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The Role of Wages in Trend Inflation: Back to the 1980s?

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Version 4

Abstract

This paper examines whether the measurement of trend inflation can be improved by using wage data in a dynamic factor model of disaggregated prices and wages for the United States. The model features time-varying coefficients and stochastic volatility. An estimate of trend inflation is a time-varying distributed lag of prices and wages, where the weight on a series depends on its time-varying volatility, persistence, and comovement with other series. The results show that wages inform estimates of trend inflation. The weight on wages was highest around 1980, drifted down through the 2000s, and returned to its 1980s value by 2022. In addition, inflation in the 2020s appears to have unmoored moderately from the 2 percent range that prevailed for decades, as the role of the persistent component of inflation increased in recent year. However, accounting for wages lowers the model's view of the increase in the volatility of trend inflation.

Keywords: Price Inflation, Wage Inflation, Unobserved Components Model, Factor Model

JEL Codes: E37, E31, C32

1. Introduction

Measuring the trend rate of inflation is a central question in empirical macroeconomics and policymaking. Over the past 50 years, the dominant factor governing movements in inflation has been changes in the trend rate of inflation—that is, the persistent component of inflation that provides a good forecast of future inflation (e.g., Stock and Watson, 2007; Rudd, 2020). Moreover, inflation trends shape monetary policy discussions (e.g., Yellen, 2015).

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The interaction of price and wage inflation has also received intense scrutiny. Wages are a substantial fraction of firms' costs, suggesting that higher nominal wages should lead to higher nominal prices. Models of the "wage-price" spiral capture this intuition (e.g., Blanchard, 1986). Empirical work has examined the interaction of wage and price inflation, with most work focusing on the predictive power of wages for price inflation (e.g., Gordon, 1988). In general, research has not found a central role for wages in inflation forecasting.

These questions have attracted substantial public attention recently. High price inflation in the United States and elsewhere in 2021 and 2022 has been accompanied by higher nominal wage growth and concerns about the possible persistence of high inflation. To address these issues, this research considers the role of wages in a model of trend inflation. The modeling framework is a dynamic factor model of disaggregated consumer prices and wages for the United States, with time-varying coefficients and stochastic volatility as in Del Negro and Otrok (2008) and Stock and Watson (2016). In the model, an estimate of trend inflation features time-varying distributed lags of weights on both prices and wages, where the weight depends on the time-varying volatility and persistence of the series and on the comovement among series. Importantly, wages receive a weight in the estimate of trend inflation even though their arithmetic contribution to price inflation is zero, reflecting the signal in wages that is useful for forecasting inflation. The results show that wages consistently inform estimates of underlying inflation. The weight on wages fell substantially between 1980 and the 2000s but returned to its average value over 1976 to 1985 by the end of 2022. In addition, the role of the persistent component of inflation has increased in recent years, suggesting a moderate unmooring of inflation from the neighborhood of 2 percent experienced from the 1990s through the 2010s. However, accounting for wages lowers the model's view of the increase in the volatility of trend inflation relative to simpler empirical models.

The analysis builds on three strands of literature. First, the model herein features cross-sectional smoothing (by looking at many series for prices and wages) and time-series smoothing (through an unobserved components model) to assess inflation developments. Previous research has considered a range of cross-sectional and time-series smoothing techniques to estimate underlying consumer price inflation, including alternative cross-sectional weights on disaggregated price changes such as trimmed means or medians (Bryan and Cecchetti, 1994) and simple distributed lags of inflation such as the four-quarter moving average (Atkeson and Ohanian, 2001). These approaches can serve as forecast benchmarks for the estimates from econometric models such as those analyzed herein. Second, research on unobserved components models or dynamic factor models of inflation has proliferated in recent years (e.g., Stock and Watson, 2007; Kiley, 2008; Reis and Watson, 2010; Mertens, 2016; Stock and Watson, 2016; and Almuzara and Sbordone, 2022).[2] The analysis herein builds directly on this work; the framework steps beyond that in Stock and Watson (2016) and Almuzara and Sbordone (2022) by adding wage series to those that inform the estimate of trend inflation.[3] Third, work has examined the role of wage inflation in forecasting inflation (e.g., Gordon, 1988; Hess and Schweitzer, 2000; Knotek and Zaman, 2014; Bidder, 2015; and Peneva and Rudd, 2017). This work has consistently found a small role for wages in forecasting price inflation in the United States.[4]

Relative to this previous work, the results in the analysis provide a new perspective on the role of wages in empirical models of price inflation. Including wages in the information set in a multivariate unobserved components model delivers a substantial, but time-varying, weight on wages in the estimate of trend inflation. This finding differs from the limited role for wages in previous empirical work on price inflation—for example, highlighting the role that time variation in relationships may challenge traditional forecasting models. The movements in the role of inflation also echo trends in the research literature and policy discussions, further demonstrating the value of the framework and suggesting a renewed impetus to studies of wage-price interactions. Concerns over a wage-price spiral were more salient in the 1970s and 1980s (e.g., Blanchard, 1986) and subsequent work downplayed the role of wages. In the empirical model herein, the weight on wages in trend inflation is high around 1980, falls through the mid-2010s, and then returns to its average level from 1976 to 1985 by 2022. Finally, none of the statistical models herein uniformly improve forecasts of inflation relative to simple approaches like the four-quarter moving average of inflation emphasized by Atkeson and Ohanian (2001); this finding is similar to that of Stock and Watson (2016). In other words, forecasting inflation is difficult, irrespective of the information set used to construct forecasts. Nonetheless, the data support a signal role for wages, and this signal is more important at certain points, including the late 1970s and early 1980s

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[2] Models of this type have proliferated outside the inflation literature as well (Stock and Watson, 2006). The multivariate unobserved components model of Del Negro and Otrok (2008), which is the closest implementation of such a model to the implementation herein except for that of Stock and Watson (2016), is a model of the business cycle.

[3] Another related strand of literature uses multivariate unobserved components models to estimate a trend in wages, as in Almuzara, Audoly, and Melcangi (2023). This work differs from that herein by focusing on wages, rather than wage-price interactions.

[4] Faust and Wright (2013), in their review of the literature on inflation forecasting, do not mention wages.

and the 2020s (to date). While a substantial weight on wages in an estimate of trend inflation from this type of model indicates that wages are important for signal extraction, it does not indicate causality and points to the need for further empirical and theoretical work.

