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Common and Idiosyncratic Inflation

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Abstract

We use a dynamic factor model to disentangle changes in prices due to economy-wide (common) shocks, from changes in prices due to idiosyncratic shocks. Using 146 disaggregated individual price series from the U.S. PCE price index, we find that most of the fluctuations in core PCE prices observed since 2010 have been idiosyncratic in nature. Moreover, we find that common core inflation responds to economic slack, while the idiosyncratic component does not. That said, even after filtering out idiosyncratic factors, the estimated Phillips curve is extremely flat post-1995. Therefore, our results suggest that the flattening of the Phillips curve is the result of macroeconomic forces.

JEL classification: C32, C43, C55, E31, E37
Keywords: Core inflation, Dynamic factor model, disaggregated consumer prices, monetary policy

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1 Introduction

One of the major challenges that the Federal Reserve faces in achieving its goal of price stability is to avoid responding to sector- or industry-specific relative price changes or—even worse—to measurement error. Rather, the Federal Reserve should respond only to macroeconomic shocks, that is, to those shocks that affect all prices and thus change the general price level of goods and services. Thus, determining how much of a current change in prices is driven by macroeconomic factors, as opposed to idiosyncratic developments or measurement error, is a crucial task for the Federal Reserve.

In this paper, we disentangle changes in prices due to economy-wide (common) shocks from changes in prices due to idiosyncratic shocks. To do so, we use a new statistical methodology that is entirely data-driven, i.e., it does not make any "structural" economic assumptions or ad hoc judgments about what factors are affecting prices. Indeed, although some idiosyncratic shocks are related to identifiable events (such as changes in Medicare reimbursement rates or one-off changes in the index for wireless telephone services), not all such shocks can be reliably traced to specific developments. Therefore, a statistical model capable of effecting this sort of decomposition is necessary.

The main product of our methodology is a decomposition of the PCE price index excluding food and energy (henceforth "core" PCE). We choose to decompose core PCE prices instead of total PCE prices for a couple of reasons. First, although the objective of the Federal Reserve is specified in terms of the inflation rate of the overall PCE price index, food and energy prices can be extremely volatile and therefore "core inflation usually provides a better indicator than total inflation of where total inflation is headed in the medium term" (Yellen, 2015, p. 10) a result more recently confirmed by Luciani and Trezzi (2019). Second, food and energy prices are often driven by idiosyncratic factors that are beyond the influence of monetary policy (Blinder, 1997).

Our methodology works in two steps: in the first step, by estimating a dynamic factor model on a dataset of disaggregated PCE prices, we decompose the inflation rate of each item into two components: the first component—the *common* component—reflects price changes that are attributable to economy-wide (i.e., *common*) factors, while the second component—the *idiosyncratic* component—captures relative price movements that reflect sector-specific developments or simple noise (for instance, sampling error). In the second step, we aggregate the common components for each individual series using the series' weights in the overall core PCE price index to construct the common component of core PCE price inflation. This yields an estimate of the portion of core PCE price inflation that can be attributed to common (or macroeconomic) factors, which we call "common core inflation."

We estimate the dynamic factor model on a dataset of 146 disaggregated monthly PCE prices from January 1995 to June 2019. The dataset that we use represents a particular disaggregation of PCE prices in which each disaggregated (or sub) price index is constructed from a distinct data source. Most PCE prices are measured using a corresponding sub-index from the CPI, a few of them are measured using PPIs, and a number of others are imputed. As a result, some disaggregated PCE prices are based on the same CPI (or PPI) series, which means that there are PCE sub-price indexes that are identical (or nearly so).[1] To avoid having sub-indexes that are highly correlated by construction, we combine all sub-indexes whose source data is the same.

Our model classifies as idiosyncratic many sizable movements in aggregate measured inflation—for example, the March 2017 dip in PCE price inflation that resulted from a collapse in the measured price of wireless telephone services—and it suggests that most of the fluctuations in core PCE prices observed since 2010 has been idiosyncratic in nature. Moreover, our estimate of common core inflation seems not to display any residual seasonality, thus showing that the residual seasonality in core PCE prices documented by Peneva (2014) is an idiosyncratic phenomenon.[2] Further, using a real-time exercise, we show that revisions to estimates of common core inflation are about ½ to ⅓ the size of the revisions seen for published core PCE price inflation. Finally, by estimating a Phillips curve model á la Yellen (2015), we compare the response of core PCE price inflation and common core inflation to changes in economic slack. We find that in the shorter term, common core inflation responds less than core PCE price inflation, but the estimated relationship is strongly statistically significant; in the longer term, however, the response of common core inflation is a bit higher. Moreover, we find that common core inflation responds to economic slack, while the idiosyncratic component does not. That said, even after filtering out idiosyncratic factors, the estimated Phillips curve is extremely flat post-1995. Therefore, our results suggest that the flattening of the Phillips curve is the result of macroeconomic forces.

Other papers have used large-dimensional dynamic factor models to study disaggregated prices in the US (e.g., Boivin et al., 2009; Maćkowiak et al., 2009; De Graeve and Walentin,

[1] An example is the PCE price index for "New Domestic Autos" (Item: 7), and the PCE price index for "New Foreign Autos" (Item: 8), which are both constructed out of the CPI for "New cars."

[2] A time series displays residual seasonality when a predictable pattern occurs over the year, despite the series being previously seasonal adjusted.

2015; Conflitti and Luciani, 2019). Among these papers, two are particularly close to ours: Reis and Watson (2010), who estimate an index of equiproportional changes in disaggregated PCE price inflation, which they label "pure" inflation; and Amstad et al. (2017), who estimate a measure of underlying inflation on a dataset composed primarily of CPIs, which they call an "Underlying Inflation Gauge" (UIG).

In addition to a number of technical aspects, the main difference between our analysis and the analyses of Reis and Watson (2010) and Amstad et al. (2017) is in the dataset used: our dataset is the only one that preserves the structure of PCE prices while at the same time restricting its scope to only those prices that are constructed from distinct sources. Indeed, because Reis and Watson (2010) did not control for the source of each disaggregated PCE price in their dataset, they were forced to clean and correct their data for excess cross-correlation, and, as a result, failed to preserve the structure of PCE prices. In contrast, Amstad et al. (2017) compose their price-only UIG for PCE prices using CPI price indexes and just a few aggregate (or lower-level disaggregate) PCE price indexes.

The rest of the paper is organized as follows. In the following two sections of the paper, we introduce the methodology and we describe the dataset used for the empirical analysis. Next, in Section 4 we discuss model specification and in Section 5 we present the estimation results. Finally, in Section 6, we discuss properties of the resulting common core inflation measure with respect to residual seasonality, data revisions, and its relationship with economic slack. Section 7 concludes.

2 Methodology

The goal of this paper is to use statistical methods to understand what portion of movements in inflation is driven by shocks that affect all prices (macroeconomic fundamentals), and what portion is driven by idiosyncratic price movements. Our methodology involves two steps.

In the first step, we decompose the rate of change for each individual price sub-index into two components. The first component—the *common* component—is meant to reflect price changes that are attributable to economy-wide (i.e., *common*) factors, such as the amount of slack in the economy or movements in the prices of non-labor inputs to production, such as commodity prices, as well as prices of imported goods and services. The assumption here is that each series is affected by these common factors, though to a degree and with a dynamic response that can vary by series. By contrast, the second component—the *idiosyncratic* component—is meant to capture relative price movements that reflect sector-specific developments, such as the massive decline in prices for wireless telephone services in March 2017, or it can also reflect measurement error, for instance, sampling error.[3] The assumption here is that idiosyncratic price movements are specific to an individual price series or a particular subset of series. Formally, let $\pi_{it} \equiv 100 \times (\frac{P_{it}}{P_{it-1}} - 1)$ be the month-on-month inflation rate, then we have:

$$\pi_{it} = \chi_{it} + \xi_{it}, \tag{1}$$

where χ_{it} is the *common* component and ξ_{it} is the *idiosyncratic* component.

In the second step, after the *common* components for each individual series have been computed, we aggregate them together to construct the common component of core PCE price inflation by using the series' weights in the overall core PCE price index. This yields an estimate of the portion of core PCE price inflation that can be attributed to common (macroeconomic) factors:

$$\chi_t^c = \sum_{i \in core} w_{it}\chi_{it} \tag{2}$$

where χ_t^c is what we call "common core inflation."[4]

In practice, to obtain the decomposition in (1) we estimate a dynamic factor model, which we will present in the next section, while to construct the common core inflation series in (2) we use the "approximate" PCE weights computed as in Dolmas (2005):[5]

$$w_{i,t} = 0.5\frac{Q_{it-1}P_{it-1}}{\sum Q_{it-1}P_{it-1}} + 0.5\frac{Q_{i,t}P_{it-1}}{\sum Q_{i,t}P_{it-1}}. \tag{3}$$

In other words, the weight for the i-th item in, say, June 2019 is equal to an average of the expenditure share of that item in May 2019, and its expenditure share had it been bought

[3] In March 2017 the price index for wireless telephone services plunged 52% (at an annual rate), shaving off about 8 basis points from the monthly percent change in core PCE prices. The plunge was due to both a methodological change to the measurement of wireless services in the CPI and the fact that in late February of 2017 both Verizon and AT&T (which in March 2017 accounted for nearly 70% of wireless subscriptions in the US) brought back unlimited data plans.

[4] Note that decomposition (1) holds also for the aggregate core index. Indeed, since $\pi_t^c = \sum_{i \in core} w_{it}\pi_{it}$, we have that $\pi_t^c = \sum_{i \in core} w_{it}\chi_{it} + \sum_{i \in core} w_{it}\xi_{it}$, and therefore $\pi_t^c = \chi_t^c + \xi_t^c$.

[5] Since the PCE price index is a Fisher index it has the drawback of non-additivity property (see Whelan, 2002, as well as Chapter 4 of the NIPA Handbook, Bureau of Economic Analysis, 2017). Therefore, only approximate weights can be computed. However, Diewert (1976, 1978) shows that a Törnqvist index numerically approximates a Fisher index (see also Dumagan, 2002), and therefore using the Törnqvist weights in (3) as in Dolmas (2005) is a valuable alternative.

in June 2019 at May 2019 prices.

Finally, it is important to point out that the dynamic factor model is estimated on a dataset of PCE prices that preserves the structure of PCE, and hence it also includes food and energy prices. Therefore, although in the second step we aggregate only the common components of core PCE, we are able to capture potential spillovers from food and energy prices to core prices.

2.1 Dynamic factor models

A factor model for inflation is based on the idea that fluctuations in disaggregated prices are due to a few common (macroeconomic) shocks $\mathbf{u}_t = (u_{1t} \cdots u_{qt})'$, which affect all prices, and to several idiosyncratic shocks $\mathbf{e}_t = (e_{1t} \cdots e_{nt})'$ resulting from sector-specific dynamics or from sampling error, which influence a subset of prices. Accordingly, each price component in the dataset can be decomposed into a common part χ_{it}, which is driven by the common shocks, and an idiosyncratic part ξ_{it}, which is driven by both sector-specific shocks and by sampling error.

Formally, let us consider a panel of n disaggregated prices $\{\boldsymbol{\pi}_t = (\pi_{1t} \cdots \pi_{nt})' : t = 1, \ldots, T\}$, then

$$\pi_{it} = \chi_{it} + \xi_{it} \tag{1}$$

$$\chi_{it} = \sum_{k=0}^{s} \boldsymbol{\lambda}_{ik} \boldsymbol{f}_{t-k}, \tag{4}$$

$$\boldsymbol{f}_t = \sum_{\ell=1}^{p} \boldsymbol{\mathcal{A}}_\ell \boldsymbol{f}_{t-\ell} + \mathbf{u}_t, \qquad \mathbf{u}_t \overset{i.i.d.}{\sim} \mathcal{N}(\mathbf{0}, \mathbf{Q}), \tag{5}$$

$$\xi_{it} = \sum_{\jmath=1}^{d_i} \rho_{i\jmath} \xi_{it-\jmath} + e_{it} \qquad \mathbf{e}_t \overset{i.i.d.}{\sim} \mathcal{N}(\mathbf{0}, \boldsymbol{\Gamma}) \tag{6}$$

where $\boldsymbol{f}_t = (f_{1t} \cdots f_{qt})'$ are the q common latent factors capturing co-movements across series and across time; $\boldsymbol{\lambda}_{ik} = (\lambda_{i1k} \cdots \lambda_{iqk})$ are the factor loadings for price i at lag k; $s \geq 0$ and $p \geq 1$ are finite integers; $\mathbf{Q}$ is a $q \times q$ positive definite covariance matrix with full rank; the roots of $\boldsymbol{\mathcal{A}}(L) = \sum_{\ell=1}^{p} \boldsymbol{\mathcal{A}}_\ell$ and of $\rho_i(L) = \sum_{\jmath=1}^{d_i} \rho_{i\jmath}$ lies all outside the unit circle; and $\boldsymbol{\Gamma}$ is a $n \times n$ positive definite covariance matrix with full rank.

In this model it assumed that (i) the common factors $\boldsymbol{f}_t$ are pervasive, i.e., they have non-negligible effects on most prices at one or more lags; (ii) the idiosyncratic components $\boldsymbol{\xi}_t = (\xi_{1t} \cdots \xi_{nt})'$ are weakly cross-sectionally correlated—hence they do not have a pervasive effect—and weakly dynamically correlated; and (iii) the common $\boldsymbol{u}_t$ and the idiosyncratic shocks $\boldsymbol{e}_t$ are independent at all leads and lags (for a rigorous treatment of this model see Barigozzi and Luciani, 2019b).

We estimate model (1), (4)-(6) by Quasi-Maximum Likelihood (QML), implemented through the Expectation-Maximization (EM) algorithm, where in the E-step the factors $\mathbf{f}_t$ are estimated with the Kalman Smoother.[6] Estimation of dynamic factor models by the EM algorithm was initially proposed by Shumway and Stoffer (1982) and Watson and Engle (1983), and further developed and studied by Doz et al. (2012) and Bai and Li (2016) in the context of large datasets.[7] The specification (4)-(5) is studied in Barigozzi and Luciani (2019b) who show that both the factors and the loadings estimated with QML converge to the true values at the standard rate $\min(\sqrt{n}, \sqrt{T})$.[8]

3 Data

The price data are taken from the National Income and Product Accounts (NIPA) Table 2.4.4U, while the nominal quantity data necessary to compute the weights are taken from the NIPA Table 2.4.6U. The data were downloaded from the Haver Analytics database on July 30, 2019; thus, the vintage of data used in the paper incorporates the 2019 annual update of the NIPAs.

