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Abstract

Policymakers tend to focus on core inflation measures because they are thought to be better predictors of total inflation over time horizons of import to policymakers. We find little support for this assumption. While some measures of core inflation are less volatile than total inflation, core inflation is not necessarily the best predictor of total inflation. The relative forecasting performance of models using core inflation and those using only total inflation depends on the inflation measure and time horizon of the forecast. Unlike previous studies, we provide a measure of the statistical significance of the difference in forecast errors.

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Core Measures of Inflation as Predictors of Total Inflation

Each month the U.S. government releases two measures of inflation at the consumer level: the consumer price index (CPI) and the price index for personal consumption expenditures (PCE).[1] While both measures draw on much of the same data, there are significant differences in terms of their scope, the weights on the various components of the indexes, and the process by which the measures are revised. Policymakers and analysts look at both measures of inflation to gauge current pressures on consumer prices and to project future inflation; over time, however, emphasis has shifted between the two measures. For example, since early 2000, the Federal Reserve has focused on the PCE index in its monetary policy reports to the Congress; prior to that time, it focused on the CPI.[2] Emphasis has also shifted over time between so-called headline, or total inflation, and so-called core inflation, which excludes the food and energy components. As discussed in Blinder and Reis (2005), one of the innovations of the Greenspan era was a shift in focus for monetary policymakers and the markets from total inflation to core inflation. In October 2007, the FOMC began releasing projections of total PCE inflation along with core PCE inflation; however, the focus in much Fed communication continues to be on core PCE inflation.

One might favor core inflation over total inflation if it were a better predictor of total inflation and therefore a better guide for monetary policymakers, who, given the lags in monetary policy's effect on the economy, need to be forward looking when setting policy.[3] Indeed, this seems to be a prevailing

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[1] The CPI is released by the U.S. Department of Labor's Bureau of Labor Statistics (BLS) and is available on the BLS website at www.bls.gov/cpi. The PCE price index is released by the Bureau of Economic Analysis (BEA), and the most recent press release is available at www.bea.gov.

[2] Federal Reserve Board of Governors, Monetary Policy Report to the Congress, February 17, 2000.

[3] Another rationale that has been offered for focusing on core over total inflation is that the food and energy components have tended to be more volatile from month to month than other components. To the extent that movements in these components are not lasting, including them would yield a noisier signal about the underlying inflation rate to which monetary policymakers should be attuned (see Motley, 1997). As shown in Crone, Khettry, Mester, and Novak (2008), energy prices exhibit substantial volatility – over 10 times as much as the total CPI when volatility is measured by standard deviation of the monthly percentage change in the index from August 1987 through October 2010. Food prices actually exhibited lower month-to-month variation than the total CPI over this period. Prices of other components, such as apparel, transportation, and commodities, exhibited higher volatility

view. For example, in recent testimony (2011), Federal Reserve Chairman Ben Bernanke said, "To assess underlying trends in inflation, economists also follow several alternative measures of inflation; one such measure is so-called core inflation, which excludes the more volatile food and energy components and therefore can be a better predictor of where overall inflation is headed."

This paper seeks evidence on this rationale and more generally on which measures of consumer price inflation yield better predictions of future inflation. Section 1 of the paper briefly reviews the differences between the PCE and CPI and describes the most popular candidates for underlying inflation. Section 2 compares the accuracy of forecasts using the common measures of underlying inflation with rolling regression out-of-sample forecasts using only the total inflation measure itself. We investigate a set of popular inflation measures, including monthly CPI and PCE inflation less food and energy (the so-called core measures), CPI and PCE inflation less energy, the Federal Reserve Bank of Cleveland's weighted median CPI, and the Federal Reserve Bank of Dallas's trimmed-mean PCE. We present root-mean-squared forecast errors (RMSEs) for the various forecasting models to compare their out-of-sample forecasting accuracy, and also perform tests to determine whether differences in MSEs across the models are statistically significant. Section 3 presents tests of the robustness of our results using real-time data for the PCE, which, unlike the CPI, undergoes a series of revisions. Section 4 compares our results with other results in the literature, and Section 5 summarizes our findings.[4,5]

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than the total CPI. The core measures of the CPI and PCE, which omit food and energy prices, are considerably less volatile than the total measure – over the period August 1987 through October 2010, the CPI less food and energy was 45 percent as volatile as the total CPI, and the PCE less food and energy was 62 percent as volatile as the total PCE. Note, though, that omitting only the energy prices (and not food prices) yields an even less volatile index.