Section 2 discusses the model used in the analysis. Section 3 presents the results for the role of wages in the multivariate unobserved components models. Section 4 reports forecast performance of various models, and section 5 concludes.

2. The Unobserved Components Model with Stochastic Volatility and Outlier Adjustments

2.1 The Multivariate Model

The multivariate unobserved components model with stochastic volatility and outlier adjustments (MUCSVO) provides a framework to extract the trend component of inflation from a set of price and wage series. Inflation in series j is the sum of a latent common factor for trend inflation, a latent common transient component, and sector-specific trends and transient components. The factor loadings for series j on the latent common factors vary over time, to allow for changes in the relationship of a series to the common factor. In addition, the latent common and sector-specific components have stochastic volatility and the model allows for outliers in the common and sectoral transitory components. The specification is taken from Stock and Watson (2016), which builds on Del Negro and Otrok (2008).

Formally, the model is given by a set of equations for N observed series, $x(j,t)$ for $j = 1{:}N$:

$$x(j,t) = a(j,\tau,t)\cdot\tau(c,t) + a(j,e,t)\cdot e(c,t) + \tau(j,t) + e(j,t) \quad (1)$$

$$\tau(c,t) = \tau(c,t-1) + \sigma(\tau,c,t)\cdot n(\tau,c,t) \quad (2)$$

$$\tau(j,t) = \tau(j,t-1) + \sigma(\tau,j,t)\cdot n(\tau,j,t) \quad (3)$$

$$e(c,t) = \sigma(e,c,t)\cdot s(c,t)\cdot n(e,c,t) \quad (4)$$

$$e(j,t) = \sigma(e,j,t)\cdot s(j,t)\cdot n(e,j,t) \quad (5)$$

$$a(j,\tau,t) = a(j,\tau,t-1) + \lambda(j,\tau)\cdot u(j,\tau,t) \quad (6)$$

$$a(j,e,t) = a(j,e,t-1) + \lambda(j,e)\cdot u(j,e,t) \quad (7)$$

$$\ln[\sigma(\tau,c,t)^2] = \ln[\sigma(\tau,c,t-1)^2] + \gamma(\tau,c)\cdot v(\tau,c,t) \quad (8)$$

$$\ln[\sigma(\tau,j,t)^2] = \ln[\sigma(\tau,j,t-1)^2] + \gamma(\tau,j)\cdot v(\tau,j,t) \quad (9)$$

$$\ln[\sigma(e,c,t)^2] = \ln[\sigma(e,c,t-1)^2] + \gamma(e,c)\cdot v(e,c,t) \quad (10)$$

$$\ln[\sigma(e,j,t)^2] = \ln[\sigma(e,j,t-1)^2] + \gamma(e,j)\cdot v(e,j,t) \quad (11)$$

Equation (1) is the observation equation in which the observed series $x(j,t)$ is a function of its own idiosyncratic trend and transitory components $(\tau(j,t), e(j,t))$ and the common trend and transitory components $(\tau(\mathrm{c},t), e(\mathrm{c},t))$, with the loadings of $x(j,t)$ on the common components denoted by $a(j,\tau,t)$ and $a(j,\mathrm{e},t)$. The trend components are random walks with stochastic volatility (denoted by $\sigma(\tau,c,t)$ and $\sigma(\tau,j,t)$), equations (2) and (3). The transitory components also have stochastic volatility (denoted by $\sigma(e,c,t)$ and $\sigma(e,j,t)$) and a jump component (denoted $s(c,t)$ and $s(j,t)$) to capture potential outliers, equations (4) and (5). The jump processes $s(c,t)$ and $s(j,t)$ equal 1 with probability (1 – p(x), x=c,j) and equal a draw from a uniform distribution over the interval 2 to 10 with probability p(x), x=c,j. As discussed in Stock and Watson (2016), this mixture model allows for outliers in the modeled series, e.g., large one-time shifts in the prices or wages modeled, as for example may have been triggered by the COVID-19 pandemic. The factor loadings are random walks (equations (6) and (7)), as is the natural logarithm of the stochastic volatilities of the shocks (equations (8) to (11)). The shocks (the set of *n, u,* and *v*) in equations (2)-(11) are i.i.d. standard Normal.

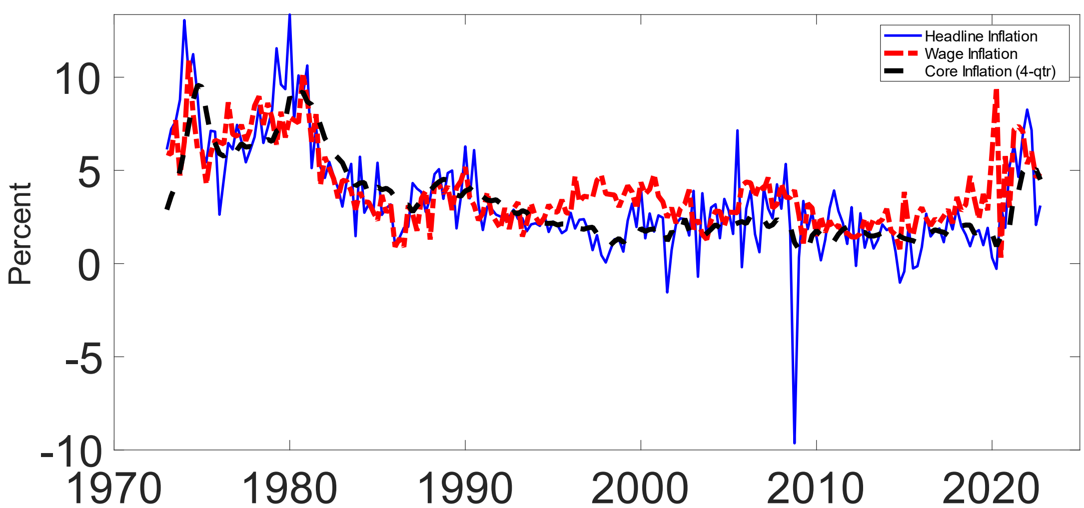
Several features of the model are noteworthy for descriptions of price and wage inflation data. The trend components allow for persistent shifts in inflation, as have been observed over the past 50 years. The presence of common and idiosyncratic trend components further allows for a common trend and for persistent differences across price categories (e.g., falling relative durable goods prices and rising relative prices for services, etc.) and across price and wage series (e.g., because wage developments will differ from price developments because of persistent productivity or other factors). The transitory, including jump, components capture fluctuations around these trends, while the stochastic volatility of trend and transitory components allows for periods of relative stability in the trend—such as the late 1990s and early 2000s—and periods of substantial movements in the trend—such as the 1970s and 1980s. Finally, the presence of stochastic volatility and time-variation in the loadings on the common components allows for changes over time on the covariance across price and wage inflation, which will imply time-variation on the weight given to price and wage inflation series in estimates of underlying trends. However, the model remains relatively simple, following Stock and Watson (2016) directly.

