Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

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2021-069

Please cite this paper as:
Ahn, Hie Joo, and Matteo Luciani (2021). "Relative prices and pure inflation since the mid-1990s," Finance and Economics Discussion Series 2021-069. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2021.069.

Relative prices and pure inflation since the mid-1990s

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Abstract

This paper decomposes consumer price inflation into pure inflation, relative price inflation, and idiosyncratic inflation by estimating a dynamic factor model á la Reis and Watson (2010) on a data set of 146 monthly disaggregated prices from 1995 to 2019. We find that pure inflation is the trend around which PCE price inflation fluctuates, while relative price inflation and idiosyncratic inflation drive the fluctuation of PCE price inflation around the trend. Unlike Reis and Watson, we find that labor market slack is the main driver of pure inflation and that energy prices account for variation in relative price inflation.

JEL classification: C32, C43, C55, E31, E52

Keywords: Pure inflation, relative price inflation, Phillips correlation, dynamic factor model, disaggregated consumer prices, monetary policy

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*We would like to thank Andrew Figura and Ed Herbst for helpful comment. Any errors are our responsibility.

Disclaimer: the views expressed in this paper are those of the author and do not necessarily reflect the views and policies of the Board of Governors or the Federal Reserve System.

1 Introduction

In an influential paper, Reis and Watson (2010) (henceforth, RW) develop a dynamic factor model to separate changes in inflation into three components: a pure inflation component, which measures common and equiproportional changes in all prices; a relative price change component, which captures common changes that raise the prices of some goods and services relative to others; and an idiosyncratic component, which captures sector-specific price changes or measurement errors that affect a single or a few sectors in isolation. Their main conclusion is that, unlike previous research on the "flattened Phillips curve" (for example, Atkeson and Ohanian (2001)), relative price inflation has a statistically significant Phillips correlation with real activity, whereas the pure inflation component does not. In addition, aggregate shocks account for most (about 90 percent) of the variability of aggregate inflation, mainly through the relative price change component. Relative price inflation, in turn, is weakly related to food and energy prices, whereas it is strongly related to the prices of nondurables and services.[1]

RW estimate their model on a panel of 187 disaggregated PCE price inflation rates from 1959:Q1 to 2006:Q2. Their sample includes a period in which inflation was (nearly) non-stationary (approximately from the mid-1970s to the mid-1980s), while over the rest of the sample, inflation was stationary. From a theoretical point of view, this combination of (nearly) non-stationary and stationary data poses a problem because both the specification of the dynamic factor model and the estimation method that RW employ might not be suited for non-stationary data (see, Barigozzi and Luciani, 2019, and Barigozzi et al., 2021, for detail). In addition, the U.S. economy has gone through structural changes in past decades that might have altered the features of the three inflation components as well as their dynamic association with real activity. For example, (1) numerous studies

[1] Miles et al. (2017) extend Reis and Watson's (2010) analysis to the era of post-Great Recession years and find that pure inflation stayed low and stable after the recession. Miles et al. (2017) attribute the low pure price inflation to declining oil prices and effective monetary policy. Ahn et al. (2021) apply Reis and Watson's (2010) method to wage inflation for 1990-2019 and find that the relative wage inflation component is better aligned with the unemployment rate gap than other aggregate wage inflation measures are.

show that the Phillips correlation has weakened substantially and almost disappeared (for example, Coibion and Gorodnichenko, 2015; Hall, 2011), (2) Eo et al. (2020) show that the dynamics of goods inflation became almost entirely dominated by transitory noises starting in the early 1990s, and (3) the oil price pass-through into U.S. inflation has become smaller (see, for example, Conflitti and Luciani, 2019). Therefore, RW's conclusion about inflation dynamics may not be true for the recent period.

In this paper, we estimate a dynamic factor model á la RW to explore inflation dynamics on a data set of 146 disaggregated PCE price inflation rates from January 1995 to December 2019—a period in which observed inflation is clearly consistent with a stationary time series model—with a particular focus on the Phillips correlation. Our results point toward an interpretation of inflation dynamics that is quite different from that of RW.

First, opposite to RW's findings, the pure inflation component exhibits a statistically significant Phillips correlation with labor market slack, whereas the relative price inflation component and the idiosyncratic component do not. Although the average Phillips correlation of pure inflation during the sample period is small, we find that the unemployment rate gap is the key driver of pure inflation during the Great Recession and the subsequent recovery, the so-called missing deflation period and missing inflation period (for example, Constâncio, 2015, Coibion and Gorodnichenko, 2015).