[4] A related, but more narrowly focused, paper is Blinder and Reis (2005), which only investigates the performance of core CPI as a predictor of total CPI and finds that current core CPI inflation is a better predictor of future total CPI inflation than current total CPI inflation itself. Unlike Blinder and Reis (2005), our paper investigates a much richer set of inflation measures, uses rolling regression forecasting models, presents statistical significance tests of the forecasts' performance, investigates whether CPI and PCE measures of inflation give independent information that helps predicts inflation, and examines the effects of using real-time data on our results.

[5] In an appendix, we discuss results based on combining components of *both* the CPI and the PCE to forecast the total inflation measures. We combine the components in two ways. First, we include components of both the CPI and PCE directly in the forecasting model. Second, we estimate latent dynamic factors of inflation using corresponding components of the CPI and PCE and include these latent factors in the forecasting model. We find

We have three main empirical findings:

(1) Core CPI outperforms total CPI as a predictor of total CPI inflation as indicated by root-mean-squared errors (RMSEs), but the differences in RMSEs are statistically significant only for the 24-month forecast horizon. The same is true for CPI less energy and the Cleveland Fed weighted median CPI.

(2) For the PCE, contrary to what is often presumed, RMSEs for forecasts based on core PCE inflation are higher (not lower) than those based on total PCE (although the difference in RMSEs is not statistically significant).

(3) Perhaps not surprisingly, we find that using final revised data as opposed to preliminary data can yield forecasts with lower RMSEs. More surprising, we find that the difference in RMSEs is statistically significant only for the two-quarter forecast horizon and not for longer horizons.

Thus, in general, although some constructed indexes of inflation show less volatility than total inflation, our results indicate that this lower volatility does not necessarily make these indexes better predictors of inflation. Hence, the rationale for policymakers focusing on core inflation as a guide for meeting their inflation objective finds little support in the data. This is particularly true for core PCE inflation, which the Fed has focused on since 2000.

1. The Standard Measures of Consumer Price Inflation: The CPI and the PCE Price Index

The CPI and the PCE price index both attempt to measure inflation at the consumer level, but they differ with respect to their scope, the sources of some of the price data, the weights assigned to the various components, and revisions to the indexes.

The CPI is designed to measure the increase in the typical urban consumer's cost of living. For most items this is measured by the out-of-pocket cost of the item. The only major exception is the cost of owner-occupied housing, which is estimated as the rental equivalent of a comparable house.[6] To

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that the two measures provide little independent information that can be exploited to yield statistically significantly more accurate forecasts.

[6] To calculate the CPI, the BLS collects price data in 87 urban areas, surveying approximately 50,000 housing units and approximately 23,000 retail establishments. Prices, including directly associated taxes, are collected for a

determine the CPI for all items, the BLS takes a weighted average of the price levels of the individual items for which it has collected prices. The CPI is a fixed-weight index, with the weights based on what consumers report they buy when responding to the Consumer Expenditure Survey. The weights are fixed for two years until another set of surveys is chosen to determine the basket or combination of goods to be included in the index. Except to update the seasonal adjustment factors, the BLS does not revise the CPI.

Unlike the CPI, the PCE index includes many items for which the consumer does not pay directly out of pocket, such as expenditures on medical care paid for by government programs or private insurance and the value of free checking and other financial services provided by financial institutions.[7]

The weights on the components in the two indexes differ because the components of the two major price indexes differ but also because the CPI is a fixed-weight index, whereas the PCE price index is a chain-weight index. The CPI is a sum of price components weighted by consumer expenditure shares that are determined in an initial period and the change in the CPI is affected by changes in the prices of individual components. In contrast, the PCE is calculated using weights that change over time as consumers change the relative weight of expenditures on the component goods. Thus, the change in the PCE index is affected not only by the change in the prices of the individual components but also by the change in the relative amount of each good or service that is purchased. Thus, the PCE accounts for substitution between goods due to price changes. Finally, unlike the CPI, the PCE price index undergoes continual revision.