2.2 Data and Specifications Considered

Data on price indexes for personal consumption expenditures (PCE) in 17 categories of goods and services and for average hourly earnings (AHE) across 13 industries is used in the analysis. The data span the period from the first quarter of 1973 to the fourth quarter of 2022. (Average hourly earnings across the complete set of industries begins in the 1970s, determining the start date; Stock and Watson (2016) used data from 1960 onwards, reflecting the time period covered by the price data.)

Figure 1 presents the history of quarterly inflation for overall PCE prices and average hourly earnings (AHE) along with the four-quarter moving average of core PCE inflation (i.e., PCE prices excluding food and energy). The smoothed version of core inflation clearly contains more of the "trend" in inflation, which contributes to the finding that this is a good forecast of PCE inflation in Atkeson and Ohanian (2001) . There is substantial trend comovement in nominal prices and wages, along with notable short-run differences (such as the jump in wage inflation during COVID-19, reflecting compositional factors).

Figure 1: PCE (Headline) and AHE (Wage) Inflation (1973:Q1-2022:Q4)



Source: U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, and author's calculations. Headline inflation is the percent change in the price index for personal consumption expenditures expressed at an annual rate. Wage inflation is the percent change in average hourly earnings for production and nonsupervisory workers expressed at an annual rate. Core inflation is the four-quarter moving sum of the percent change in the price index for personal consumption expenditures excluding food and energy.

Table 1: Price and Wage Indexes Considered, with Means, Standard Deviations, & Correlation with Core PCE Inflation for 1973:Q1 to 2022:Q4

Price or Wage Index	Mean	Standard Deviation	Correlation with Core Inflation
PCE Price indexes			
Durable goods			
Motor vehicles and parts	2.57	5.25	0.57
Furn. & dur. household equip.	1.08	4.24	0.71
Rec. goods & vehicles	-2.75	4.64	0.79
Other durable goods	1.74	5.69	0.62
Nondurable goods			
Food & bev. for off-premises consumption	3.45	4.61	0.46
Clothing & footwear	0.70	4.05	0.52
Gasoline & other energy goods	4.92	37.66	0.18
Other nondurables goods	3.31	3.16	0.76
Services			
Housing and utilities			
Housing excl. gas & elec. util.	4.20	2.15	0.73
Gas & electric utilities	3.63	8.25	0.55
Health care	4.79	3.37	0.82
Transportation services	3.76	5.12	0.63
Recreation services	3.59	2.14	0.70
Food serv. & accom.	4.16	2.72	0.82
Fin. services & insurance	3.76	7.22	0.41
Other services	3.81	2.73	0.72
Final consumption expenditures of nonprofit institutions serving households	1.45	7.34	0.25
Average Hourly Earnings of Production and Nonsupervisory Workers (Industries)			
Goods-producing			
Mining and Logging	4.04	4.48	0.56
Durable Goods	3.73	2.87	0.74
Nondurable Goods	3.92	2.89	0.71
Services-providing			
Wholesale Trade	3.72	2.21	0.62
Retail Trade	3.44	2.69	0.44
Transportation and Warehousing	3.10	3.06	0.53
Utilities	4.03	3.40	0.47
Information	3.73	2.59	0.37
Financial Activities	4.51	2.48	0.59
Professional and Business Services	3.96	2.09	0.49
Education and Health Services	4.31	2.28	0.72
Leisure and Hospitality	4.30	3.49	0.61
Other Services	4.59	2.92	0.72

Source: U.S. Bureau of Economic Analysis, U.S. Bureau of Labor Statistics, and author's calculations. Core inflation is the percent change in the price index for personal consumption expenditures excluding food and energy.

Table 1 presents the mean, standard deviation, and correlation with core inflation for the inflation data on PCE prices and AHE used in the analysis. Several results are apparent. There are substantial differences in average rates of change across price and wage measures, reflecting sectoral differences; there are also substantial differences in volatility and in the correlation with core inflation. In general, there is more dispersion in the average rates of change in prices across expenditure types than there is in wages across industries, as should be expected given the ability of workers to move across industries. Rates of change in wages are as correlated with core inflation as are the price indexes for expenditure categories, reflecting the common influence of nominal price inflation on prices and wages. These facts motivated the structure of the model—which allows for differences in trend rates of change across series and in correlation—and will determine the role of each series as a signal in forecasting inflation. The analysis will consider 5 unobserved component models:

1. The MUCSVO model for the 17 detailed components of PCE prices in table 1 (and considered in Stock and Watson, 2016);
2. The MUCSVO model for the 17 detailed components of PCE prices and 13 detailed AHE series in table 1;
3. The MUCSVO model for three components of PCE prices—prices excluding food and energy, prices for food, and prices for energy (also considered in Stock and Watson, 2016);
4. The MUCSVO model for three components of PCE prices in the previous model and for two aggregate AHE series (AHE for goods-producing and for services-providing industries);
5. A UCSVO model for overall PCE prices—that is, a model like that in Stock and Watson (2007) with outlier adjustments.

The fifth model—the UCSVO model—is governed by the same equations as the MUCSVO models, with the deletion of the common factor components and loadings (as there is only one series, and hence the common and series-specific trend and transitory components are one).

A key concept in the analysis is the rate of trend PCE price inflation. The model contains price and wage series, but the question of interest is the role of wages in trend price inflation. According to the empirical models, the aggregate trend in PCE price inflation is given by

$$Trend\ PCE\ Inflation(t) = \sum_{j=1}^{N} w(j,t) \cdot [a(j,\tau,t) \cdot \tau(c,t) + \tau(j,t)]\ . \qquad (12)$$

In equation (12), the contribution of series j to trend inflation depends on its expenditure weight $w(j,t)$ and the trend associated with series j, which depends on the loading on the common trend and the sector's idiosyncratic trend. Wages do not have an expenditure weight, and their role in assessing the trend stems solely from the information they contain as signals to inform the estimates of trend for the prices that enter the PCE price index. The definition of the aggregate trend and the allowance in the model for series-specific trends implies that a differential trend in wages can be accounted for in the model without affecting the estimate of trend price inflation, although an additional common factor for wages is not included in the model. Such an additional common factors for wages, separate from a common factor for prices, are not introduced to maintain some degree of parsimony.

