PCE Inflation and Core Inflation

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Research Department
Working Paper 1203

Federal Reserve Bank of Dallas

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ABSTRACT: This paper investigates the forecasting accuracy of the trimmed mean inflation rate of the Personal Consumption Expenditure (PCE) deflator. Earlier works have examined the forecasting ability of limited-influence estimators (trimmed means and the weighted median) of the Consumer Price Index but none have compared the weighted median and trimmed mean of the PCE. Also addressed is the systematic bias that appears due to the differences in the means of inflation measures over the sample. This paper supports earlier results that limited-influence estimators provide better forecasts of future inflation than does the popular measure of core inflation, PCE inflation minus food and energy; therefore, these limited-influence estimators are core inflation.

Key words: core inflation, inflation, Personal Consumption Expenditure deflator, forecasting

(JEL E31, E37)

I would like to thank Dean Croushore, Alan Detmeister, John Duca, Ed Gamber, Ingunn Lonning, Rebecca Neumann, Athanasios Orphanides, Yelena Takhtamanova and Kenneth West for helpful comments. The views expressed are those of the author's and are not necessarily those of the Federal Reserve Bank of Dallas or the Federal Reserve System.

Introduction

Over the past decade researchers have more closely examined the measurement and concept of core inflation, with the focus shifting from the consumer price index (CPI) to the Personal Consumption Expenditure deflator (PCE) since it is the Federal Reserve's preferred price index.[1] The PCE minus food and energy is often used to measure underlying or core inflation, while the weighted median or trimmed mean inflation rate have been largely ignored.

Previous work by Smith (2004) focuses on CPI and PCE inflation, finding that the weighted median of each forecasts future inflation better than their respective minus food and energy inflation rates. The analysis did not include a trimmed mean for the PCE since the research on the optimal trimming of the PCE was then unavailable. Rich and Steindel (2005) recently examine the CPI and PCE but ignore the trimmed mean.[2]

This paper tests which simple measure can best predict future PCE inflation or which measure is core inflation. This definition is consistent with most notions of core inflation,[3] for which limited-influence estimators perform best. The use of prices excluding food and energy to track core inflation implies that supply shocks only come from the food and energy sectors. However, supply shocks can and do arise from other sectors (Ball and Mankiw, 1995) and when they do, they are often excluded on an ad hoc basis. For example, in 1998 the tobacco litigation settlement pushed up inflation minus food and energy but the Fed (1999) did not want to react to this increase so it noted how inflation less food and energy would have been lower excluding tobacco prices. The trimmed mean and weighed median omit unusually large price changes regardless of their origin.

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[1] The PCE has been used in the Federal Reserve's inflation outlook since 2000. The PCE may be a more desirable since it uses chain-type weights instead of fixed weights and is more comprehensive than the CPI (Dolmas, 2005).
[2] The trimmed mean and weighted median are limited-influence estimators, which omit very high or low values.
[3] See Eckstein (1981), Bryan and Cecchetti (1994), Bryan, Cecchetti and Wiggins (1997), Quah and Vahey (1995) and the Bank of International Settlements (1999).

The paper expands the set of candidate measures for core inflation to include the PCE trimmed mean, which the Dallas Fed began to compute in 2005 (Dolmas, 2005). Specifically, I conduct in-sample and out-of-sample forecasts comparing four candidate measures: PCE inflation, PCE minus food and energy inflation (PCEX), PCE weighted median inflation (PCEMED) and PCE trimmed mean inflation (PCETM) using several different models of inflation dynamics. In addition, the paper addresses the issue of bias in the sample.[4] Bias or the differences in the means must be corrected since it can affect the forecasting ability of the candidate measures when the variables have unit roots and are co-integrated.

The paper finds that the trimmed mean forecasts future inflation well. Together with Smith (2004), this provides evidence that adjusting for the bias yield better measures of core inflation. One issue beyond this paper's scope is using real-time instead of revised PCE data. While this would be more relevant, it is difficult to implement for several reasons. First, the PCEX is only available since 1996. Second, to compute a real-time weighted median or trimmed mean PCE inflation requires historical real-time component level data, which are unavailable.