PCE price data are available at different levels of disaggregation, the highest of which includes roughly 220 price indexes, with a complete set of observations available since 1990. Our reference starting point is the level of disaggregation used by the Dallas Fed to produce the Trimmed Mean PCE inflation index (see Dolmas, 2005), which comprises 178 disaggregated prices and which is the highest level of disaggregation for which it is possible

[6] The EM algorithm is an iterative method to find maximum likelihood estimates of parameters in models with unobserved latent variables. At a given iteration $j \geq 0$, in the E-step the expected log-likelihood (evaluated using the estimate of the parameters obtained at step $j-1$) is created; then, in the M-step the parameters of the model are estimated by maximizing the expected log-likelihood. In the case of model (1), (4)-(6), in the E-step given an estimate of the parameters $\widehat{\boldsymbol{\lambda}}_{ik}^{(j)}$, $\widehat{\boldsymbol{\mathcal{A}}}_{\ell}^{(j)}$, $\widehat{\mathbf{Q}}^{(j)}$, and $\widehat{\mathbf{\Gamma}}^{(j)}$—for simplicity we are assuming $\rho_{ij} = 0$—the factors are estimated by running the Kalman filter and the Kalman smoother. Then, given $\widehat{\mathbf{f}}_t^{(j)}$, in the M-step the parameters are estimated equation-by-equation by running OLS, where the OLS formulas are modified to account for the estimation error in $\widehat{\mathbf{f}}_t^{(j)}$. See Barigozzi and Luciani (2019b) for a rigorous treatment of the EM algorithm in Dynamic Factor Models.

[7] Recent applications of this approach include Reis and Watson (2010), Bańbura and Modugno (2014), Juvenal and Petrella (2015), Luciani (2015), and Coroneo et al. (2016).

[8] Other papers that have estimated a dynamic factor model with dynamic loadings are (Antolin-Diaz et al., 2017; Luciani and Ricci, 2014; Bai and Wang, 2015; D'Agostino et al., 2016) in a Bayesian and stationary framework, and Barigozzi and Luciani (2019a,c) in a non-stationary framework.

to obtain a complete set of data starting in the late 1970s.

Disaggregated PCE prices can be broadly classified as "market-based," which are defined "as those goods and services that have been produced for sale at prices that are economically significant," and therefore for which "their current market price provides a rational and viable basis for valuing" them (Bureau of Economic Analysis, 2017, p. 2-5); and "non-market-based", which consist of "goods and of individual or collective services that are produced by nonprofit institutions and by government that are supplied for free or at prices that are not economically significant" (Bureau of Economic Analysis, 2017, p. 2-5) and of services provided by business provided either without charge or for a small fee that does not reflect the entire value of the service.[9] In other words, a "market-based" good/service can be actually bought, and therefore it is possible to record a price for it; a "non-market-based" good/service cannot be bought, and therefore its price is imputed by the BEA based on the costs of production (for nonprofit institutions and government) or some other assumptions (for business).[10]

"Market-based" goods and services are about 87% of total PCE, and most of them are constructed by taking the corresponding (or conceptually closest) CPI, with only a few exceptions where a PPI series is used (e.g., airfares and some medical prices). By contrast, most "non-market-based" prices are imputed by the BEA, with just a few exceptions that are constructed out of CPIs and/or PPIs. Because it is not always the case that there exists a corresponding CPI or PPI for each PCE price, some disaggregated PCE prices are constructed out of the same CPI (or PPI) index, and hence are identical (or nearly so).[11]

In the level of disaggregation used by the Dallas Fed, we identified 21 groups of prices that have the same source. In computing an inflation index, the fact that two prices have the same source, and therefore are identical, does not necessarily pose a problem. However, this situation is problematic if the goal is to estimate a dynamic factor model.

[9] For example, education and health services provided by non-profit institutions are typically provided at below-market prices. Another example is checking account maintenance, which are often provide by banks without charge.

[10] An example here could help: one of the consumption categories is "lotteries," but what is the price for lotteries? For example, suppose John buys a scratch lottery ticket for, say, $2 and suppose John does not win. Now, John has consumed $2 in participation in a lottery, but what is the price that John paid? In this specific case, the BEA impute the PCE price index for "lotteries" by using the overall CPI. Another example is "standard clothing issued to military personnel", which is imputed by using the PPI for "apparel".

[11] An example is the PCE price index for "Bicycles and accessories" (Item: 53), the PCE price index for "Pleasure boats" (Item: 55), the PCE price index for "Pleasure aircraft" (Item: 56), and the PCE price index for "Other recreational vehicles" (Item: 7), which are all constructed out of the CPI "Sports vehicles including bicycles."

Indeed, dynamic factor models are estimated under the assumption that the idiosyncratic components are only mildly cross-sectionally correlated. However, if two prices in the dataset are sourced from the same price index, they will be perfectly correlated, as will be their idiosyncratic components.

It is therefore clear that, with 21 groups of prices (for a total of 53 PCE price indexes involved) constructed out of the same source, the assumption of mildly cross-sectionally correlated idiosyncratic components is likely not to be satisfied. This is not just a theoretical issue, as the literature has shown that when there is an excess of cross-sectional correlation between the idiosyncratic components, both estimation of dynamic factor models, as well as their forecasting properties, deteriorates (Boivin and Ng, 2006; Luciani, 2014). Moreover, in Appendix A.2 we show that failing to account for the source of each disaggregated PCE price, severely affects the estimate of common core inflation.

For this reason, we aggregate the 53 price indexes that are constructed out of the same source, into 21 alternative price indexes. As a result, our dataset includes 146 disaggregated PCE prices from January 1995 to June 2019.[12] The complete list of prices is available in Appendix B, while detailed information on the data sources and all aggregations performed is available in the complementary appendix.[13]

4 Number of factors

Before estimating the model, we need to determine the number of factors q and the number of lags s in the factor loadings. In order to estimate the number of factors, we use the information criterion proposed by Hallin and Liška (2007), which exploits the behavior of the eigenvalues of the spectral density matrix of $\boldsymbol{\pi}_t$ averaged across all frequencies. This criterion indicates the presence of just one common factor (not shown).

To choose the number of lags s in the factor loadings, we proceed as follows: Having determined q, we choose s such that the share of the variance explained by the first $r = q(s+1)$ principal components of the covariance matrix of $\boldsymbol{\pi}_t$ coincides with the share of

[12] The main reason why we choose to start our analysis in 1995 is that starting from 1995 core PCE price inflation is likely a stationary variable. Indeed, while it is possible to estimate model (1), (4)–(3) in a non-stationary setting (see Barigozzi and Luciani, 2019b), it is undeniably more complicated, and therefore we limited the sample to the period in which PCE price inflation has behaved like a stationary variable.

[13] For even more detailed information on the source data for each PCE price index in the NIPA Table 2.4.4U, see the Excel file that can be downloaded from the BEA website at `https://www.bea.gov/media/3051`.

the variance explained by the q principal components of the spectral density matrix of $\boldsymbol{\pi}_t$ (averaged over all frequencies)—see also D'Agostino and Giannone (2012).[14] By looking at Table 1, we can see that $r \simeq 3$, i.e., $s \simeq 2$.

Table 1: PERCENTAGE OF EXPLAINED VARIANCE

	1	2	3	4	5	6	7	8	9	10
q	8.7	15.0	20.5	25.5	30.0	34.2	38.0	41.6	44.9	48.0
r	3.7	7.2	9.8	12.1	14.2	16.2	18.2	20.0	21.9	23.7

This table reports the percentage of total variance explained by the q largest eigenvalues of the spectral density matrix of $\Delta\boldsymbol{\pi}_t$ and by the $r = q(s+1)$ largest eigenvalues of the covariance matrix of $\Delta\boldsymbol{\pi}_t$.

Having selected a benchmark specification using statistical criteria, we look at how this specification characterizes PCE prices in terms of common and idiosyncratic dynamics. To this end, Figure 1 shows the percentage of variance of each individual inflation series explained by the common component. In addition to our benchmark specification with $q = 1$ and $s = 2$ (red bars), we also consider two alternative specifications: the first one has $q = 1$ and $s = 0$ (blue bars), so that, in this specification each disaggregated price loads the common factor only contemporaneously (the rationale for including this specification is to show what benefits we obtain from including lagged factor loadings). The second alternative specification has $q = 1$ and $s = 5$ (green bars); this is a much richer specification in which each disaggregated price can load the common factor in a time window of six months.[15]

In Figure 1, we have divided the disaggregated prices into six subplots, each of which represents a different category of disaggregated prices. The results shown on the left side of plot A confirm our initial hypothesis that food prices are driven to a great extent by idiosyncratic factors (e.g., weather or disease). Moving to energy prices, which are heavily influenced by oil prices, the common component explains a good fraction of the variance in energy prices when we add lags in the factor loadings, suggesting that the model view oil price shocks as a common macroeconomic shock (see Conflitti and Luciani, 2019, for a detailed discussion on the effect of oil prices on common and idiosyncratic PCE prices).

Moving to core goods prices (plots E and F), we can see that with a few exceptions, core goods prices are driven mainly by idiosyncratic dynamics. Compared to core goods prices, core services prices (plots C and D) seem to be driven by common dynamics to

[14] The rationale for this approach is that if the model is the true data generating process, then the spectral density matrix of $\boldsymbol{\pi}_t$ has q eigenvalues that diverge with n, while the covariance matrix of $\boldsymbol{\pi}_t$ has at most $q(s+1)$ diverging eigenvalues.

[15] Appendix A.1 shows robustness analysis of all the results presented in Section 5 and Section 6 with respect to the two alternative model specifications considered in this section.

a greater extent, with several items for which the common component accounts for more than 10% of the overall variance. Finally, some non-market prices are quite influenced by the common factor, especially when lags in the loadings are included; most likely, this reflects the use of an all-item CPI or financial market series to impute these prices.

Table 2 reports the average share of the variance of each price category explained by the three models computed using both monthly and quarterly inflation rates. These results clearly corroborate the conclusion reached from Figure 1; specifically, they show that for either frequency: (i) idiosyncratic dynamics explain the bulk of variation in disaggregated PCE prices; (ii) including lags of the factors seems to matter (particularly for energy prices); (iii) between our benchmark specification supported by the statistical criteria ($s = 2$), and the richer specification (with $s = 5$), the latter provides no particular advantage. Finally, when looking at quarterly rates, which smooth out part of the noise in the monthly data, we can see a notable pick up in the share of variation of core services prices accounted for by the common component.

Table 2: COMMON DYNAMICS IN HIGHLY DISAGGREGATED PCE PRICES

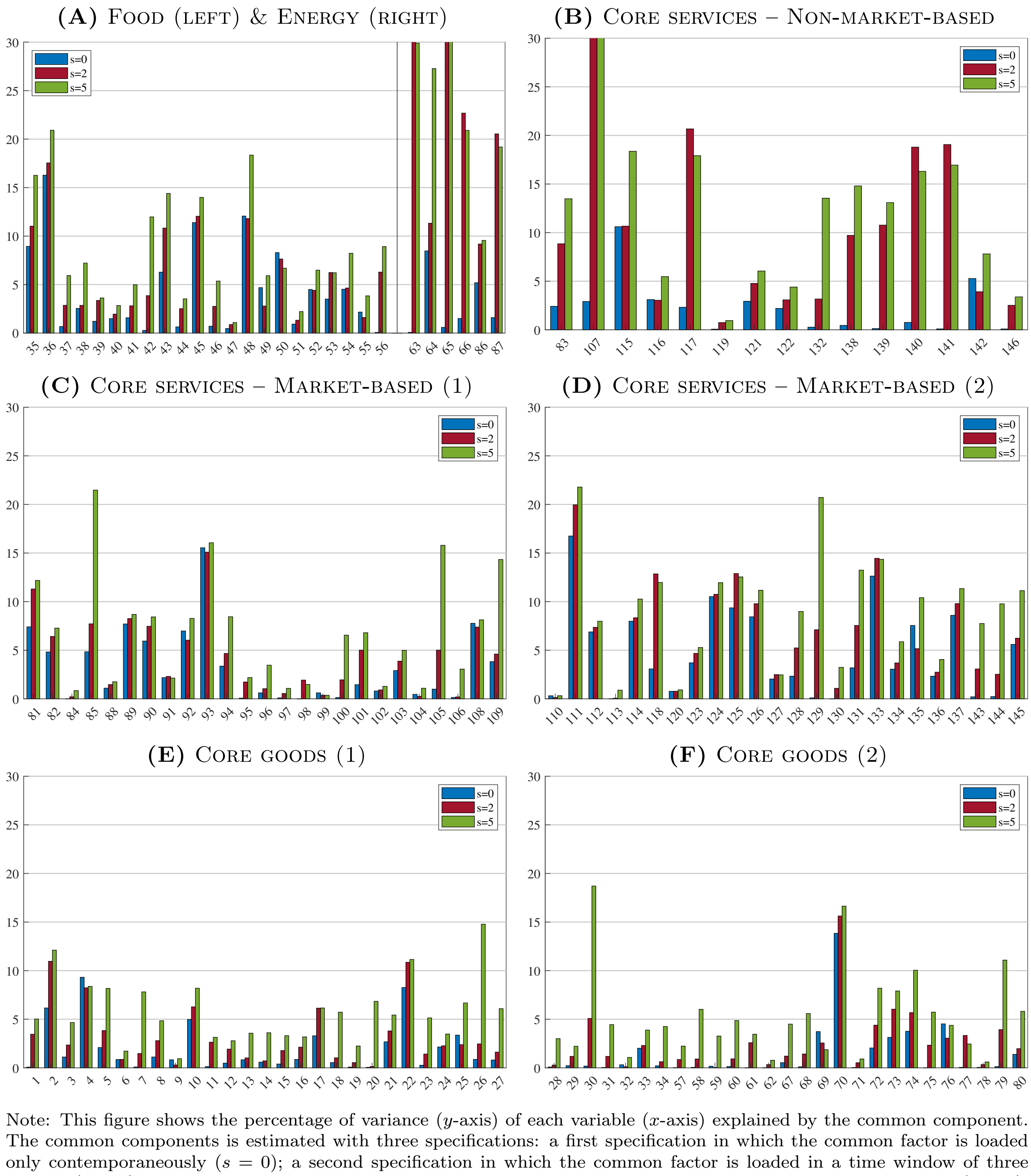
	Panel A: Monthly rates			Panel B: Quarterly rates		
	$s = 0$	$s = 2$	$s = 5$	$s = 0$	$s = 2$	$s = 5$
Total	3.0	5.7	8.2	9.3	13.2	13.9
Food	4.3	5.5	8.1	16.5	18.4	19.9
Energy	2.9	22.2	23.2	9.0	31.3	33.0
Core	2.7	4.9	7.4	8.0	11.3	11.9
Goods	1.7	2.8	5.5	5.3	6.8	7.7
Sevices (mkt)	4.0	5.4	7.8	11.8	14.4	14.8
Services (nmkt)	2.2	11.1	12.8	5.1	17.0	17.2

Notes: This table reports the average (within category) percentage of variance of each variable explained by the common component. The common components are estimated with three specifications: in the first specification each disaggregated price loads the common factor only contemporaneously ($s = 0$); in the second specification, our benchmark specification, each disaggregated price can load the common factor in a time window of three months ($s = 2$); in the last specification, each disaggregated price can load the common factor in a time window of six months ($s = 5$). On Panel A the share of variance is computed using monthly inflation rates, i.e., $\pi_{it} = 100 \times ((P_{it}/P_{it-1}) - 1)$, whereas in Panel B it is computed using quarterly inflation rates at an annual rate, i.e., $\pi_{it} = 100 \times ((P_{it}/P_{it-4})^4 - 1)$. "Services (mkt)" denotes market-based services, while "Services (nmkt)" denotes non-market-based services.

