its weight on food & non-alcoholic beverages and on furnishings & household items and on restaurants & hotels; food & nonalcoholic beverages receive a weight of 0.125. Together, these three categories receive 90% of the weight in the CSI index. Compared with HICPxEUF, which is comprised of the non-energy components in HICP categories 03-12, CSI places substantially more weight on household furnishings and on restaurants & hotels, and substantially less on recreation & culture and on miscellaneous goods & services.

The US and EA components represent different categories. Still, there are similarities and differences between the US and EA CSI indexes that merit comment. The component that receives the most weight in the US, housing excluding energy, receives no weight in the EA and indeed housing essentially does not move cyclically in the EA.

A surprising finding, evident in Chart 18, is that EA CSI inflation is quite similar to HICPxEUF. This is especially intriguing because the CSI weights in Table 4.2 differ substantially from the consumption share weights for some components. Especially over the past ten years, CSI inflation essentially looks like a smoothed version of HICPxEUF.

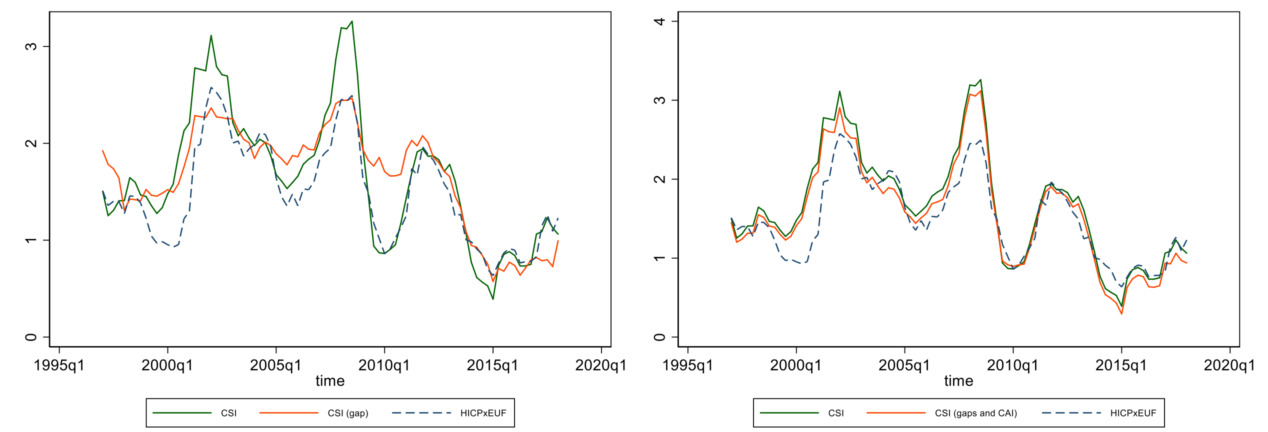
4.5 Sensitivity analysis

As can be seen in Chart 16, the band-passed cyclical activity variables, and their average which is the cyclical activity index, at times give different readings on slack than either the European Commission unemployment gap or the IMF output gap. We therefore estimated an alternative CSI, using as the dependent variable in Equation (1) a gap index, computed as the average of the unemployment gap and the output gap, where both gaps were standardized to have mean zero and variance one and (as in Chart 16) the unemployment gap was normalized to co-vary positively with the output gap.

The resulting CSI-gap series is plotted in Chart 19 (left), along with the CSI series estimated using the (band-pass) cyclical activity index and HICPxEUF. The resulting CSI inflation series is rather different from the CSI inflation series fit to the band-pass filtered activity index, in particular it exhibits smaller cyclical movements in 2007-2010. This finding is similar to that for the US, where the corresponding sensitivity check also showed differences between the CSI estimated using a conventional gap (the US slack index) or the band-passed cyclical activity index (Chart 14).

Chart 19

Sensitivity check: CSI inflation and CSI fit to gap index, 1997q4-2018q1



Source: Authors' calculations.
Notes: The CSI index is fit to the cyclical activity index, which is the average of the three band-passed activity series. In the left figure, the alternative CSI (green) is fit to a gap index, which is the average of the standardized EC unemployment gap (inverted) and the IMF output gap, In the right figure, the weights on the activity variables were also estimated econometrically, using the activity index, the EC unemployment gap, and the IMF output gap.