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representative sample of all goods and services purchased for consumption. Prices are not collected for "investment items," such as stocks, bonds, real estate, and life insurance. Since the CPI is released monthly, prices of fuels and a few select items are surveyed each month in all 87 locations, but prices of other goods and services are collected every month in only the three largest urban areas (New York, Los Angeles, and Chicago) and every other month elsewhere. This description of the CPI is based on information from the BLS website. In particular, see www.bls.gov/news.release/cpi.nr0.htm, www.bls.gov/gov/cpi/cpiovrvw.htm, and www.bls.gov/cpi/cpifaq.htm.

[7] About 25 percent of PCE spending is not reflected in the CPI. For those items that are included in both indexes, the PCE generally uses the same price data as the CPI. For items covered by the PCE but not by the CPI or for items that are defined differently in the two indexes, the BEA uses various sources for the price data. See Clark (1999) for further discussion.

The inflation rates computed from the CPI and the PCE follow similar patterns;[8] however, the difference between the two measures has varied significantly in different time periods, suggesting that the two indexes may convey independent information about the underlying rate of inflation that can be useful in forecasting. (The results presented in the appendix suggest that this is not the case.)

Several measures of inflation thought to be better predictors of underlying inflation have been constructed. Most have concentrated on eliminating certain components from the overall measure that are thought to be particularly volatile. For example, the core CPI and core PCE are constructed by eliminating the food and energy price components. The Federal Reserve Bank of Cleveland's weighted median CPI and 16 percent trimmed-mean measures and the Federal Reserve Bank of Dallas' trimmed-mean PCE inflation measure eliminate a percentage of the month's most volatile components regardless of sector.[9] See Wynne (2008) for a discussion of conceptual issues surrounding the measurement of core inflation.

2. Do Measures of Underlying Inflation Help Predict Total Inflation?

Given the lags in monetary policy's effect on the economy, policymakers need to be forward looking when setting policy. Thus, if any of these measures of underlying inflation is found to be a better predictor of future total inflation, this supports the case for focusing on that measure as a guide for monetary policy. There is a sizable literature that investigates the prediction of total inflation by various measures of underlying inflation. Cogley (2002) discusses the rationales behind various measures of underlying inflation and proposes and evaluates several as predictors of medium-run inflation. See also Rich and Steindel (2005), Clark (2001), and Smith (2004) for recent studies and reviews of the literature. In this paper, we confine ourselves to models that include only various measures of underlying inflation variables as predictors, since we are interested in testing the assumption that core inflation measures are

[8] A test of cointegration using monthly data from September 1987 through December 2010 indicates that total CPI and total PCE are cointegrated (p-value 0.0543). We find that core CPI and core PCE, core CPI and total CPI, and core PCE and total PCE, respectively, are not cointegrated.

[9] For a description of the Cleveland Fed's measures, see Bryan and Cecchetti (1994) and Bryan, Cecchetti, and Wiggins (1997) for a description. Note, though, that the Cleveland Fed calculates the price change for a component as a simple percentage change rather than as a log difference as in these two papers. For a description of the Dallas Fed's measure, see Dallas's website at www.dallasfed.org/data/pce/descr.html.

better predictors of total inflation. But we note that the focus on inflation measures is supported by the finding of Ang, Bekaert, and Wei (2007) that in the post-1995 period, forecasting models of total inflation that include only past inflation measures have been more accurate than models that also include measures of real economic activity or the structure of interest rates.[10] It is also supported by Stock and Watson's (2007) empirical evidence that since 1984 univariate models of inflation have produced smaller forecast errors (at least for forecast horizons longer than one quarter) than models that also include economic activity variables. (Note that this contrasts with the period 1970-1983.)

Like Blinder and Reis (2005), we estimate regressions of the form:

$$\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_{t,} \tag{2}$$

where $\pi_{t,t+h}$ is the percentage change in the total inflation index, y, between months t and t+h (annualized) and $x_{t-12,t}$ is the percentage change in an inflation index, z, over the past 12 months. That is,

$$\pi_{t,t+h} = \left[\left(\frac{y_{t+h}}{y_t} \right)^{(12/h)} - 1 \right] \times 100 \quad \text{and} \quad x_{t-12,t} = \left(\frac{z_t}{z_{t-12}} - 1 \right) \times 100 \,. \tag{3}$$

We examine the predictability of total inflation over four different forecasting horizons: h = 6 months, 12 months, 24 months, and 36 months, with either the 12-month change in total inflation, the 12-month change in the measure of underlying inflation, or both as the variables on the right-hand side of the forecasting equation.[11]

We use a fixed-window rolling regression technique to examine forecast accuracy. That is, we first estimate the model using the 101 months of data from August 1987 to December 1995 and then use those coefficients to predict total inflation over the next 6 months, 12 months, 24 months, and 36 months. From these we construct the first forecast error for each forecasting horizon. We then re-estimate the model using data from September 1987 to January 1996 and use those coefficients to predict total

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[10] In their paper, the most accurate forecasting model for total CPI was a regime-switching model, and the most accurate model for forecasting total PCE was a random walk.