Second, pure inflation is the trend around which PCE price inflation fluctuates, whereas higher-frequency variation in PCE price inflation is accounted for by relative price inflation and idiosyncratic inflation. Quite differently, RW's estimates show that the downward trend in inflation during the 1970s and 1980s was accounted for by relative price inflation.

Third, relative price inflation, which is essentially driven by energy price inflation, is the main driver of the variability in headline PCE price inflation. Quite differently, in RW, relative price inflation, which they find is partially driven by energy price inflation, accounts for only half of the variability of headline inflation.

Last, the idiosyncratic component accounts for more than 95 percent of the volatility in disaggregated price inflation, while RW attribute only three-fourths of the variability to the idiosyncratic component. However, in line with RW, the idiosyncratic component is the main driver of the PCE price index excluding food and energy (henceforth "core" PCE).

The rest of the paper is structured as follows. In section 2 we present the model, and in section 3 we present the estimates. Section 4 concludes.

2 Methodology

2.1 A dynamic factor model á la Reis and Watson (2010)

Let $\boldsymbol{\pi}_t = (\pi_{1t} \cdots \pi_{nt})'$, with $t = 1, \dots, T$, be an $n \times 1$ vector of disaggregated monthly inflation rates with sample mean $\bar{\boldsymbol{\pi}}_t = (\bar{\pi}_{1t} \cdots \bar{\pi}_{nt})'$; a dynamic factor model is written as

$$\boldsymbol{\pi}_t - \bar{\boldsymbol{\pi}}_t = \boldsymbol{\Lambda}\mathbf{F}_t + \mathbf{u}_t \tag{1}$$

$$\boldsymbol{\Phi}(L)\mathbf{F}_t = \boldsymbol{\epsilon}_t \tag{2}$$

$$\beta_i(L)u_{it} = e_{it} \qquad i = 1, \dots, n \tag{3}$$

where $\mathbf{F}_t$ is a vector of r common factors capturing co-movements across series and across time, $\boldsymbol{\Lambda}$ is an $n \times r$ matrix of factor loadings, $\boldsymbol{\Phi}(L)$ and $\beta_i(L)$ are stationary polynomials, and $\mathbf{u}_t$ is an $n \times 1$ vector of the idiosyncratic component. In this model, it is assumed that (i) the common factors $\mathbf{F}_t$ are pervasive, (ii) the idiosyncratic components $\mathbf{u}_t$ are weakly cross-sectionally correlated and weakly dynamically correlated; and (iii) the common shocks $\boldsymbol{\epsilon}_t$ and the idiosyncratic shocks $\boldsymbol{e}_t = (e_{1t} \cdots e_{nt})'$ are two independent sources of fluctuations.

In the specification of model (1)–(3) used by RW, the common factors $\mathbf{F}_t$ are decomposed in two components: the first component, the scalar a_t, captures absolute price changes that affect all prices equiproportionately; the second component, the $(r-1) \times 1$ vector $\mathbf{R}_t$, captures relative price changes. So, let $\mathbf{F}_t = (a_t, \mathbf{R}_t)'$, then $\boldsymbol{\Lambda}\mathbf{F}_t$ can be written as

$$\boldsymbol{\Lambda}\mathbf{F}_t = \mathbf{I}a_t + \boldsymbol{\Gamma}\mathbf{R}_t, \tag{4}$$

where $\mathbf{I}$ is an $n \times 1$ vector of ones and $\mathbf{\Gamma}$ is an $n \times (r-1)$ matrix. Following RW, we consider a model with three factors ($r = 3$), four lags in the VAR in (2), and one lag in the AR models in (3), and we use the normalizations that the columns of $\mathbf{\Gamma}$ are mutually orthogonal and add up to zero.

The two components a_t and $\mathbf{R}_t$ in (4) are not separately identifiable, because an absolute change in prices cannot be distinguished from a change in "average relative prices" given that there are many ways to define the average.[2] Therefore, RW identify the two independent components from the following:

$$\nu_t = a_t - E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^T] \tag{5}$$

and

$$\boldsymbol{\rho}_t = E[\mathbf{F}_t|\{\mathbf{R}_\tau\}_{\tau=1}^T] = \mathbf{\Gamma}\mathbf{R}_t + E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^T], \tag{6}$$

where ν_t is the "pure" inflation component and ρ_t is the relative price change component. The pure inflation component captures price changes that have an equiproportional effect on all prices and are uncorrelated with changes in relative prices at any point in time. The relative-price component captures all the common changes in prices that are associated with changes in relative prices at some point in time.