The models are estimated using Bayesian methods and estimation of the posterior proceeds using Markov Chain Monte Carlo (MCMC) methods. The estimation details follow Stock and Watson (2016) and the reader is referred to Stock and Watson (2015) for details. Detailed estimate results are presented in the online appendix.

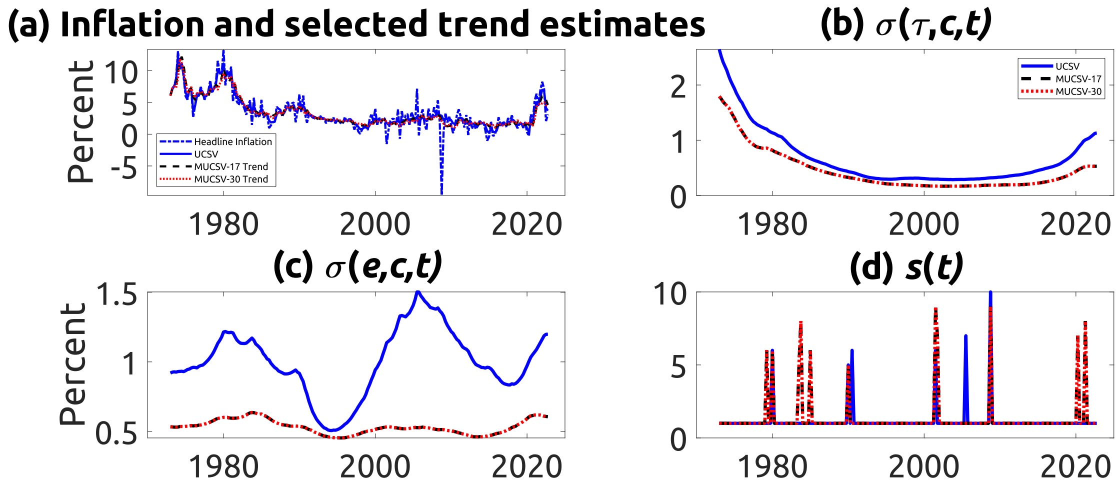
3. Results

3.1 Selected Results from the MUCSVO models

Several aspects of the models are helpful in understanding their properties and the role that wages may play in assessing trend inflation. Figure 1 presents these aspects, using estimates from the model based on the entire sample and the estimated posterior distribution. (That is, these are two-sided, or smoothed estimates, based on the entire data set.).

As shown in panel (a), the models—univariate (UCSV), multivariate with 17 price measures (MUCSV-17), and multivariate with 17 price measures and 13 wage measures (MUCSV-30)—provide broadly similar estimates of trend inflation, and these estimates behave similarly to core inflation. In terms of characterizing the degree to which trend and transitory inflation components account for inflation fluctuations, the overall takeaway point is the same for any of the models.

Figure 2: Estimated Properties of the Models (based on the entire sample)



Panels (b) and (c) present the standard deviations of the common trend and common transitory components for the UCSV, MUCSV-17, and MUCSV-30 models. The univariate model has more variability in the trend and transitory components, and the larger model, including the model with wages, sees less increase in the variance of trend shocks. This is to be expected: the UCSV model only consider total PCE inflation and hence needs to account for the volatility in food and energy inflation; in contrast, the MUCSV models can attribute volatility in components to the series specific trend or transitory shocks, and this results in lower standard deviations of the common trend and transitory components. A corollary of this finding is that the trend estimates from these models reacts less to data than that of the UCSV model; this is not apparent in panel (a) because of the scale of movements in inflation across decades but will be apparent in subsequent results.

Another notable finding in panel (b) is the recent movement in the estimate of the volatility of the trend in inflation. The univariate model reports a large increase after 2019, whereas the multivariate model does not. This highlights the value of the additional information in the multivariate model for assessing questions such as the degree to which the movements in inflation form 2020-22 represent transitory factors.

Finally, panel (d) reports when outliers are identified by each model. The MUCSV models identify outliers in 2020 and 2021—the COVID-19 pandemic—whereas the univariate model does not. This suggests that the multivariate models may have advantages to the univariate models in dealing with extreme situations. (For example, the large swings in motor vehicle prices during the COVID19 period.) That said, one element of the results in figure 2 is that the multivariate models look very similar along the reported dimensions—there are no discernable differences between the models with and without wages.

3.2 The role of wages

Give the previous findings, a natural question is what role, if any, do wages paly in understanding price inflation and its trend. Several results suggest wages play an important role.

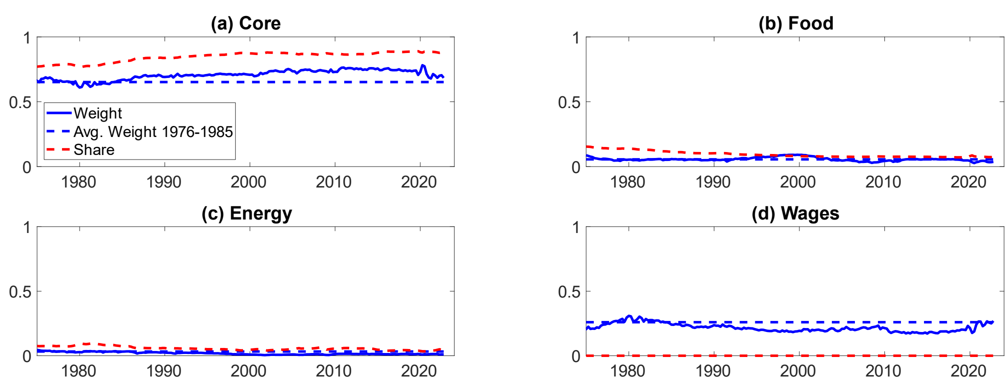
Equation (12) defined the aggregate trend in PCE inflation in terms of the model's estimates of common and idiosyncratic trends in the prices entering the PCE price index. A linear approximation to the one-sided (filtered) estimate of trend inflation can also be expressed in terms of the data as in equation (13):

$$Trend\ PCE\ Inflation(t) = \sum_{j=1}^{N} \sum_{i=0}^{\infty} \omega(j, t-i) \cdot x(j, t-i)\ . \tag{13}$$

