PCE Inflation and Core Inflation

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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)

Over the past decade researchers have more closely examined the concept and measurement of core inflation. Most of this work has focused on the consumer price index but research is now focusing on the Personal Consumption Expenditure deflator (PCE) since it is the preferred measure of inflation of the Federal Reserve.[1] Generally, the PCE minus food and energy is discussed as a measure of underlying inflation or core inflation and the weighted median or trimmed mean inflation rate has been largely ignored.

Previous work by Smith (2004) focuses on both the Consumer Price Index (CPI) and the PCE and finds that the weighted median of each forecasts future inflation better than their respective minus food and energy inflation rates. Therefore, the weighted median is a better measure of core inflation, defined as the best predictor of future inflation. The analysis did not include a trimmed mean for the PCE since the research suggesting the optimal trimming of the PCE was not available. Recent work by Rich and Steindel (2005) examines both the CPI and PCE but still ignores the trimmed mean.[2]

The focus of this paper is to test which measure can best predict future PCE inflation or which measure is core inflation. There are other definitions of core inflation but the best forecaster definition appeals to the notation underlying most discussions of core inflation[3]; the limited-influence estimators capture this intuition of core inflation. By using the inflation rate minus food and energy as core inflation, policy makers are stating 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 arise in another sector they are often excluded on an

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

ad hoc basis. For example, in 1998 the tobacco litigation settlement pushed up inflation minus food and energy but policy makers did not want to react to this increase so they noted how inflation minus food and energy would have changed if they also excluded tobacco prices ("Monetary Policy Report to Congress, July 1999). The trimmed mean and weighed median exclude unusually large price changes no matter from which sector they arise.

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 concludes that the trimmed mean forecasts future inflation well. In addition, these results in combination with the results from Smith (2004) provide evidence that adjusting for the bias leads to better measures of core inflation. One issue that this paper cannot address is that the PCE data are revised. It would be better to forecast using real-time candidate measures; however, this is difficult for several reasons. First, the PCEX is only available since 1996. Second, to compute a real-time weighted median or trimmed mean PCE inflation rate requires historical real-time component level data, which is not available. Going forward, one can obtain the real-time trimmed mean by downloading the monthly releases from the Dallas Fed website but several years of data need to be collected before it can be used in econometric analysis.

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

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.

1. In-Sample Prediction

The data are obtained from the Federal Reserve Bank of Dallas.[5] I calculate the 1-month and 12-month PCE inflation rates and PCEX inflation rates as the percentage change.[6] Using the same component level data as is used to compute the published trimmed mean, I compute the weighted median PCE inflation rate and the trimmed mean PCE inflation rate. The weight for each component 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 weighted median is calculated as

$$\begin{aligned} \overline{\pi}_{\alpha} &= \frac{1}{N-2m}\sum_{i=m}^{N-m} w_{t-k}^{i}\pi_{t-k,t}^{i} \\ \pi_{t-k,t}^{i} &= \left(\frac{P_t^i}{P_{t-k}^i}\right)-1, \quad m = N\alpha \end{aligned} \qquad (1)$$

where m is the largest integer less than or equal to $N\alpha$; w is the weight; i indicates the component; k = 1 and 12; α = 0.50; and N = number of components = 186. Dolmas (2005) finds the optimal trim is 19.4% in the lower tail and 25.4% in the upper tail. I use that optimal trim to calculate the trimmed mean PCE inflation rate for k = 1 and 12. The trimmed mean with an asymmetric trim is calculated as

[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.

