NBER WORKING PAPER SERIES

CORE INFLATION AND TREND INFLATION

James H. Stock
Mark W. Watson

Working Paper 21282
http://www.nber.org/papers/w21282

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2015

We thank Marco del Negro and Giorgio Primiceri for discussions on numerical methods. We also thank seminar participants at the Universitat Pompeu Fabra EC2 conference, the National Bank of Belgium, the Society for Nonlinear Dynamics and Econometrics Oslo meetings, and the Board of Governors of the Federal Reserve. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Core Inflation and Trend Inflation
James H. Stock and Mark W. Watson
NBER Working Paper No. 21282
June 2015
JEL No. E31

ABSTRACT

An important input to monetary policymaking is estimating the current level of inflation. This paper examines empirically whether the measurement of trend inflation can be improved by using disaggregated data on sectoral inflation to construct indexes akin to core inflation, but with time-varying distributed lags of weights, where the sectoral weight depends on the time-varying volatility and persistence of the sectoral inflation series, and on the comovement among sectors. The model is estimated using U.S. data on 17 components of the personal consumption expenditure inflation index. The modeling framework is a dynamic factor model with time-varying coefficients and stochastic volatility as in del Negro and Otrok (2008); this is the multivariate extension of the univariate unobserved components-stochastic volatility model of trend inflation in Stock and Watson (2007). Our main empirical results are (i) the resulting multivariate estimate of trend inflation is similar to the univariate estimate of trend inflation computed using core PCE inflation (excluding food and energy) in the first half of the sample, but introduces food in the second half of the sample: early in the sample, food inflation was noisy and a poor indicator of trend inflation, but now food inflation is less volatile, more persistent, and a useful indicator; (ii) the model-based filtering uncertainty about trend inflation is substantially reduced by using the disaggregated series in a multivariate model, relative to computing the trend using only headline inflation; (iii) the multivariate trend and the univariate trend constructed using core measures of inflation forecast average inflation over the 1-3 year horizon more accurately than a variety of other benchmark inflation measures, although there is considerable sampling uncertainty in these forecast comparisons.

James H. Stock
Department of Economics
Harvard University
Littauer Center M26
Cambridge, MA 02138
and NBER
James_Stock@harvard.edu

Mark W. Watson
Department of Economics
Princeton University
Princeton, NJ 08544-1013
and NBER
mwatson@princeton.edu

A Replication files is available at:
http://www.princeton.edu/~mwatson/ddisk/core_and_trend_inflation_replication_files.zip

1. Introduction

A classic yet still-important problem of measuring the rate of price inflation is filtering out the noise in inflation data to provide an estimate of the "trend" value of inflation. Following Bryan and Cecchetti (1994), we think of trend inflation as the long-term estimate of the inflation rate based on data on prices through the present. Having a good estimate of trend inflation is an important input to monetary policy and to a myriad of private decisions. For example, as this is written, a pressing question in the United States and the Eurozone is how far trend inflation actually is below the 2% target. Because there are multiple sources of noise in inflation data and because the nature of the noise can change over time, the task of estimating trend inflation is both difficult and of ongoing relevance.

Producing an accurate estimate of trend inflation requires distinguishing which variations in inflation are persistent from those that are unlikely to persist into the future. Broadly speaking, there are two distinct approaches to this signal extraction problem.

The first approach is to use cross-sectional data on inflation (sectoral-level inflation data), with a weighting scheme that downweights series with large non-persistent variation. The most important example of this approach is the standard measure of core inflation, which excludes food and energy prices (Gordon (1975), Eckstein (1981); see Wynne (2008) for a discussion of the history of core inflation). Other methods that exploit cross-sectional smoothing include using trimmed means or medians of sectoral inflation rates, see Bryan and Cecchetti (1994); these methods impose zero/one weighting on each component, with weights that vary over time.[1] For recent references on core inflation see Crone, Khettry, Mester, and Novak (2013).

The second common approach to the signal extraction problem is to use univariate time-series smoothing methods. Simple yet effective smoothers include the IMA(1,1) model of Nelson and Schwert (1977) and the four-quarter average of quarterly inflation (Atkeson and Ohanian (2001)). Stock and Watson (2007) and Cogley and Sargent (2015) provide methods that allow

[1] The Cleveland Fed publishes a median and trimmed mean CPI (https://www.clevelandfed.org/en/Our%20Research/Indicators%20and%20Data/Current%20Median%20CPI.aspx) and the Dallas Fed publishes a monthly trimmed mean PCE inflation index (http://www.dallasfed.org/research/pce/).

for time-variation in the filter depending on changes in the signal-to-noise ratio via time variation in the innovation variance of persistent and non-persistent components.

We follow this literature on core and trend inflation and consider only estimates derived from the price indexes and corresponding expenditure share weights used in the construction of the headline inflation series of interest. A vast literature considers the problem of using other series, such as measures of economic activity, interest rates, and terms of trade to forecast inflation. At an abstract level, the distinction between using only price data, and price data combined with other data, can be thought of as measurement vs. forecasting; the focus here is measurement. At a practical level, at least for the U.S., some forecasting models using non-price data can improve upon forecasts based solely on prices, but those improvements are small and, in many cases, ephemeral, which underscores the practical relevance of considering estimates of trend inflation based on constituent sectoral price data.

This paper combines the cross-sectional and time-series smoothing approaches to examine four questions about the measurement of trend inflation and its relation to core inflation. First, can more precise measures of trend inflation be obtained using disaggregated sectoral inflation measures, relative to time series smoothing of headline inflation? Second, if there are improvements to be had by using sectoral inflation measures, do the implied sectoral weights evolve over time or are they stable, and how do they compare to the corresponding sectoral shares in consumption? Third, how do the implied time-varying weights and the resulting multivariate estimate of trend inflation compare to conventional core inflation measures? And fourth, do these trend inflation measures improve upon conventional core inflation when it comes to forecasting inflation over the one through three year horizon?

We investigate these questions empirically using a univariate and multivariate unobserved-components stochastic volatility outlier-adjusted (UCSVO) model that allows for common persistent and transitory factors, time-variation in the factor loadings, and stochastic volatility of the common and sectoral components. The time-varying factor loadings allow for changes in the comovements across sectors, such as the reduction in energy price pass-through into core. Introducing separate sectoral and common stochastic volatility in transitory and permanent innovations allows for changes in the persistence of sectoral inflation innovations and for sector-specific changes in volatility. One source of the changing volatility in the component inflation rates is changes in the methods and/or underlying data sources used to construct the historical series. A strength of the method implemented here is that the resulting estimates of historical trends adjust for changes in measurement methods as well as for fundamental changes in the volatility and persistence of the component series.

At a technical level, the model closest to that used here is del Negro and Otrok (2008), which has time-varying factor loadings and stochastic volatility (their application is to international business cycles, not inflation). Our model has some technical differences to fit our application to U.S. sectoral data, including distinct sectoral trends, a common trend, and model-based detection of and adjustment for outliers.

The data we use are 17 sectors comprising the personal consumption expenditure (PCE) price index for the United States, 1959Q1-2014Q4. Our main findings are: (i) the multivariate trend estimates are substantially more precise than the univariate estimates: the model-based estimate of the root mean squared error of the smoothed multivariate estimate of the latent trend is roughly half that of the univariate trend estimate based solely on headline inflation; (ii) although the implied weights in the multivariate trend on most sectoral components are close to their share weights, the implied weight on some series varies substantially as the series drops out of or enters the multivariate trend; (iii) broadly speaking, the multivariate trend estimate is a temporally smoothed version of core (ex food & energy) through the 1970s, but starting in the 1980s places more weight on food (both off-premises and food services & accommodation) and less weight on financial services, so that the composition of multivariate trend in the 2000s is roughly similar to PCE ex energy; and (iv) viewed as forecasts, the multivariate and univariate trend estimates improve upon headline inflation alone, but (consistent with other research) neither the multivariate trend estimates nor the univariate trend in core or PCE ex energy make statistically significant forecasts improvements over the univariate trend estimate based on headline inflation.

In addition to the literatures discussed above on core and trend inflation, this work is related to three other large literatures. First, our modeling framework extends work estimating common factors of multiple inflation series, including Cristadoro, Forni, Reichlin, and Veronese (2005), Amstad and Simon M. Potter (2007), Altissimo, Mojon, and Zaffaroni (2009), Boivin, Giannoni, and Mihov (2009), Reis and Watson (2010), and Sbrana, Silvestrini, and Venditti (2015). Mumtaz and Surico (2012) introduce stochastic volatility and time-varying factor dynamics into a model of 13 international inflation rates. Second, the issues of including or excluding energy inflation is related to the literature on changes in the pass-through of energy prices to headline or core inflation (something allowed for in our model); see Hooker (2002), De Gregorio, Landerretche, and Neilson (2007), van den Noord and André (2007), Chen (2009), Blanchard and Galı (2010), Clark and Terry (2010), and Baumeister and Peersman (2013). Also related is work that uses series other than price series to measure trend inflation, e.g. Mertens (2012), Garnier, Mertens, and Nelson (2013), and Mertens and Nason (2015).

The next section presents the univariate and multivariate UCSVO models and discusses their estimation. Section 3 provides the resulting univariate trend estimates for headline, core, and PCE ex energy. Section 4 presents multivariate results, first for the 17-sector model then for a model with only three components: core, food, and energy. Section 5 compares the forecasting performance of the various trend estimates over the 1-3 year horizon, and Section 6 concludes.

2. The Unobserved Components Model with Stochastic Volatility, Common Factors, and Outlier Adjustment

The univariate UCSVO model. The univariate unobserved components/stochastic volatility outlier-adjustment (UCSVO) model used in this paper expresses the rate of inflation as the sum of a permanent and transitory component, where the innovations to both components have variances that evolve over time according to independent stochastic volatility processes, and where the innovation to the temporary component can have heavy tails (outliers):

$$\pi_t = \tau_t + \varepsilon_t \tag{1}$$

$$\tau_t = \tau_{t-1} + \sigma_{\Delta\tau,t} \times \eta_{\tau,t} \tag{2}$$

$$\varepsilon_t = \sigma_{\varepsilon,t} \times s_t \times \eta_{\varepsilon,t}. \tag{3}$$

$$\Delta\ln(\sigma^2_{\varepsilon,t}) = \gamma_\varepsilon \nu_{\varepsilon,t} \tag{4}$$

$$\Delta\ln(\sigma^2_{\Delta\tau,t}) = \gamma_{\Delta\tau} \nu_{\Delta\tau,t} \tag{5}$$

where $(\eta_\varepsilon, \eta_\tau, \nu_\varepsilon, \nu_{\Delta\tau})$ are iidN(0, I_4), and where s_t is an i.i.d. multinomial variable.

This model expresses the rate of inflation π_t as the sum of a permanent component τ_t (trend) and a transitory component ε_t (1), in which τ_t follows a martingale (2) and the transitory component is serially uncorrelated (3), and in which both innovations follow a logarithmic random walk stochastic volatility process (4) and (5). Conditional on the stochastic volatility process, the transitory innovation ε_t is modeled in (3) as a mixture of normal via the i.i.d. multinomial variable s_t, which is set *a-priori* to take on the values 1, 5, and 10 with probabilities .975, 1/60, and 1/120. This mixture model allows for outliers in the rate of inflation, which correspond to large one-time shifts in the price level.

The UCSVO model (1) - (5) has only two parameters, γ_ε and $\gamma_{\Delta\tau}$, which govern the scale of the innovation in the stochastic volatility process. At a given point in time, the autocovariance structure of π_t is that of a IMA(1,1) process, however the mixture-of-normals distribution of the transitory innovation means that the filtered estimate of π_t is not always well approximated by a local IMA(1,1) filter.