Table 3 reports the share of the variance of the aggregate indexes for total, food, energy, and core PCE price inflation that is explained by the three alternative model specifications.[16] Table 4, instead, investigates further core PCE price inflation by showing

[16] The variance for the monthly inflation rate in core PCE prices was computed by excluding the observations for September and October 2001. In September 2001, Core PCE price inflation was -0.56% (-6.5 % at an annual rate), while in October 2001, it was +0.72% (+8.9 % at an annual rate). The 2001 swing in the PCE price index excluding food and energy was driven by the price index for life insurance, which

Figure 1: Common dynamics in highly disaggregated PCE prices



Note: This figure shows the percentage of variance (y-axis) of each variable (x-axis) explained by the common component. The common components is estimated with three specifications: a first specification in which the common factor is loaded only contemporaneously ($s = 0$); a second specification in which the common factor is loaded in a time window of three months ($s = 2$); and a third specification in which the common factor is loaded in a time window of six months ($s = 5$). Each set of bars represents a different item—the numbers on the x-axis are the identifier of each item, which can be matched with those in the tables in Appendix B. Note that the y-axis is cut at 30 percent. For two energy prices ("Gasoline & Other Motor Fuel" and "Fuel oil"), the share is over 30 percent; likewise, for "Gambling" (upper right plot), which is constructed using the CPI index for all items, and which is therefore highly influenced by energy prices the share 30 percent.

plunged 55 percent in September 2001 and jumped 121 percent in October 2001 as a result of the 9/11 terrorist attacks.

the share of variance of monthly core PCE price inflation at different frequencies that is explained by the common component.[17] While common dynamics account for less than 10% of the fluctuations of the core PCE price index (fourth row of Panel A in Table 3), they account for a large share of the mid- to low-frequency fluctuations (i.e., those with period longer than one year), and for a minimal share of the ultra-high frequency fluctuations with period shorter than six months. A similar conclusion can be reached by looking at Panel B in Table 3, as quarterly growth rates cut out part of the high-frequency variability in monthly inflation rates.

Table 3: Common dynamics in aggregated PCE prices

	Panel A: Monthly rates			Panel B: Quarterly rates		
	$s = 0$	$s = 2$	$s = 5$	$s = 0$	$s = 2$	$s = 5$
Total	3.3	44.7	37.0	7.5	63.3	59.8
Food	25.7	27.0	29.1	51.0	55.6	56.0
Energy	0.4	41.9	33.5	1.3	60.2	54.7
Core	4.2	8.6	9.2	11.8	17.8	20.7

Notes: This table reports the percentage of variance of each core, energy, and food, PCE price index explained by the common component. The common components are estimated with three specifications: in the firs specification each disaggregated price loads the common factor only contemporaneously ($s = 0$); in the second specification, our benchmark specification, each disaggregated price can load the common factor in a time window of three months ($s = 2$); in the last specification, each disaggregated price can load the common factor in a time window of six months ($s = 5$).

Table 4: Common Dynamics in core PCE Price inflation at different frequencies

Frequency $\omega = \frac{2T}{\tau}$	$s = 0$	$s = 2$	$s = 5$
$\tau \geq 60$	23.6	18.6	12.4
$12 \leq \tau < 60$	11.0	24.5	34.5
$6 \leq \tau < 12$	0.7	8.5	11.8
$\tau < 6$	0.6	3.2	1.8

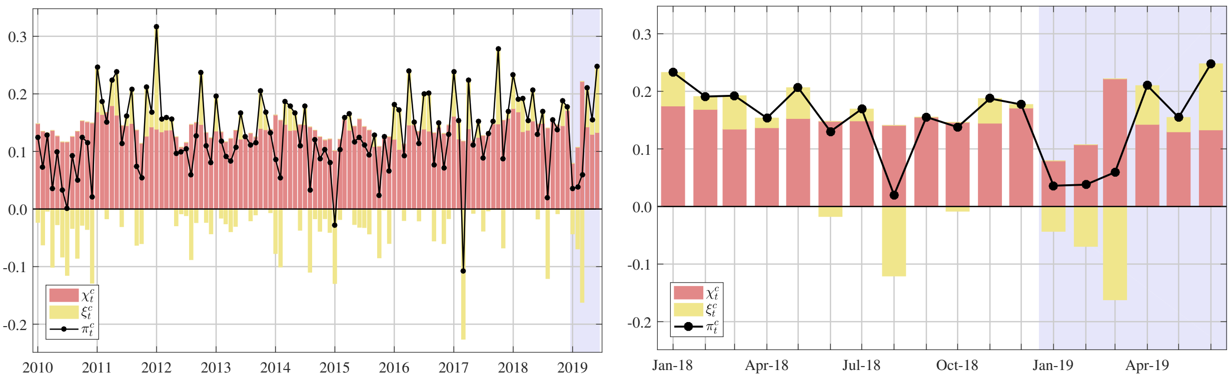
Notes: This table reports the share of variance of monthly core PCE price inflation at different frequencies explained by the common component computed as explained in footnote 17 . The period τ of each fluctuations is expressed in number of months, so that the first row ($\tau \geq 60$) reports the share of variance of fluctuations in core PCE price inflation longer than five years explained by the common component. The variance for the portion of core PCE price inflation with frequency less than six months was computed by excluding the observations for September and October 2001 (see footnote 16).

[17] To compute the share of variance of core PCE price inflation at different frequencies, we first decomposed core PCE price inflation (and the common component) into four different series, each isolating fluctuations with different frequencies. Then, we computed the share of variance. To isolate fluctuations of different frequencies, we use cosine projections as in Müller and Watson (2017).

5 Application to core PCE price inflation

Figure 2 shows the common and idiosyncratic decomposition of monthly core PCE price inflation. In each plot, the red bar is common core inflation, that is, the portion of the one-month percent change in the core PCE price index that is attributable to common shocks, while the yellow bar gives the idiosyncratic component. By construction, these two components sum to overall core PCE inflation, which is shown in the plots as a black line. Finally, the panel on the left covers the period from 2010 to 2019, while the right panel zooms in on the experience of the last two calendar years with 2019 shaded in light blue.

Figure 2: COMMON AND IDIOSYNCRATIC DECOMPOSITION
CORE PCE PRICES – MONTHLY PERCENT CHANGE



Notes: in each plot, the red bar is common core inflation, while the yellow bar gives the idiosyncratic component. By construction, these two components sum to overall core PCE inflation (the black line). The plot on the left covers the period 2010 to 2019—with 2019 shaded in blue—while the right panel zooms in on the period 2018 to 2019.

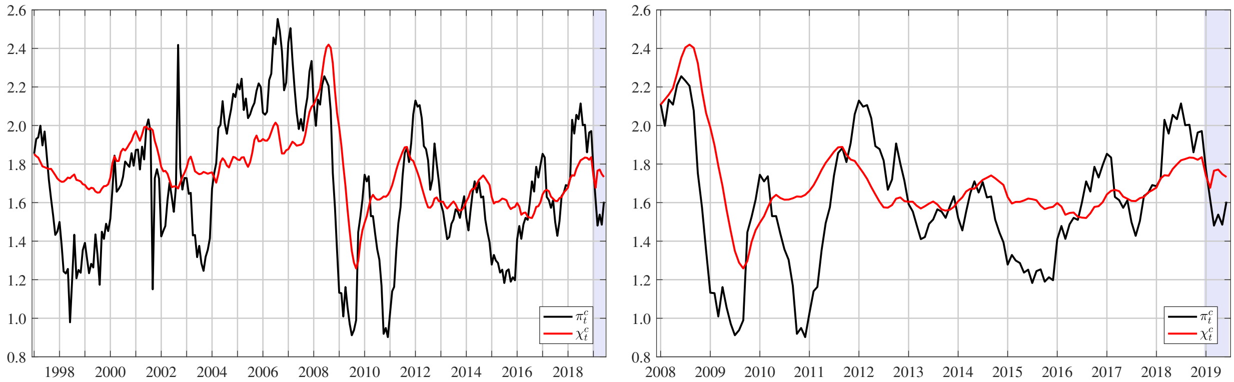
By looking at the left plot of Figure 2, we can see that the idiosyncratic component held down core PCE price inflation for most of 2010. Indeed, in 2010 several well-known idiosyncratic negative shocks lowered core inflation, such as the collapse of the index for luggage in January, the very low reading for Medicare hospital services prices in October, and an exceptionally long series of negative readings in the index for apparel. Similarly, idiosyncratic factors held down core inflation in both 2014 and 2015, two years in which medical prices were low in part due to the implementation of the Affordable Care Act. Another episode worth noting is March 2017, when core PCE price inflation was heavily affected by the collapse in the price index for wireless telephone services. Finally, in several years the contribution of the idiosyncratic component is positive at the beginning of the year (in January in particular), while it is negative in the second half of the year. This regularity is related to the issue of residual seasonality in core PCE price inflation, which we discuss in detail in Section 6.1.

Moving to the right panel, we can see that in 2018 idiosyncratic inflation was slightly positive in 9 out of 12 months and strongly negative in August, when prices were held down by, among other factors, the lowest-ever reading for the percent change in the CPI for dental services. As a result, the total contribution of idiosyncratic inflation was nearly zero over 2018 as a whole. Finally, in January, February, and March 2019, idiosyncratic shocks (mainly to non-market-based prices) held down core PCE price inflation by a cumulative 27 basis points, while in April, May and June 2019, they boosted core inflation by a cumulative 20 basis points.

Figure 3 shows the common and idiosyncratic decomposition of the 12-month percent change in the core PCE price index. Here, the red line denotes year-on-year common core inflation, i.e., the common component's contribution to the overall 12-month percent change of the core PCE price index (which is given by the black line). Put differently, the red line tells us what core inflation would have been had there been no idiosyncratic price shocks over the past 12 months.

Figure 3: Common and idiosyncratic decomposition

Core PCE prices — year-on-year inflation



Notes: in each plot, the red line is common core inflation, while the black line is core PCE price inflation. The plot on the left covers the period 1997 to 2019, while the right panel zooms in on the period 2008 to 2019. The shaded blue area highlights data for 2019.

As we can see from Figure 3, core PCE price inflation and common core inflation moved largely in sync in 2008 and 2009, when the economy was affected by a large macroeconomic shock, and macroeconomic variation likely dominated idiosyncratic variation in the data. After that, idiosyncratic variation has been more important, and core PCE prices have fluctuated around a fairly stable rate of common core inflation. In particular, our model classifies the 2010 downturn in core PCE price inflation as entirely idiosyncratic, and it also suggests that the 2015 and 2017 downturns in core PCE price inflation were due to idiosyncratic dynamics. As a result, since 2010, while year-on-year core PCE prices inflation fluctuated within a range of 1.2 percentage points, common core inflation fluctuated within a much narrower range of 0.4 percentage point. Hence, these results suggest that most of the swings in core PCE price inflation during the current expansion were mostly idiosyncratic in nature.

6 Additional properties of the model

6.1 Residual seasonality

In recent years some researchers have shown that core PCE price inflation is affected by residual seasonality, i.e., despite being based on data that are seasonally adjusted by statistical agencies, a predictable seasonal pattern is still visible in the overall index. Specifically, Peneva (2014) shows that core PCE price inflation exhibits a regular downward pattern from the first to the second half of the year.[18]

In Table 5, we repeat the exercise used by Peneva and Sadée (2019) to characterize the importance of residual seasonality in core PCE price inflation. Specifically, Table 5 shows the average difference between the annualized three-month inflation rate and the average of the annualized inflation rates for the four three-month sub-periods, for both core PCE price inflation and common core inflation. As we can see, common core inflation is considerably less affected by residual seasonality than core PCE price inflation, particularly if we consider the data that reflect the 2018 comprehensive revision. In other words, the results in Table 5 confirm that the issue of residual seasonality is by nature idiosyncratic; hence, common core inflation gives a more reliable signal of where core inflation actually is than does the core index itself.

6.2 Real-time reliability

A crucial issue when dealing with model-based estimates of unobserved variables is their reliability in real time. There are two reasons why a model-based estimate of an unobserved variable revises in real time: first, because the data themselves get revised, and second, because new observations can change both the parameter estimates and the smoothed estimates of latent states. The goal of this section is to study the real-time properties of common core inflation and to asses the empirical relevance of these two problems.

[18] Moreover, Peneva and Sadée (2019) show that, although the 2018 comprehensive NIPA data revision has partially attenuated the problem, residual seasonality is still present in core PCE price inflation.

Table 5: Residual seasonality

	$\boldsymbol{\pi}_t^c$		$\boldsymbol{\chi}_t^c$	
Sample	2007:1-2017:12	2008:1-2018:12	2007:1-2017:12	2008:1-2018:12
Vintage	June 29, 2018	July 30, 2019	June 29, 2018	July 30, 2019
Jan-Mar	0.14	0.04	0.05	-0.01
Apr-Jun	0.23	0.12	0.05	-0.01
Jul-Sep	-0.10	-0.19	0.04	-0.01
Oct-Dec	-0.27	0.03	-0.13	0.03

Note: The table shows the average difference between the annualized three-month inflation rate and the average of the annualized inflation rates for the four three-month sub-periods. The row "Sample" indicates over which sample the average difference is computed. The row "Vintage" indicates the day when the BEA published the vintage of data upon which it is computed the residual seasonality.

In order to estimate common core inflation in real time, we retrieved real-time data vintages for our dataset starting in August of 2009, that is after the 2009 NIPA comprehensive data revision, for a total of 121 data vintages, including the one used to produce the benchmark results reported previously.[19]

Figure 4 shows both real-time, *quasi*-real-time, and final estimates of year-on-year common core inflation, as well as real-time and final year-on-year core PCE price inflation for selected vintages.[20] Specifically, for each year, we show the vintage of data ending in June, i.e., the one incorporating the annual update of the NIPAs, which normally is published at the end of July (or beginning of August) of the same year. The only exception to this pattern is the middle plot in the fourth row, which shows results obtained with the vintage ending in May 2019, i.e., the second-to-last vintage that we analyze.