[6] $\pi_{t-k,t} = \left(\frac{P_t}{P_{t-k}}\right)-1$ where k = 1 and 12 for both the PCE price index and the PCE minus food and energy price index. The monthly inflation rates are annualized.

$$\bar{\pi}_{\alpha,\beta} = \frac{1}{1-\alpha-\beta}\sum_{i=\hat{i}_t(\alpha)}^{\hat{i}_t(1-\beta)} w^i_{t-k}\pi^i_{t-k,t}$$

$$\pi^i_{t-k,t} = \left(\frac{P^i_t}{P^i_{t-k}}\right) - 1, \quad \alpha = .194, \beta = .254 \qquad (2)$$

Many studies often compute the annual (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. The dependent variable in the analysis is a *k*-period ahead inflation rate.[7]

Figure 1 shows that there are some differences among the candidate measures. From the figure, the difference in the means of the candidate measures can be noticed. This difference in the means is discussed below. Additionally, there are 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 the variance of PCE inflation (4.02) but it is surprising that the PCEX inflation rate's variance (3.53) is large and close to the variance 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 rate) and the independent variables (year-over-year

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

[8] A large part of the swings in the PCEX inflation rate in 2001 is due to September 11 effects. Removing the September and October 2001 observations, the variance falls to 3.11, which is still quite substantially larger than the variances of the trimmed mean and weighted median.

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 found in the data over this sample.[9]

The sample begins in 1982 since I want 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. 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.[10]

The in-sample results indicate that the trimmed mean is a better predictor of future inflation than the PCEX inflation rate, which is the emphasized measure of core inflation. 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 ($x_{t,t-12}$) PCE inflation rate, PCEX inflation rate, PCEMED inflation rate or the PCETM inflation rate shows that the traditional core inflation measure, PCEX, is not a good forecaster (largest sum of squared residuals (SSR)). This reinforces the conclusion from Smith (2004) that removing food and energy does not necessarily lead to a good forecast of future inflation. In Table 1, the results for both the non-bias adjusted

[9] See Freeman (1998), Stock and Watson (1999), Smith (2004) and Rich and Steindel (2005) for more details.
[10] I correct this bias by equating the means of the independent variables to the mean of the dependent variable. See Smith (2004) for more details.

and the bias-adjusted models are shown and support the position that the trimmed mean inflation rate may have information for predicting future inflation.[11]

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 inflation 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 I ran additional regressions with the remaining combinations of variables. From these results, it appears that the PCEX and PCEMED make a small contribution to prediction that should be explored further in models with more sophisticated inflation dynamics.

Using the bias-adjusted data, I test the predictive power of two additional models. I compare the forecasting accuracy of the four candidate measures in a distributed lag model and an exponential decay model. In these models, I use monthly inflation rates for the independent variables and continue to use the 12-month ahead PCE inflation rate as 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

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

[11] The SSR for the models using PCEX inflation are much larger than for the other explanatory variables. Over the first two years of the sample PCEX inflation rates are substantially higher than the overall inflation rate, which produces large errors.

where π is the 12-month ahead PCE inflation rate and x is the monthly PCE, PCEX, PCEMED or PCETM inflation rate.[12] 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.[13] Since the exponential decay model is better, I test if two variable exponential decay regressions can outperform prediction based only on the PCETM inflation rate. The results suggest that the trimmed mean combined with lagged PCE inflation may provide enhanced prediction of inflation but to verify these results out-of-sample forecasts are needed.

2. Out-of-Sample Forecasting

The out-of-sample forecasts provide more information on whether the trimmed mean is useful for monetary policy decisions. Policy makers need a forecast of inflation that forecasts well out-of-sample. These out-of-sample forecasts also address the issue of whether the bias in these inflation measures is predictable.[14]

I forecast over three time horizons: 12, 18 and 24 months. I forecast the k-month ahead inflation rate (k = 12, 18 and 24) with 1-step ahead recursive forecasts from 1990:1 until the end of the sample. Both the bias measure and the parameters are updated monthly in the recursive forecasts. I forecast using equations 3, 4, 5 and 6. Equation 3 is similar to a random walk forecast and is a random walk forecast when using PCE inflation as the explanatory variable and

[12] 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.
[13] 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.
[14] If the bias is unpredictable, then adjusting the data should not improve the forecasts as it does.

equation 4 combines two variables.[15] Equation 5 is the distributed lag model and equation 6 is the exponential decay model.

The results for the out-of-sample forecasts are consistent with the in-sample results. In Table 3, either the PCETM or PCEMED inflation rate is the best forecaster at all time 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. The modified Diebold-Mariano test statistic is estimated with Newey-West corrected standard errors that allow for heteroskedastic autocorrelated errors. I use the modified Diebold-Mariano test statistic since my models in general are not nested.