Following RW, we first estimate the system of equations (1)–(4) by maximum likelihood via theExpectation-Maximization (EM) algorithm. Next, we identify ν_t by subtracting the projection $E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^T]$ from a_t and estimate $\boldsymbol{\rho}_t$ by adding $E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^T]$ to $\mathbf{\Gamma}\mathbf{R}_t$. The projection $E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^T]$ is computed by means of the Kalman smoother of a_t from a state space model, where the observation equation is $\mathbf{R}_t = (0 \quad \mathbf{I})(a_t \quad \mathbf{R}_t')'$ and the state equation is (2).[3] The goal of this second step is to exclude all the information on past, present, and future relative inflation factors from the pure inflation factor.

[2] RW illustrates this identification issue as follows. For an $(r-1) \times 1$ vector α, we have $Ia_t + \Gamma R_t = I(a_t + \alpha' R_t) + (\Gamma - I\alpha')R_t$. The pair (a_t, R_t) cannot be distinguished from $(a_t + \alpha' R_t, R_t)$ without a further identifying restriction.

[3] For more details on the estimation of model, we refer the reader to the appendix in the working paper version of RW. In addition, see Barigozzi and Luciani (2020) for the consistency of the EM algorithm when estimating large-dimensional dynamic factor models.

Finally, to decompose headline inflation into pure inflation, relative price inflation, and idiosyncratic inflation, we aggregate the estimates obtained for each disaggregated price by using the weights in the overall PCE price index:

$$\nu_t^h = \nu_t + \sum_{i=1}^{n} w_{it}\bar{\pi}_i \tag{7}$$

$$\rho_t^h = \sum_{i=1}^{n} w_{it}(\mathbf{\Gamma}_i\mathbf{R}_t + E[a_t|\{\mathbf{R}_\tau\}_{\tau=1}^{T}]) \tag{8}$$

$$u_t^h = \pi_t^h - \nu_t^h - \rho_t^h \tag{9}$$

where the superscript h stands for "headline," w_{it} is the weight in PCE of item i at time t, and u_t^h is the idiosyncratic component. These quantities can also be easily estimated for core PCE price inflation, energy price inflation, and food price inflation by simply using the corresponding weights.

To conclude, note that we construct ν_t^h and ρ_t^h differently from that of RW. We estimate ν_t^h and ρ_t^h using the series' weights in PCE, which allows us to construct inflation measures that are comparable to headline PCE price inflation and core PCE price inflation. Quite differently, RW estimate the index of pure inflation from $\nu_t^h = \nu_t$ and the index of relative price inflation from $\rho_t^h = \boldsymbol{\beta}'\mathbf{R}_t$, where $\boldsymbol{\beta}$ is the OLS coefficient of the regression of $\mathbf{R}_t$ on $z_t = \pi_t^h - a_t$. RW employ this projection to construct relative price inflation because they lost some of the PCE price items when they removed series that exhibit identical variations; in other words, their data set does not preserve the structure of PCE. A more detailed discussion is found in section 3.1.

2.2 Potential issues in the Reis and Watson's (2010) model

As we mention in the introduction, RW estimate the model on a very long sample covering more than 50 years. However, this sample includes a period in which inflation was (nearly) non-stationary (approximately from the mid-1970s to the mid-1980s), while in the rest of the sample inflation was stationary. There are two potential issues related to non-stationarity in the data: one is the model misspecification and consequent bias in the estimated parameters; the other is the link (or dependence) between the order of integration of idiosyncratic components and the estimation of the factor loadings. Regarding the first issue, because part of the sample is stationary and another part is non-stationary, it is clear that there is a structural break in the dynamics of the factors. In the presence of such a structural break, a dynamic factor model that does not consider potential model instability arising from the structural break will likely produce biased parameter estimates.