We make three remarks about the sensitivity of the CSI to the choice of the cyclical activity index (our benchmark) vs. a gap for the EA. First, mechanically this difference seems to be driven by different behaviours of the two slack measures around the time of the financial crisis recession. Second, the weights of the gap CSI are fall mainly on furnishings, housing excluding energy, and miscellaneous goods and services.

Third, the choice between the two slack measures can be informed empirically. The usual way to approach the question of the relation between slack and inflation is to start with a slack measure and to examine its link to inflation. But, in keeping with the examination of multiple slack measures in Section 2, an alternative framing is, of various possible measures of slack, which moves most closely with inflation? One way to answer that question is to compute the linear combinations of slack measures, and separately of inflation components, that have the greatest correlation using constrained canonical correlation analysis. We undertook this exercise using the cyclical activity index (Chart 16), the EC unemployment gap, and the IMF output gap. The estimated weight on the CAI is 0.82, on the unemployment gap is 0.18, and on the output gap is 0.00. Augmenting the CAI by the two gaps yields a negligible improvement in fit (the correlation increases from 0.868 to 0.876). The resulting CSI, shown in the right panel of Chart 19, is essentially the same as the benchmark CSI index based on only the (band-passed) CAI. We interpret these results as indicating that, when the data on inflation are allowed to choose the slack index, the choice is not a conventional gap but rather the cyclical (band-passed) measures. Said differently, the band-passed measures, not conventional gaps, are the measures that commove most closely with the cyclically sensitive components of inflation.

5 Conclusions

Different components of inflation have very different cyclical properties. Goods that are traded in international markets tend to have little cyclical variability. Health care prices also have only a small cyclical component, perhaps because they are poorly measured or because they are, in many cases, negotiated prices paid on behalf of consumers. In contrast, prices that are determined largely in local markets, such as prices at restaurants and hotels, have large cyclical components. Such prices get the most weight in the CSI index, both in the Euro Area and in the United States. In addition, some components of inflation are better measured than others, and our results suggest that cyclical movements in headline and core inflation are, in part, masked by noise imparted by the poorly measured components.

We see the main use of the CSI index as an early indicator that tight – or loose – economic conditions are having an effect on the rate of inflation. Given a set of historically estimated weights, the CSI index can be computed in real time, and in principle can be computed monthly (although we have only done so quarterly). Given the challenges of estimating slack in real time, the CSI index provides a new window on movements in the rate of inflation. Because the CSI index tends to focus its weights on sectors with locally determined prices, it provides a way to separate out prices that are domestically determined from prices that are heavily influenced by international conditions.

In the United States, the CSI index has been rising for the past three years, in contrast to overall PCE inflation, which has been largely quiescent (our data on components go through 2018q1); however, that increase is modest, from 2.1% to 2.6% over the 2014-2018q1 period.

In the Euro area, the CSI rate of inflation is remarkably similar to core HICP inflation, and over the past two years (2016q1 to 2018q1), both CSI and core HICP inflation increased only 0.3 percentage points, from 0.9% to 1.2% for HICPxEUF and from 0.8% to 1.1% for CSI. The EA CSI index places most of its weight on furnishings (which includes domestic services, household services, and nondurable household goods), and on restaurant and hotel services. The household furnishings index has been volatile since 2015q1 but on net has shown little change. In contrast, the restaurant and hotel component of CSI has rising 0.7pp since 2015q1, of which 0.3pp of the increase has been since 2017q1.

The Eurostat components differ from the BEA components at the second-tier level and it is possible that the BEA framework, which is organized around the NIPA categories of goods and services, is more conducive to isolating cyclical movements than is the Eurostat framework. This suggests extending the CSI concept to the next level of aggregation, or perhaps working with different aggregation than used by Eurostat. We leave that to future work.

Appendix: Data sources and transformations

Data on PCE component shares and price indexes for the United States are from the US NIPA Tables 2.3.4U and 2.3.5U. Real data and PCE aggregates (PCE-total and PCExFE) were obtained from FRED. Euro area HICP components data are from the ECB data warehouse. Real data for the EA were obtained from FRED and the IMF and OECD Web sites.

The band-pass filter is a two-sided Butterworth filter of degree 6, with lower and upper cutoffs corresponding to periods of 32 and 6 quarters, respectively. The series were padded using an AR(6) prior to filtering.

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