The rest of this paper is organized as follows. Section 1 examines the in-sample prediction and Section 2 investigates the out-of-sample forecasts. Finally, Section 3 concludes.

2. In-Sample Prediction

Using data from the Federal Reserve Bank of Dallas, I calculate the 1-month and 12-month PCE and PCEX annualized inflation rates as percentage changes.[5] Using the same underlying component level data, I compute the weighted median and trimmed mean PCE

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[4] Bias is the difference between the mean of the dependent inflation variable and the means of the independent inflation variables.

[5] See http://dallasfed.org/data/pce/index.html. Detailed component level data are available upon request from the FRB Dallas. Data vintage is April 2006. See Dolmas (2005) for more details on the calculation of the weights.
$\pi_{t-k,t} = \left(\frac{P_t}{P_{t-k}}\right) - 1$ where k = 1 and 12 for the PCE and PCE minus food and energy price indexes.

inflation rates. Each component's weight every month is the average of the actual share of nominal expenditures in the current month and the hypothetical share assuming that the quantities from period t+1 were purchased at the prices given in period t.

The components are ordered from the smallest inflation rate to the largest. Then, the weighted median is calculated by finding the smallest N_M such that

$$\sum_{i=1}^{N_M} w^i \geq \frac{1}{2} \qquad (1)$$

and then the weighted median is

$$\pi^{median} = \pi^{N_M}$$

w is the weight; *i* indicates the component; and *N* = number of components = 186.

Using Dolmas' (2005) optimal trim of 19.4% in the lower tail and 25.4% in the upper tail,[6] I calculate the trimmed mean PCE inflation rate for *k* = 1 and 12:

$$\begin{aligned} \bar{\pi}_{\alpha,\beta} &= \frac{1}{1-\alpha-\beta}\sum_{i=\hat{i}_t(\alpha)}^{\hat{i}_t(1-\beta)} w_{t-k}^i \pi_{t-k,t}^i \\ \pi_{t-k,t}^i &= \left(\frac{P_t^i}{P_{t-k}^i}\right) - 1, \end{aligned} \qquad (2)$$

where $\alpha = .194, \beta = .254$ and $\hat{i}(\alpha) = \min\left[I : \sum_{i=1}^{I} w_{i,t} \geq \alpha\right]$ (Dolmas, 2005).

Many studies often compute 12-month trimmed mean by compounding the monthly trimmed means. A more accurate method is to compute the year-over-year trimmed mean from the component level data by calculating the year-over-year component inflation rates and then finding the trimmed mean or weighted median. This paper produces the year-over-year trimmed means from the component level data and does not compound the monthly trimmed means to obtain the annual trimmed mean. Since Smith (2004) finds that the results are consistent using

[6] Dolmas (2005) calculates the optimal trim under a variety of methods. I use the trimming based on the "three equally likely" scenario, which is an average of the three trimming procedures he uses.

either approach, I use the more accurate year-over-year trimmed mean. The dependent variable in the analysis is a *k*-period ahead inflation rate.[7]

There are some differences among the candidate measures. In Figure 1, the difference in the means of the candidate measures is noticeable, as discussed below. There are also large differences in the variances of the measures. It makes sense that the variance of the limited-influence estimators (trimmed mean: 1.16 and weighted median: 1.15) would be smaller than that of PCE inflation (4.02) but it is surprising that the PCEX inflation rate's variance (3.53) is large and close to that of the PCE inflation rate. Given the popular notion that the PCEX removes supply shocks, it does not appear to remove much of the variation.[8]

For each inflation series, I assume a unit root and co-integrating relationship between the dependent variable (*k*-period-ahead inflation) and the independent variables (year-over-year or monthly inflation rates). The co-integrating relationship has a co-integrating vector of 1. A unit root structure is consistent with the high degree of persistence in the data over the sample.[9]

The sample begins in 1982 to examine forecasts over a single monetary policy regime. Different monetary policy regimes may affect which candidate measure is core inflation (Smith, 2005). Over the sample period (January 1982 –April 2005) the means of the candidate measures are not equal to the mean of the dependent variable.[10] This bias needs to be corrected otherwise the candidate measure with its mean closest to the 12-month ahead inflation rate may have an advantage in forecasting because of the unit root and co-integrating relationships.[11]

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[7] $\pi_{t,t+k} = \left(\frac{P_{t+k}}{P_t}\right) - 1$ is *k*-month ahead PCE inflation (*k* =12 for the in-sample and *k* = 12, 18 and 24 for forecasts).