This difference between (1) - (5) and the Stock-Watson (2007) UCSV model is that the USCVO model includes an explicit model-based treatment of outliers. As will be seen below, large one-time spikes in inflation are observed in the data, especially in the sectoral components.[2] Stock and Watson (2007) made preliminary judgmental adjustments for outliers prior to model estimation, however that approach is not feasible for real-time trend estimation because it requires knowing *ex post* whether a large change will mean-revert. Ignoring outliers is not appealing because doing so runs the risk of mistaking a single large outlier for a more systematic increase in the volatility of the transitory component. Because we are interested in real-time trend estimation, (3) therefore extends the Stock-Watson (2007) model to make outlier adjustments part of the model by modeling the transitory innovation as a mixture-of-normals.

The multivariate UCSVO model. This multivariate UCSVO (MUCSVO) model extends the UCSVO model to include a common latent factor in both the trend and idiosyncratic components of inflation, where the factor loadings are also time-varying. Let the subscripts *c* denote the common latent factor and *i* denote the sector. The multivariate model is the del Negro and Otrok (2008) dynamic factor model with time-varying factor loadings and stochastic volatility, extended to have permanent and transitory components and extended to handle outliers in the transitory disturbance.

---

[2] An example of such a sectoral outlier is the April 2009 increase in the Federal cigarette tax, which resulted in a 22% increase in cigarette prices that month. This tax increase drove a one-time jump in the rate of PCE inflation for other nondurable goods (the category that contains tobacco) in 2009Q2 of 10.4% at an annual rate, well above the 2.7% average rate of inflation for that category in 2008 and 2009 excluding that quarter.

The multivariate UCSV model is,

$$\pi_{i,t} = \alpha_{i,\tau,t}\ \tau_{c,t} + \alpha_{i,\varepsilon,t}\ \varepsilon_{c,t} + \tau_{i,t} + \varepsilon_{i,t}, \tag{6}$$

$$\tau_{c,t} = \tau_{c,t\text{-}1} + \sigma_{\Delta\tau,c,t} \times \eta_{\tau,c,t} \tag{7}$$

$$\varepsilon_{c,t} = \sigma_{\varepsilon,c,t} \times s_{c,t} \times \eta_{\varepsilon,c,t} \tag{8}$$

$$\tau_{i,t} = \tau_{i,t\text{-}1} + \sigma_{\Delta\tau,i,t} \times \eta_{\tau,i,t} \tag{9}$$

$$\varepsilon_{i,t} = \sigma_{\varepsilon,i,t} \times s_{i,t} \times \eta_{\varepsilon,i,t} \tag{10}$$

$$\alpha_{i,\tau,t} = \alpha_{i,\tau,t\text{-}1} + \lambda_{i,\tau}\zeta_{i,\tau,t} \text{ and } \alpha_{i,\varepsilon,t} = \alpha_{i,\varepsilon,t\text{-}1} + \lambda_{i,\varepsilon}\zeta_{i,\varepsilon t} \tag{11}$$

$$\Delta\ln(\sigma^2_{\Delta\tau,c,t}) = \gamma_{\Delta\tau,c}\nu_{\Delta\tau,c,t},\ \Delta\ln(\sigma^2_{\varepsilon,c,t}) = \gamma_{\varepsilon,c}\nu_{\varepsilon,c,t},\ \Delta\ln(\sigma^2_{\Delta\tau,i,t}) = \gamma_{\Delta\tau,i}\nu_{i,t}, \text{ and}$$

$$\Delta\ln(\sigma^2_{\varepsilon,i,t}) = \gamma_{\varepsilon,i}\nu_{i,t}, \tag{12}$$

where the disturbances ($\varepsilon_{c,t}$, $\varepsilon_{i,t}$, $\eta_{c,t}$, $\eta_{i,t}$, $\zeta_{c,t}$, $\zeta_{i,t}$, $\nu_{\Delta\tau,c,t}$, $\nu_{\varepsilon,c,t}$, $\nu_{\Delta\tau,i,t}$, $\nu_{\varepsilon,i,t}$) are i.i.d. standard normal. Following Del Negro and Otrok (2008), we adopt an inverse Gamma prior for λ. In addition, the prior for the initial values $\alpha_{\tau,c,0}$ or $\alpha_{\varepsilon,c,0}$ is $\alpha \sim N(0,\ \kappa_1^2\, ll' + \kappa_2^2\, I_n)$ where l is an $n \times 1$ vector of 1's, so that κ_1 governs the prior uncertainty about the average value of factor loadings, and κ_2 governs the variability of each factor loading from the average value.

Equation (6) represents sector i inflation as the sum of a latent common factor for trend inflation is $\tau_{c,t}$, a latent common transient component $\varepsilon_{c,t}$, and sector-specific trends and transient components, where the factor loadings evolve according to a random walk (11). Equations (7) - (10) allow for stochastic volatility in the latent common and sector-specific components, where the stochastic volatility evolves according to a logarithmic random walk (12). Like the univariate model, the multivariate model allows for outliers in the common and sectoral transitory components through the independent multinomial variables $s_{c,t}$ and $s_{i,t}$ in (8) and (10), where the s_t variables take on 1, 5, 10 with probability .975, 1/60, and 1/120.

The trend sectoral inflation is the sum of the contribution of the common latent factor to that sector and the sectoral trend, that is, the sectoral trend is $\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}$. The aggregate trend inflation is the sum of the sectoral trend, weighted by the share weight w_{it} of sector i in total inflation:

$$\text{Aggregate trend} = \tau_t = \sum_{i=1}^{17} w_{it}\left(\alpha_{i,\tau,t}\tau_{c,t} + \tau_{i,t}\right). \tag{13}$$

The definition (13) of the aggregate trend τ_t nests a range of possibilities, from the common trend providing all the trend movements in sectoral inflation (so that there are n-1 cointegrating vectors among the n sectors) to all sectoral inflation being independent with no cointegration. In this latter case, the common trend in aggregate inflation would just be the sum of the idiosyncratic trends, weighted by the sectoral share weights.

Estimation. Estimation of the univariate and multivariate models proceeds using Markov Chain Monte Carlo (MCMC) methods. The parameters γ_ε and $\gamma_{\Delta\tau}$ (univariate model) and γ_i (multivariate model) have an independent U(0,.5) prior. The initial value for the trend has a diffuse prior in the univariate model as do the initial values for the idiosyncratic trends in the multivariate model. The initial value of the common trend is set to zero in the multivariate model. The parameters for the prior on $\alpha_{\tau,c,0}$ or $\alpha_{\varepsilon,c,0}$ in the multivariate model are κ_1 = 10 and κ_2 = 0.4. The stochastic volatility is handled following Kim, Shephard, and Chib (1998), modified to use the Omori, Chib, Shephard, and Nakajima (2007) 10-component Gaussian mixture approximation for the log-chi squared error. The MCMC iterations in Stock and Watson (2007) have been corrected for an error pointed out by Del Negro and Primiceri (2014) that applies generally to models with stochastic volatility.

Throughout this paper, we refer to the smoothed estimate of an unobserved component at date t to be the posterior mean of the component, given the full data set. The filtered estimate of an unobserved component at date t is the conditional mean given only the data through date t, except that the parameters are evaluated using their posterior mean given the full data set. Thus the same posterior distribution of the parameters is used in the filtered and smoothed estimates, a treatment that parallels the standard frequentist approach in which the one-sided filtered and two-sided smoothed estimates are evaluated at the full-sample parameter estimates.

3. Data and Univariate Results

The data. The full data set consists of quarterly data from 1959Q1-2015Q1 on 17 components of inflation used to construct the PCE price index. The lowest-level components in NIPA Table 2.3.4 consist of 16 components (4 durable goods sectors, 4 nondurable good sectors, and 8 service sectors). Core PCE excludes two of these 16 components (food for off-premises consumption and gasoline & energy goods), and additionally excludes energy & gas utilities. Because energy & gas utilities does not appear separately in Table 2.3.4, but rather is contained in housing & utilities, core PCE cannot be constructed directly from these 16 components. So that our 17-sector treatment nests core, we further disaggregate housing & utilities into gas & electric utilities and housing excluding gas & electric utilities, for a total of 17 sectoral components. Expenditure share weights for these components can be computed using the nominal PCE values in NIPA table 2.3.5. These components and their expenditure share weights for selected periods are given in Table 1.

In addition, we consider three aggregate indexes: the headline (all-components) PCE price index (PCE-all), the Bureau of Economic Analysis's PCE price index excluding energy (PCExE), and the BEA core PCE price index excluding food and energy (PCExFE).

The data are all final estimates of these series. Some of the component series have undergone significant methodological changes over the years and have been subject to major historical revisions. For example, in 2013 the price index for financial services was revised, including changing the method for measuring implicitly priced services produced by commercial banks (Hood (2013)). Prior to the revision, the category "financial services furnished without payment" (e.g. checks processed without fees) used imputed prices based on market interest rates, so those prices fluctuated substantially during periods of interest rate volatility. The 2013 revision changed the method for computing the reference interest rate for unpriced financial services, reducing the volatility of this component. Because this revision was implemented retroactively only to 1985, different methods are used to compute this component of the financial services price index pre-1985 and post-1985.

As another example, in the 2009 revision, the category of food and tobacco (which until then had been excluded from core) was distributed across three categories: food & beverages purchased for off-premise consumption, other non-durable goods (which since 2009 includes tobacco), and food services & accommodations; only the first of these is now excluded from core PCE. Because the fully revised series reflect this change, it does not cause a break in the data used in this paper, however it does mean that previous research on core PCE examined a somewhat different concept than the current definition of core. Changing definitions and measurement methods combined with partial historical adjustment are commonplace, and we return to the implications of these methodological changes below.

Univariate results for PCE-all, PCExE, and PCExFE. Figure 1 shows PCE-all inflation, its smoothed estimate from the UCSVO model and the smoothed trend estimate from the Stock-Watson (2007) UCSV model (no judgmental or model-based outlier adjustment). As can be seen in the figure, both estimates of trend inflation are considerably less volatile post-1990 than during the 1970s. Mechanically, this arises because the variance of the trend innovation of inflation fell, relative to the variance of the idiosyncratic innovation, starting in the early 1980s through the 1990s. These univariate results extend and are consistent with those in Stock and Watson (2007).

Comparison of the trend estimates with and without the outlier adjustment shows some notable differences. The outlier adjustment treats three events as outliers, the sharp one-quarter drops in headline inflation in 1986Q2, 2006Q4, 2008Q4. Each of these outliers was associated with sharp falls in oil prices, so that in effect the outlier adjustment is trimming out large oil price changes. In each of these quarters, the UCSV trend places some probability on this event being a permanent not transitory innovation in inflation, so the trend adjusts downward then reverts, whereas the UCSVO trend treats these large movements as entirely transitory and does not adjust.

Given the relatively smooth UCSVO trend in Figure 1, a logical question is whether the errors associated with the estimation of the trend are small enough to be ignored for purposes of forecasting. Because we never observe the trend, this question cannot be answered just based on data, however it can be answered within the context of the model. Within the model, forecast errors are the sum of three uncorrelated parts: (i) filtering error in estimation of the trend, (ii) evolution of the (true unobserved) trend over the forecast horizon, and (iii) unanticipated transitory disturbances. Based on the UCSVO model estimates using PCE-all, during the 1970s the filtering error was relatively unimportant, accounting for less than 15% of the 8 quarter ahead forecast error variance. In contrast, with inflation more stable during the 1990s and 2000s, roughly 35% of the 8-quarter ahead forecast error variance arises from filtering error. These estimates suggest that reducing the filtering error has the potential to make trend estimates more precise and, possibly, to improve mid-term forecasts.