The second issue is related to the EM algorithm employed by RW. The EM algorithm produces consistent parameter estimates as long as the idiosyncratic components are stationary (Barigozzi and Luciani, 2019). If the idiosyncratic components are non-stationary, however, the factor loadings are not consistently estimated with the EM algorithm. The intuition is the following. The factor model can be understood as a regression model where the factors are the regressors, the factor loadings are the coefficients, and the idiosyncratic components are the residuals. The OLS estimate of a regression model with a non-stationary residual yields inconsistent estimates of the parameters

In this paper, we take a pragmatic approach to tackle the issues brought about by having a non-stationary sub-sample. Namely, instead of building a new model that copes with the non-stationarity, we only use the sample period in which the data are stationary.

3 Empirical application

3.1 Dataset

The model is estimated on a data set of 146 disaggregated PCE price inflation rates from January 1995 to December 2019. This data set represents a particular disaggregation of PCE prices in which each disaggregated price index is constructed from a distinct data source. For the complete list of prices and detailed information on the data sources, we refer the reader to Luciani (2020).

The PCE price index is constructed by the Bureau of Economic Analysis (BEA). Because the BEA does not record goods and services prices, it relies (mostly) on price indexes constructed by the Bureau of Labor Statistics to compile PCE prices. Specifically, most PCE prices are constructed by taking the corresponding (or conceptually closest) Consumer Price Index (CPI), a few of them are constructed by using a Producer Price Index (PPI) series (for example, airfares and some medical prices), and a few of them are imputed by the BEA. Because there is not always 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).[4]

When estimating a dynamic factor model, it is crucial to avoid having disaggregated inflation rates that are highly correlated by construction, or else the model's estimation would considerably worsen (see, for example, Barigozzi and Luciani, 2020). Thus, having a data set in which each disaggregated price index is constructed from a distinct data source is crucial, because this setup avoids bringing on board spurious correlation in the estimation of factors.[5]

Now, although RW do not control for the source of each disaggregated PCE price in their data set, they clean and correct their data set for excess cross correlation using statistical methods. However, by doing so, they lose some items in the PCE basket, and thus their data set does not cover 100 percent of consumer spending. In other words, RW's data set does not preserve the structure of PCE prices, whereas our data set does.

Finally, to construct the aggregated quantities in equations (7) to (9), we use the approximate PCE weights computed as in Dolmas (2005), as the PCE price index is a Fisher index. It is well known that a Fisher index has the non-additive property (see Whelan, 2002, as well as Bureau of Economic Analysis, 2017, chapter 4), meaning that the aggregate index is not a weighted average of its disaggregated components. In principle, proper weights for PCE prices do not exist. Diewert (1976, 1978), however, shows that a

[4] For example, the PCE price indexes for "bicycles and accessories," "Pleasure boats," "Pleasure aircraft," and "Other recreational vehicles," are all constructed out of the CPI "Sports vehicles including bicycles." The price changes of these four items are either identical or almost the same.

[5] Luciani (2020) shows that when the source of PCE prices is not considered, the model parses as common the strong correlation between prices that are constructed from the same CPI (or PPI), thus overestimating the share of fluctuations accounted for by the common factors.

Törnqvist index numerically approximates a Fisher index. Therefore, we use the Törnqvist weights as in Dolmas (2005) and Luciani (2020) to approximate the headline PCE price inflation.

3.2 Decomposition of PCE price variability

Figure 1 shows the decomposition of month-over-month PCE price inflation (black line) into pure inflation (red line), relative price inflation (blue line), and idiosyncratic inflation (yellow line). Table 1 reports the percentage of variance accounted for by each of these components.