Each plot in Figure 4 has five lines: the thick red line is the real-time estimate of common core inflation. The thick yellow line is the *quasi*-real-time estimate of common core inflation. The thin red line is the final estimate of common core inflation. The thick black line is year-on-year core PCE price inflation computed using the data actually available at each point in time, while the thin black line is the final estimate of year-on-year core PCE price inflation computed. Finally, note that in the right plot on the fourth row,

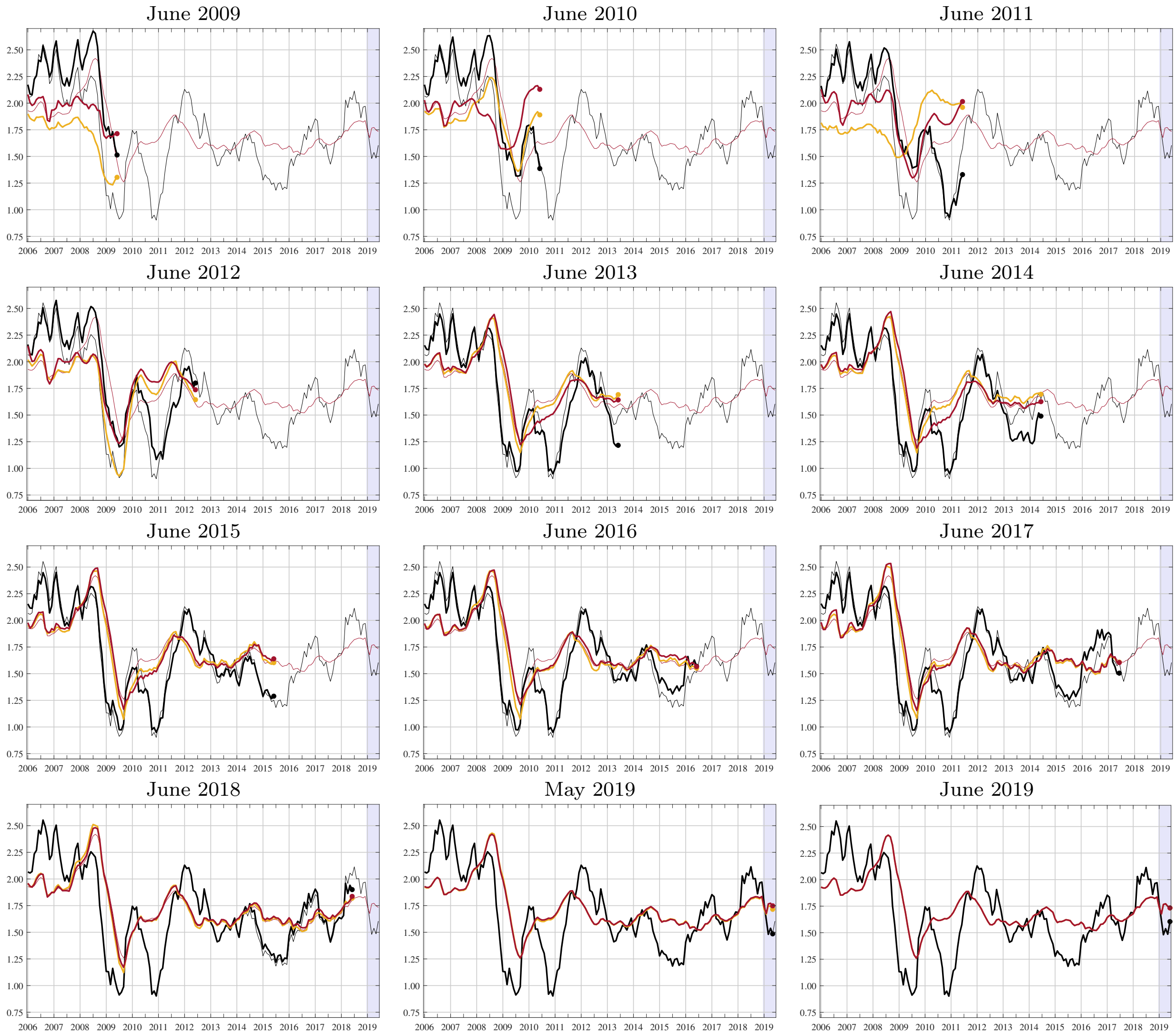
[19] Because the structure of PCE changed as a result of the 2009 comprehensive revision, it is challenging to extend the real-time analysis further back in time.

[20] The "final" estimate of common core inflation is the one computed using the latest available data (meaning the data published by the BEA on July 30, 2019) and presented in Section 5. The "quasi-real-time" estimate is also obtained using the vintage of data from July 30, 2019, but the model is estimated on expanding windows, where the first window ends in June 2009 and the last one in June 2019. Because the quasi-real-time exercise uses already-revised data, the common component estimates obtained from this exercise are free of the data revision problem; hence any potential revision to our measures is the sole result of parameter estimation and filtering.

the black and the blue line overlap, and likewise, the yellow and red line.

Table 6 shows the mean absolute revision for core PCE price inflation and common core inflation computed over all the 121 vintages. Here we define a "revision" as the difference between the real-time (or *quasi*-real-time estimate) estimate and the final estimate. Put differently, in each plot, the revision of common core inflation is the difference between the red (yellow) dot and the thin red line—in the case of core PCE prices is the difference between the black dot and the thin black line.

Figure 4: Real-time estimates — year-on-year inflation



Note: In each plot, the thick red line is the real-time estimate of common core inflation. The thick yellow line is the *quasi*-real-time estimate of common core inflation. The thin red line is the final estimate of common core inflation. The thick black line is year-on-year core PCE price inflation computed using the data actually available at each point in time. Finally, the thin black line is the final estimate of year-on-year core PCE price inflation computed.

As can be seen from Figure 4, the 2013 comprehensive revision of the NIPAs had a huge impact on core PCE prices, and likewise, on common core inflation.[21] This is why we have computed the average size of the revision for the pre-2013 comprehensive revision vintages and the post-2013 comprehensive revision vintages.

Between June 2009 and May 2013, our estimate of common core inflation underwent sizable revisions, though the average size of these revisions is a bit smaller than those for core PCE price inflation. There are two reasons why the common component revised a lot in this period. The first one is related to the comprehensive revision of the NIPAs, i.e., to data revision. The second one is related to the behavior of core PCE price inflation, which affects model estimation. Indeed, as can be seen from the revision to the *quasi*-real-time estimate, the model was fooled by the double dip in core PCE price inflation that occurred between the fourth quarter of 2008 and the end of 2010. As a result, the *quasi*-real-time estimate of common core inflation stabilizes only after 2012. That said, despite the model undergoing huge revisions, in real-time, the model classified the downturn in 2008-2009 as common, and the one in 2010 as idiosyncratic.

In summary, by looking at Table 6, we can see that in the first part of the sample the average size of the revisions in common core inflation is 21 basis points, 15 of which can be attributed to parameter estimates, and just 6 to data revision.

In contrast to the period between June 2009 and May 2013, from June 2013 onwards, common core inflation underwent very small revisions. Indeed, as can be clearly seen from Figure 4, following the 2013 comprehensive update of the NIPAs, the real-time estimate of core PCE price inflation provides a much better signal of the final estimate—the average absolute revision of core PCE price inflation after the 2013 annual update is about 40% smaller than the revision pre-2013 annual update. Similarly, after June 2013, common core inflation is very close to the final estimate, and the size of the revision is substantially smaller than that of core PCE price inflation. Finally, the average absolute revision for the *quasi*-real-time estimate post-2013 is in line with the revision of the real-time estimate, thus indicating that common core inflation revised because of estimation uncertainty, not because of the revision of the PCE data itself.

[21] The 2013 comprehensive revision of the NIPAs had a particularly relevant effect on the imputed price of banking services and on the price of medical and hospitalization insurance, and income loss insurance.

Table 6: Average absolute revision

Inflation	Sample	$\boldsymbol{\pi}_t^c$	$\boldsymbol{\chi}_{t,RT}^c$	$\boldsymbol{\chi}_{t,QRT}^c$
month-on-month	2009:6 – 2013:5	5.5	1.8	1.8
	2013:6 – 2019:6	3.6	1.7	1.6
year-on-year	2009:6 – 2013:5	23.1	21.1	15.5
	2013:6 – 2019:6	13.9	3.6	4.0

Note: The average absolute revision is expressed in basis points

6.3 Phillips curve relations

In this section, we compare core PCE price inflation and common core inflation in terms of their relationship with economic slack. To this end, we estimate a specification of the Phillips curve that is very similar to the one used by Yellen (2015). In this specification, core PCE price inflation (π_t^c) is a function of its first four lags ($\pi_{t-1}^c, \ldots, \pi_{t-4}^c$), of longer-run inflation expectations as measured by the Michigan survey (π_{t-1}^e), of economic slack as measured by the CBO unemployment gap ($\widetilde{u}_t$), and of relative import prices ($\pi_t^m - \pi_{t-1}^c$):[22]

$$\pi_t^c = \alpha + \beta_1 \pi_{t-1}^c + \ldots + \beta_4 \pi_{t-4}^c + \gamma \pi_{t-1}^e + \delta \widetilde{u}_t + \phi(\pi_t^m - \pi_{t-1}^c) + \varepsilon_t. \tag{7}$$

The model is estimated on quarterly data on a sample starting in 1995:Q4 and ending in 2019:Q2, with all inflation rates expressed at an annual rate. Finally, the model is estimated with restricted least squares by imposing the restriction that the sum of the coefficients of inflation expectations and lagged inflation is equal to one, which implies that changes in expected inflation are (eventually) passed through one for one to actual inflation: $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$.

Table 7 shows estimates of the Phillips curve model (7) when the endogenous variable is core PCE price inflation (π_t^c), common core inflation (χ_t^c), or the idiosyncratic component of core PCE price inflation ($\xi_t^c = \pi_t^c - \chi_t^c$).[23] In addition to the coefficient on the unemployment gap, $\widetilde{u}_t$, which characterizes the slope of the Phillips curve, we are also particularly interested in the sum of the coefficients of the lagged inflation coefficients, $\sum_{p=1}^4 \pi_{t-p}$, which

[22] Import price inflation (π_t^m) is defined as in Peneva and Rudd (2017) as the annualized log difference of the price index for imports of nonpetroleum goods excluding natural gas, computers, peripherals, and parts. The difference with core PCE prices is weighted by the two-quarter moving average of the share of nominal imports in nominal core PCE (see Peneva and Rudd, 2017).

[23] Note that the Phillips curve for ξ_t^c is estimated by OLS, i.e., without imposing the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$. Indeed, as can be seen $\widehat{\gamma} < 0$ when estimated with OLS, which indicates that the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$ does not hold.

characterize the persistence of inflation. Indeed, the combination of these two coefficients gives the long-run multiplier of the unemployment rate gap—the more persistent inflation is, the larger is the cumulative long-run effect of a change in the unemployment gap (with the limiting case being when the sum of the coefficients is 1, so that a change in the unemployment gap permanently affects inflation).

Table 7: PRICE INFLATION PHILLIPS CURVE: 1995:Q4–2019:Q2

Variable	**Coefficient**	$\boldsymbol{\pi_t^c}$	$\boldsymbol{\chi_t^c}$	$\boldsymbol{\xi_t^c}$
Persistence	$\sum_{j=1}^{4} \beta_j$	0.252 (0.152)	0.587 (0.082)	0.112 (0.178)
Inflation expectations	γ	0.748 (0.152)	0.413 (0.082)	-0.238 (0.269)
Unemployment gap	δ	-0.051 (0.030)	-0.031 (0.008)	-0.009 (0.029)
Import prices	ϕ	0.085 (0.016)	0.044 (0.005)	0.038 (0.016)
Long-run multiplier $\widetilde{u}_t$	$\delta/\mathcal{B}$	-0.067	-0.075	-0.010
Long-run multiplier $(\pi_t^m - \pi_{t-1}^c)$	$\phi/\mathcal{B}$	0.114	0.108	0.043
R^2		0.280	0.659	0.131

Notes: Standard error in parenthesis. The Phillips curves for π_t^c and χ_t^c are estimate with Restricted OLS by imposing the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$. The Phillips curve for ξ_t^c is estimated by OLS. $\mathcal{B} = 1 - \sum_{j=1}^{4} \beta_j$.

Looking at Table 7, we can see that when the endogenous variable is π_t^c the coefficient for the unemployment gap is small and statistically significant just at the 10% confidence level, whereas when the model is estimated using χ_t^c as an endogenous variable, the coefficient for $\widetilde{u}_t$ is even smaller, but strongly statistically significant.[24] However, the main difference between the two estimated Phillips curves comes from the estimated persistence of the series, which is much higher in the case of common core inflation. As a result, the long-run multiplier of the unemployment rate gap estimated with common core inflation is a touch higher than that estimated with core PCE price inflation.

Finally, as we can see from the last column of Table 7, the idiosyncratic component has no relationship whatsoever with economic slack. However, the coefficient from import prices is smaller than the one estimated on both π_t^c and χ_t^c, but statistically significant. This result is not totally surprising because import prices affect primarily goods prices,

[24] Our finding that the coefficient on the unemployment gap is very low and not statistically significant is consistent with the extensive literature that has documented how the relationship between economic slack and price inflation has become much weaker over time (see among others Powell, 2018; Hooper et al., 2019), and is in line with those reported by Powell (2018).

and, as we discussed in Section 4, goods prices are more idiosyncratic than services prices. That said, as we can see from the very low R^2, the idiosyncratic component is very little related to economic fundamentals, thus indicating that the signal is contained in common core inflation, i.e., we have been successful in parsing the noise out to the idiosyncratic component.

To summarize, the results in Table 7 show that, once the idiosyncratic factors are filtered out, the Phillips curve fits much better the data, and the estimated slope of the Phillips curve is strongly statistically significant (a result also found by Ball and Mazumder, 2019, and Stock and Watson, 2019). However, in contrast with (Ball and Mazumder, 2019), we find that even after filtering out idiosyncratic factors, the Phillips curve is extremely flat post-1995. In other words, our results suggest that the flattening of the Phillips curve is not about noise or non-macroeconomic factors. Rather, the flattening of the Phillips curve is the result of macroeconomic forces.

7 Conclusions

In this paper, we disentangle changes in prices due to economy-wide (common) shocks from changes in prices due to idiosyncratic shocks. To do so, we introduce a new statistical model that is entirely data-driven, i.e., it does not make any "structural" economic assumptions or ad hoc judgments about what factors are affecting prices. We estimate the model on a dataset of 146 disaggregated PCE prices from January 1995 to June 2019. Our model classifies as idiosyncratic many well-known episodes, such as the March 2017 collapse in the index of wireless telephone services, and it suggests that most of the fluctuations in core PCE prices since 2010 have been idiosyncratic in nature. Moreover, our estimate of common core inflation seems not to suffer from any residual seasonality, and it revises less in real time than does published core PCE price inflation. Finally, we find that common core inflation responds to economic slack, while the idiosyncratic component does not. That said, even after filtering out idiosyncratic factors, the estimated Phillips curve is extremely flat post-1995. Therefore, our results suggest that the flattening of the Phillips curve is the result of macroeconomic forces.