Figure 2 compares the smoothed USCVO trend for PCE-all with PCExFE, PCExE, and the UCSVO smoothed trends for the xFE and xE measures. The PCE-all trend measure is often close to the xFE and xE trend measures, with notable exceptions during periods of persistent energy swings (the late 1970s and 2006-2010). Of the three inflation series, the model detects (and ignores) outliers only for PCE-all.

Figure 3 shows the smoothed estimates of the stochastic volatility of the permanent and transitory components from the UCSVO model for PCE-all, PCExFE, and PCExE. The time path of the volatility of the permanent component is similar for all three series. The main differences between the three filters arise in the volatility of the transitory innovation (Figure 3(b)) and in the treatment of outliers (the model detects outliers only for PCE-all; Figure 3(c)). For all three series, the ratio of the transitory to permanent variance is greater post-1990 than during the 1970s, implying more time series smoothing for the estimate of trend inflation post-1990 than in the 1970s.

4. Multivariate Results

17-sector model. Figure 4 shows the multivariate and univariate UCSVO smoothed estimates of trend inflation based on all 17 sectors, along with PCExE and PCExFE. The multivariate trend estimate diverges from the univariate trend at a number of dates. Broadly speaking, the multivariate trend looks more like a time-averaged version of the two core measures than like the univariate trend in PCE. The divergence between the univariate PCE-all trend and the multivariate trend is largest in the mid-1970s, the early 1980s, in the 2000s, and in the final quarters of the data set. Figure 4b focuses on the trends since 2000. During 2001-2007, the multivariate trend tracks PCExE and PCExFE, while in contrast the univariate PCE-all trend tracks PCE-all; because of rising energy prices over this period, the univariate PCE trend is approximately 0.3-0.5 percentage point higher than the multivariate trend. During 2009-10, the univariate trend remains above both core and the multivariate trend, mechanically because the univariate trend excludes the large negative spike in inflation in 2008Q4. During 2014Q3-2015Q1, the univariate trend does not treat the large prolonged decline in energy prices (led by the fall in oil prices from July 2014 to February 2015) as an outlier or noise but rather as being persistent, so the univariate trend tracks downward and in fact estimates negative trend inflation in 2015Q1. In contrast, the multivariate trend falls, along with PCExE and PCExFE, but by a modest amount.

The similarities between the multivariate trend, PCExE, and PCExFE in Figure 4 raise the question of whether the multivariate trend is in effect a temporally smoothed version of core inflation and, more generally, what are the time-varying weights implicitly used in the multivariate trend. At any given point in time, the filtered multivariate trend is a nonlinear function of current and past values of the 17 sectoral inflation rates. Because of the time-varying parameters in the MUCSVO model, these weights evolve over time, and they involve lags because of the time series smoothing implied by the model. The function of current and past values is also nonlinear because of the outlier variable. For these reasons, an exact representation in terms of a time-varying linear weighted average is not feasible. Nevertheless, useful insights into the cross-sectional smoothing can be obtained by looking at approximate time-varying weights. Specifically, at a given date, a linear approximation to the filtered index can be computed using a Kalman filter based on (6) – (10), holding fixed the values of the time-varying factor loadings and volatilities ($\alpha_{c,t}$, $\alpha_{i,t}$, $\Delta\ln(\sigma^2_{\Delta\tau,c,t})$, $\Delta\ln(\sigma^2_{\varepsilon,c,t})$. $\Delta\ln(\sigma^2_{\Delta\tau,i,t})$, and $\Delta\ln(\sigma^2_{\varepsilon,i,t})$) at their full-sample posterior mean values at that date.

Figure 5 plots the approximate linear weights on the 17 components implicit in the filtered multivariate estimate of the trend, specifically, the sum of the weights on the current and first three lagged values of the component inflation series. Comparing the approximate MUCSVO weight to the expenditure share shows whether, at a given date, the sector is getting more or less weight in the MUSCVO trend than it does in PCE-all.

As can be seen in Figure 5, roughly half of the 17 components receive weight similar to their expenditure shares. The fact that so many of these weights track expenditure shares is by itself interesting, since the expenditure shares are not used in the MUCSVO model (expenditure shares are used in (13) to construct the overall trend estimates based on the 17 filtered individual trends and the filtered common trend, but not in the calculation of those filtered individual and common trends). Components with weights that track expenditure shares include motor vehicles & parts, recreational goods & vehicles, other durable goods, other nondurable goods, housing excluding gas & electric utilities, health care, transportation services, NPISHs, and other services.

Other series have large swings in their weights. The weight on food & beverages for off-premises consumption ("food at home") increases substantially and, since the mid-1990s, essentially equals its expenditure share, and the weight on food services & accommodations rises from its share in the mid-1970s to nearly double its share since the mid-1980s. Relative to their expenditure shares, the weights fell on financial services & insurance (since the late 1970s), on clothing and footwear (since the early 1980s), on furnishings & durable household equipment (since the mid-1980s), and on recreation services (since the mid-1980s). Except during the 1960s, gasoline & energy goods ("energy products") receives essentially zero weight.

Figure 6 shows these sectoral weights aggregated to core, food, and energy, where food is food for off-premises consumption, energy is gasoline & other energy goods and gas & electric utilities, and core consists of the remaining 14 sectors. As can be seen from these weights, the multivariate trend estimate evolves from having nearly all its weight on the core sectors to placing increasing weight on food around 1990.

To better understand the reasons for these time-varying weights, we now take a closer look at three of the components, which are plotted in Figures 7-9. The first (Figure 7) is food services & accommodations, which tracks PCE-all inflation for the full sample, in many periods with less volatility than PCE inflation. For this series, the factor loading coefficients (panels (b) and (c) are fairly stable, and the factor loading coefficient on the common trend has a confidence band that excludes zero for the full sample. The variance of the transitory innovation is greater in the 1970s than in the 1990s, consistent with the estimated trend for this series having more time series smoothing in the second half of the sample than the first. Because this series stably tracks PCE inflation for the full sample period, with less short-run volatility than PCE inflation, it is not surprising that this component receives considerable weight (roughly twice its expenditure share) over the full sample in the MUCSVO trend estimate.

Figure 8 shows the same set of graphs as Figure 7, but for food & beverages for off-premises consumption. This series is very noisy early in the sample but less so later in the sample, and these changes in its short-run volatility are associated with a sharp decrease in the variance of the idiosyncratic transitory innovation. The loading on the common trend increases over the sample period. Accordingly, this series receives very little weight in the MUCSVO trend pre-1980, however as the volatility of the series subsides in the 1980s and then further in the 1990s, the weight on this series rises to its expenditure share.

The final series (Figure 9) is furnishing & durable household equipment, which smoothly tracks PCE inflation early in the sample but diverges and exhibits volatility since the mid-1990s. Its loading on the common trend falls in the 1980s and the variance of its idiosyncratic transitory component rises in the late 1980s. While this component receives considerable weight – more than twice its expenditure share – in the MUCSVO trend through the early 1980s, its weight drops to its expenditure share since 1900.

Three-sector model. The results for the 17-setor model raise the question of whether similar results can be obtained using a simpler 3-sector model consisting of core (PCExFE), energy (the two components excluded from core, combined with their share weights), and food (off-premises). We therefore estimated this 3-component model using the multivariate model of Section 2.

Figure 10 compares the resulting filtered and smoothed 3-sector estimated multivariate trend to the 17-sector estimated multivariate trend. While not identical, the two estimated trends are clearly very similar. A recent episode in which these trends diverge somewhat is 2008, when the three-sector trend was somewhat higher than the 17-sector trend. During most of the 1990s and since 2011 the differences between the two multivariate trends is quite small, typically less than 0.1 percentage point (although the gap is larger in 2015Q1).

Root Mean Square Estimation Error. One of the motivating questions of this work is whether using sectoral information can improve the precision of the estimator of the trend in headline inflation. Because trend inflation is never observed, the precision of the various estimators cannot be computed directly from the data. We therefore use the 17-variable model to estimate the precision of different estimators of trend inflation. As analogy, were the model linear and time-invariant, the Kalman filter could be used to estimate the variance of the conditional mean of trend inflation given all 17 series or a weighted average of the series such as core. Similarly, the 17-sector model can be used to compute the variance of various estimators of the trend, including the univariate trends of Section 3 and contemporaneous values of inflation (PCE, PCExE, or PCExFE). We compute these RMSEs using the full-sample posterior means so these RMSEs focus on the different amounts of information used to estimate the trends, given the parameters.

Table 2 summarizes these model-based estimated root mean squared errors (RMSE) for the multivariate and univariate trend estimators, for contemporaneous inflation as a measure of the trend, and for four-quarter averages of inflation as measures of the trend. The table has four noteworthy features. First, smoothing over time improves the estimates of PCE inflation, either by four-quarter averaging or, for additional improvements, using the univariate trend estimate. The gains from temporal smoothing are large, reducing the RMSE by 30% for PCE-all over the full sample. Second, further reductions in the RMSE are obtained by cross-sectional smoothing, either using 3 variables or, better, all 17 variables. Together, time-series and cross-sectional smoothing reduces the RMSE for PCE-all by nearly two-thirds, relative to using contemporaneous measure of inflation. In a practical sense, this reduction is very large, from a RMSE of 1 percentage point for PCE to only 0.31 percentage point post-1990 for the 17-variable trend. Third, the multivariate trend estimate is substantially more precise post-1990 than before. Fourth, if the aim is to estimate the trend in PCExE or PCExFE, while there are meaningful gains to time-series smoothing, the gains from cross-sectional smoothing are small, especially in the post-1990 period.

The improved precision using the multivariate model corresponds to tighter posterior coverage regions for the multivariate trend estimates, compared to univariate estimates, at a given date. These tighter bands are illustrated in Table 3 for trend inflation estimates at selected dates of interest, including the drop in energy prices and negative PCE inflation during 2008Q4 and 2009Q1, and the period of falling energy prices in 2014Q3-2015Q1. In both cases, the multivariate estimate differs substantially from the univariate trend estimate of PCE and has a much tighter coverage interval. Also in both cases, both the point estimates and 67% intervals are similar for the multivariate and for the univariate PCExE and PCExFE trends, except for temporary deviations during 2008Q3-2008Q4.

5. Forecasting performance

The definition of trend inflation as the forecast of inflation over the long run suggests using forecasting performance to evaluate candidate estimates of trend empirically. Following much of the literature on inflation forecasting using core inflation, we focus on forecasts at the 1-3 year horizon.

Figure 11 summarizes the rolling forecasting performance of the filtered univariate and multivariate trend measures, compared with core PCE and PCE ex energy.[3] The rolling RMSEs of the different forecasts are typically quite close, but differences emerge in a few episodes. During the 1970s, the multivariate trend estimate behaved like core inflation, and as a forecast core inflation was outperformed by PCE ex energy and by the univariate trend. In contrast, during the 1980s, the multivariate trend has the lowest RMSE. During the 2000s, typically the worst performance comes from the UCSV univariate trend estimate, with the univariate core trend estimate having the best performance at the end of the sample.

Table 4 compares the mean squared forecast errors (MSFEs) over 1990Q1-2015Q1 using the multivariate (17- and 3-variable model) trend inflation estimates, the three univariate trend inflation estimates, and the six benchmark inflation forecasts in Table 2: random walk models using (separately) lagged PCE-all, lagged PCExE, and lagged PCExFE, and the Atkeson-Ohanian (2001) four-quarter random walk model computed using (separately) PCE-all, PCExE, and PCExFE. Results are shown forecasts of average inflation over the 4, 8, and 12-quarter horizons. The table reports mean square forecast errors (MSFE) and the difference between MSFE for each of the forecasts and the 17-variable model. Heteroskedasticity- and autocorrelation-robust standard errors are given in parentheses. Panel (a) shows results for the entire sample period; panel (b) excludes the large forecast errors for 2008Q4 and 2009Q1 associated with collapse in oil prices.