The estimate of trend inflation in period *t* from the models is a moving average of the history of all the series up to period *t* (as this is a one-sided estimate) that enter the model, with time-varying weights on the series $\omega(j, t-i)$. These weights reflect a number of factors. First, there is the direct effect of an individual price series through its expenditure weight $w(j, t-i)$ (i.e., the direct weight that enters equation (12)). For example, a series that was independent of all other series but had a substantial idiosyncratic trend and substantial expenditure weight would receive a substantial weight—as such a series' idiosyncratic trend would influence the overall trend through its arithmetic weight $w(j, t-i)$ in overall PCE prices. Only PCE price series have this type of weight; the weight on wages from such effects is by definition zero. The remaining determinants of the weights on series in the estimate of trend inflation reflect the signal value a series has in estimating the common and idiosyncratic trends for prices through the filtering process associated with the state-space model. Wages can have substantial weight in the estimate of trend inflation through these channels—that is, through signal value for the common trend or for idiosyncratic trends. For example, it is possible that wages inform the idiosyncratic trends for key services categories because wages are a large component of costs in the production of such services. More generally, wages may simply be good signals because nominal wage growth is influenced by inflation and by factors that influence inflation; under this general logic, wage developments are useful for assessing trend inflation, but may or may not play a causal role in inflation developments.

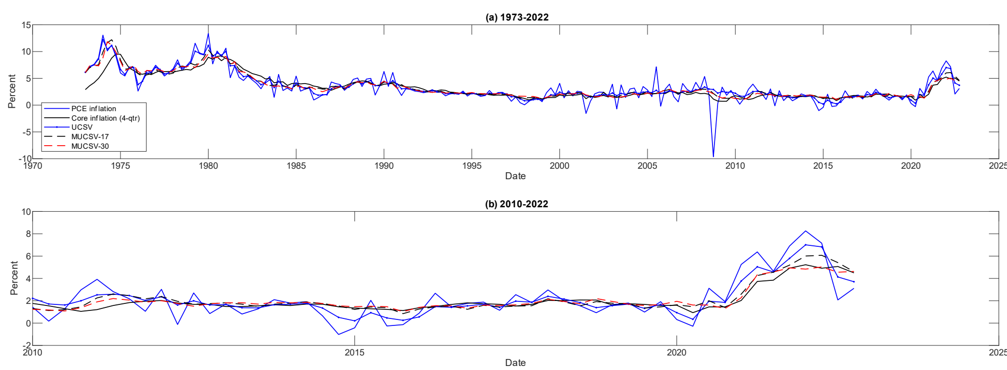
Figure 3 presents estimates of the weights (summed over the first four lags in equation (13)) for the estimate of trend inflation from the large multivariate model with 17 price and 13 wage measures, based on the full-sample posterior estimates, along with the average weight for the period from 1976 to 1985. The weights are reported for the components of core prices, energy prices, food prices, and wages. The figure also reports the expenditure shares (the arithmetic weights in the PCE price index) for the categories, which is zero for wages. As can be seen in panel (d), the weight in wages is substantial—at around 30 percent in 1980. Note that this weight fell from the early 1980s through the 2010s (to a low near 15 percent) but rises substantially by 2022 to reach its average over the period from 1976 to 1985 (a level above 25 percent). This suggests that recent developments have once again made wages an important signal of inflationary developments. It is notable, but not surprising, that wages receive a larger weight than their expenditure share of zero and this weight subtracts from that of core prices, whose weights lie below their expenditure share. Finally, both wages in goods-producing industries and in service-providing industries receive substantial weights (about 1/3 and 2/3 of the total weight, not shown). Some discussions have focused primarily on wages in services-providing industries as inflation signals, and the analysis herein suggests a broader set of wage measures contain information useful in an assessment of inflation.

Figure 3: Expenditure Shares and Weights in Trend Inflation for Prices and Wages (one-sided weights, based on full-sample posterior distribution)



To see the relevance of wages measures somewhat more clearly, figure 4 presents the filtered estimates of trend inflation from several models for the entire period and focusing on the post-2009 experience. Panel (a) presents the entire history, and the impression is similar to that from figure 2: All the models provide similar information regarding the big movements in trend inflation across decades. Panel (b) focuses on the most recent decade. The models performed similarly when inflation was stable—that is, before 2019. Since 2019, there is more variation. In particular, both the univariate and multivariate model using only prices (MUCSV-17) saw large swings up and down in trend inflation from 2020-22. For example, the univariate estimate of trend inflation (blue dotted line) peaked above 7 percent at the end of 2021 and fell to about 3 percent by the end of 2022. The multivariate model with prices only, MUCSV-17 (black dashed line), produces an estimate of trend inflation that rises to above 6 percent by the beginning of 2022 and falls to about 4 percent by the end of 2022. In contrast, the model with wages produces a trend that is much smoother, reflecting the information in wages and the broad tendency for additional smoothing to occur when more (relevant) information is included in a model. According to this (MUCSV-30) model (red-dashed line), trend inflation reached 5 percent by the end of 2021 and remained at 4.5 percent at the end of 2022.

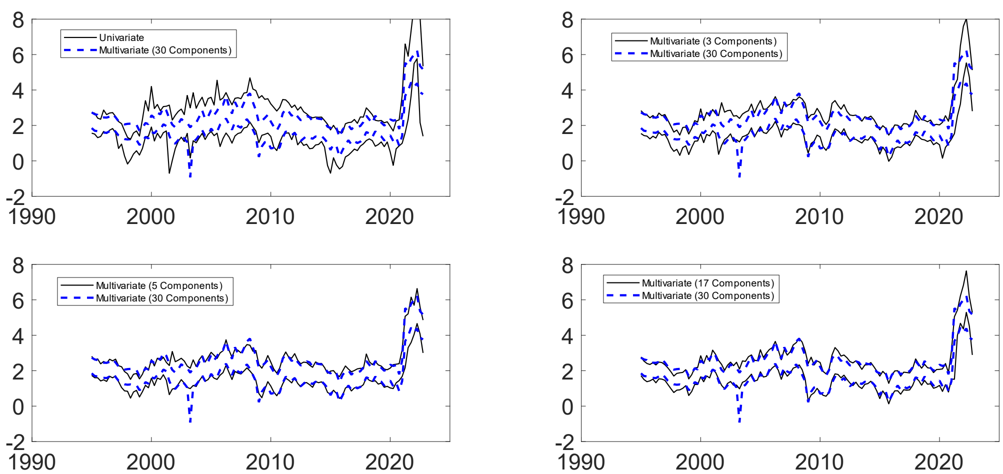
Figure 4: Estimates of Trend Inflation from Models with and without Wages (two-sided (smoothed) estimates)