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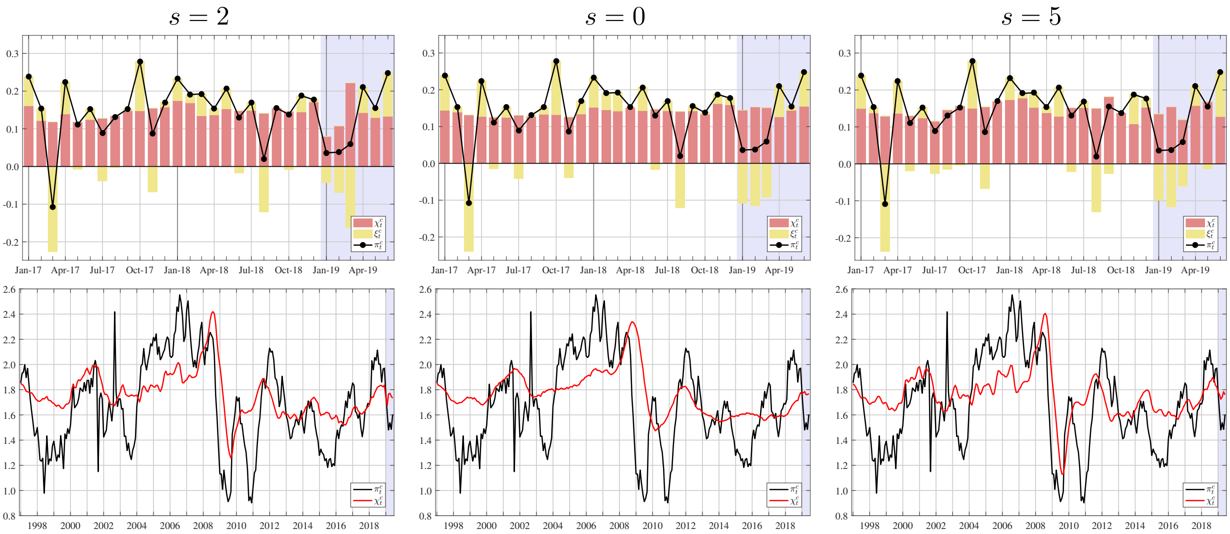
Appendix A Robustness analysis

A.1 Alternative model specifications

In this section we repeat the analysis of Section 5 by using the two alternative specifications of the dynamic factor model that we already considered in Section 4.

Figure A1 shows the common-idiosyncratic decomposition for the monthly percentage change (top row), and the 12-month percent change (bottom row), of the core PCE price index. Note that the top-left plot is a zoomed version of the left plot in Figure 2, while the bottom-left plot is identical to the right plot in Figure 3.

Figure A1: Common and idiosyncratic decomposition
Alternative model specifications

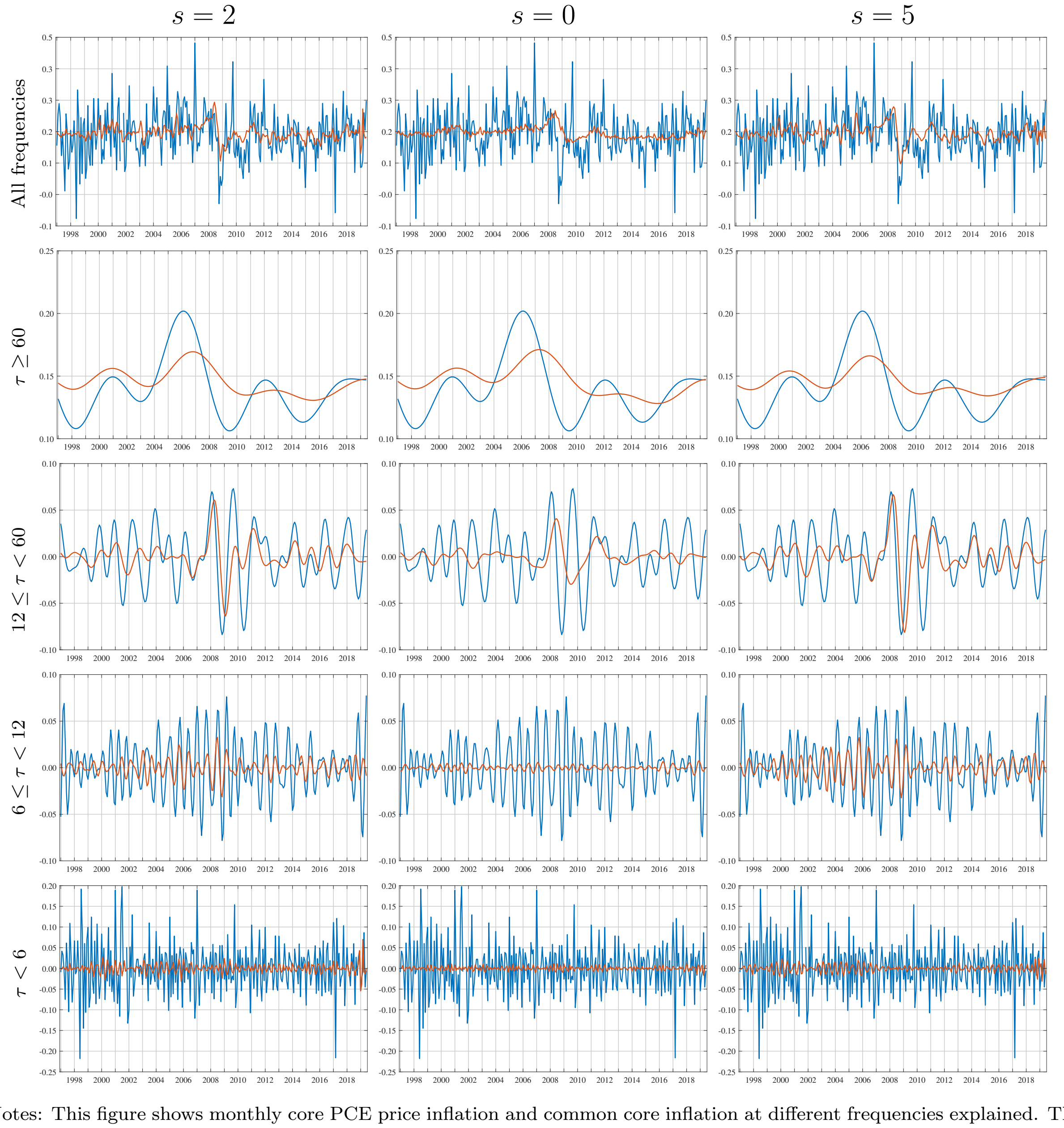


Notes: in each plot of the top row, the red bar is month-on-month common core inflation, while the yellow bar gives the idiosyncratic component. By construction, these two components sum to overall core PCE inflation (the black line). In each plot of the bottom row, the red line is year-on-year common core inflation, while the black line is year-on-year core PCE price inflation. In all plots the shaded blue area highlights data for 2019. Each column represents a different model specification: in the left column, each disaggregated price loads the common factor only contemporaneously ($s = 0$); in the middle column, our benchmark specification, each disaggregated price can load the common factor in a time window of three months ($s = 2$); in the right column, each disaggregated price can load the common factor in a time window of six months ($s = 5$).

Starting with the monthly percent changes, as we can see from the top row of Figure A1, the three models interpret largely in the same way core PCE price inflation in the last two and half years. All three models identify large negative contributions of the idiosyncratic component in March 2017, August 2018, and in the first three months of 2019. Likewise, all models signal positive contributions from the idiosyncratic component for January 2017, October 2017, January 2018, and the second three months of 2019. Of course, the magnitude of these estimated contributions is not the same, but it is qualitatively similar.

Moving to the 12-month percent change, as we can see from the bottom row of Figure A1, the model which does not allow for lags in the factor loadings yields an estimate of

Figure A2: Core PCE price inflation at different frequencies



Notes: This figure shows monthly core PCE price inflation and common core inflation at different frequencies explained. The period τ of each fluctuations is expressed in number of months, so that the second row ($\tau \geq 60$) shows that part of core PCE price inflation (common core inflation) that is explained by fluctuation with period longer than five years.

year-on-year common core inflation that is much smoother compared to the other models. By contrast, the difference between the model with $s = 2$ and the model with $s = 5$ is minimal. Figure A2 strengthens this conclusion.

Finally, Figure A2 shows monthly Core PCE price inflation and monthly common core inflation at different frequencies. As we can see from the second row, the three models yield very similar estimates of the fluctuations of common core inflation with period longer than 10 years. The difference between the model with no lags and those with lags emerges when considering fluctuations between 1 and 5 years, and fluctuations with period between 6 months and one year. By including lags in the factor loadings, we capture a larger fraction of fluctuations at these frequencies.

A.1.1 Additional properties of the model

Table A1 presents the same statistics presented in Section 6.1 about residual seasonality, while Table A2 repeats the real-time and *quasi*-real-time exercise presented in Section 6.2. As we can see from the two tables, our benchmark model with $s = 2$ and the model with $s = 5$ have similar properties—the only exception being the fact that the model with $s = 5$ underwent smaller revisions between June 2009 and May 2013. In contrast, the model with no lags in the factor loadings has different properties. On the one hand, it exhibits even less residual seasonality than our benchmark model; on the other hand, year-on-year common core inflation estimated with this model revises more than our benchmark model.

Table A1: Residual seasonality
Alternative model specifications

	$s = 2$		$s = 0$		$s = 5$	
Vintage	06/18	07/19	06/18	07/19	06/18	07/19
Jan-Mar	0.05	-0.01	0.05	0.03	0.05	-0.01
Apr-Jun	0.05	-0.01	0.01	0.00	0.09	-0.03
Jul-Sep	0.04	-0.01	0.00	-0.02	0.02	0.00
Oct-Dec	-0.13	0.03	-0.06	-0.01	-0.16	0.03

Notes: this table shows the average difference between the annualized three-month common core inflation rate and the average of the annualized inflation rates for the four three-month sub-periods. The column $s = 2$ reports results for our benchmark model, which coincides with those shown in the column χ_t^c in Table 5. Column $s = 0$ reports results for the model with no lags in the factor loadings, while column $s = 5$ report results for the specification in which each disaggregated price can load the common factor in a time window of six months. Finally, the row "Vintage" indicates the month when the BEA published the vintage of data upon which it is computed the residual seasonality (see also the note for Table 5).

Finally, Table A3 reports estimates of the Phillips curve described in Section 6.3. As we can see from the table, the estimated parameters for our benchmark model with $s = 2$ and for the model with $s = 5$ have similar properties. The estimates for the model with $s = 0$ differs in a few aspects: first, common core inflation estimated with $s = 0$ is more persistent, hence although the estimated coefficient for the unemployment gap is smaller than the other two specifications, the long-run multiplier is estimated to be higher. Second,

Table A2: Average absolute revision
Alternative model specifications

Inflation	Sample	Real Time $s=2$	Real Time $s=0$	Real Time $s=5$	*Quasi* Real Time $s=2$	*Quasi* Real Time $s=0$	*Quasi* Real Time $s=5$
month-on-month	2009:6 – 2013:5	1.8	2.5	1.9	1.8	2.8	1.9
	2013:6 – 2019:6	1.7	0.5	2.1	1.6	0.6	2.0
year-on-year	2009:6 – 2013:5	21.1	25.9	17.4	15.5	26.1	15.2
	2013:6 – 2019:6	3.6	3.3	5.2	4.0	6.3	5.3

Note: The average absolute revision is expressed in basis points

a larger portion of the idiosyncratic component estimated when $s = 0$ respond to economic fundamentals.

Table A3: Price inflation Phillips curve: 1995:Q4–2019:Q2
Alternative model specifications

Coefficient	$\boldsymbol{\chi}_t^c$ $(s=2)$	$\boldsymbol{\chi}_t^c$ $(s=0)$	$\boldsymbol{\chi}_t^c$ $(s=5)$	$\boldsymbol{\xi}_t^c$ $(s=2)$	$\boldsymbol{\xi}_t^c$ $(s=0)$	$\boldsymbol{\xi}_t^c$ $(s=5)$
$\sum_{j=1}^4 \beta_j$	0.587 (0.082)	0.861 (0.041)	0.549 (0.081)	0.112 (0.178)	-0.044 (0.171)	0.14 (0.179)
γ	0.413 (0.082)	0.139 (0.041)	0.451 0.081	-0.238 (0.269)	-0.37 (0.285)	-0.137 (0.273)
δ	-0.031 (0.008)	-0.012 (0.004)	-0.028 (0.009)	-0.009 (0.029)	-0.03 (0.031)	-0.011 (0.029)
ϕ	0.044 (0.005)	0.013 (0.002)	0.047 (0.005)	0.038 (0.016)	0.072 (0.017)	0.031 (0.016)
$\delta/\mathcal{B}$	-0.075	-0.088	-0.062	-0.01	-0.028	-0.013
$\phi/\mathcal{B}$	0.108	0.091	0.103	0.043	0.069	0.036
R^2	0.659	0.897	0.603	0.131	0.265	0.110

Notes: Standard error in parenthesis. $\mathcal{B} = 1 - \sum_{j=1}^4 \beta_j$. The Phillips curves for χ_t^c are estimate with Restricted OLS by imposing the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$. $\mathcal{B} = 1 - \sum_{j=1}^4 \beta_j$. The Phillips curves for ξ_t^c are estimate with OLS.

A.2 Alternative dataset

In Section 3, we made the point that taking into account the source of each disaggregated PCE price index is crucial when estimating a dynamic factor model. This is the case because whenever two (or more) prices in the dataset are constructed from the same CPI (or PPI), they will be perfectly correlated, as will be their idiosyncratic components, thus violating the assumption of mildly cross-sectionally correlated idiosyncratic components. This is not just a theoretical issue, as the literature has shown that when there is an excess of cross-sectional correlation between the idiosyncratic components, both estimation of dynamic factor models, as well as their forecasting properties, deteriorates (Boivin and Ng, 2006; Luciani, 2014).

Recall that, at that level of disaggregation used by the Dallas Fed to compute Trimmed Mean PCE, there are 21 groups of prices (for a total of 53 PCE price indexes involved) constructed out of the same CPI (or PPI). In Section 3, we argue that, with so many prices constructed out of the same source, the excess cross-correlation problem must be quite severe. Table A4, which shows the number of cross-correlations in the data that are within a specific range, confirms this guess: in the Dallas Fed dataset there are forty-three cross-correlations higher than 0.9, whereas in our dataset there are just two.

Table A4: Number of cross correlation within a range

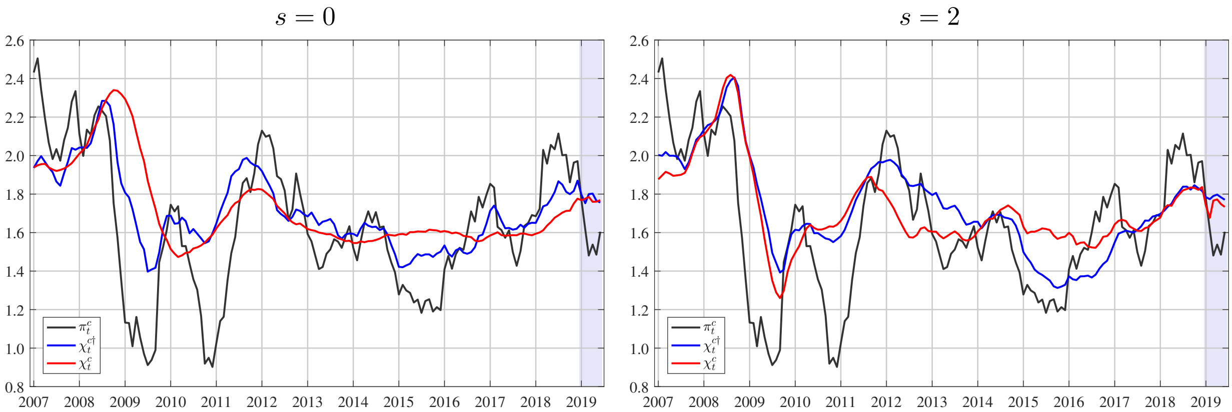
Range	Our dataset	Dallas Fed
0.9 – 1.0	2	43
0.8 – 0.9	2	3
0.7 – 0.8	2	11
0.6 – 0.7	5	9
0.5 – 0.6	11	19

Each cell reports the number of cross correlations in the data data are within the interval $[a, b)$. The second column reports result obtained on the dataset described in Section 3 containing 146 disaggregated PCE prices, while the third column reports result obtained on the dataset used by the Dallas Fed containing 178 disaggregated PCE prices.