Three main conclusions emerge from Table 4. First, for many of the forecasts the MSFE over the entire sample period is nearly twice as large as the MSFE for the sample that excludes the two quarters 2008Q4 and 2009Q1. The quarters dominate the full-sample MSFE and result in large standard errors for the estimates. Second, now concentrating on panel (b) which excludes these two quarters, the multivariate trend forecasts (both 3- and 17-variable) improve upon simply using lagged inflation (the random walk model), using core inflation, and using four-quarter averages of inflation. Third, the univariate trend for PCExFE provides the lowest MSFE forecast at the 8- and 12-quarter horizon, whether or not 2008Q4-2009Q1 is excluded, and the forecasts based on the univariate trend in PCExE are nearly as good as those based on PCExFE. Fourth, among those inflation forecasts that perform relatively well, the small

[3] As discussed above, although the filters are one-sided the parameter paths are not (they are evaluated using the full-sample posterior), so this exercise is not a pseudo out-of-sample forecast comparison in the usual sense.

differences in RMSEs among those forecasts are not statistically significant. In particular, from the perspective of statistical significance, over the post-1990 period only the random walk forecast performs worse than than the 17-variable model at standard significance levels. This finding is consistent with Crone, Khettry, Mester, and Novak (2013), who find no statistically significant improvements in forecasts made using core inflation.

6. Discussion and Conclusions

The results in Section 4 found that the multivariate estimates of trend inflation substantially enhanced the precision of trend estimates of PCE inflation, both through time-series and cross-sectional smoothing. But in Section 5, while these improvements in the precision of the estimates of trend inflation resulted in lower mean squared forecast errors, those forecasting improvements are not statistically significant. There are at least two explanations that could reconcile these seemingly conflicting results. First, the improvements in the precision of the trend estimates, while economically meaningful, are relatively small compared to the forecast errors made by any of the inflation forecasts. Thus the improvements in the precision of the trend estimates might simply be too small to result in statistically significant forecast improvements, given the large forecast errors of all inflation forecasts. Second, because the precision of the various trend estimates was estimated using the 17-sector model, if the model is misspecified those improvements in precision could be overestimated in the first place. These explanations are not mutually exclusive and while both contain elements of plausibility, neither is entirely satisfactory. For example, the ordering across trend estimates of trend precision differs from the ordering of forecast improvement, raising some questions about the first explanation. But because the same model was used to estimate the precisions of the various trend estimates, model misspecification would need to affect the respective precision estimates differently. While recognizing the limitations of the model-based precision estimates, our interpretation of these results is that the multivariate trend estimates improve precision, but not by enough to make a statistically significant difference in forecasting. Given the widely recognized difficulty of forecasting inflation, this is perhaps not surprising.

These results also lead to two other high-level conclusions. The first is that the reduced volatility of food prices, relative to before the mid-1980s, led the multivariate model to include food in the trend estimate post-1990, with a weight close to its expenditure share. This finding suggests paying more attention to PCExE than to PCExFE. Second, the multivariate model has the advantage of producing measures of precision of trend estimates (posterior coverage regions). Currently, the width of these 67% regions is approximately 0.6 percentage point using the 17-variable trend estimate. We see merit to reporting these estimates of the precision of trend inflation along with estimates of that trend.

References

Altissimo, Filippo, Benoit Mojon, and Paolo Zaffaroni (2009). "Can Aggregation Explain the Persistence of Inflation?" *Journal of Monetary Economics* 56(2), 231-241.

Amstad, Marlene, and Simon M. Potter (2007). "Real Time Underlying Inflation Gauges for Monetary Policy Makers." Unpublished manuscript, Federal Reserve Bank of New York

Atkeson, A. and L.E. Ohanian (2001), "Are Phillips Curves Useful for Forecasting Inflation?" *Federal Reserve Bank of Minneapolis Quarterly Review* 25(1):2-11.

Baumeister, Christiane and Gert Peersman. 2013. "Time-Varying Effects of Oil Supply Shocks on the U.S. Economy." *American Economic Journal: Macroeconomics*, vol. 5, pp. 1-28.

Blanchard, Olivier J., and Jordi Galí. 2010. "The Macroeconomic Effects of Oil Price Shocks: Why Are the 2000s So Different from the 1970s?" In *International Dimensions of Monetary Policy,* edited by Jordi Galí and Mark J.Gertler. University of Chicago Press.

Boivin, Jean, Marc P. Giannoni, and Ilian Mihov (2009). "Sticky Prices and Monetary Policy: Evidence from Disaggregated Data." *American Economic Review*, 99(1): 350–84.

Bryan, Michael F. and Cecchetti, Stephen G. (1994). "Measuring Core Inflation," in N. Gregory Mankiw, ed., *Monetary Policy*. Chicago: University of Chicago Press, pp. 195-215.

Chen, Shiu-Sheng (2009). "Oil Price Pass-Through into Inflation." *Energy Economics* 31(1): 126-133.

Clark, Todd E. (1999) "A Comparison of the CPI and the PCE Price Index." Federal Reserve Bank of Kansas City, *Economic Review*, 84 (Third Quarter), 15–29.

Clark, Todd E. (2001) "Comparing Measures of Core Inflation." Federal Reserve Bank of Kansas City, *Economic Review*, 86 (Second Quarter), 5–31.

Clark, Todd E. and Stephen J. Terry (2010). "Time Variation in the Inflation Passthrough of Energy Prices," *Journal of Money, Credit and Banking* 42(7), 1419-1433.

Cogley, Timothy. (2002) "A Simple Adaptive Measure of Core Inflation." *Journal of Money, Credit, and Banking*, 34, 94–113.

Cogley, Timothy and Thomas J. Sargent (2015). "Measuring Price-Level Uncertainty and Instability in the U.S., 1850-2012," *The Review of Economics and Statistics*, forthcoming.

Cristadoro, Riccardo, Mario Forni, Lucrezia Reichlin, and Giovanni Veronese (2005), "A Core Inflation Indicator for the Euro Area," *Journal of Money, Credit, and Banking*, Vol. 37, No. 3, pp. 539-560.

Crone, Theodore M., N. Neil K. Khettry, Loretta J. Mester, and Jason A. Novak (2013). "Core Measures of Inflation as Predictors of Total Inflation," *Journal of Money, Credit and Banking* 45, no. 2-3, 505-519.

De Gregorio, José, Oscar Landerretche, and Christopher Neilson (2007). "Another Pass-through Bites the Dust? Oil Prices and Inflation." *Economia* 7(2), 155-208.

del Negro, Marco and Christopher Otrok (2008). "Dynamic factor models with time-varying parameters: Measuring changes in international business cycles." *Staff Report, Federal Reserve Bank of New York, no. 326*.

del Negro, Marco and Giorgio E. Primiceri (2014). "Time Varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum." *Review of Economic Studies*, forthcoming.

Eckstein, Otto (1981). *Core Inflation*. New York: Prentice Hall, 1981.

Garnier, Christine, Elmar Mertens, and Edward Nelson (2013). "Trend Inflation in Advanced Economies." FEDS Discussion Paper 2013-74.

Gordon, Robert (1975). "Alternative Responses of Policy to External Supply Shocks." *Brookings Papers on Economic Activity*, volume 1, pp. 183 – 206.

Hood, Kyle K. (2013) "Measuring the Services of Commercial Banks in the National Income and Products Accounts: Changes in Concepts and Methods in the 2013 Comprehensive Revision." *Survey of Current Business*, February 2013, 8-19.

Hooker, Mark A. (2002). "Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime," *Journal of Money, Credit, and Banking* 34(2), 540-561.

Kim, Sanjoon, Neil Shephard and Siddhartha Chib (1998). "Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models," *Review of Economic Studies*, 65, 361-393.

Mertens, Elmar (2012). "Measuring the level and uncertainty of trend inflation." Manuscript. Board of Governors of the Federal Reserve System, Washington, D.C.

Mertens, Elmar and James M. Nason (2015). "Inflation and Professional Forecast Dynamics: An Evaluation of Stickiness, Persistence, and Volatility." Manuscript. Board of Governors of the Federal Reserve System, Washington, D.C.

Mumtaz, Haroon and Paolo Surico (2012). "Evolving International Inflation Dynamics: World and Country-Specific Factors." *Journal of the European Economics Association* 10(4), 716-734.

Nelson, C.R. and G.W. Schwert (1977), "Short-Term Interest Rates as Predictors of Inflation: On Testing the Hypothesis that the Real Rate of Interest Is Constant," *American Economic Review* 67:478-486.

Omori, Yasuhiro, Siddhartha Chib, Neil Shephard, and Jouchi Nakajima, (2007). "Stochastic Volatility with Leverage: Fast and Efficient Likelihood Inference," *Journal of Econometrics* 140(2), 425-449.

Reis, Ricardo, and Mark W. Watson. (2010) "Relative Goods' Prices, Pure Inflation, and the Philips Correlation." *American Economic Journal: Macroeconomics*, 2, 128-57.

Rich, Robert, and Charles Steindel. (2005) "A Review of Core Inflation and an Evaluation of Its Measures." Federal Reserve Bank of New York Staff Report 236.

Sbrana, Giacomo, Andrea Silvestrini, and Fabrizio Venditti (2015). "Short Term Inflation Forecasting: The M.E.T.A. Approach." Manuscript, Bank of Italy.

Stock, James H. and Mark W. Watson (2007), "Why Has U.S. Inflation Become Harder to Forecast?", *Journal of Money, Credit and Banking*, 39(1), 3-33.

van den Noord, Paul and Christophe André (2007). "Why Has Core Inflation Remained So Muted in the Face of the Oil Shock?" OECD Economics Department Working Paper 551.

Wynne, Mark A. (2008). "Core Inflation: A Review of Some Conceptual Issues," *Federal Reserve Bank of St. Louis Review*, May/June 2008, 90(3 Part 2), 205-28.

Table 1. The 17 Components of the PCE Price Index Used in this Study
and their Expenditure Shares

Sector	1960-2015	1960-1979	1980-1999	2000-2015
Durable goods				
Motor vehicles and parts	0.053	0.060	0.054	0.042
Furnishings and durable household equipment	0.036	0.044	0.033	0.028
Recreational goods and vehicles	0.029	0.026	0.029	0.032
Other durable goods	0.016	0.015	0.016	0.016
Nondurable goods				
Food and beverages purchased for off-premises consumption*	0.117	0.160	0.104	0.077
Clothing and footwear	0.054	0.071	0.051	0.034
Gasoline and other energy goods*	0.037	0.044	0.035	0.032
Other nondurable goods	0.078	0.080	0.074	0.081
Services				
Housing & utilities				
Housing excluding gas & electric utilities	0.153	0.146	0.155	0.161
Gas & electric utilities*	0.025	0.026	0.028	0.021
Health care	0.114	0.071	0.127	0.155
Transportation services	0.032	0.030	0.034	0.032
Recreation services	0.029	0.021	0.031	0.038
Food services and accommodations	0.064	0.064	0.066	0.061
Financial services and insurance	0.063	0.047	0.068	0.076
Other services	0.081	0.081	0.077	0.087
Final consumption expenditures of nonprofit institutions serving households (NPISHs)	0.020	0.016	0.019	0.026

Notes: Each column shows the average expenditure share over the sample period indicated.
*Excluded from core PCE.

Table 2. Model-based estimated root mean squared error of various estimates of trend inflation: Model-based filtered estimates (multivariate and univariate), contemporaneous inflation, and four-quarter average inflation.