[11] For example, future CPI inflation in July 2002 over the 6-month horizon is the annualized percentage change in the CPI from July 2002 to January 2003.

inflation over the next 6 months, 12 months, 24, months, and 36 months. From these we construct the second forecast error for each forecasting horizon. We continue this until the last window of data, which runs from May 2003 to October 2010. These rolling regressions allow the parameters of the forecasting equation to change over time, which allows for structural changes and reduces the influence of parameter estimation noise. We report the root-mean-squared errors (RMSEs) of these rolling regression out-of sample forecasts for each of the models from January 1996 through October 2010. To evaluate the forecasting accuracy, we also report the Giacomini-White statistic for testing whether there is a statistically significant difference in MSEs between the alternative model and the baseline model, which includes only total inflation on the right-hand side of the forecasting equation. This test statistic can be used, since all of our models are estimated using a window of a fixed length (101 months). In our case, the GW statistic is given by:

$$\frac{n^{-1}\sum_{t=1}^{T}(\varepsilon_{b,t}^{2}-\varepsilon_{a,t}^{2})}{\sqrt{\sigma^{2}/n}} \xrightarrow{d} N(0,1) \text{ as } n \to \infty, \tag{4}$$

where σ^2 is the variance of the difference in the squared forecast errors, which is estimated using the Newey-West method to correct for autocorrelation in the differences in the forecast errors from the competing models.[12] The terms $\varepsilon_{h,t}$ and $\varepsilon_{a,t}$ represent the forecast errors for time *t* of the baseline model and the alternative model, respectively. This GW statistic is a two-sided test statistic with a standard *t*-distribution and critical values. Negative values indicate that forecasts from the baseline model are more accurate than the alternative, and positive values indicate that the alternative model yields more accurate forecasts than the baseline model.

Tables 1a and 1b present the results of our out-of-sample forecasts using measures of total CPI and PCE and various measures of the underlying inflation rate for these two series. Our baseline model

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[12] In computing the Newey-White standard errors we used $h-1$ lags, but our results are robust using longer lags. (We investigated up to $10+h-1$ lags.)

includes only total inflation as a right-hand-side variable. We examine two types of alternative models: the first includes only measures of underlying inflation; the second includes both underlying inflation and total inflation. The first number in each row represents the out-of sample RMSE of the forecasts. We find some support that CPI less food and energy (core) inflation is a better predictor of future total CPI inflation than total CPI inflation itself, since at all forecast horizons, the model that uses core CPI as the only right-hand-side variable in the forecasting regression leads to smaller out-of-sample RMSEs than the baseline model (see Table 1a, row 2). This result is similar to that of Blinder and Reis (2005). We also find that at all forecast horizons, the model with the Cleveland Fed weighted median CPI has a lower RMSE than the baseline total inflation model (see Table 1a, row 5). For the other models, the comparison of RMSEs differs across forecast horizons.

A lower RMSE does not guarantee a forecast that is statistically significantly more accurate. The GW statistics presented in Table 1a test the accuracy of the alternative forecasting models relative to the baseline model. These statistics indicate only a few cases where an alternative model using underlying inflation alone yields a statistically significantly better forecast than the baseline model: at the 24-month horizon when core CPI, CPI less energy, or the Cleveland Fed weighted median is used. There are two cases in which including underlying inflation with total inflation produces a more accurate forecast than the baseline model: at the 24-month and 36-month horizons, using the Cleveland Fed weighted median and total CPI. In addition, at the six-month horizon, the baseline model is statistically significantly more accurate than the model that uses CPI less energy and the total CPI, and the model that uses the Cleveland Fed weighted median and total CPI. Although we do not show this result in the table, when we perform the same analysis over the period January 1976 through August 1986, we find that the alternative models using core CPI measures never produce statistically significantly more accurate forecasts than the baseline model, and in several cases, produce significantly less accurate forecasts than the baseline model.