[8] Swings in the PCEX inflation rate in 2001 largely owe to September 11 effects. Omitting the September and October 2001 reading, the variance falls to 3.11, which exceeds those of the trimmed mean and weighted median.

[9] See Freeman (1998), Stock and Watson (1999), Smith (2004) and Rich and Steindel (2005) for more details.

[10] Equating the means of the independent variables to the dependent variable's mean corrects the bias (Smith, 2004).

[11] The unit root and co-integration imply that the coefficients sum to one, obviating the need for a constant to absorb the difference in means.

In-sample results indicate that the trimmed mean is a better predictor of future inflation than the generally used PCEX inflation rate. The simplest model is

$$\pi_{t+12,t} - x_{t,t-12} = \varepsilon_{t+12}, \tag{3}$$

where x is PCE, PCEX, PCEMED or PCETM. When PCE is the explanatory variable this model is a random walk. Examining the simplest models where 12-month ahead PCE inflation rate ($\pi_{t+12,t}$) is predicted by the previous 12-month ($x_{t,t-12}$)inflation rates among the price indexes considered shows that the traditional core inflation measure, PCEX, is not a good forecaster (largest sum of squared residuals (SSR)). This accords with Smith's (2004) conclusion that removing food and energy does not yield a good forecast of future inflation. Table 1 reports the results for the non-bias adjusted and the bias-adjusted models and shows that the trimmed mean inflation rate may have more information for predicting future inflation.[12]

The results using two candidate inflation measures as independent variables illustrate that the trimmed mean is important to prediction. The regression is

$$\pi_{t+12,t} = (1-\beta)\pi_{t,t-12} + \beta x_{t,t-12} + \varepsilon_{t+12}, \tag{4}$$

where x is PCEX, PCEMED or PCETM and π is PCE inflation. A combination of PCE inflation with either PCETM or PCEMED inflation has the smallest SSR. The coefficient on the PCETM is .66 (.22) in the non-bias-adjusted regression and .85 (.21) in the bias-adjusted, which are not significantly different from one. For the median, the coefficient is .72 (.16). For the bias-adjusted results other runs indicate that the PCEX and PCEMED make a small contribution to prediction that should be explored further in models with more sophisticated dynamics.

Using bias-adjusted data, I test the predictive power of two more models, comparing the forecasting accuracy of the four candidate measures in a distributed lag and exponential decay

[12] The SSR for models using PCEX inflation are much larger than for the other explanatory variables. In the first two years of the sample PCEX inflation rates are much higher than overall inflation rates, which yield large errors.

models. In these models, monthly inflation rates are the independent variables and the 12-month-ahead PCE inflation rate (π) is the dependent variable. The distributed lag regression is

$$\pi_{t+12,t} = (1-\beta(1))x_{t,t-1} + \beta(L)Lx_{t,t-1} + \varepsilon_{t+12}, \tag{5}$$

and the exponential decay model is

$$\pi_{t+12,t} = x_{t,t-1} + \beta x_{t-1,t-2} + \beta^2 x_{t-2,t-3} + ... + \varepsilon_{t+12}, \tag{6}$$

where x is the monthly PCE, PCEX, PCEMED or PCETM inflation rate.[13] The results in Table 2 indicate that the trimmed mean is the best predictor (smallest Akaike Information Criterion (AIC) or Schwarz Criterion (SIC)) of future inflation and the PCEX inflation rate is the worst.

In addition, the exponential decay model predicts future inflation better than the distributed lag model.[14] Since the exponential decay model is better, I test if two variable exponential decay regressions outperforms prediction based only on the PCETM inflation rate. The results suggest that the trimmed mean combined with lagged PCE inflation may better predict inflation but to verify these results out-of-sample forecasts are needed.