	1965Q1 – 2015Q1				1965Q1 – 1989Q4				1990Q1 – 2015Q1		
	τ^{PCE}	τ^{xe}	τ^{xfe}		τ^{PCE}	τ^{xe}	τ^{xfe}		τ^{PCE}	τ^{xe}	τ^{xfe}
Multivariate trends											
17-variable	0.39	0.37	0.31		0.46	0.45	0.37		0.32	0.25	0.24
3-variable	0.55	0.51	0.47		0.68	0.64	0.59		0.39	0.32	0.32
Univariate trends											
PCE	0.84				0.97				0.69		
PCExE		0.61				0.80				0.35	
PCExFE			0.49				0.60				0.34
Contemporaneous inflation											
PCE	1.33				1.29				1.37		
PCExE		0.76				0.98				0.45	
PCEXFE			0.64				0.77				0.47
4-quarter average inflation											
PCE	1.02				1.21				0.78		
PCExE		0.84				1.12				0.43	
PCEXFE			0.76				1.01				0.39

Notes: Entries are the root mean squared error of the trend estimator for that row, treated as an estimate of the trend for that column. All RMSEs were computed using the 17-sector model, with parameter paths evaluated at their posterior means. Units are percentage points at an annual rate.

Table 3. Multivariate and univariate filtered estimates of trend inflation for selected dates: posterior median and 67% intervals

Date	Inflation	Multivariate			Univariate								
					PCE-all			PCExE			PCExFE		
		16%	50%	83%	16%	50%	83%	16%	50%	83%	16%	50%	83%
2008Q1	3.41	2.45	2.75	3.12	2.78	3.28	3.76	2.12	2.42	2.73	1.96	2.22	2.50
2008Q2	4.16	2.50	2.86	3.28	3.07	3.62	4.15	2.11	2.41	2.71	1.89	2.15	2.41
2008Q3	4.05	2.85	3.20	3.63	3.21	3.76	4.28	2.07	2.37	2.68	1.77	2.04	2.31
2008Q4	-5.78	1.97	2.33	2.73	2.83	3.55	4.25	0.57	1.45	2.15	1.11	1.63	1.99
2009Q1	-2.27	1.03	1.37	1.73	2.29	3.27	4.09	0.24	0.88	1.70	0.79	1.33	1.78
2009Q2	1.79	0.52	0.86	1.23	1.74	2.41	3.05	0.91	1.30	1.71	1.24	1.58	1.89
2009Q3	2.51	0.59	0.91	1.26	1.97	2.51	3.02	0.70	1.07	1.50	1.10	1.44	1.76
2009Q4	2.72	1.11	1.45	1.82	2.13	2.62	3.11	1.19	1.53	1.85	1.39	1.67	1.95
2014Q1	1.36	1.15	1.38	1.61	0.83	1.29	1.75	1.03	1.27	1.51	1.11	1.31	1.50
2014Q2	2.31	1.73	1.98	2.24	1.34	1.88	2.39	1.36	1.63	1.95	1.34	1.55	1.80
2014Q3	1.22	1.42	1.65	1.88	0.96	1.43	1.93	1.32	1.55	1.80	1.29	1.47	1.65
2014Q4	-0.42	1.17	1.45	1.69	-0.36	0.28	1.06	1.10	1.35	1.59	1.10	1.31	1.51
2015Q1	-1.99	0.70	1.03	1.31	-1.90	-1.12	0.27	0.72	1.06	1.37	0.89	1.15	1.40

Note: Units are percentage points at an annual rate.

Table 4. Mean squared forecast errors (MSFEs) for various price-based inflation forecasts: model-based estimated trends and benchmark forecasting models

(a) 1990Q1-2015Q1

	4 quarter-ahead forecasts			**8 quarter-ahead forecasts**			**12 quarter-ahead forecasts**	
	MSFE	**Difference**		**MSFE**	**Difference**		**MFSE**	**Difference**
Mulivariate UCSVO Forecasts								
17comp	0.90 (0.37)			0.65 (0.20)			0.57 (0.13)	
3comp	0.94 (0.43)	0.04 (0.07)		0.74 (0.26)	0.09 (0.07)		0.66 (0.19)	0.09 (0.07)
Univariate UCSVO Forecasts								
PCE-all	1.14 (0.52)	0.24 (0.17)		0.94 (0.34)	0.28 (0.15)		0.87 (0.25)	0.30 (0.15)
PCExE	0.79 (0.26)	-0.11 (0.12)		0.56 (0.12)	-0.10 (0.10)		0.49 (0.09)	-0.08 (0.08)
PCExFE	**0.74 (0.22)**	-0.16 (0.16)		**0.50 (0.09)**	-0.15 (0.15)		**0.45 (0.09)**	-0.12 (0.12)
Forecasts using Contemporaneous Values of Inflation								
PCE-all	2.36 (1.14)	1.47 (0.82)		2.16 (1.00)	1.51 (0.81)		2.22 (1.02)	1.65 (0.91)
PCExE	0.91 (0.30)	0.01 (0.09)		0.69 (0.16)	0.03 (0.06)		0.66 (0.14)	0.09 (0.04)
PCExFE	0.85 (0.24)	-0.05 (0.16)		0.60 (0.10)	-0.05 (0.12)		0.59 (0.10)	0.02 (0.07)
Forecasts using 4-Quarter Averages of Inflation								
PCE-all	1.14 (0.52)	0.24 (0.17)		0.94 (0.34)	0.28 (0.15)		0.87 (0.25)	0.30 (0.15)
PCExE	0.84 (0.27)	-0.06 (0.11)		0.62 (0.14)	-0.03 (0.09)		0.54 (0.10)	-0.03 (0.08)
PCExFE	0.80 (0.23)	-0.10 (0.16)		0.56 (0.10)	-0.09 (0.14)		0.50 (0.10)	-0.07 (0.12)

(b) 1990Q1-2015Q1, excluding 2008Q4-2009Q1

	4 quarter-ahead forecasts			**8 quarter-ahead forecasts**			**12 quarter-ahead forecasts**	
	MSFE	**Difference**		**MSFE**	**Difference**		**MFSE**	**Difference**
Mulivariate UCSVO Forecasts								
17comp	0.51 (0.08)			0.47 (0.07)			0.44 (0.08)	
3comp	**0.47 (0.07)**	-0.04 (0.03)		0.47 (0.08)	0.00 (0.03)		0.47 (0.09)	0.03 (0.04)
Univariate UCSVO Forecasts								
PCE-all	0.56 (0.10)	0.05 (0.08)		0.57 (0.11)	0.10 (0.07)		0.57 (0.12)	0.13 (0.09)
PCExE	0.55 (0.09)	0.04 (0.03)		0.48 (0.07)	0.01 (0.04)		0.46 (0.09)	0.02 (0.04)
PCExFE	0.55 (0.10)	0.04 (0.04)		**0.46 (0.07)**	-0.01 (0.06)		**0.44 (0.10)**	-0.00 (0.07)
Forecasts using Contemporaneous Values of Inflation								
PCE-all	1.59 (0.55)	1.08 (0.54)		1.71 (0.64)	1.23 (0.61)		1.87 (0.77)	1.43 (0.75)
PCExE	0.65 (0.12)	0.15 (0.07)		0.59 (0.10)	0.12 (0.05)		0.61 (0.11)	0.17 (0.06)
PCExFE	0.67 (0.12)	0.17 (0.07)		0.57 (0.08)	0.10 (0.04)		0.57 (0.09)	0.13 (0.04)
Forecasts using 4-Quarter Averages of Inflation								
PCE-all	0.56 (0.10)	0.05 (0.08)		0.57 (0.11)	0.10 (0.07)		0.57 (0.12)	0.13 (0.09)
PCExE	0.58 (0.10)	0.07 (0.03)		0.53 (0.08)	0.06 (0.03)		0.49 (0.09)	0.06 (0.04)
PCExFE	0.60 (0.10)	0.09 (0.04)		0.51 (0.08)	0.04 (0.06)		0.48 (0.10)	0.04 (0.06)

Notes: The entries labeled "MSFE" are the mean square forecast errors. The entries labeled "Difference" are the difference between that row's MSFE for and the MSFE for the 17-component multivariate UCSVO model. HAC standard errors are shown in parentheses. Minimum MSFE forecasts for a given horizon are shown in bold. Units are squared percentage points at an annual rate.

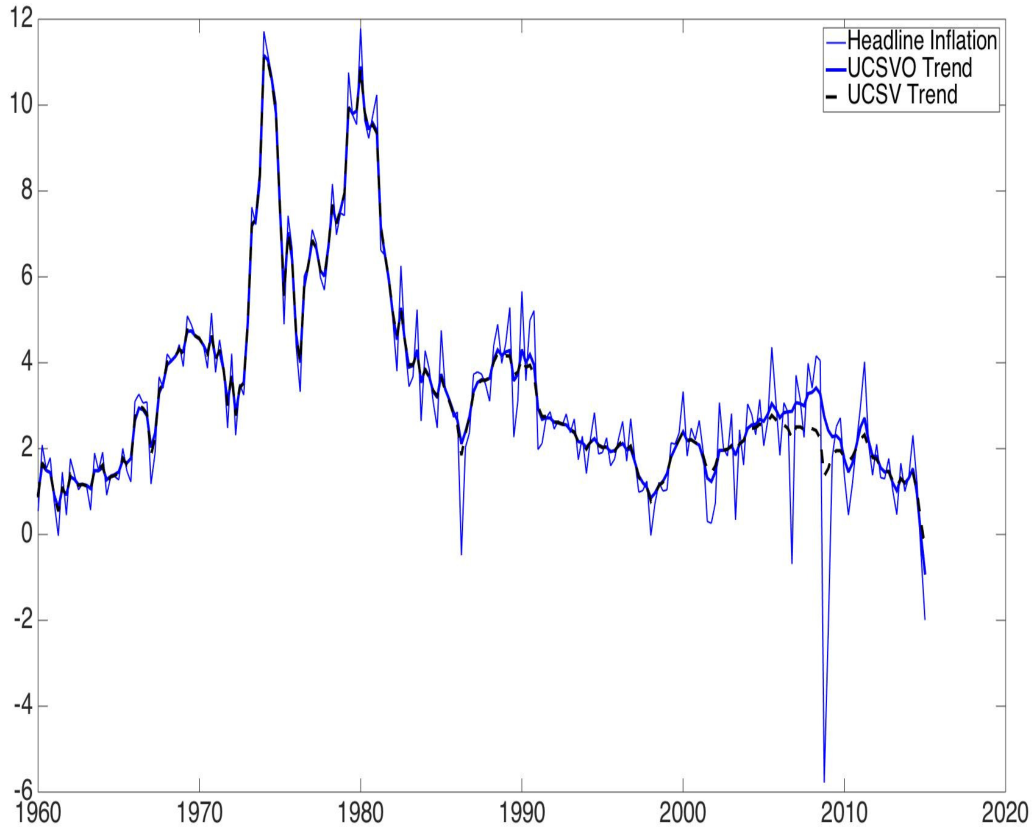

Figure 1. Headline PCE inflation and its smoothed trends from the univariate UCSVO and UCSV models.