For the PCE, our results are more uniform. In the majority of cases, the alternative models in Table 1b have higher RMSEs than the baseline total PCE inflation model, the alternative models never statistically significantly outperform the baseline model, and in two cases, the baseline model is significantly more accurate than the alternative (at the 12-month horizon in the alternative model with the PCE less energy and the total PCE [see Table 1b, row 6], and at the 6-month horizon in the alternative model with the Dallas Fed trimmed-mean PCE and the total PCE [see Table 1b, row 7]).

Thus, the results reported in Tables 1a and 1b suggest that reliance on measures of underlying inflation as more significantly reliable predictors of total inflation than total inflation itself is not well supported.[13,14]

We also investigated whether combining measures of CPI and PCE would improve the forecasts. As discussed in the appendix, no model that included the combined measures outperformed our baseline models.[15]

3. The Effect of Using Real-Time Data for the PCE Forecasts

A forecasting model is only as good as its underlying data, and one problem that could limit the effectiveness of PCE models is that the data often undergo benchmark revisions. (This is not the case for the CPI.) This is problematic because when testing potential models, we normally use the most recent revised set of data to estimate model coefficients rather than using the data that were available to a forecaster at the time of his/her forecast. Using revised data does not resemble the true forecasting experience encountered by policymakers and other forecasters. Thus, the model should be built with data known at implementation time and forecast accuracy should be judged against revised data.

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[13] Our results are similar when we estimate the forecasting equation using data from August 1987 to December 1996 and then produce out-of-sample forecasts based on these parameters instead of the parameters from the rolling regressions.

[14] For both the CPI and PCE, pseudo random walk forecasts in which the forecast of total inflation *k* periods ahead is total inflation over the past 12 months produce statistically significantly higher RMSEs over all forecast horizons than our baseline or alternative models.

[15] In particular, we find that including PCE inflation when forecasting CPI inflation typically produces higher RMSEs at short to medium forecasting horizons (6 months to 24 months), but these differences are not statistically significant. Including CPI inflation when forecasting PCE inflation typically produces higher RMSEs across all forecasting horizons, but the differences are not statistically significant. This suggests that while the measures are constructed differently, they provide little independent information that can be exploited to yield statistically significantly more accurate forecasts.

Using the Federal Reserve Bank of Philadelphia's real-time data set, we investigated the effect of using real-time data as opposed to final revised data on PCE forecasts. The real-time data set provides snapshots of data series as they existed in given historical periods ("vintages").[16] For example, the 2001Q1 vintage of the real GDP series yields the data series from its inception to 2000Q4 as it was given in 2001Q1 (which was the date of the initial release of 2000Q4 real GDP). Monthly real-time data on the PCE price index are not available. To construct a quarterly real-time PCE price index, we divide real-time nominal personal consumption expenditures by real-time real personal consumption expenditures. By selecting different vintages, we can reconstruct a forecasting model based on the data that forecasters had available to them at each historical period. Unfortunately, the available data do not allow us to construct a real-time measure of core PCE, so our comparison is between a model using final PCE data vs. a model using real-time PCE data, where, in both cases, the objective is to forecast final PCE.

3.1 Forecasting Model

We use the same model formulation and fixed-window rolling regression techniques as in our previous exercises, but each time we roll forward a quarter and estimate a new forecasting equation, we select the appropriate vintage of data to construct a PCE inflation series so that we emulate the data forecasters had available to estimate the forecast model. For example, for the first forecasting equation we use the 1996Q2 PCE vintage and estimate the equation over the 1987Q3 to 1996Q1 period. For the next forecasting equation we use the 1996Q3 vintage and estimate the equation over the 1987Q4 to 1996Q2 period, and so on. We compare this rolling real-time vintage model against a baseline model that is estimated using "final" data, i.e., the most up-to-date vintage of PCE inflation (hereafter referred to as the 2010Q4 PCE inflation vintage).