3. Out-of-Sample Forecasting

The out-of-sample forecasts provide more information on whether the trimmed mean is useful for policy makers. These out-of-sample forecasts also address the issue of whether the bias in these inflation measures is predictable.[15]

I forecast over 12, 18 and 24 month horizons. I forecast the k-month ahead inflation rate (k = 12, 18 and 24) with 1-step ahead recursive forecasts from 1990:1 to the end of sample. Both the bias measure and the parameters are updated monthly in the recursive forecasts. I forecast

[13] The distributed lag regression has a lag polynomial of order 23. The exponential decay model has an infinite lag structure. In practice, I use 24 lags of the monthly inflation rates and constrain the coefficients to sum to one.
[14] I also estimated two variable distributed lag models. In these models, there are 46 estimated coefficients. The AIC and SIC for these models are much larger. Results are available from the author upon request.
[15] If the bias is unpredictable, then adjusting the data should not improve the forecasts as it does.

using equations 3, 4, 5 and 6, assuming that inflation has a unit root and that the inflation measures are co-integrated. Equation 3 is similar to a random walk forecast and is a random walk forecast when PCE inflation is the explanatory variable and equation 4 combines two variables.[16] Equations 5 and 6 are the respective distributed lag and exponential decay models.

The out-of-sample forecast results are consistent with the in-sample results. In Table 3, either the PCETM or PCEMED inflation rate is the best forecaster at all horizons. In the models, the PCETM or PCEMED inflation rate has a smaller RMSE (root mean square error) than the PCE inflation rate or more interestingly, PCEX inflation rate. However, to be truly relevant for forecasting future inflation, the forecasts using the limited-influence estimator (PCETM or PCEMED) must be significantly different from the other models. To test if the RMSEs are statistically different I use the modified Diebold-Mariano forecast comparison test suggested by Harvey, Leybourne and Newbold (1997). The modified Diebold-Mariano test statistic is

$$S_1^* = S_1\left(\frac{T+1-2(h+1)+h(h+1)/T}{T}\right)^{-1/2}$$
$$S_1 = \frac{\bar{d}}{[\hat{V}(\bar{d})]^{1/2}} \qquad (7)$$

where $\bar{d}$ is the mean difference of the prediction errors and $\hat{V}(\bar{d})$ is the estimated variance. Since the models are not nested, I use the modified Diebold-Mariano test statistic, estimated with Newey-West corrected standard errors allowing for heteroskedastic autocorrelated errors.

I compare the forecast errors from each model with those of the best model.[17] The results indicate that using the PCETM or PCEMED inflation rate to forecast is significantly better than using the PCEX inflation rate to forecast. For most of the models there is no statistical

[16] A random walk model is a good benchmark forecast model. See Atkeson and Ohanian (2001).
[17] The explanatory variables are the previous 12-month inflation rates for all three horizons in the basic models, and are the previous 1-month annualized inflation rates in the distributed lag and exponential decay models.

difference of the forecast errors from the models using the PCETM or PCEMED. In addition, the modified Diebold-Mariano test suggests that using a single variable is as good as using a combination of two variables to forecast future inflation. Finally, I compare the best forecast (single variable) from each of the three models. These results suggest that the type of model used to forecast inflation is less important. Each one of these models smoothes inflation in some manner and provides a good forecast. Future research might more extensively examine inflation dynamics when forecasting. These out-of-sample results confirm that using the PCEX inflation rate as core inflation is not motivated by the fact that the PCEX inflation rate provides good forecasts of future inflation or good information about future movements of inflation.

Figure 2 shows the better forecasting accuracy of the PCETM inflation rate. Although, the forecasted PCETM inflation rate does not perfectly track the 12-month ahead inflation rate, the two series do appear to move toward each other over a 1 to 2 year time horizon.

4. Conclusions

This paper expands the literature on core inflation and confirms that limited-influence estimators provide information about movements in future inflation and are good measures of core inflation. Smith (2004) finds for the CPI that the weighted median is core inflation; this paper finds that a limited-influence estimator such as the trimmed mean or weighted median is a good measure of core inflation for the PCE. Additionally, both papers demonstrate that the bias arising from differences in means needs to be taken into account when forecasting.

Rich and Steindel (2005) find that the limited-influence estimators are not consistently better predictors of inflation. However, their samples span a few monetary policy regimes and they find parameter instability suggesting their results are sensitive to monetary policy regimes, which Smith (2005) finds can affect which price measure is the best forecaster of future inflation.