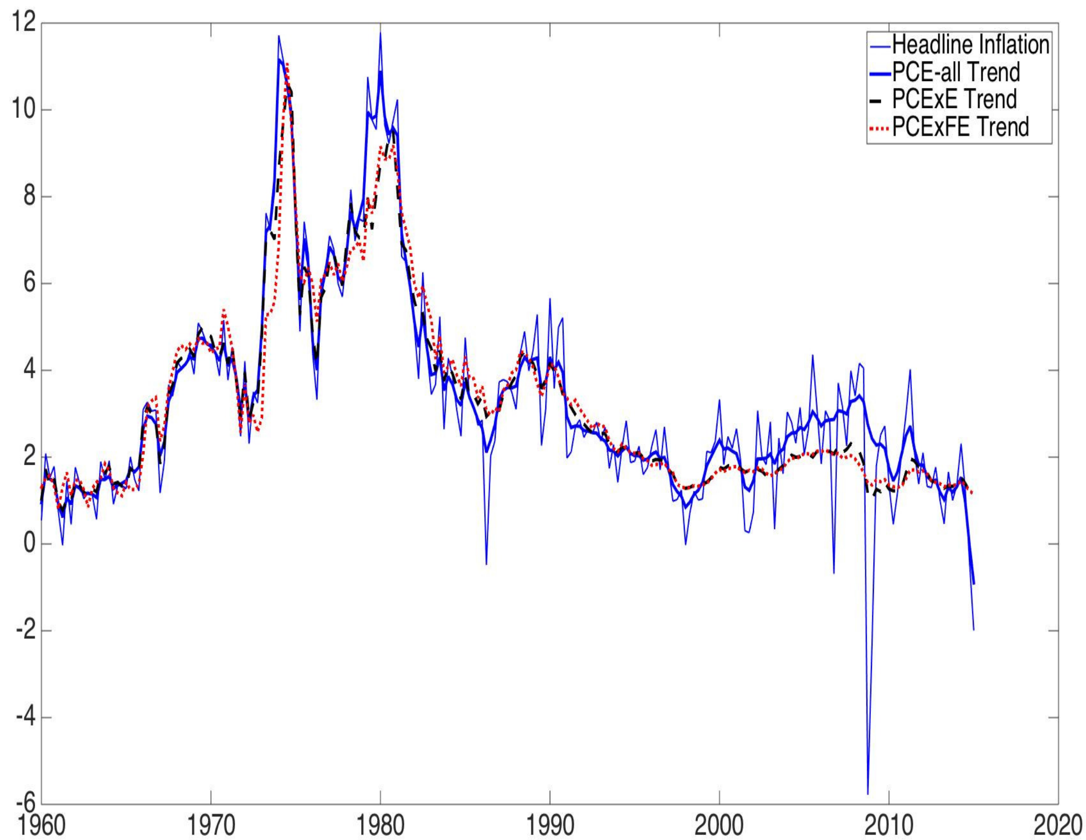

Figure 2. Headline PCE inflation and the smoothed trends for PCE-all, PCE-xE and PCExFE

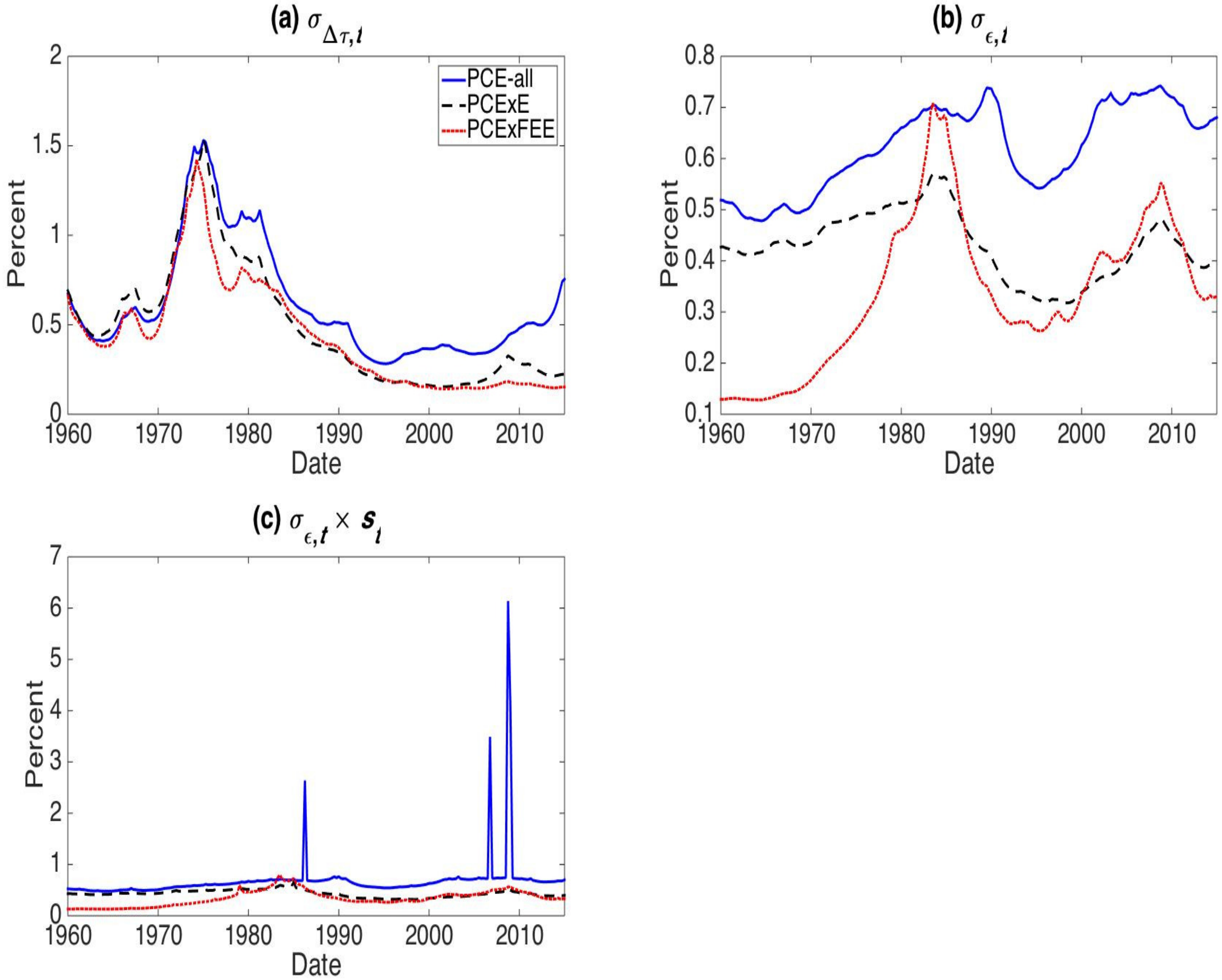

Figure 3. Smoothed univariate UCSVO estimates of the permanent and transitory volatilities for PCE-all, PCExFE, and PCExE: (a) $\sigma_{\Delta\tau,t}$, (b) $\sigma_{\varepsilon,t}$, and (c) $s_t \times \sigma_{\varepsilon,t}$

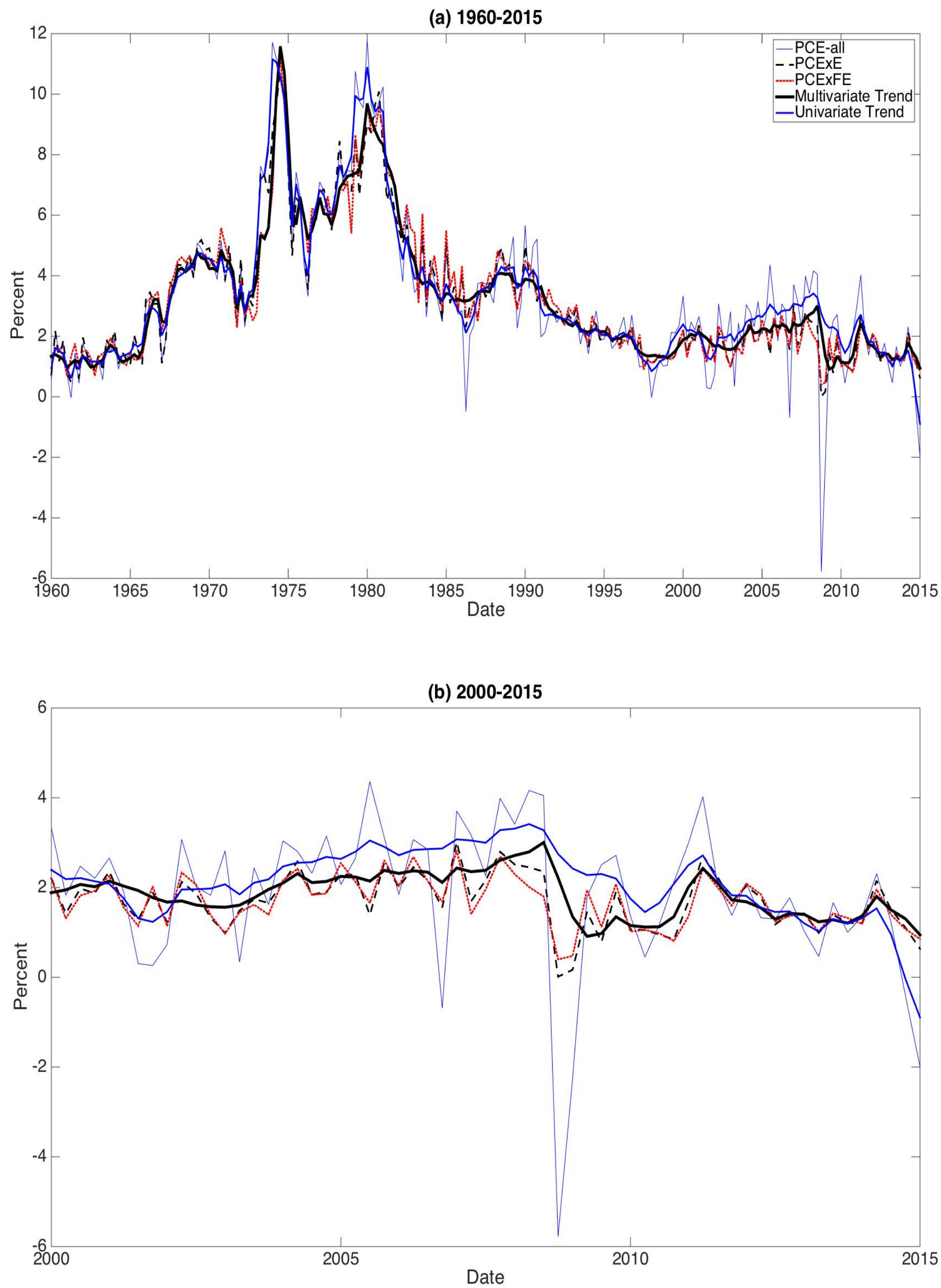

Figure 4. PCE-all, PCExE, PCExFE inflation and multivariate and univariate smoothed estimates of trend inflation, (a) 1960-2015 and (b) 2000-2015.