The relevant question then is: What happens to our estimates if we do not group PCE prices based on their source? To answer this question, Figure A3 compares our estimate of common core inflation with the one estimated on the level of disaggregation used by the Dallas Fed. As we can see, when estimating the dynamic factor model on the Dallas Fed dataset, common core inflation fluctuates way more implying a different interpretation of core PCE price inflation between 2013 and 2017. However, these additional fluctuations are the result of the model parsing as *common* the strong correlation between prices that are constructed from the same CPI (or PPI); this strong correlation is spurious, and as shown in Table A4, we successfully removed it.

Figure A3: Common core year-on-year inflation

Estimates on alternative datasets



Notes: in each plot, the red line is common core inflation estimated on our dataset, the blue line is common core inflation estimated on the Dallas Fed dataset, and the black line is year-on-year core PCE price inflation. Each column represents a different model specification. The shaded blue area highlights data for 2019.

Appendix B Data

The price data are taken from the National Income and Product Accounts (NIPA) Table 2.4.4U , while the quantity data necessary to compute the weights are from taken the NIPA Table 2.4.6U. The data were downloaded from Haver on July 30, 2019. In the tables below column “ID” reports the position of each item in our dataset. Column “w” reports the approximate weight of each item in the Total PCE price index—the weights reported are those as of June 2019. Finally, columns “$s = 0$”, “$s = 2$”, and “$s = 5$” reports the share of variance explained by the common component for the three different model specification. More detailed information about the dataset used, including the source of each PCE price index, and the list of aggregation performed, are available in the complementary appendix.

Table B1: Food

ID	PCE Component	w	$s=0$	$s=2$	$s=5$
35	Cereals	0.4	9.0	11.0	16.3
36	Bakery Products	0.6	16.4	17.5	20.9
37	Beef and Veal	0.3	0.7	2.9	5.9
38	Pork	0.2	2.6	2.9	7.2
39	Other Meats	0.2	1.3	3.4	3.6
40	Poultry	0.4	1.5	2.0	2.9
41	Fish and Seafood	0.1	1.5	2.8	5.0
42	Fresh Milk	0.2	0.3	3.9	12.0
43	Processed Dairy Products	0.4	6.3	10.8	14.4
44	Eggs	0.1	0.6	2.5	3.5
45	Fats and Oils	0.2	11.5	12.0	14.0
46	Fresh Fruit	0.3	0.7	2.8	5.4
47	Fresh Vegetables	0.3	0.5	0.9	1.1
48	Processed Fruits & Vegetables	0.2	12.2	11.8	18.3
49	Sugar and Sweets	0.3	4.7	2.8	5.9
50	Food Products, Not Elsewhere Classified	1.1	8.3	7.6	6.7
51	Coffee, Tea & Other Beverage Materials	0.1	1.0	1.3	2.2
52	Mineral Waters, Soft Drinks & Vegetable Juices	0.6	4.4	4.4	6.5
53	Spirits	0.2	3.5	6.3	6.2
54	Wine	0.3	4.5	4.6	8.2
55	Beer	0.5	2.2	1.6	3.8
56	Food Produced & Consumed on Farms	0.0	0.1	6.3	8.9

Table B2: Energy

ID	**PCE Component**	w	$s=0$	$s=2$	$s=5$
63	Gasoline & Other Motor Fuel	2.2	0.1	36.6	29.9
64	Lubricants & Fluids	0.1	8.5	11.4	27.3
65	Fuel Oil	0.1	0.6	32.7	32.4
66	Other Fuels	0.0	1.5	22.8	20.9
86	Electricity	1.3	5.2	9.2	9.6
87	Natural Gas	0.4	1.6	20.6	19.2

Table B3: Core Services Non-Market-Based

ID	**PCE Component**	w	$s=0$	$s=2$	$s=5$
83	Rental Value of Farm Dwellings	0.1	2.4	8.9	13.5
107	Gambling	1.0	2.9	47.1	39.6
115	Commercial Banks	1.0	10.6	10.7	18.4
116	Other Depository Institutions & Regulated Invest Companies	1.0	3.1	3.0	5.5
117	Pension Funds	0.4	2.3	20.7	17.9
119	Life Insurance	0.6	0.1	0.7	0.9
121	Net Health Insurance	1.6	2.9	4.8	6.1
122	Net Motor Vehicle & Other Transportation Insurance	0.6	2.2	3.1	4.4
132	Labor Organization Dues	0.1	0.3	3.2	13.6
138	Social Assistance	1.0	0.5	9.7	14.8
139	Social Advocacy & Civic & Social Organizations	0.1	0.1	10.8	13.1
140	Religious Organizations Services to Households	0.1	0.8	18.9	16.3
141	Foundations and grantmaking and giving services to households	0.0	0.1	19.2	17.0
142	Domestic Services	0.2	5.3	3.9	7.8
146	Final Consumption Expenditures of Nonprofit Institutions Serving Households	3.0	0.1	2.5	3.4

Table B4: Core goods (I)

ID	PCE Component	w	$s = 0$	$s = 2$	$s = 5$
1	New Autos	0.4	0.1	3.5	5.0
2	New Light Trucks	1.6	6.2	11.0	12.1
3	Net Purchases of Used Motor Vehicles	1.1	1.2	2.3	4.7
4	Tires	0.2	9.4	8.2	8.4
5	Accessories & Parts	0.3	2.1	3.8	8.2
6	Furniture	0.9	0.8	0.9	1.7
7	Clocks, lamps, lighting fixtures, and other household decorative items	0.3	0.1	1.5	7.8
8	Carpets & Other Floor Coverings	0.2	1.1	2.8	4.9
9	Window Coverings	0.2	0.8	0.3	0.9
10	Major appliances	0.4	5.0	6.3	8.2
11	Small Electric Household Appliances	0.1	0.1	2.6	3.1
12	Dishes and Flatware	0.1	0.5	1.9	2.8
13	Nonelectric Cookware & Tableware	0.2	0.8	1.0	3.6
14	Tools, Hardware & Supplies	0.2	0.6	0.7	3.6
15	Outdoor Equipment & Supplies	0.0	0.4	1.8	3.3
16	Televisions	0.2	0.8	2.1	3.2
17	Other Video Equipment	0.1	3.3	6.1	6.2
18	Audio Equipment	0.2	0.5	1.0	5.7
19	Audio discs, tapes, vinyl, and permanent digital downloads	0.0	0.1	0.5	2.3
20	Video Cassettes & Discs, Blank & Prerecorded	0.1	0.1	0.1	6.9
21	Photographic Equipment	0.0	2.7	3.8	5.4
22	Personal Computers & Peripheral Equipment	0.4	8.2	10.9	11.2
23	Computer Software & Accessories	0.7	0.2	1.4	5.1
24	Telephone hardware, calculators, and other consumer items	0.3	2.1	2.3	3.5
25	Sporting Equipment, Supplies, Guns & Ammunition	0.5	3.4	2.4	6.7
26	Sports & Recreational Vehicles	0.4	0.9	2.4	14.8
27	Recreational Books	0.2	0.8	1.6	6.1

Table B5: CORE GOODS (II)

ID	PCE Component	w	$s = 0$	$s = 2$	$s = 5$
28	Musical Instruments	0.0	0.1	0.3	3.0
29	Jewelry	0.4	0.2	1.2	2.2
30	Watches	0.1	0.2	5.1	18.7
31	Medical equipment and supplies	0.3	0.0	1.2	4.5
32	Corrective Eyeglasses & Contact Lenses	0.3	0.3	0.1	1.1
33	Educational Books	0.1	2.0	2.3	3.9
34	Luggage & Similar Personal Items	0.2	0.2	0.6	4.2
57	Womens & Girls Clothing	1.3	0.0	0.9	2.2
58	Mens & Boys Clothing	0.7	0.1	0.9	6.0
59	Childrens & Infants Clothing	0.1	0.2	0.0	3.3
60	Sewing machines, fabrics, and supplies	0.0	0.1	0.9	4.9
61	Standard Clothing Issued to Military Personnel	0.0	0.0	2.6	3.5
62	Shoes & Other Footwear	0.6	0.0	0.3	0.8
67	Prescription Drugs	3.2	0.5	1.2	4.5
68	Nonprescription Drugs	0.5	0.1	1.4	5.6
69	Games, Toys & Hobbies	0.5	3.8	2.6	1.9
70	Pets & Related Products	0.5	14.0	15.6	16.6
71	Flowers, Seeds & Potted Plants	0.2	0.0	0.5	0.9
72	Film & Photographic Supplies	0.0	2.1	4.4	8.2
73	Household Cleaning Products	0.3	3.1	6.0	7.9
74	Household Paper Products	0.3	3.8	5.7	10.1
75	Household Linens	0.3	0.0	2.3	5.7
76	Miscellaneous Household Products	0.2	4.5	3.0	4.4
77	Personal Care Products	1.0	0.1	3.3	2.5
78	Tobacco	0.7	0.0	0.3	0.6
79	Newspapers & Periodicals	0.4	0.1	3.9	11.1
80	Stationery & Miscellaneous Printed Materials	0.2	1.4	2.0	5.8

Table B6: CORE SERVICES MARKET-BASED (I)

ID	PCE Component	w	$s = 0$	$s = 2$	$s = 5$
81	Rent of primary residence	4.2	7.5	11.3	12.2
82	Imputed Rental of Owner-Occupied Nonfarm Housing	11.5	4.8	6.4	7.3
84	Water Supply & Sewage Maintenance	0.5	0.0	0.2	0.8
85	Garbage & Trash Collection	0.2	4.9	7.7	21.5
88	Physician Services	3.9	1.1	1.5	1.7
89	Dental Services	0.9	7.8	8.3	8.7
90	Paramedical Services	2.7	6.0	7.5	8.4
91	Hospitals	8.0	2.2	2.3	2.1
92	Nursing Homes	1.4	7.0	6.0	8.3
93	Motor Vehicle Maintenance & Repair	1.3	15.7	15.1	16.0
94	Motor Vehicle Leasing	0.5	3.3	4.7	8.4
95	Motor Vehicle Rental	0.1	0.1	1.7	2.2
96	Parking Fees & Tolls	0.2	0.6	1.0	3.5
97	Railway Transportation	0.0	0.1	0.5	1.1
98	Intercity bus fare	0.1	0.0	1.9	1.5
99	Intracity mass transit	0.2	0.6	0.4	0.4
100	Air Transportation	0.7	0.1	2.0	6.5
101	Water Transportation	0.0	1.5	5.0	6.8
102	Membership Clubs & Participant Sports Centers	0.4	0.8	0.9	1.3
103	Other recreation services	0.6	2.9	3.9	5.0
104	Admission to movies, theaters, and concerts	0.4	0.5	0.3	1.1
105	Spectator Sports	0.2	1.0	5.0	15.8
106	Audio-Video, Photographic & Info Processing Services	1.0	0.1	0.2	3.1
108	Veterinary & Other Services for Pets	0.3	7.8	7.4	8.1
109	Maintenance & Repair of Rec Vehicles & Sports Equipment	0.0	3.9	4.6	14.3

Table B7: CORE SERVICES MARKET-BASED (II)

ID	PCE Component	w	$s=0$	$s=2$	$s=5$
110	Food at employee sites and schools	0.3	0.3	0.1	0.3
111	Other Purchased Meals	4.8	16.9	19.9	21.8
112	Alcohol in Purchased Meals	0.8	6.9	7.4	8.0
113	Hotels and Motels	0.8	0.0	0.1	0.9
114	Housing at Schools	0.3	8.0	8.3	10.3
118	Financial Service Charges, Fees & Commissions	2.6	3.1	12.9	12.0
120	Net Household Insurance	0.1	0.8	0.8	0.9
123	Communication	1.7	3.8	4.7	5.3
124	Higher Education	1.3	10.5	10.8	12.0
125	Elementary & Secondary Schools	0.3	9.3	12.9	12.5
126	Day Care & Nursery Schools	0.1	8.5	9.8	11.2
127	Commercial & Vocational Schools	0.4	2.1	2.5	2.5
128	Legal services	0.8	2.3	5.2	9.0
129	Tax Preparation & Other Related Services	0.2	0.1	7.1	20.8
130	Employment Agency Services	0.0	0.0	1.1	3.2
131	Other Personal Business Services	0.1	3.1	7.5	13.3
133	Funeral & Burial Services	0.2	12.7	14.5	14.4
134	Hairdressing Salons & Personal Grooming Establishments	0.6	3.1	3.7	5.9
135	Apparel services other than laundry and dry-cleaning	0.5	7.6	5.2	10.4
136	Laundry & Dry Cleaning Services	0.1	2.3	2.7	4.0
137	Child Care	0.3	8.6	9.8	11.3
143	Moving, Storage & Freight Services	0.1	0.2	3.1	7.8
144	Repair of household items	0.1	0.2	2.5	9.8
145	Other Household Services	0.2	5.7	6.2	11.1

Common and Idiosyncratic Inflation

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Complementary Appendix

Table CA1 shows detailed information about the dataset used to estimate the common and idiosyncratic decomposition of core PCE prices. The table has five columns: columns “ID”, “Item”, and “Haver” report for each price index the identification number on our dataset, on NIPA Table 2.4.4U, and on the Haver USNA database, respectively. Column “PCE Component” reports the name of each PCE price component, while the column “Price index source data” reports the source that the BEA uses to construct that PCE price.[1] The sixth column of the table reports for some item a flag in four different symbols:

◇ All the entries that have a flag denoted by the “•” symbol are “PCE” price indexes that (actually) do not exist, i.e., they are not available in the NIPA Table 2.4.4U. These price indexes are constructed by us and are aggregation of PCE price indexes that are (actually) available in Table 2.4.4U. These PCE price indexes have all the same source data, and therefore they are nearly identical. There are overall 14 of such “PCE” price indexes, and specific information on each of them are available in Table CA2.