The general tendency of additional information, when relevant, to result in smoothing (in this application) also implies narrower confidence intervals associated with the estimate of trend inflation. Figure 5 presents the width of the 90 percent confidence interval for the one-sided (filtered) estimates of trends from the models considered. The width of the confidence interval from the univariate model averages 1.9 percentage points, while that of the multivariate model with 13 wage series (MUCSV-30) is 1.1 percentage points. Note that the width of the confidence interval from the MUCSV-5 model—the model with core, food, and energy prices and wages for goods-producing and services-providing industries—is similar to that of the MUCSV-17 model that includes all the disaggregated price indexes, highlighting how wage measures are as valuable as detailed price information. Nonetheless, the confidence intervals are wide, reflecting the fact that estimation of trend inflation is challenging. Finally, both the models with wages—the MUCSV-5 and MUCSV-30 models—show less extreme movements in the estimate of trend inflation in the 2020s, highlighting the potential value of wages for gauging trend inflation in this period, as was suggested by the rise in the weight on wages shown in figure 3. In contrast, the models without wages (the UCSV, MUCSV-3, and MUCSV-17 models) show large increases and then decreases in the estimate of trend inflation in the 2020s.

Figure 5: 90-percent Confidence Intervals for Trend Inflation

(one-sided estimates)



4. Forecasting accuracy

Section 3 highlighted several dimensions along which the wage series were useful in assessing inflation developments. Much of the literature on dynamic factor models in macroeconomics, and especially the related literature on unobserved components models of inflation, has focused on forecast accuracy. Table 2 reports the mean-squared forecast area for various models—each of the statistical models considered herein and the most recent four-quarter moving average of core inflation (the Atkeson-Ohanian (2001) approach). The table also reports the difference between the approach and the Atkeson-Ohanian approach. The table presents the statistics for three forecast horizons—average inflation over the following 4, 8, and 12 quarters. The forecast errors are based on recursive estimation of the models beginning in 1995:Q1.

Table 2: Mean-Squared Forecast Errors (MSFE) for PCE Inflation Over 1995-2022

	Four-Quarter Horizon		Eight-Quarter Horizon		Twelve-Quarter Horizon	
Model	**MSFE (S.E.)**	**Diff. from row 1 (S.E.)**	**MSFE (S.E.)**	**Diff. from row 1 (S.E.)**	**MSFE (S.E.)**	**Diff. from row 1 (S.E.)**
4-qtr. core inflation	1.58 (0.60)		1.19 (0.56)		**0.63 (0.17)**	
UCSV	1.54 (0.55)	-0.04 (0.28)	1.41 (0.60)	0.22 (0.14)	0.83 (0.20)	0.20 (0.11)
MUCSV-3	1.50 (0.53)	-0.07 (0.19)	1.17 (0.46)	-0.02 (0.15)	0.73 (0.20)	0.11 (0.09)
MUCSV-17	1.58 (0.56)	0.01 (0.19)	1.23 (0.50)	0.04 (0.12)	0.76 (0.20)	0.13 (0.07)
MUCSV-5	**1.39 (0.47)**	**-0.19 (0.20)**	**1.07 (0.42)**	**-0.12 (0.17)**	0.67 (0.18)	0.04 (0.05)
MUCSV-30	1.57 (0.55)	-0.01 (0.12)	1.20 (0.49)	0.01 (0.10)	0.70 (0.18)	0.07 (0.06)
Model average	1.47 (0.53)	-0.10 (0.16)	1.17 (0.50)	-0.03 (0.10)	0.67 (0.18)	0.05 (0.05)

In general, the models have similar forecast performance: The differences in MSFEs are in some cases noticeable, but the differences are small overall and in a statistical sense. The wage models perform as well as the models without wages, and the MUCSV-5 model (the small model with wages) performs best at the four- and eight-quarter horizons. This occurs because the wages models perform somewhat better when 2020 and 2021 wage data enters, and the four- and eight-quarter horizons include one or both of these years; the twelve-quarter horizon does not include information from those years in the forecasts (i.e., the forecast errors for those years reflect only pre-2020 information). Overall, the forecast results suggest that wages are among the useful set of information, but do not substantially increase forecast accuracy. This is consistent with the balance of earlier results, where wages are more useful at some times and help to parse the signals in incoming data, but only to a moderate degree on average over time.

4. Summary

This paper examines whether the measurement of trend inflation can be improved by using wage data in a dynamic factor model of disaggregated prices and wages for the United States. The model features time-varying coefficients and stochastic volatility. An estimate of trend inflation is a time-varying distributed lag of prices and wages, where the weight on a series depends on its time-varying volatility, persistence, and comovement with other series.

The results show that wages inform estimates of trend inflation. The weight on wages was highest around 1980, drifted down through the 2000s, and returned to its average value from 1976 to 1985 by 2022. This pattern is reminiscent of the pattern in concerns over wage developments in inflation discussions, as the possibility of a wage-price spiral was palpable in the 1970s and 1980s but less salient in the 1990s and 2000s. The increase in the weight on wages in recent years suggests value in greater focus on wage developments in inflation assessments, although the statistical model herein does not speak to potential causal mechanisms. Finally, the return of a substantial role for wages coincides with an increase in the role of trend (persistent) inflation shocks in inflation dynamics in the 2020s, although the magnitude of this increase is smaller in a model with wages than in the univariate model. The results from models of this type can complement other approaches to assessing the persistence of recent high inflation.[5]

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Data Appendix

The data used in this study were downloaded from public sources on February 14, 2023.

The PCE price and expenditure data used in this study is taken from the website of the U.S. Bureau of Economic Analysis National Income and Product Accounts. The tables used are NIPA tables 2.3.4U and 2.3.5U.