I compare the forecast errors from each model with those of the best model.[16] 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

[15] A random walk model is a good benchmark forecast model. See Atkeson and Ohanian (2001).

[16] Under the basic models, the explanatory variables are the previous 12-month inflation rates for all three forecast horizons. Under the distributed lag and exponential decay models, the explanatory variables are the previous 1-month inflation rates annualized.

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.

Finally, 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.

3. 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 that arises due to the differences in the means needs to be accounted for when forecasting.

Recent work by Rich and Steindel (2005) does not consistently find that the limited-influence estimators are good measures of core inflation but I would suggest that their finding may be due to the fact that they do not limit themselves to one monetary policy regime.[17] Smith (2005) finds that the monetary policy regime is important to which measure is considered core inflation or the best forecaster of inflation.

One potential issue with trimmed mean and weighted median is that the data are revised. An area of future research is to consider a real-time weighted median or trimmed mean inflation series and test how accurate forecasts would have been using those real-time data. This is a challenging task because it requires collecting real-time data on a set of highly disaggregated components of the PCE. In the future, I can collect the trimmed mean data as it is released by the Dallas Fed and build a real-time data set for the trimmed mean. For the historical data, real-time components are needed. Even given these potential limitations, there appears to be significant information in the trimmed mean about future inflation.

References

Atkeson, Andrew and Lee E. Ohanain (2001). "Are Phillips Curves Useful for Forecasting Inflation?" *Federal Reserve Bank of Minneapolis Quarterly Review* 25, 2-11.

Ball, Laurence and N. Gregory Mankiw (1995). "Relative-Price Changes as Aggregate Supply Shocks." *Quarterly Journal of Economics* 110, 161-193.

Bank of International Settlements (1999). *Measures of underlying inflation and their role in the conduct of monetary policy*. Proceedings of the workshop of central bank model builders.

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

Bryan, Michael F., Stephen G. Cecchetti and Rodney L. Wiggins II (1997). "Efficient Inflation Estimators." National Bureau of Economic Research Working Papers No. 6183.

Diebold, Francis X. and Roberto S. Mariano (1995). "Comparing Predictive Accuracy." *Journal of Business & Economics Statistics* 13, 253-63.

[17] Rich and Steindel's samples from 1959-2004 and 1978-2004 encompass several monetary policy regimes which may contribute to their inconsistent results. They also find parameter instability that may indicate a break in the data, which I would suggest signifies a change in the monetary policy regime.

Dolmas, Jim (2005). “Trimmed Mean PCE Inflation.” Research Department Working Paper 0506. Federal Reserve Bank of Dallas. July 2005.

Eckstein, Otto (1981). *Core Inflation.* Englewood Cliffs, NJ. Prentice Hall.

Freeman, Donald G. (1998). “Do Core Inflation Measures Help Forecast Inflation?” *Economics Letters* 58, 143-147.

Greenspan, Alan (1999). “Monetary Policy Report to Congress.” Federal Reserve Board of Governors. July 1999.

Harvey, David, Stephen Leybourne and Paul Newbold (1997). “Testing the equality of prediction mean squared errors.” *International Journal of Forecasting* 13, 281-291.

Quah, Danny and Shaun P. Vahey (1995). “Measuring Core Inflation?” *Economic Journal* 105, 1130-1144.

Rich, Robert and Charles Steindel (2005). “A Review of Core Inflation and an Evaluation of Its Measures.” Staff Report no. 236. Federal Reserve Bank of New York. December 2005.

Smith, Julie K. (2004). “Weighted Median Inflation: Is This Core Inflation?” *Journal of Money, Credit and Banking* 36, 253-63.

Smith, Julie K. (2005). “Inflation Targeting and Core Inflation.” *Canadian Journal of Economics* 38, 1018-36.

Stock, James H. and Mark W. Watson (1999). “Forecasting Inflation.” *Journal of Monetary Economics* 44, 293-335.

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	Bias adjusted 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.