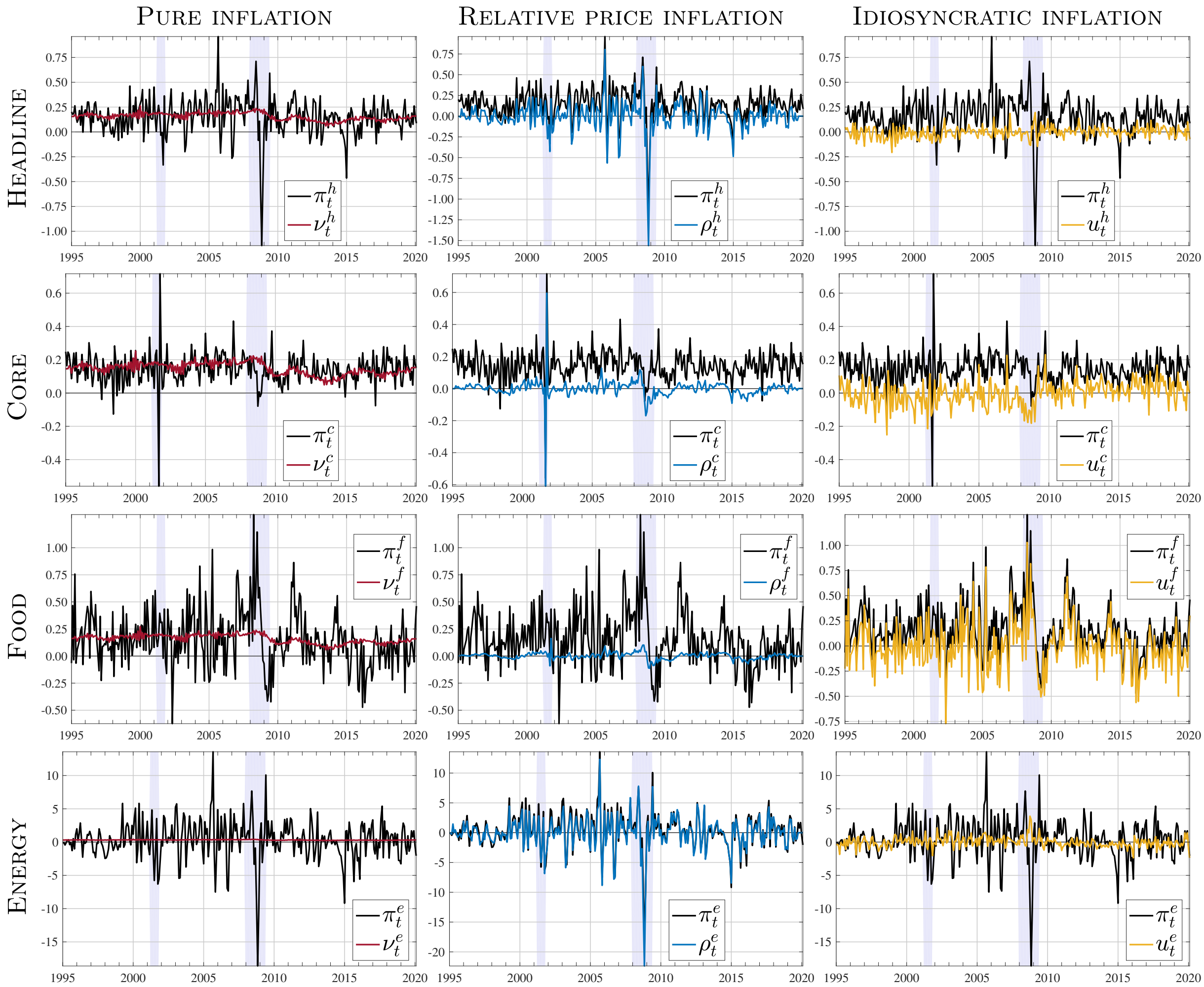
Table 1: VARIANCE DECOMPOSITION (PERCENT)

		PANEL A: AHN-LUCIANI			PANEL B: REIS-WATSON		
		$\boldsymbol{\nu}_t$	$\boldsymbol{\rho}_t$	$\mathbf{u}_t$	$\boldsymbol{\nu}_t$	$\boldsymbol{\rho}_t$	$\mathbf{u}_t$
(1)	Avg. Dis.	1.3	2.8	95.9	5	19	76
(2)	Headline	3.5	92.9	3.6	16	51	33
(3)	Core	9.4	39.1	51.5	24	32	44
(4)	Food	4.5	4.7	90.8		20	
(5)	Energy	0.1	93.7	6.3		30	

Notes: Avg. Dis. stands for average of disaggregate prices. Line (1) shows the average percentage of variance of each disaggregated price inflation index accounted for by the three components ν_t, ρ_t, and u_t. Lines (2) to (5) show the average percentage of variance of the headline, core, food, and energy price inflation indexes accounted for by the three components. The numbers in panel B are taken from table 1 and table 2 in RW and then multiplied by 100. The numbers in column $\mathbf{u}_t$ are computed by subtracting the other two columns from 100 the other two columns. Note that the numbers in panel B are the average squared coherence over all frequencies. Finally, the numbers in line (1) are medians. The empty cells in panel B are those numbers not reported by RW.