The average hourly earnings (AHE) series used are published by the U.S. Bureau of Labor Statistics. The series were downloaded from FRED, Federal Reserve Bank of St. Louis. The series used in the paper have the following FRED mnemonics:

AHETPI CES0600000008 CES0800000008 CES1000000008
CES3000000008 CES3100000008 CES3200000008 CES4000000008
CES4142000008 CES4200000008 CES4300000008 CES4422000008
CES5000000008 CES5500000008 CES6000000008 CES6500000008
CES7000000008 CES8000000008.

Appendix—Estimation Details

The Bayesian estimation approach is identical to that in Stock and Watson (2015) and the reader is referred to that reference for details. As described in the main text, the model is given by the following set of equations describing a set of N series, $x(j,t)$ for $j = 1{:}N$:

$$x(j,t) = a(j,\tau,t)\cdot\tau(c,t) + a(j,e,t)\cdot e(c,t) + \tau(j,t) + e(j,t) \tag{1}$$

$$\tau(c,t) = \tau(c,t-1) + \sigma(\tau,c,t)\cdot n(\tau,c,t) \tag{2}$$

$$\tau(j,t) = \tau(j,t-1) + \sigma(\tau,j,t)\cdot n(\tau,j,t) \tag{3}$$

$$e(c,t) = \sigma(e,c,t)\cdot s(c,t)\cdot n(e,c,t) \tag{4}$$

$$e(j,t) = \sigma(e,j,t)\cdot s(j,t)\cdot n(e,j,t) \tag{5}$$

$$a(j,\tau,t) = a(j,\tau,t-1) + \lambda(j,\tau)\cdot u(j,\tau,t) \tag{6}$$

$$a(j,e,t) = a(j,e,t-1) + \lambda(j,e)\cdot u(j,e,t) \tag{7}$$

$$\ln[\sigma(\tau,c,t)^2] = \ln[\sigma(\tau,c,t-1)^2] + \gamma(\tau,c)\cdot v(\tau,c,t) \tag{8}$$

$$\ln[\sigma(\tau,j,t)^2] = \ln[\sigma(\tau,j,t-1)^2] + \gamma(\tau,j)\cdot v(\tau,j,t) \tag{9}$$

$$\ln[\sigma(e,c,t)^2] = \ln[\sigma(e,c,t-1)^2] + \gamma(e,c)\cdot v(e,c,t) \tag{10}$$

$$\ln[\sigma(e,j,t)^2] = \ln[\sigma(e,j,t-1)^2] + \gamma(e,j)\cdot v(e,j,t) \tag{11}$$

The jump processes $s(c,t)$ and $s(j,t)$ equal 1 with probability (1 – p(x), x=c,j) and equal a draw from a uniform distribution over the interval 2 to 10 with probability p(x), x=c,j. This uniform distribution is approximated by an equally spaced grid of 9 points.

Priors for $\gamma(\tau,c), \gamma(\tau,j), \gamma(e,c), \gamma(e,j)$ are Uniform over the interval 0 to 0.20. These priors are approximated by an equally spaced grid of 5 points.

Priors for p(x) are Beta(2.5,37.5).

Priors for the initial conditions of the trends and stochastic volatility are loose.

The posteriors are approximated by MCMC draws, with 50,000 draws following a 10,000-draw burn-in period. Results are saved every 10 draws, resulting in 5,000 draws for the approximations.

Figure 2 highlighted some key results for posterior estimates of the trends, stochastic volatility, and jump processes for the 17 and 30 component models (that is, the large models without wages and with wages). The following tables summarize estimates of the posteriors for (τ,c), $\gamma(\tau,j)$, $\gamma(e,c)$, $\gamma(e,j)$ and p(x) for the 30 component and 5 component models (that is, the models with wages). The results for other models are similar to estimation results in Stock and Watson (2016) and not reported.

Table A1: Prior and Posterior Distributions for $\boldsymbol{\gamma}(.,c)$

VALUE	PRIOR PROBABILITY	POSTERIOR PROBABILILTY			
		30 COMPONENT MODEL		5 COMPONENT MODEL	
		$\gamma(e,c)$	$\gamma(\tau,c)$	$\gamma(e,c)$	$\gamma(\tau,c)$
0	0.2	0	0	0.03	0
0.05	0.2	0.03	0	0.07	0
0.1	0.2	0.18	0	0.15	0.02
0.15	0.2	0.35	0.10	0.28	0.25
0.2	0.2	0.43	0.90	0.48	0.73

Table A2: Prior and Posterior Distributions for p(c) (selected quantiles)

	16%	**50%**	**67%**
30 components	0.02	0.04	0.06
5 components	0.03	0.05	0.09

Table A3: Prior and Posterior Distributions for $\gamma(e,j)$ in 30 component Model

Value		0	0.05	0.1	0.15	0.2
Prior Probability		0.2	0.2	0.2	0.2	0.2
Posterior Probabilities						
PCE Prices	Motor vehicles and parts	0.05	0.06	0.14	0.29	0.46
	Furn. & dur. household equip.	0.01	0.1	0.31	0.35	0.23
	Rec. goods & vehicles	0.49	0.29	0.13	0.06	0.03
	Other durable goods	0.01	0.07	0.24	0.32	0.36
	Food & bev. for off-premises consumption	0	0	0	0.1	0.9
	Clothing & footwear	0.21	0.45	0.21	0.1	0.04
	Gasoline & other energy goods	0	0.01	0.2	0.35	0.45
	Other nondurables goods	0.1	0.14	0.24	0.28	0.24
	Housing excl. gas & elec. util.	0.1	0.11	0.18	0.29	0.33
	Gas & electric utilities	0	0.04	0.16	0.33	0.47
	Health care	0	0.01	0.15	0.37	0.46
	Transportation services	0	0	0.07	0.38	0.55
	Recreation services	0.01	0.03	0.09	0.24	0.64
	Food serv. & accom.	0.07	0.14	0.28	0.32	0.2
	Fin. services & insurance	0	0	0.01	0.18	0.81
	Other services	0.01	0.09	0.43	0.32	0.16
	NPISH	0	0	0.03	0.25	0.72
AHE	Mining and Logging	0	0.15	0.43	0.27	0.14
	Durable Goods	0.37	0.37	0.17	0.06	0.03
	Nondurable Goods	0.19	0.35	0.26	0.14	0.06
	Wholesale Trade	0.01	0.26	0.37	0.24	0.12
	Retail Trade	0	0.13	0.48	0.28	0.11
	Transportation and Warehousing	0	0.22	0.47	0.22	0.08
	Utilities	0	0.33	0.39	0.2	0.08
	Information	0	0	0.15	0.42	0.43
	Financial Activities	0.05	0.17	0.3	0.28	0.2
	Professional and Business Services	0	0.02	0.24	0.41	0.32
	Education and Health Services	0	0.06	0.21	0.33	0.4
	Leisure and Hospitality	0.18	0.15	0.13	0.2	0.34
	Other Services	0	0.01	0.11	0.32	0.56