We estimate the two models, one for the rolling real-time vintages and one for the 2010Q4 vintage, as follows:

$$\pi_{t,t+h} = \alpha + \beta x_{t-4,t} + \varepsilon_{t,} \tag{7}$$

[16] For further discussion, please see the Federal Reserve Bank of Philadelphia's website at http://www.philadelphiafed.org/econ/forecast/reaindex.html.

where $\pi_{t,t+h}$ is the percentage change in the PCE index, y, between quarters t and t+h (annualized) and $x_{t-4,t}$ is the percentage change in the PCE index, z, over the past 4 quarters. That is,

$$\pi_{t,t+h} = \left[\left(\frac{y_{t+h}}{y_t} \right)^{(4/h)} - 1 \right] \times 100 \quad \text{and} \quad x_{t-4,t} = \left(\frac{z_t}{z_{t-4}} - 1 \right) \times 100 . \tag{8}$$

We examine the predictability of total PCE inflation for both models over four different forecasting horizons: h = 2 quarters, 4 quarters, 8 quarters, and 12 quarters (quarterly equivalents to our monthly horizons used earlier). For each model over the 4 forecasting horizons, we calculate RMSEs to evaluate forecasting errors and the GW statistic to compare our rolling real-time vintage forecasting model with the baseline model (2010Q4 vintage).

3.2 Results

Table 2 shows the results for this set of regressions. The baseline final data PCE forecasting model had smaller RMSEs for all forecasting horizons, and it is significantly more accurate than the rolling real-time vintage model at the 2-quarter horizon. Thus, revisions to PCE inflation do not necessarily improve forecasting effectiveness; it depends on the forecast horizon.

4. Comparison to Other Results in the Literature

Other papers have examined the forecasting ability of alternative core inflation measures for future total inflation. These include Cogley (2002), Rich and Steindel (2005), Clark (2001), Smith (2004), Kiley (2008), and Meyer and Pasaogullari (2010), among others. The findings differ across the studies, reflecting differences in the inflation measures, forecasting models, and time periods used. In general, researchers find that some type of alternative CPI measure is better at predicting future total CPI than is total CPI, but the particular alternative measure differs across the studies. The PCE has been studied less in the literature, and there does not appear to be a consensus regarding forecast performance.

Cogley (2002) proposes an adaptive measure of core inflation that allows for changes in mean inflation due to changes in policy regimes. This measure is approximated by a simple exponentially smoothed function of inflation. Based on in-sample fit, Cogley concludes that the exponentially smoothed measure is a better predictor of total CPI inflation than the core, median CPI, or trimmed-mean.

Rich and Steindel (2005) examine the CPI and the PCE and several alternative measures of each, including exponentially smoothed measures as in Cogley (2002). Their prediction model differs somewhat from ours, and they do not look at total inflation's ability to predict future total inflation or assess the statistical significance of various models. They find that no single alternative measure of inflation performs better than the rest at predicting future total inflation; the best predictor varies across sample periods and forecasting horizons, similar to our findings.

Clark (2001) estimates the same model as Rich and Steindel using the CPI and its less volatile alternatives; he does not study the PCE. He compares the in-sample 12-month horizon and 24-month horizon forecasting performance using regression R-squared goodness-of-fit measures (our forecasts are out-of-sample); he does not compute out-of-sample RMSEs.[17] Over the 1967-2000 sample period he finds that only CPI less energy has statistically significant predictive power for total CPI at the 12-month forecasting horizon; CPI less energy and the trimmed-mean CPI and median CPI are statistically significant predictors at the 24-month forecasting horizon. Over a shorter sample period, 1985-2000, he finds that all alternative CPI measures are statistically significant at the 12-month horizon but that the core CPI is the weakest of all the alternatives in terms of predictive power. In contrast, we find that core CPI has the lowest RMSE for our out-of-sample forecasts at the 12-month horizon.

Smith (2004) evaluates several alternative inflation measures as predictors of both the CPI and the PCE on the basis of out-of-sample RMSEs using monthly data from January 1982 through June 2000. Among several models, she finds the best performing model is an exponential decay model and that the median CPI outperforms the CPI, the trimmed-mean CPI, and the core CPI as a predictor of future CPI.[18] She also finds that median PCE outperforms the PCE and the core PCE as a predictor of future PCE.

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[17] Clark does not compare the forecasting performance of the alternative measures with that of total inflation itself.

[18] Smith uses the "research series" for the CPI and core CPI, which is available upon request from the BLS. The research series controls for changes in the methodology used to construct the CPI by computing the pre-January 1998 index using the method that has been in use since January 1998.