There are important differences between our results and those of RW. First, disaggregated inflation became more idiosyncratic starting in the mid-1990s (line (1) of table 1). Indeed, the idiosyncratic component accounts for more than 95 percent of the variability in disaggregated PCE prices, which is higher than the estimated contribution from RW, 75 percent. Second, similar to RW, the relative price inflation component explains most of the variation in headline PCE price inflation (first row of figure 1 and line (2) of table 1). However, the role of pure inflation became smaller than RW's estimate, as pure inflation

Figure 1: PCE price decomposition
(month-over-month inflation)



accounts for less than 5 percent of the fluctuations in headline inflation and 10 percent of core inflation, on average, from the mid-1990s. Both figures are about 10 to 15 percentage points lower than the contributions reported in RW.

Third, we find that relative price inflation accounts for most of the volatility in energy price inflation (fourth row of figure 1), whereas RW find that the association between the two is fairly limited. In particular, RW claim that conventional measures of relative inflation, such as nondurables, food, and energy prices, are not comprehensive enough to capture relative price inflation. In relative terms, RW find that relative price inflation is correlated more with the prices of nondurable goods than with energy prices. Quite differently, we find that relative price inflation accounts for most of the volatility in energy price inflation.

Fourth, compared to RW, we find that idiosyncratic inflation accounts for a larger share of fluctuations in core PCE price inflation (about half, versus one-third in RW), while relative price inflation accounts for a smaller share (about two-fifths, versus one-third in RW). Our result is also in line with the findings from Eo et al. (2020) who show that the dynamics of goods inflation changed and became almost entirely dominated by transitory noises starting in the early 1990s.

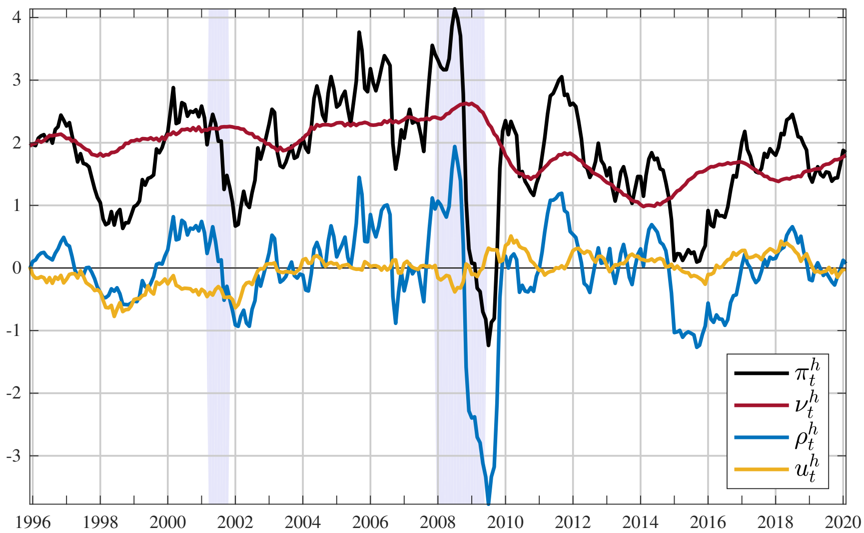
Finally, 90 percent of the fluctuations in PCE food price inflation are accounted for by the idiosyncratic component, while the relative price component, which in RW accounts for one-fifth of the fluctuations, accounts just for 5 percent.

Next, figure 2 shows the decomposition for year-over-year headline PCE price inflation. We find that pure inflation is the "trend" (or low-frequency component) around which headline inflation fluctuates, whereas RW find that the relative price change component drives the trend in PCE price inflation during the 1970s and 1980s. Meanwhile, relative price inflation is essentially the portion of headline PCE price inflation accounted for by energy prices, while idiosyncratic inflation is a moderately persistent residual. Therefore, despite its relatively small contribution to the volatility of headline PCE price inflation, pure inflation is the most important component in understanding the inflation dynamics over the medium term. In the next section, we investigate the drivers of pure inflation.

3.3 Drivers of pure inflation

To find out which variables account for the variability of each inflation component, RW compute the average squared coherence over different frequencies between each inflation component and selected macroeconomic variables. Their main findings are (1) that pure inflation is correlated with nominal interest rates but not with either monetary aggregates or real activity; and (2) that relative price inflation is associated with real activity.