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Table 1: Comparison of basic models (in-sample)

Dependent variable: $\pi_{t+12,t}$

Explanatory variables: $x_{t,t-12}$

	Non-bias adjusted SSR	**Bias adjusted SSR**
<u>Models</u>		
PCE	196.02	192.46
PCEX	1137.60	1027.49
PCEMED	242.35	156.55
PCETM	**176.09**	**153.55**
PCE and PCEX	180.37	179.93
PCE and PCEMED	181.44	**150.33**
PCE and PCETM	**168.71**	152.39
PCEX and PCETM		**142.07**
PCEX and PCEMED		152.96
PCEMED and PCETM		151.89

Bold indicates best model.

Table 2: Comparison of in-sample models

Dependent variable: $\pi_{t+12,t}$

Explanatory variables: monthly inflation rates

	Bias adjusted	
	AIC	**SIC**
<u>Models</u>		
<u>Distributed lag</u>		
PCE	2.48	2.78
PCEX	2.54	2.84
PCEMED	2.36	2.66
PCETM	**2.22**	**2.52**
<u>Exponential decay</u>		
PCE	2.49	2.50
PCEX	2.64	2.66
PCEMED	2.25	2.26
PCETM	**2.11**	**2.13**
PCE and PCEX	2.46	2.50
PCE and PCEMED	2.22	2.26
PCE and PCETM	**1.91**	**1.95**
PCEX and PCETM	2.13	2.16
PCEX and PCEMED	2.24	2.28
PCEMED and PCETM	2.10	2.14

Bold indicates best model.

Table 3: Comparison of out-of-sample forecasts

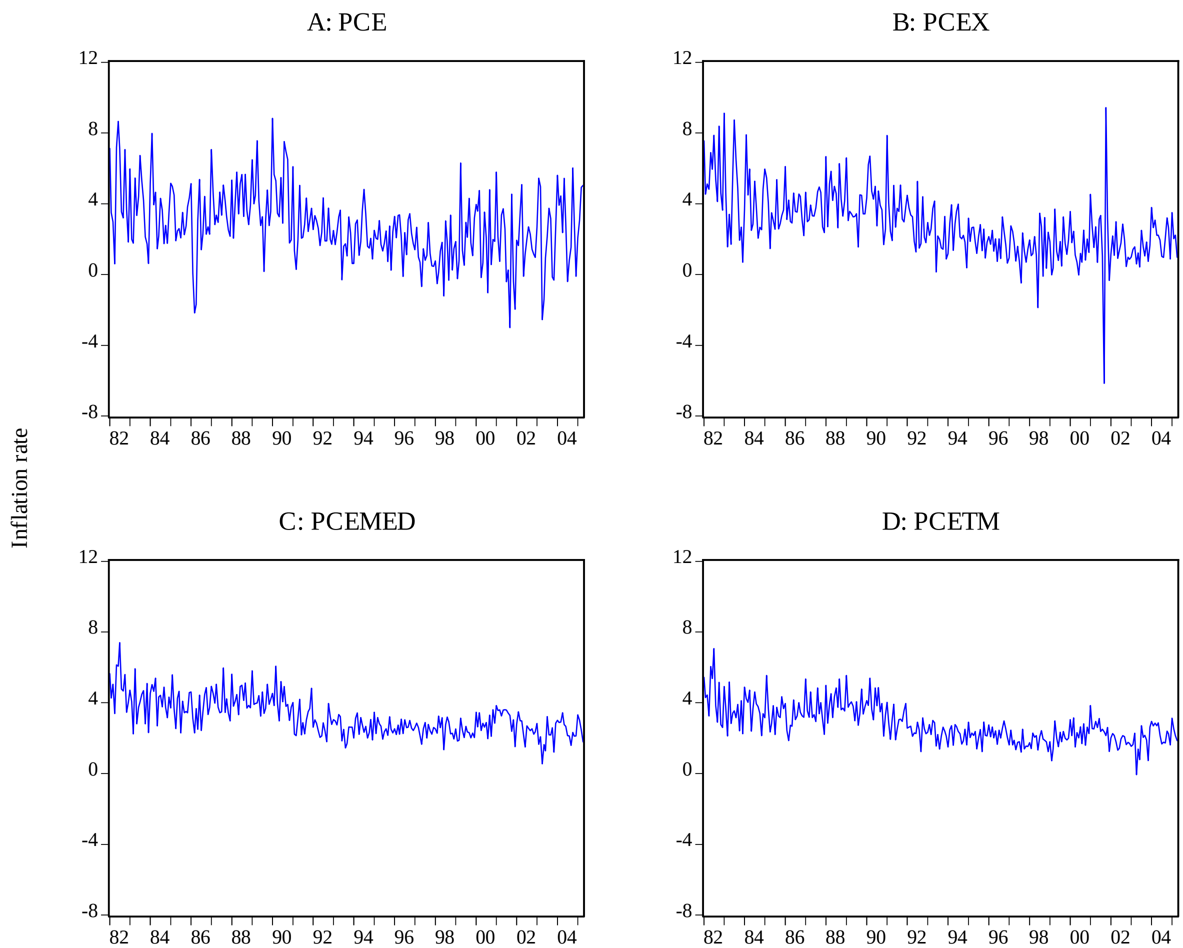
Dependent variable: $\pi_{t+k,t}$ $k =$ 12, 18 and 24