Table A4: Prior and Posterior Distributions for $\gamma(\tau, j)$ in 30 component Model

Value		0	0.05	0.1	0.15	0.2
Prior Probability		0.2	0.2	0.2	0.2	0.2
Posterior Probabilities						
PCE Prices	Motor vehicles and parts	0.23	0.22	0.2	0.19	0.16
	Furn. & dur. household equip.	0.27	0.24	0.21	0.16	0.13
	Rec. goods & vehicles	0.2	0.2	0.21	0.2	0.2
	Other durable goods	0.24	0.22	0.22	0.18	0.14
	Food & bev. for off-premises consumption	0.21	0.21	0.18	0.21	0.2
	Clothing & footwear	0.25	0.24	0.23	0.16	0.12
	Gasoline & other energy goods	0.22	0.22	0.21	0.19	0.16
	Other nondurables goods	0.15	0.15	0.14	0.2	0.35
	Housing excl. gas & elec. util.	0	0	0.03	0.19	0.78
	Gas & electric utilities	0.22	0.22	0.21	0.2	0.16
	Health care	0.09	0.15	0.28	0.27	0.21
	Transportation services	0.27	0.26	0.21	0.15	0.11
	Recreation services	0.3	0.26	0.2	0.14	0.09
	Food serv. & accom.	0.09	0.11	0.16	0.25	0.39
	Fin. services & insurance	0.22	0.21	0.21	0.19	0.17
	Other services	0.22	0.21	0.21	0.2	0.16
	NPISH	0.12	0.15	0.24	0.25	0.24
AHE	Mining and Logging	0.27	0.25	0.21	0.16	0.12
	Durable Goods	0.3	0.26	0.2	0.14	0.1
	Nondurable Goods	0.27	0.26	0.21	0.15	0.12
	Wholesale Trade	0.28	0.26	0.21	0.15	0.1
	Retail Trade	0.33	0.28	0.2	0.12	0.07
	Transportation and Warehousing	0.23	0.24	0.21	0.18	0.14
	Utilities	0.29	0.26	0.21	0.15	0.1
	Information	0.31	0.28	0.19	0.13	0.08
	Financial Activities	0.25	0.24	0.22	0.16	0.12
	Professional and Business Services	0.09	0.12	0.21	0.28	0.3
	Education and Health Services	0.31	0.29	0.2	0.12	0.08
	Leisure and Hospitality	0.25	0.24	0.21	0.17	0.13
	Other Services	0.28	0.27	0.21	0.14	0.1

Table A5: Prior and Posterior Distributions for p(j) in 30 component model (selected quantiles)

		16%	50%	67%
PCE Prices	Motor vehicles and parts	0.03	0.05	0.08
	Furn. & dur. household equip.	0.01	0.02	0.03
	Rec. goods & vehicles	0.03	0.05	0.07
	Other durable goods	0.03	0.05	0.08
	Food & bev. for off-premises consumption	0.01	0.02	0.04
	Clothing & footwear	0.02	0.03	0.04
	Gasoline & other energy goods	0.07	0.11	0.15
	Other nondurables goods	0.03	0.05	0.08
	Housing excl. gas & elec. util.	0.02	0.03	0.05
	Gas & electric utilities	0.05	0.08	0.12
	Health care	0.02	0.04	0.06
	Transportation services	0.01	0.02	0.03
	Recreation services	0.02	0.04	0.06
	Food serv. & accom.	0.01	0.02	0.03
	Fin. services & insurance	0.04	0.07	0.09
	Other services	0.01	0.02	0.03
	NPISH	0.01	0.02	0.03
AHE	Mining and Logging	0.02	0.03	0.05
	Durable Goods	0.03	0.05	0.07
	Nondurable Goods	0.02	0.03	0.05
	Wholesale Trade	0.01	0.02	0.03
	Retail Trade	0.02	0.03	0.05
	Transportation and Warehousing	0.01	0.02	0.04
	Utilities	0.01	0.02	0.04
	Information	0.01	0.02	0.04
	Financial Activities	0.01	0.02	0.03
	Professional and Business Services	0.01	0.02	0.03
	Education and Health Services	0.02	0.04	0.06
	Leisure and Hospitality	0.03	0.05	0.08
	Other Services	0.01	0.02	0.04

Table A6: Prior and Posterior Distributions for $\gamma(e, j)$ in 5 component model

Value		0	0.05	0.1	0.15	0.2
Prior Probability		0.2	0.2	0.2	0.2	0.2
Posterior Probabilities						
PCE Prices	Core goods and services	0.26	0.22	0.2	0.18	0.15
	Food	0	0	0	0.14	0.85
	Energy	0	0.01	0.23	0.37	0.39
AHE	Good Producing	0.36	0.3	0.19	0.1	0.04
	Services Providing	0.09	0.2	0.28	0.25	0.17

Table A7: Prior and Posterior Distributions for $\gamma(\tau, j)$ in 5 component model

Value		0	0.05	0.1	0.15	0.2
Prior Probability		0.2	0.2	0.2	0.2	0.2
Posterior Probabilities						
PCE Prices	Core goods and services	0.14	0.17	0.21	0.25	0.23
	Food	0.15	0.16	0.17	0.22	0.3
	Energy	0.2	0.22	0.2	0.21	0.18
AHE	Good Producing	0.27	0.25	0.21	0.16	0.11
	Services Providing	0.19	0.21	0.21	0.2	0.19

Table A8: Prior and Posterior Distributions for p(j) in 5 component model (selected quantiles)

		16%	50%	67%
PCE Prices	Core goods and services	0.03	0.06	0.1
	Food	0.01	0.02	0.03
	Energy	0.08	0.12	0.16
AHE	Good Producing	0.02	0.03	0.05
	Services Providing	0.01	0.03	0.05