Figure 2: PCE PRICE DECOMPOSITION
(YEAR-OVER-YEAR INFLATION)



To understand what drives pure inflation and relative price inflation, we use an approach different from RW. We base our analysis on a Phillips curve, a tool commonly used in central banks (see, for example, Yellen, 2015, and Powell, 2018).

In our Phillips curve model, PCE price inflation is a function of: its first four lags; longer-run inflation expectations in the previous period as measured by the Michigan survey (π^e_{t-1}); economic slack as measured by the CBO unemployment gap ($\widetilde{u}_t$); the exchange rate (e_t), as measured by the trade weighted U.S. Dollar Index computed by the Federal Reserve Board; and the oil price (o_t), as measured by the Refiners' Acquisition Cost of Crude Oil. The Phillips curve that we estimate in the case of headline PCE price inflation is as follows:

$$\pi_t^h = \alpha + \sum_{j=1}^{4} \beta_j \pi^h_{t-j} + \gamma \pi^e_{t-1} + \delta \widetilde{u}_t + \phi e_t + \psi o_t + \varepsilon_t. \tag{10}$$

We estimate equation (10) on quarterly data over the period 1995:Q1 to 2019:Q4, with all inflation rates expressed at an annual rate. The model is estimated with Restricted OLS by imposing the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$, which implies that changes in expected inflation are (eventually) passed through one for one to headline inflation. We also estimate equation (10) by replacing headline inflation with pure inflation and relative price inflation. However, when estimating the model for relative price inflation, we do not impose the restriction on γ as it is strongly rejected by the data.

Table 2 reports the estimated coefficients.

Table 2: PHILLIPS CURVE: 1995:Q1–2019:Q4
(HEADLINE PCE PRICE INFLATION)

Variable	**Coefficient**	$\boldsymbol{\pi}_t^h$	$\boldsymbol{\nu}_t^h$	$\boldsymbol{\rho}_t^h$
Persistence	$\sum_{j=1}^{4} \beta_j$	0.239 [0.992]	0.874 [0.381]	0.224 [0.134]
Inflation expectations	γ	0.761 [0.103]	0.126 [0.040]	0.116 [0.446]
Unemployment rate gap	δ	-0.074 [0.050]	-0.026 [0.009]	-0.046 [0.056]
Exchange rate	ϕ	-0.031 [0.010]	-0.002 [0.002]	-0.021 [0.011]
Oil price	ψ	0.015 [0.002]	0.000 [0.000]	0.015 [0.002]
R^2		0.719	0.921	0.624

Notes: Standard errors are in parentheses. The Phillips curves for π_t^h and v_t^h are estimated using Restricted OLS by imposing the restriction $\gamma = 1 - (\beta_1 + \ldots + \beta_4)$, whereas the Phillips curve for ρ_t^h is estimated using simple OLS. $\mathcal{B} = 1 - \sum_{j=1}^{4} \beta_j$.

The results in column $\boldsymbol{\nu}_t^h$ suggest that both inflation expectations and labor market slack are important drivers of pure inflation. Both coefficients are strongly statistically significant. Meanwhile, the coefficients on the exchange rate and the oil price are not statistically different from zero. Notably, the opposite is true for relative price inflation, as shown in column $\boldsymbol{\rho}_t^h$. The exchange rate and the oil price affect relative price inflation (both coefficients are strongly statistically significant), while the coefficient on the unemployment rate gap is not statistically significant. Finally, given that fluctuations in headline inflation are mainly accounted for by relative price inflation, not surprisingly, the Phillips correlation of headline inflation is not statistically significant either (column $\boldsymbol{\pi}_t^h$).[6]

To summarize, our analysis indicates that for the post-1995 period, pure inflation has a statistically significant Phillips correlation with real activity, whereas relative price inflation

[6] We also experiment with the unemployment rate and employment-to-population ratio, and the results are similar.

does not. This finding is exactly opposite to the conclusion of RW.[7]

Having determined what drives pure inflation, we can look back at figure 2. Year-over-year pure inflation was reasonably stable around an average rate of 2.2 percent (with a standard deviation of 0.2) from the mid-1990s until the Great Recession. However, starting at the end of 2008, pure inflation declined slowly and reached its lowest level of 1 percent at the beginning of 2014. After that, it rose again and ended 2019 at 1.8 percent. What explains these movements in pure inflation?