Bias adjusted

	12-month			**18-month**			**24-month**		
	RMSE	RMSE(j)/ RMSE (best model)		RMSE	RMSE(j)/ RMSE (best model)		RMSE	RMSE(j)/ RMSE (best model)	
<u>Basic</u>									
PCE	0.797	1.171	*	0.815	1.241	**	0.859	1.307	**
PCEX	1.669	2.450	**	1.681	2.560	**	1.718	2.613	**
PCEMED	0.719	1.055		0.677	1.031		**0.658**		
PCETM	**0.681**			**0.657**			0.668	1.016	
PCE and PCEX	0.849	1.243	**	0.882	1.333	**	0.932	1.421	**
PCE and PCEMED	0.696	1.019		0.669	1.011		**0.656**		
PCE and PCETM	**0.683**			**0.662**			0.661	1.008	
	Note: PCETM vs. PCE and PCETM **are not** significantly different.			Note: PCETM vs. PCE and PCETM **are not** significantly different.			Note: PCEMED vs. PCE and PCEMED **are not** significantly different.		
<u>Distributed lag</u>									
PCE	0.840	1.287	**	0.862	1.390	**	0.921	1.456	**
PCEX	0.795	1.218		0.805	1.297	*	0.849	1.343	**
PCEMED	0.726	1.112	**	0.661	1.065		0.644	1.018	
PCETM	**0.653**			**0.620**			**0.633**		
<u>Exponential decay</u>									
PCE	0.854	1.115	*	0.781	1.237	**	0.823	1.294	**
PCEX	0.888	1.159	**	0.793	1.256	**	0.817	1.284	*
PCEMED	0.817	1.067	**	0.661	1.047		**0.636**		
PCETM	**0.766**			**0.631**			0.639	1.003	
PCE and PCEX	0.754	1.168							
PCE and PCEMED	0.708	1.098	**						
PCE and PCETM	**0.645**								
PCEX and PCETM	0.683	1.059							
PCEX and PCEMED	0.748	1.160	**						
PCEMED and PCETM	0.711	1.103							
	Note: PCETM vs. PCE and PCETM **are not** significantly different.								
<u>Single variable (best models)</u>									
Basic	0.681	1.043		0.657	1.059		0.658	1.039	
Distributed lag	**0.653**			**0.620**			**0.633**		
Exponential decay	0.766	1.173		0.631	1.018		0.636	1.006	

Bolded results indicate the best model. Modified Diebold-Mariano results are presented comparing the best model (bold) to the others. * indicates significance at the 10% level and ** indicates significance at the 5% level.

Figure 1: Monthly Inflation Rates



Means over full sample (1982:01-2005:04)

PCE 12-month ahead mean:	2.74
PCE 1-month mean:	2.76
PCEX 1-month mean:	2.86
PCEMED 1-month mean:	3.21
PCTM 1-month mean:	2.79

Figure 2: Comparison of forecasts (12 month)