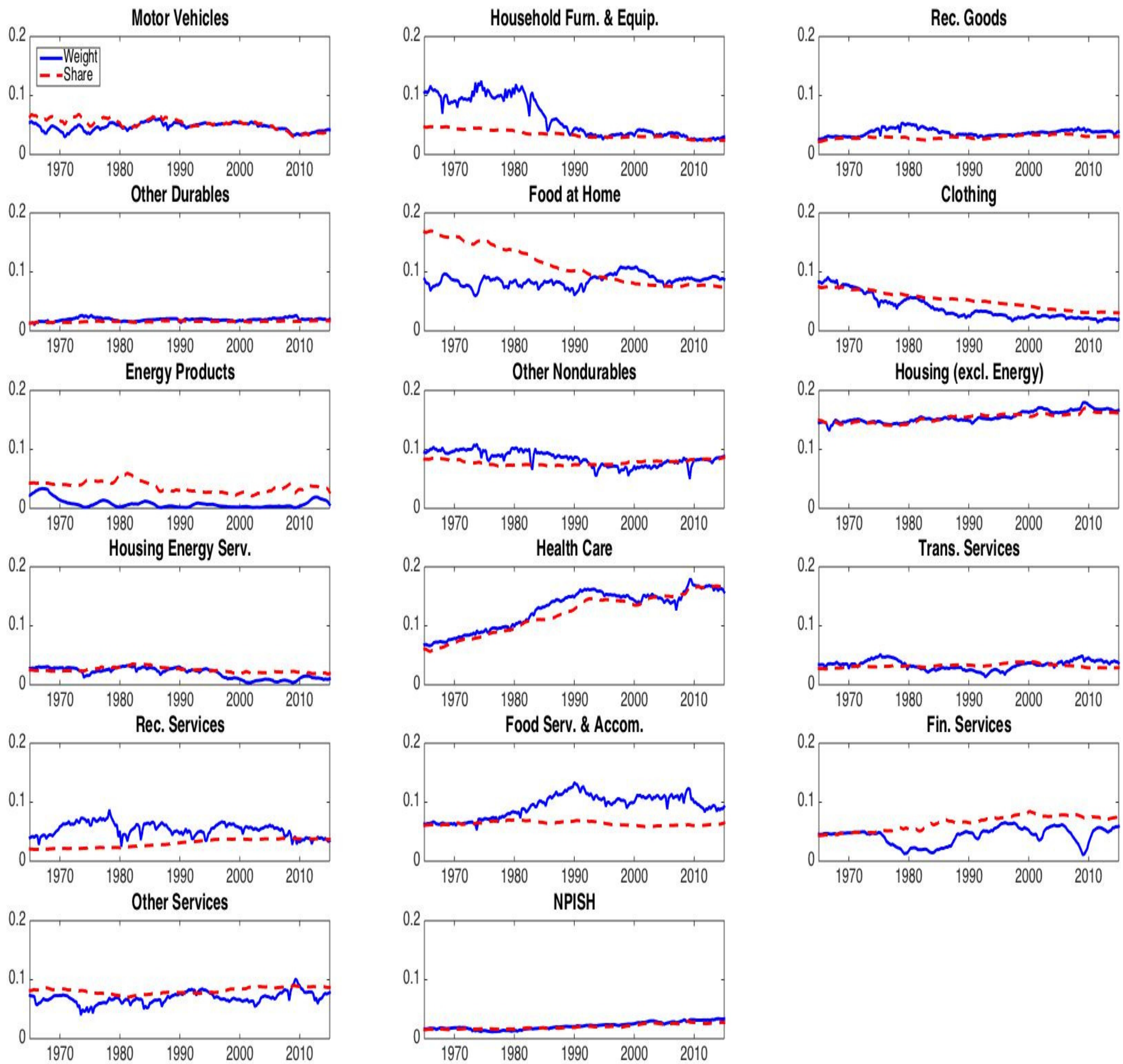

Figure 5. Implied approximate linear weights on the 17 inflation components (contemporaneous + three lags) in the filtered MUCSVO trend estimate (solid line), along with the expenditure share (dashed) .

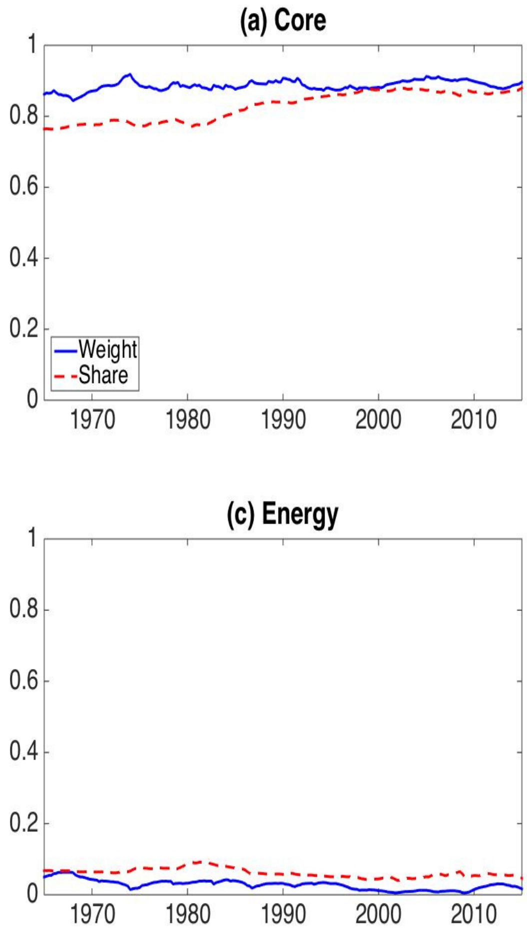

Figure 6. Implied approximate linear weights on sectoral inflation (contemporaneous + three lags) in the filtered MUCSVO trend estimate (solid line), along with the expenditure share (dashed), aggregated over the 14 sectors comprising core inflation, food, and the two energy sectors.

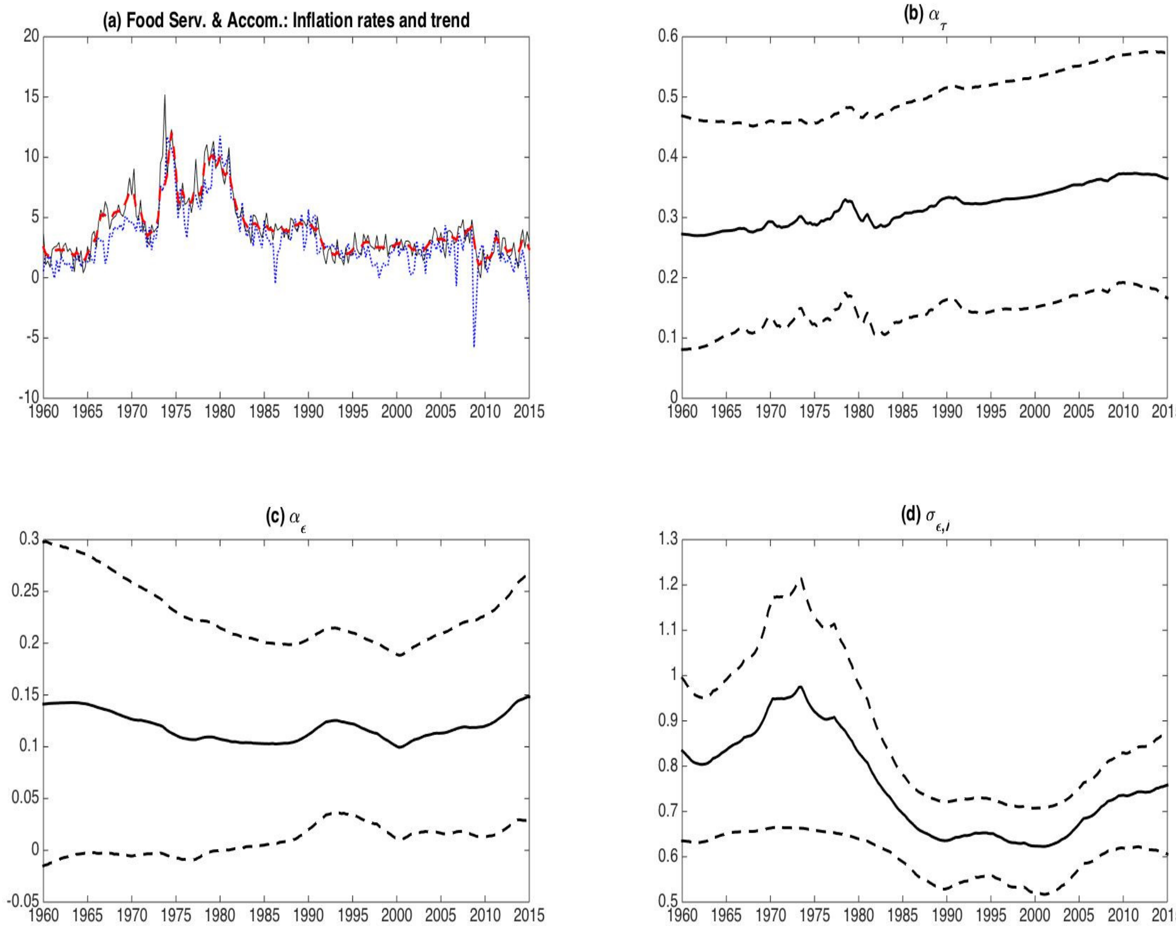

Figure 7. Food services & accommodations: (a) Series (solid), its trend (dashed, red), and PCE inflation (dots, blue); posterior mean (solid) and pointwise 67% credible interval (dashed) for (b) factor loading on common trend (c) factor loading on common transitory component, and (d) standard deviation of transitory component.

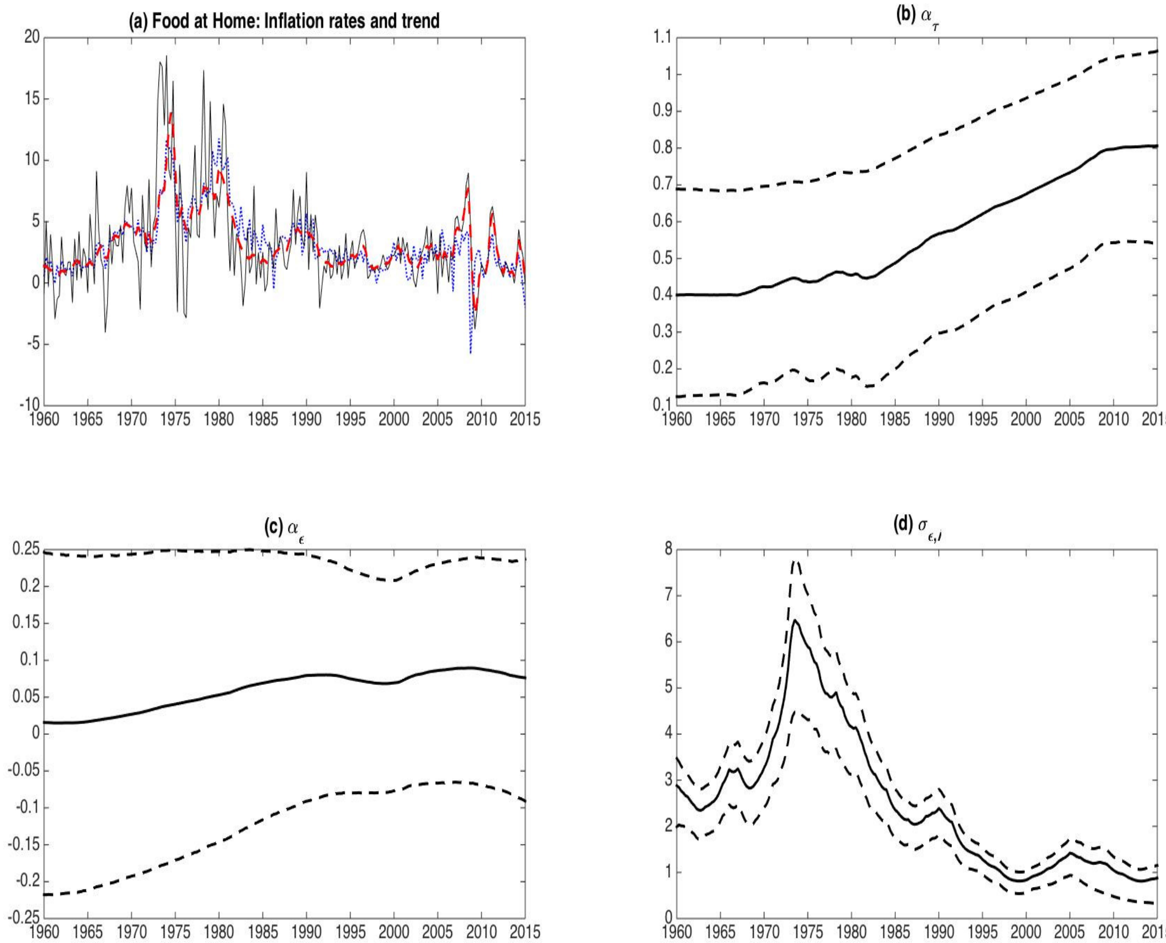

Figure 8. Food & beverages for off-premises consumption: (a) Series (solid), its trend (dashed, red), and PCE inflation (dots, blue); posterior mean (solid) and pointwise 67% credible interval (dashed) for (b) factor loading on common trend (c) factor loading on common transitory component, and (d) standard deviation of transitory component.