To analyze how much each explanatory variable in our Phillips curve model contributes to pure inflation, we rewrite equation (10) as follows:

$$\begin{aligned}\nu_t^h &= c(L)\gamma\pi_{t-1}^e + c(L)\delta\widetilde{u}_t + c(L)\phi e_t + c(L)\psi o_t + c(L)(\alpha + \varepsilon_t) \\ &= \omega(L)\pi_{t-1}^e + \rho_u(L)\widetilde{u}_t + \rho_e(L)e_t + \rho_o(L)o_t + \Xi_t. \qquad (11)\end{aligned}$$

where $c(L) = (1 - \beta_1 L - \ldots - \beta_4 L^4)^{-1}$.

Figure 3: Cumulative contribution to pure inflation

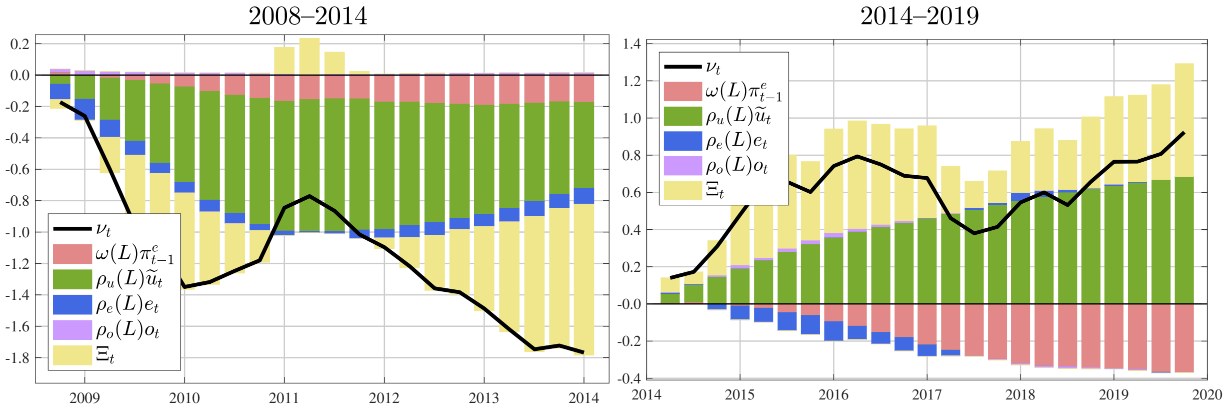


Figure 3 shows the contribution of each of the five terms on the right-hand side of

[7] Recent studies investigate the Phillips correlation based on state-level data (for example, Hazell et al. (2020) and Fitzgerald et al. (2020)). Hazell et al. (2020) construct state-level price indexes for non-tradable goods and find that the Phillips correlation is small and stable with the full sample estimate being -0.0062. Quite differently, Fitzgerald et al. (2020) find that, once the endogeneity of monetary policy is considered, the Phillips correlation is large and stable (-0.3). In the model of pure inflation, the coefficient on the unemployment rate gap is -0.026, larger in absolute value than the coefficient of Hazell et al. (2020) but smaller in absolute value than that of Fitzgerald et al. (2020).

equation (11) for the two sub periods, 2008 to 2014 and 2014 to 2019. The swings in pure inflation during the two sub periods are mainly accounted for by the unemployment rate gap (green bars) and by factors not considered in our Phillips curve model (yellow bars)—that is, Ξ_t in (11). In contrast, inflation expectations played a negligible role. This decomposition confirms that labor market slack is a key driver of pure inflation, which contrasts with the main conclusion of RW.

4 Conclusions

In this paper, we decompose consumer price inflation into pure inflation, relative price inflation, and idiosyncratic inflation by estimating a dynamic factor model á la Reis and Watson (2010). The model is estimated on a data set of 146 monthly disaggregated prices, all constructed from a distinct data source, over a sample starting in January 1995 and ending in December 2019.

We find that pure inflation is the trend around which PCE price inflation fluctuates and that the fluctuations around this trend are driven by both relative price inflation and idiosyncratic inflation. Pure inflation is mostly driven by labor market slack and inflation expectations, whereas supply shocks, such as changes in the oil price or the exchange rate, have no effect on pure inflation.

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