   – Suppose we have to aggregate the price and the quantity index of n items. Let q_{it} be the quantity index for item i at time t, and let p_{it}

[1] For detailed information on source data for PCE price index we refer the reader to the excel file that can be downloaded at `https://www.bea.gov/media/3051`.

be the price index for item i at time t. Then, let P_t the aggregate price index, then for the Fisher formula we have:

$$P_t = P_{t-1}\sqrt{\frac{\sum_{i=1}^{n} p_{it}q_{it-1}}{\sum_{i=1}^{n} p_{it-1}q_{it-1}} \times \frac{\sum_{i=1}^{n} p_{it}q_{it}}{\sum_{i=1}^{n} p_{it-1}q_{it}}} \qquad \text{for } t = 1, \ldots, T-1 \tag{1}$$

$$P_T = \frac{1}{n}\sum_{i=1}^{n} p_{iT} \tag{2}$$

where (2) is necessary to fix the scale.

– Note that formula (1) is not always necessary. Indeed, in many of the aggregation that we perform, the indexes that we are aggregating are actually the same. In some other cases, the index are identical for most of the sample, but not for all the sample. This is the case because of some change of methodology in the way the BEA sourced or built the index. In those cases, formula (1).

– Once P_t is constructed, we construct the quantity index as if $p_{1t} = p_{2t} = \ldots = p_{nt} = P_t$, and hence $Q_t = \sum_{i=1}^{n} q_{it}$. In other words no Fisher formula is necessary for quantities.

◇ All entries that have a flag denoted by the "$\star$" symbol are PCE price indexes available on Table 2.4.4U, which are aggregation of other subindexes with the same source data. There are overall 7 of such PCE price indexes and specific information on each of them is available in Table CA3.

◇ All entries that have a flag denoted by the "$\circ$" symbol are PCE price indexes that have multiple source data. This is the case because they are aggregation of different price indexes that have different source data.

◇ Finally, all entries that have a flag denoted by the "†" symbol are PCE price indexes constructed by the BEA by different methodologies and for which we refere the reader to the BEA website for more information.

All the PCE price indexes listed in Table CA1 are also used by the Dallas Fed for the construction of the Trimmed Mean PCE index, with the exception of the prices with a flag denoted by the "$\bullet$" or "$\star$" symbol. Indeed, rather than using these price indexes, the Dallas Fed uses the subcomponents listed in Table CA2 and Table CA3.

Table CA1: DATA AND DATA SOURCES

ID	Item	Haver	PCE Component	Price index source data	
1	6	JCDMNM	New Autos		⋆
2	9	JCDMTNM	New Light Trucks	CPI New trucks	
3	10	JCDMVUM	Net Purchases of Used Motor Vehicles		⋆
4	19	JCDMTTM	Tires	CPI Tires	
5	20	JCDMTVM	Accessories & Parts	CPI Vehicle parts and equipment other than tires	
6	23	JCDFUM	Furniture	CPI Furniture and bedding	
7	24	JCDFOLM	Clocks, lamps, lighting fixtures, and other household decorative items	CPI Clocks, lamps, and decorator items	
8	25	JCDFOFM	Carpets & Other Floor Coverings	CPI Floor covering	
9	26	JCDFOTM	Window Coverings	CPI Window coverings	
10			Major appliances		•
11	29	JCDFKSM	Small Electric Household Appliances	CPI Other appliances	
12	31	JCDFGDM	Dishes and Flatware	CPI Dishes and flatware	
13	32	JCDFGKM	Nonelectric Cookware & Tableware	CPI Nonelectric cookware and tableware	
14	34	JCDFSTM	Tools, Hardware & Supplies	CPI Tools, hardware, and supplies	
15	35	JCDFSLM	Outdoor Equipment & Supplies	CPI Outdoor equipment and supplies	
16	39	JCDFTVM	Televisions	CPI Televisions	
17	40	JCDFTOM	Other Video Equipment	CPI Other video equipment	
18	41	JCDFTUM	Audio Equipment	CPI Audio equipment	
19	43	JCDFTPM	Audio discs, tapes, vinyl, and permanent digital downloads	CPI Audio discs, tapes, and other media	
20	44	JCDFTCM	Video Cassettes & Discs, Blank & Prerecorded	CPI Video discs and other media	
21	45	JCDOWPM	Photographic Equipment	CPI Photographic equipment	
22	47	JCDFCPM	Personal Computers & Peripheral Equipment	CPI Personal computers and peripheral equipment	
23	48	JCDFCSM	Computer Software & Acc	CPI Computer software and accessories	
24			Telephone hardware, calculators, and other consumer items		•
25	50	JCDRSM	Sporting Equipment, Supplies, Guns & Ammunition	CPI Sports equipment	

• See Table CA2 ⋆ See Table CA3 ◦ See Table CA4 † See the excel file downloadable from the BEA website at `https://www.bea.gov/media/3051`

Table CA1: Data and data sources (continuted)

ID	Item	Haver	PCE Component	Price index source data	
26	51	JCDRSVM	Sports & Recreational Vehicles		⋆
27	58	JCDRBM	Recreational Books	CPI Recreational books	
28	59	JCDFTIM	Musical Instruments	CPI Music instruments and accessories	
29	62	JCDOJJM	Jewelry	CPI Jewelry	
30	63	JCDOJWM	Watches	CPI Watches	
31			Medical equipment and supplies		•
32	66	JCDOOEM	Corrective Eyeglasses & Contact Lenses	CPI Eyeglasses and eyecare	
33	67	JCDEBM	Educational Books	CPI Educational books and supplies	
34	68	JCDOLM	Luggage & Similar Personal Items	CPI Miscellaneous personal goods	
35	75	JCNFOFGM	Cereals	CPI Cereals and cereal products	
36	76	JCNFOFKM	Bakery Products	CPI Bakery products	
37	78	JCNFOFBM	Beef and Veal	CPI Beef and veal	
38	79	JCNFOFPM	Pork	CPI Pork	
39	80	JCNFOFRM	Other Meats	CPI Other meats	
40	81	JCNFOFJM	Poultry	CPI Poultry	
41	82	JCNFOFLM	Fish and Seafood	CPI Fish and seafood	
42	84	JCNFOFIM	Fresh Milk	CPI Milk	
43	85	JCNFOFDM	Processed Dairy Products	BEA Composite index of various CPIs	†
44	86	JCNFOFEM	Eggs	CPI Eggs	
45	87	JCNFOFWM	Fats and Oils	CPI Fats and oils	
46	89	JCNFOFFM	Fresh Fruit	CPI Fresh fruits	
47	90	JCNFOFVM	Fresh Vegetables	CPI Fresh vegetables	
48	91	JCNFOFTM	Processed Fruits & Vegetables	CPI Processed fruits and vegetables	
49	92	JCNFOFSM	Sugar and Sweets	CPI Sugar and sweets	
50	93	JCNFOFOM	Food Products, Not Elsewhere Classified	CPI unpublished detailed categories	†

• See Table CA2 ⋆ See Table CA3 ○ See Table CA4 † See the excel file downloadable from the BEA website at `https://www.bea.gov/media/3051`

Table CA1: Data and data sources (continued)

ID	Item	Haver	PCE Component	Price index source data	
51	95	JCNFOFCM	Coffee, Tea & Other Beverage Materials	CPI Beverage materials including coffee and tea	
52	96	JCNFOFNM	Mineral Waters, Soft Drinks & Vegetable Juices	CPI Juices and nonalcoholic drinks	
53	98	JCNFOLDM	Spirits	CPI Distilled spirits at home	
54	99	JCNFOLEM	Wine	CPI Wine at home	
55	100	JCNFOLBM	Beer	CPI Beer, ale, and other malt beverages at home	
56	101	JCNFEFM	Food Produced & Consumed on Farms	BEA Composite of USDA prices received by farmers	†
57	104	JCNLFFM	Womens & Girls Clothing	CPI Womens and girls apparel	
58	105	JCNLMFM	Mens & Boys Clothing	CPI Mens and boys apparel	
59	106	JCNLFIM	Childrens & Infants Clothing	CPIs Infants and toddlers apparel	
60			Sewing machines, fabrics, and supplies		•
61	109	JCNLXIM	Standard Clothing Issued to Military Personnel	PPI Apparel	
62	110	JCNLSM	Shoes & Other Footwear	CPI Footwear	
63	113	JCNLGOM	Gasoline & Other Motor Fuel	CPI Motor fuel	
64	114	JCNLGLM	Lubricants & Fluids	CPI Motor oil, coolant, and fluids	
65	116	JCNOFUM	Fuel Oil	CPI Fuel oil	
66	117	JCNOFLM	Other Fuels	CPI Propane, kerosene, and other firewood	
67	121	JCNODPM	Prescription Drugs	CPI Prescription drugs	
68	122	JCNODNM	Nonprescription Drugs	CPI Nonprescription drugs	
69	125	JCNOGTM	Games, Toys & Hobbies	CPI Toys	
70	126	JCNRPM	Pets & Related Products	CPI Pets and pet products	
71	127	JCNGARM	Flowers, Seeds & Potted Plants	CPI Indoor plants and flowers	
72	128	JCNOGFM	Film & Photographic Supplies	CPI Film and photographic supplies	
73	130	JCNOLPM	Household Cleaning Products	CPI Household cleaning products	
74	131	JCNOLFM	Household Paper Products	CPI Household paper products	
75	132	JCNOLNM	Household Linens	CPI Other linens	

• See Table CA2 ⋆ See Table CA3 ○ See Table CA4 † See the excel file downloadable from the BEA website at `https://www.bea.gov/media/3051`

Table CA1: Data and data sources (continued)

ID	Item	Haver	PCE Component	Price index source data	
76	134	JCNOLOM	Miscellaneous Household Products	CPI Miscellaneous household products	
77	135	JCNOPM	Personal Care Products		⋆
78	139	JCNOTM	Tobacco	CPI Tobacco and smoking products	
79	141	JCNMGM	Newspapers & Periodicals	CPI Newspapers and magazines	
80	142	JCNONM	Stationery & Miscellaneous Printed Materials	CPI Stationery, stationery supplies, and gift wrap	
81			Rent of primary residence		•
82	156	JCSRDM	Imputed Rental of Owner-Occupied Nonfarm Housing		⋆
83	159	JCSHRM	Rental Value of Farm Dwellings	BEA extrapolation	†
84	163	JCSLWSM	Water Supply & Sewage Maintenance	CPI Water and sewage maintenance	
85	164	JCSLWRM	Garbage & Trash Collection	CPI Garbage and trash collection	
86	166	JCSLEM	Electricity	CPI Electricity	
87	167	JCSLGM	Natural Gas	CPI Utility (piped) gas service	
88	170	JCSMPM	Physician Services	PPI Offices of physicians	
89	171	JCSMDM	Dental Services	CPI Dental services	
90	172	JCSMOM	Paramedical Services		○
91			Hospitals		•
92	183	JCSMHNM	Nursing Homes	PPI Nursing care facilities	
93	188	JCSTURM	Motor Vehicle Maintenance & Repair	CPI Motor vehicle maintenance and repair	
94	190	JCSTVLM	Motor Vehicle Leasing	CPI Leased cars and trucks	
95	193	JCSTVRM	Motor Vehicle Rental	CPI Car and truck rental	
96	194	JCSTUTM	Parking Fees & Tolls	CPI Parking fees and tolls	
97	197	JCSTIRM	Railway Transportation	CPI Intercity train fare	
98			Intercity bus fare		•
99			Intracity mass transit		•
100	203	JCSTIPM	Air Transportation	PPI Domestic scheduled passenger air transportation	

• See Table CA2 ⋆ See Table CA3 ○ See Table CA4 † See the excel file downloadable from the BEA website at `https://www.bea.gov/media/3051`

Table CA1: Data and data sources (continued)

ID	Item	Haver	PCE Component	Price index source data	
101	204	JCSTIWM	Water Transportation	CPI Ship fare	
102	207	JCSRCCM	Membership Clubs & Participant Sports Centers	CPI Club dues and fees for participant sports and group exercises	
103	208		Other recreation services		•
104	210		Admission to movies, theaters, and concerts		•
105	212	JCSRSSM	Spectator Sports	CPI Admission to sporting events	
106	214	JCSREPM	Audio-Video, Photographic & Info Processing Services		○
107	222	JCSREGM	Gambling		⋆
108	227	JCSROVM	Veterinary & Other Services for Pets	CPI Pet services including veterinary	
109	229	JCSREVM	Maintenance & Repair of Rec Vehicles & Sports Equipment	CPI Sporting goods	
110			Food at employee sites and schools		•
111	237	JCSFPOM	Other Purchased Meals		○
112	241	JCSFPBM	Alcohol in Purchased Meals	CPI Alcoholic beverages away from home	
113	246	JCSHOTM	Hotels and Motels	CPI Other lodging away from home including hotels and motels	
114	247	JCSHSM	Housing at Schools	CPI Housing at school, excluding board	
115	251	JCSBSCM	Commercial Banks	BEA extrapolation	†
116	252	JCSOBDM	Other Depository Instns & Regulated Invest Companies	BEA annual composite index.	†
117	253	JCSOBPM	Pension Funds	BEA input cost index	†
118	254	JCSNFCM	Financial Service Charges, Fees & Commissions		○
119	267	JCSOBIM	Life Insurance	BEA input cost index	†
120	268	JCSLIM	Net Household Insurance	PPI Homeowners insurance	
121	271	JCSMIM	Net Health Insurance		○
122	275	JCSVIM	Net Motor Vehicle & Other Transportation Insurance	PPI Private passenger auto insurance	†
123	277	JCSLTPM	Communication		○

• See Table CA2 ⋆ See Table CA3 ○ See Table CA4 † See the excel file downloadable from the BEA website at https://www.bea.gov/media/3051

Table CA1: DATA AND DATA SOURCES (CONTINUED)

ID	Item	Haver	PCE Component	Price index source data	
124	287	JCSOEUM	Higher Education		⋆
125	291	JCSEESM	Elementary & Secondary Schools	CPI Elementary and high school tuition and fixed fees	
126	292	JCSEENM	Day Care & Nursery Schools	CPI Day care and nursery school	
127	293	JCSEOVM	Commercial & Vocational Schools	CPI Technical and business school tuition and fees	
128			Legal services		•
129	297	JCSBOTM	Tax Preparation & Other Related Services	CPI Tax preparation and other accounting fees	
130	298	JCSBOEM	Employment Agency Services	PPI Employment placement services	
131	299	JCSBOOM	Other Personal Business Services	CPI Miscellaneous personal services	
132	300	JCSBOUM	Labor Organization Dues	BEA input cost index	†
133	302	JCSOBFM	Funeral & Burial Services	CPI Funeral expenses	
134	305	JCSOPBM	Hairdressing Salons & Personal Grooming Estab	CPI Haircuts and other personal care services	
135			Apparel services other than laundry and drycleaning		•
136	308	JCSOPDM	Laundry & Dry Cleaning Services	CPI Laundry and drycleaning services	
137	312	JCSSSCM	Child Care	CPI Child care and nursery school	
138	313	JCSSSWM	Social Assistance	BEA input cost index	†
139	320	JCSSSVM	Social Advocacy & Civic & Social Organizations	BEA input cost index	†
140	321	JCSSSRM	Religious Organizations Services to Households	BEA input cost index	†
141	322	JCSSSFM	Foundations and grantmaking and giving services to households	BEA input cost index	†
142	324	JCSLDM	Domestic Services	BEA Composite index of various CPIs	†
143	325	JCSLOSM	Moving, Storage & Freight Services	CPI Moving, storage, and freight expenses	
144			Repair of household items		•
145	328	JCSLOOM	Other Household Services	CPI Household operations	
146	338	JNPCFM	Final Consumption Expenditures of Nonprofit Institutions Serving Households	BEA input cost index	†