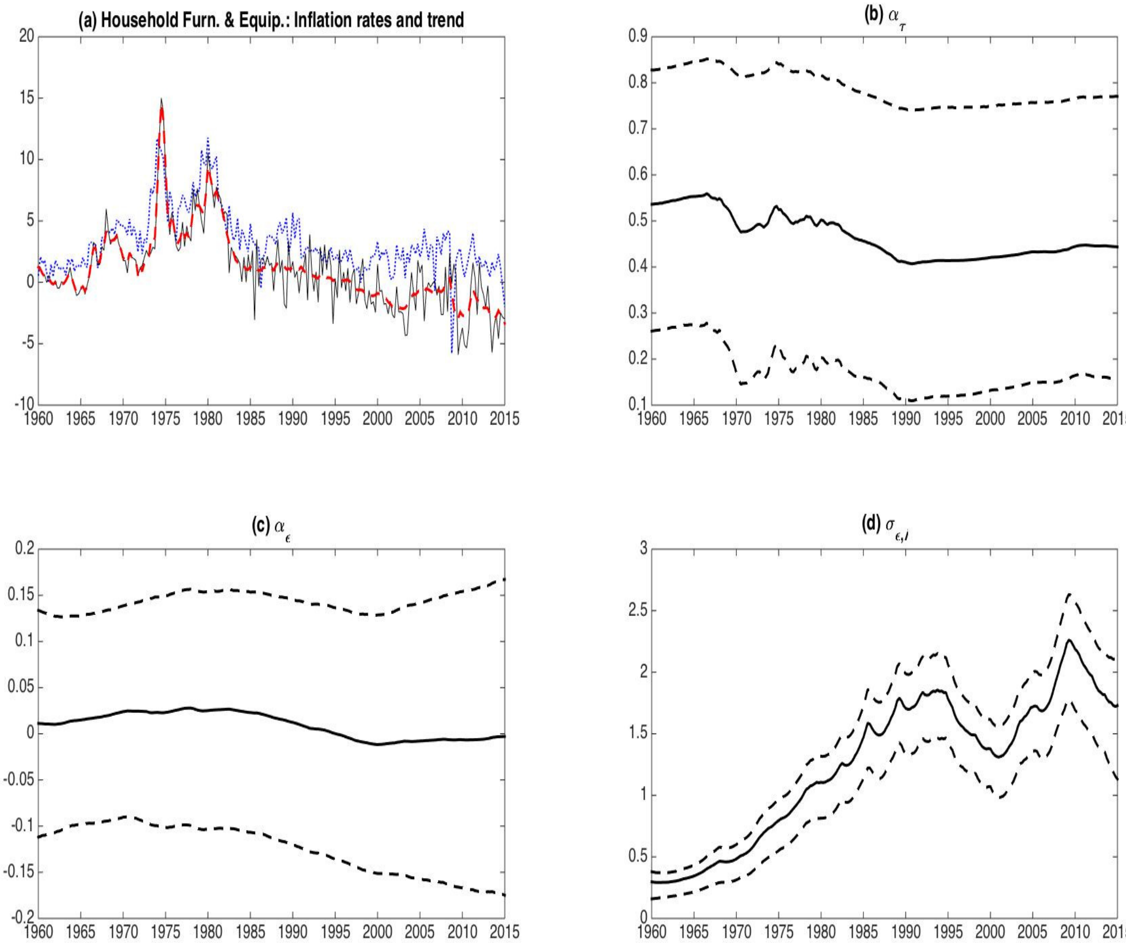

Figure 9. Furnishings & durable household equipment: (a) Series (solid), its trend (dashed, red), and PCE inflation (dots, blue); posterior mean (solid) and pointwise 67% credible interval (dashed) for (b) factor loading on common trend (c) factor loading on common transitory component, and (d) standard deviation of transitory component.

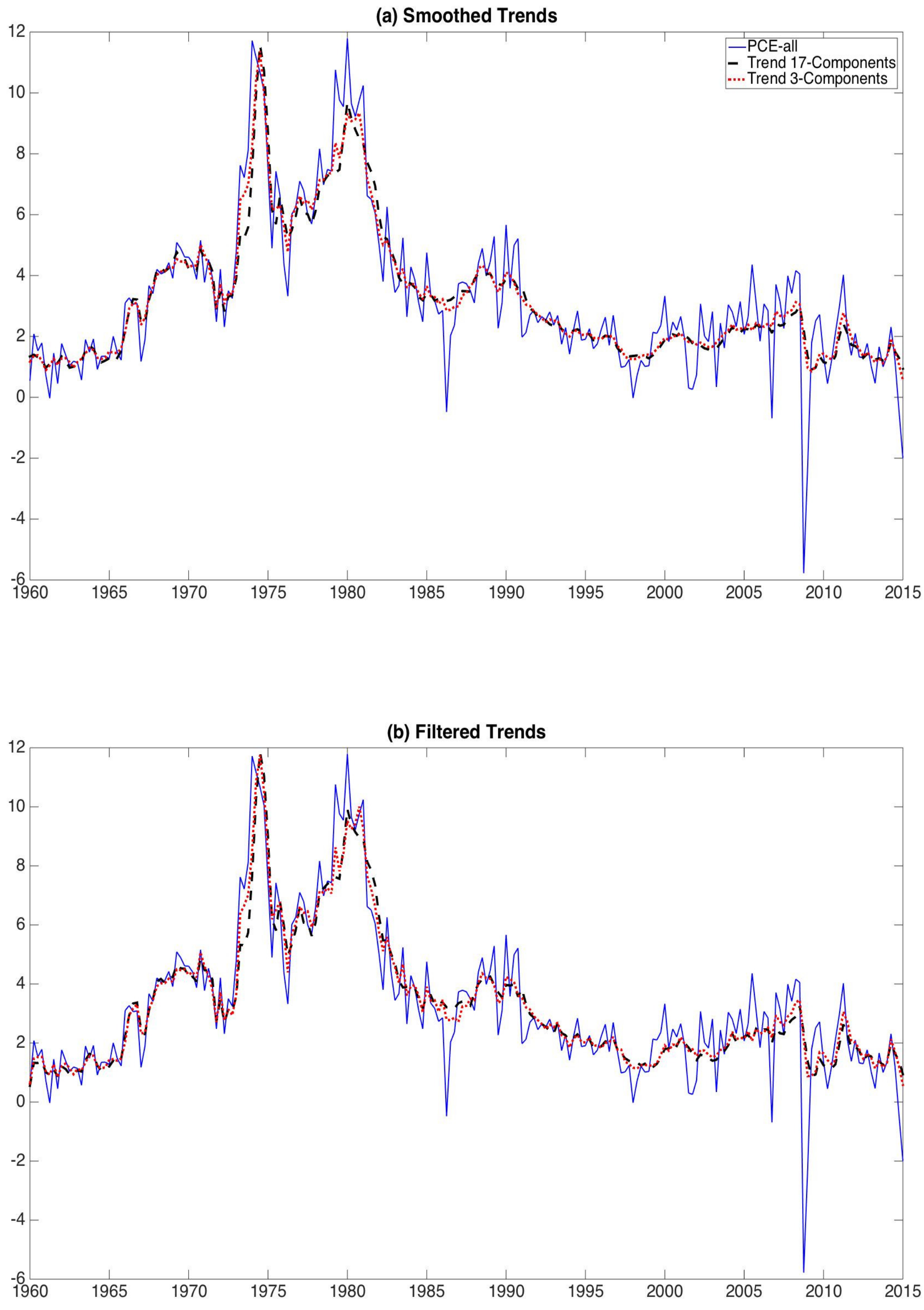

Figure 10. Multivariate trend estimates from the 3- and 17-component models, along with PCE-all inflation.

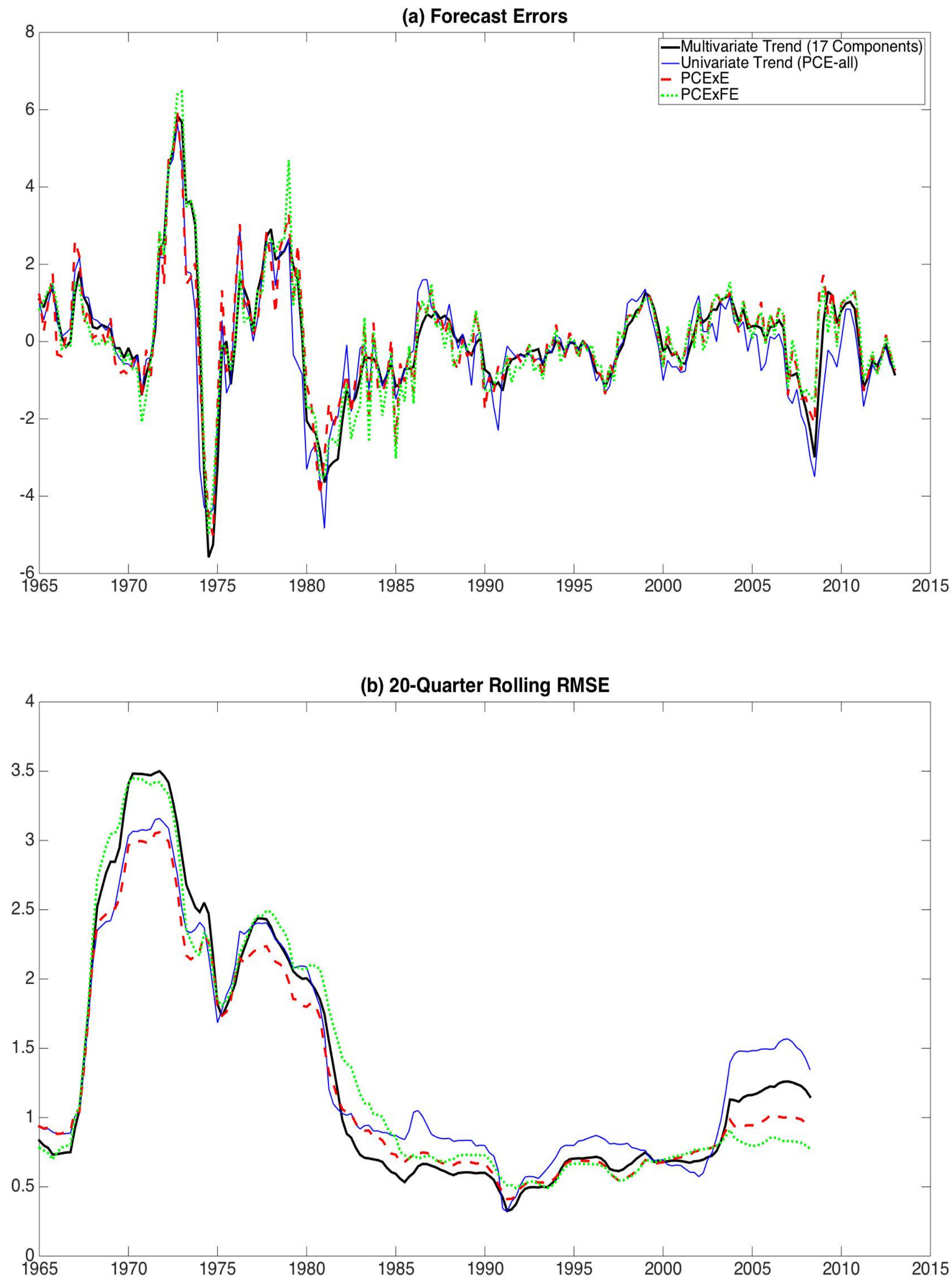

Figure 11. Inflation forecast errors (upper panel) and rolling root mean-squared errors (lower panel) for 8 quarter-ahead forecasts using multivariate and univariate UCSVO models and using core (PCExE) and (PCExFE) inflation.