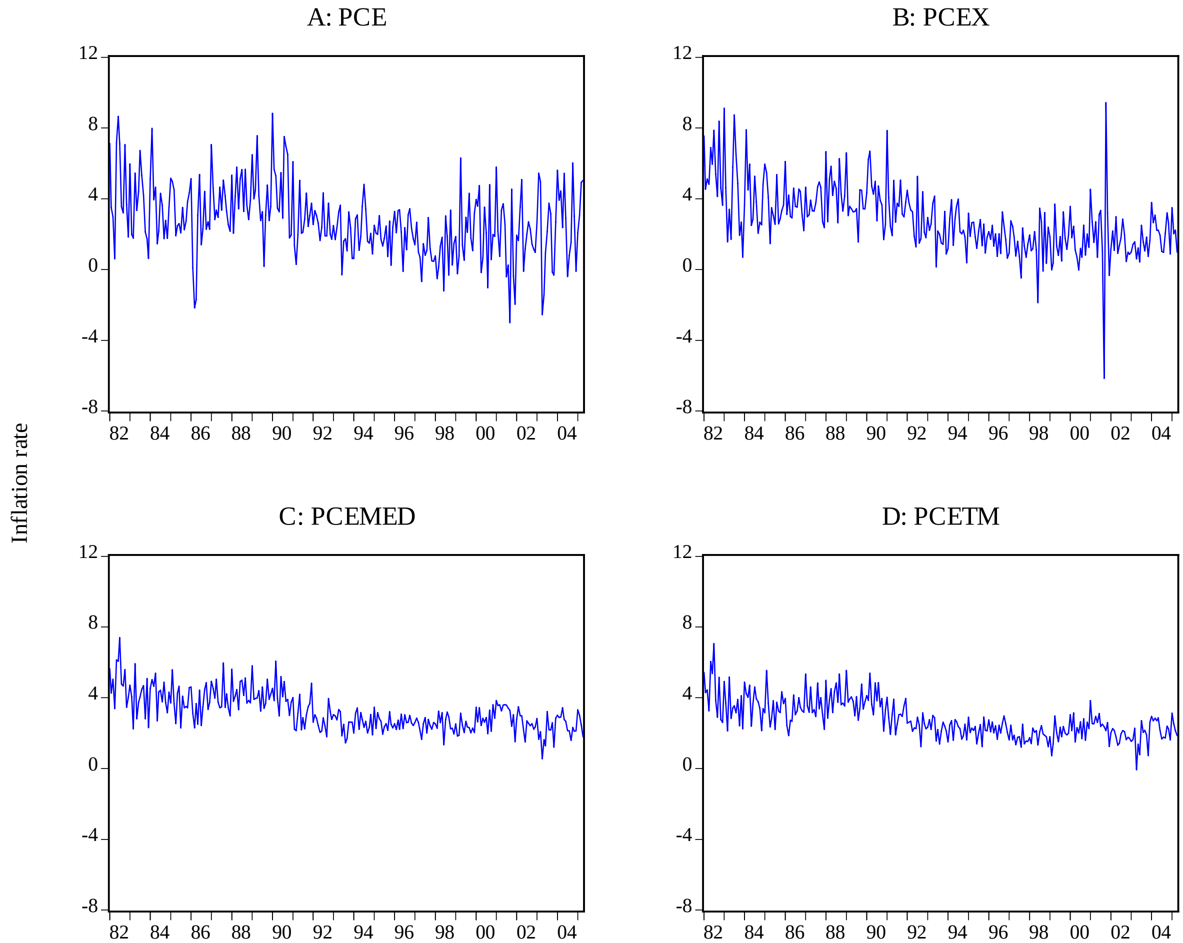
Table 3: Comparison of out-of-sample forecasts

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

	12-month RMSE	**12-month** RMSE(j)/ RMSE (best model)		**Bias adjusted 18-month** RMSE	**Bias adjusted 18-month** RMSE(j)/ RMSE (best model)		**24-month** RMSE	**24-month** RMSE(j)/ RMSE (best model)	
Basic									
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.		
Distributed lag									
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**		
Exponential decay									
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.								
Single variable (best models)									
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)