• See Table CA2 ⋆ See Table CA3 ○ See Table CA4 † See the excel file downloadable from the BEA website at `https://www.bea.gov/media/3051`

Table CA2: NOTES TO TABLE 1 FOR ENTRIES WITH ● SYMBOL

ID	Note
10	The price index for “Major Appliances” is the aggregation of the PCE price index for “Major Household Appliances” (Item 28, Haver JCDFKKM) and the PCE price index for “Tenant Landlord Durables” (Item 155, Haver JCSHTDM@USNA), which are both constructed out of the CPI “Major Appliances”
24	The price index for “Telephone hardware, calculators, and other consumer items” is the aggregation of the PCE price index for “Calculators/Typewriters/Other Info Processing Equipmentt” (Item 49, Haver JCDFCOM) and the PCE price index for “Telephone & Facsimile Equipment” (Item 69, Haver JCDOTM), which are both constructed out of the CPI “Telephone hardware, calculators, and other consumer items”.
31	The price index for “Medical equipment and supplies” is the aggregation of the PCE price index for “Therapeutic Medical Equipment” (Item 65, Haver JCDOOTM) and the PCE price index for “Other Medical Products” (Item 123, Haver JCNODOM), which are both constructed out of the CPI “Medical equipment and supplies”.
60	The price index for “Sewing machines, fabrics, and supplies” is the aggregation of the PCE price index for “Clothing Materials” (Item 108, Haver JCNLOLM) and the PCE price index for “Sewing Items Price” (Item 133, Haver JCNOLSM), which are both constructed out of the CPI “Sewing machines, fabrics, and supplies”.
81	The price index for “Rent of primary residence” is the aggregation of the PCE price index for “Tenant-Occupied Mobile Homes Price Index” (Item 153, Haver JCSHTBM), the PCE price index for “Tenant-Occupied Stationary Homes” (Item 154, Haver JCSHTSM), and the PCE price index for “Group Housing” (Item 160, Haver JCSHOM), which are all constructed out of the CPI “Rent of primary residence”.
82	The PCE price index for “Imputed Rental of Owner-Occupied Nonfarm Housing” has two subcomponents, (1) “Owner-Occupied Mobile Homes” (Item 157, Haver JCSHRBM), (2) “Owner-Occupied Stationary Homes” (Item 158, Haver JCSHRSM), which are both constructed using the “CPI Owners’ equivalent rent of primary residence”. In the disaggregation used by the Dallas Fed instead of the index for “Imputed Rental of Owner-Occupied Nonfarm Housing” the single components are included.
91	The price index for “Hospitals” is the aggregation of the PCE price index for “Nonprofit Hospitals’ Services to Households” (Item 180, Haver JCSMPNM), the PCE price index for “Proprietary Hospitals” (Item 181, Haver JCSMPPM), and the PCE price index for “Govt Hospitals Price” (Item 182, Haver JCSMPPM), which are all constructed out of the PPI “Hospitals”.

Table CA2: NOTES TO TABLE 1 FOR ENTRIES WITH ● SYMBOL (CONTINUED)

ID	Note
98	The price index for "Intercity bus fare" is the aggregation of the PCE price index for "Intercity Buses" (ID 199, Haver JCSTIBM) and the PCE price index for "Other Road Transportation Service" (ID 202, Haver JCSTIOM), which are both constructed out of the "CPI Intercity bus fare".
99	The price index for "Intracity mass transit" is the aggregation of the PCE price index for "Taxicabs" (Item 200, Haver JCSTLBM) and the PCE price index for "Intracity Mass Transit" (Item 201, Haver JCSTLTM), which are both constructed out of the "CPI Intercity bus fare".
103	The price index for "Other recreation services" is the aggregation of the PCE price index for "Amusement Parks, Campgrounds & Related Recreational Services" (Item 208, Haver JCSRCPM) and the PCE price index for "Package Tours" (Item 228, Haver JCSRKM), which are both constructed out of the CPI "Other recreation services".
104	The price index for "Admission to movies, theaters, and concerts" is the aggregation of the PCE price index for "Motion Picture Theaters" (Item 210, Haver JCSRSPM), the PCE price index for "Live Entertainment, ex Sports" (Item 211, Haver JCSRSTM), and the PCE price index for "Museums & Libraries" (Item 213, Haver JCSOSLM), which are all constructed out of the CPI "Admission to movies, theaters, and concerts".
110	The price index for "Food at employee sites and schools" is the aggregation of the PCE price index for "Elementary & Secondary School Lunches" (Item 235, Haver JCSFPGM), the PCE price index for "Higher Education School Lunches" (Item 236, Haver JCSFPUM), the PCE price index for "Food Supplied to Civilians" (Item 243, Haver JCSFEVM), and the PCE price index for " Food Supplied to Military" (Item 244, Haver JCSFEAM), which are all constructed out of the CPI "Food at employee sites and schools".
128	The price index for "Legal services" is the aggregation of PCE price index for "Legal Services" (Item 295, Haver JCSOBLM) and PCE price index for "Prof Assn Dues" (Item 301, Haver JCSBOPM), which are both constructed out of the CPI "Legal services".
135	The price index for "Apparel services other than laundry and drycleaning" is the aggregation of the PCE price index for "Miscellaneous Personal Care Services" (Item 308, Haver JCSOPOM), the PCE price index for "Clothing Repair, Rental& Alterations" (Item 309, Haver JCSOPRM), and the PCE price index for "Repair & Hire of Footwear" (Item 310, Haver JCSOPSM), which are all constructed out of the CPI " Apparel services other than laundry and drycleaning".

Table CA3: Notes to Table 1 for entries with ⋆ symbol

ID	Note
1	The PCE price index for "New Autos" has two subcomponents, (1) "New Domestic Autos" (Item 7, Haver JCDMNDM), and (2) "New Foreign Autos" (Item 8, Haver JCDMNFM), which are both constructed using the "CPI New cars". In the disaggregation used by the Dallas Fed instead of the index for "New Autos" the single components are included.
3	The PCE price index for "Net purchases of used motor vehicles" has two subcomponents, (1) "Used autos" (Item 11, Haver JCDMUM), which in its turn has three subcomponents (1a) "Net transactions in used autos" (Item 12, Haver JCDMUNM), (1b) "Used auto margin" (Item 13, Haver JCDMUGM), and (1c) "Employee reimbursement" (Item 14, Haver JCDMURM); and (2) "Used light trucks" (Item 15, Haver JCDMTUM), which in its turn has two subcomponents (2a) "Net transactions in used truck" (Item 16, Haver JCDMTUNM), and (2b) "Used truck margin" (Item 17, Haver JCDMTUGM). Item 12 and 16 are constructed out of the ("CPI Used cars and trucks"), and similarly Item 13 and 17 ("PPI Used vehicle sales at new car dealers"), whereas Item 14 is sourced from the "CPI Car and truck rental". In the disaggregation used by the Dallas Fed instead of the index for "SNet purchases of used motor vehicles" the two subcomponent components (Item 11 and 15) are included.
26	The PCE price index for "Sports and recreational vehicles" has three subcomponents, (1) "Motorcycles" (Item 52, Haver JCDOWLM), (2) "Bicycles and accessories" (Item 53, Haver JCDOWBM), and (3) "Pleasure boats, aircraft, and other recreational vehicles" (Item 54, Haver JCDBBM), which in its turn can be further decomposed in (3a) "Pleasure boats" (Item 55, Haver JCDBBBM), (3b) "Pleasure aircraft" (Item 56, Haver JCDBBPM), and (3c) "Other recreational vehicles" (Item 57, Haver JCDBBOM). The source of all these components is the same ("CPI Sports vehicles including bicycles"), the only exception being the PCE price index for "Motorcycles" that is sourced from the "CPI New motorcycles". In the disaggregation used by the Dallas Fed instead of the index for "Sports and recreational vehicles" the single components (Item 52, 53, 55, 56, and 57) are included.
77	The PCE price index for "Personal Care Products" has three subcomponents, (1) "Hair/Dental/Shave/Miscellaneous Pers Care Prods ex Elec Prod" (Item 136, Haver JCNOPPM), (2) "Cosmetic/Perfumes/Bath/Nail Preparatns & Implements" (Item 137, Haver JCNOPCM), and (3) "Elec Appliances for Personal Care" (Item 138, Haver JCNOPEM). Item 136 and 138 are both constructed out of the "CPI Hair, dental, shaving, and miscellaneous personal care products", while Item 137 is constructed out of the "CPI Cosmetics/perfumes/bath/nail preparations and implements". In the disaggregation used by the Dallas Fed instead of the index for "Personal Care Products" the single components are included.

Table CA3: Notes to Table 1 for entries with $\star$ symbol (continued)

ID	Note
107	The PCE price index for "Gambling" has two subcomponents, (1) "Owner-Occupied Mobile Homes Price Index" (Item 221, Haver JCSROGM), (2) "Casino Gambling" (Item 222, Haver JCSROLM), and "Pari-Mutuel Net Receipts" (Item 223, Haver JCSROBM), which are both constructed using the "CPI All Items". In the disaggregation used by the Dallas Fed instead of the index for "Imputed Rental of Owner-Occupied Nonfarm Housing" the single components are included.
124	The PCE price index for "Higher Education" has two subcomponents, (1) "Proprietary & Public Higher Education" (Item 286, Haver JCSOEUPM), and (2) "Nonprofit Pvt Higher Education Services to Households" (Item 287, Haver JCSOEUNM), which are both constructed using the "CPI College tuition and fees". In the disaggregation used by the Dallas Fed instead of the index for "Higher Education" the single components are included.
144	The price index for "Repair of household items" is the aggregation of PCE price index for "Repair of Furniture, Furnishings & Floor Coverings" (Item 326, Haver JCSLORM) and the PCE price index for "Repair of Household Appliances" (Item 327, Haver JCSLOPM), which are both constructed out of the "Repair of household items"

Table CA4: NOTES TO TABLE 1 FOR ENTRIES WITH ∘ SYMBOL

ID	Note
90	The PCE price index for "Paramedical services" has three subcomponents, (1) "Home health care" (ID 173, Haver JCSMOAM), which is constructed out of the PPI "Home health care services"; (2) "Medical laboratories" (ID 174, Haver JCSMOLM), which is constructed out of the by the BEA as a composite index of fixed-weighted PPIs for "Medical laboratories" and for "Diagnostic imaging centers"; and (3) "Other professional medical services" (ID 175, Haver JCSMOLM), which in its turn has two subcategories both constructed out of the CPI "Services of other medical professionals". Note that also in the disaggregation used by the Dallas Fed index for "Paramedical services", rather then the components, is included.
106	The PCE price index for "Audio-video, photographic, and information processing equipment services" has five subcomponents, (1) "Cable & Satellite Television & Radio Services" (Item 215, Haver JCSROTM), which is constructed out of the CPI "Cable and satellite TV and radio services"; (2) "Photo Processing" (Item 216, Haver JCSRODM), which is constructed out of the CPI "Film processing"; (3) "Photo Studios" (Item 217, Haver JCSROUM), which is constructed out of the CPI "Photographer fees"; (4) "Repair of Audio-Visual, Photo & Info Process Equipment" (Item 218, Haver JCSREEM), which is constructed out of the CPI "Video and audio"; and (5) "Video Media Rental Price" (Item 219, Haver JCSROYM), which is constructed out of the CPI "Rental of video or audio discs and other media". Note that also in the disaggregation used by the Dallas Fed index for "Audio-video, photographic, and information processing equipment services", rather then the components, is included.
111	The PCE price index for "Other Purchased Meals" has three subcomponents, (1) "Meals at Limited Service Eating Places" (Item 236, Haver JCSFPLM), which is constructed out of the CPI "Limited service meals and snacks"; (2) "Meals at Other Eating Places" (Item 237, Haver JCSFPEM) and (3) "Meals at Drinking Places" (Item 238, Haver JCSFPDM), which are both constructed out of the CPI "Full service meals and snacks". Note that also in the disaggregation used by the Dallas Fed index for "Other Purchased Meals", rather then the components, is included.

Table CA4: Notes to Table 1 for entries with ◦ symbol (continued)

ID	Note
118	The PCE price index for "Financial service charges, fees, and commissions" has four subcomponents: (1) "Financial service charges and fees" (Item 253, Haver JCSNFVM), which is constructed out of the CPI "Checking account and other bank services"; (2) "Securities commissions" (Item 254, Haver JCSNFSM); (3) "Portfolio management and investment advice services" (Item 262, Haver JCSNFPM), which is constructed as a fixed weighted average of the PPI "Portfolio Management" and the PPI "Investment advice"; and (4) "Trust, fiduciary, and custody acitivities" (Item 263, Haver JCSNFTM), which is constructed out of the PPI "Commercial bank trust services". The subcomponent "Securities commissions" has three subcomponents: (2.1) "Direct commissions" (Item 255, Haver JCSNFSDM), which in its turn has two subcomponents (2.1.1) "Exchange-listed equities" (Item 256, Haver JCSNFSEM), which is constructed out of the PPI "Brokerage services, equities and ETFs", and (2.1.2) "Other direct commissions" (Item 257, Haver JCSNFSOM), which is constructed out of the PPI "Brokerage services, all other securities"; (2.2) "Indirect commissions" (Item 258, Haver JCSNFIM), which in its turn has two subcomponents (2.2.1) "Over-the-counter equity securities" (Item 259, Haver JCSNFIVM), which is constructed out of the PPI "Dealer transactions, equities securities", and (2.2.2) "Other imputed commissions" (Item 260, Haver JCSNFIOM), which is constructed out of the "Dealer transactions, debt securities and all other trading"; and (2.3) "Mutual fund sales charges" (Item 261, Haver JCSBKFM), which is constructed by the BEA as an Implicit price index. Note that also in the disaggregation used by the Dallas Fed index for "Financial service charges, fees, and commissions", rather then the components, is included.
121	The PCE price index for "Net Health Insurance" has three subcomponents: (1) "Health Insurance: Medical Care & Hospitalization " (Item 270, Haver JCSMHIM), which is constructed out of the PPI "Homeowner's insurance"; (2) "Health Insurance: Income Loss" (Item 271, Haver JCSMIIM), which is constructed out of the CPI "All items"; and (3) "Health Insurance: Workers' Compensation", which is constructed out of the PPI "Worker's compensation insurance". See also BEA. Note that also in the disaggregation used by the Dallas Fed index for "Net Health Insurance", rather then the components, is included.