Kiley (2008) uses the methodology of Stock and Watson (2007) and examines three models to extract trend CPI and trend PCE inflation. He then examines 4-quarter-horizon forecasts of these trends over various sample periods (whereas our models forecast total CPI or PCE inflation). (He also examines forecasts of trend core inflation, which we do not do.) Over the time period 1996Q3 to 2007Q1, which most closely resembles ours, Kiley's results are similar to ours. He finds that the RMSE is lower in the model that uses total CPI compared to the model that uses core and total CPI. We find that over the 12-month horizon, the RMSE in our benchmark model is lower than in the alternative model using core CPI and total CPI. (We find this difference is not statistically significant. Kiley does not compute statistical significance of his RMSEs.) However, his results differ from ours for the PCE: he finds a lower RMSE for the model that uses total and core PCE than in the model that uses total PCE, whereas we find a higher RMSE in the benchmark model compared to the alternative model that uses core and total PCE (although we find that this difference is not statistically significant).

Meyer and Pasaogullari (2010) compare RMSEs across univariate forecasting models of one-year-ahead CPI inflation. The explanatory variables they investigate include past CPI inflation, core PCI, the Cleveland Fed's median and trimmed-mean measures, real GDP growth, and inflation expectations measures from the Philadelphia Fed's *Survey of Professional Forecasters* and the University of Michigan Survey of Consumers. Instead of the fixed-window rolling regressions we use, they use a recursive method that starts with 40 quarters of data and adds an additional data point to the sample in each successive quarter. (They note that their results are robust to doing rolling regressions.) Similar to our results, they find that the models based on core inflation can sometimes yield lower RMSEs than the baseline model, but this depends on their sample period; they did not test the statistical significance of these differences in RMSEs.

5. Conclusions

Policymakers who have an inflation goal might be better off being guided by a measure of inflation that excludes components that exhibit sharp changes in relative prices that are unrelated to changes in underlying inflation. Such a measure might yield better predictions of future total inflation. There are several potential alternatives for such a measure. Because of the volatility of energy prices, measures that exclude the energy component tend to be less volatile than total inflation measures. The most popular core inflation measure drops both the food and energy components, although this series demonstrates more volatility than a measure that omits only the energy components and retains the food components.

We find that since August 1987, core CPI inflation (i.e., total CPI less food and energy) and the Cleveland Fed weighted median inflation outperform the total CPI in terms of RMSEs as an out-of-sample predictor of total CPI inflation across each of our four forecasting horizons (6-month, 12-month, 24-month, and 36-month). However, the differences in RMSEs are statistically significant only at the 24-month horizon. In addition, the RMSE of the model using CPI less energy is significantly lower than the RMSE of the model using the total CPI at the 24-month horizon.

Based on our results, we cannot reach a similar conclusion for the PCE, because contrary to what is often posited, we find that total PCE inflation tends to outperform core PCE inflation as a predictor of total PCE inflation in terms of RMSEs over most forecast horizons, although the differences are not statistically significant. Thus, the rationale for focusing on core PCE because it is a better predictor of future PCE inflation is not supported by the data.

Perhaps not surprisingly, we find that revised data can yield statistically significantly better forecasts than preliminary data; however, this is true only at a 2-quarter horizon; at longer horizons the differences in forecast performance are not statistically significant.

Finally, we note that the results for inflation prediction vary considerably across studies, depending on the forecasting model, time period, and measures of inflation used. Thus, we cannot conclude that one particular alternative measure of inflation does a substantially better job at predicting inflation across all time horizons or sample periods. In many cases, the differences in RMSEs across our forecasting models were not statistically significant. Thus, policymakers who have total inflation in their loss function may want to look at a variety of inflation measures – including total inflation – when assessing underlying inflation.

Table 1a

Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Baseline Model

Dependent Variable: Total CPI

	Independent Variables	Forecasting horizon: 6 months	12 months	24 months	36 months	
Baseline Model						
1.	Total CPI	2.062	1.520	0.999	0.685	RMSE
Alternative Models without Total Inflation as an Independent Variable						
2.	Core CPI	1.965	1.361	0.857	0.563	RMSE
		1.042	0.889	1.663 **	1.252	GW Stat
3.	CPI Less Energy	2.064	1.384	0.793	0.521	RMSE
		−0.019	0.850	1.891 **	1.602	GW Stat
4.	Cleveland Fed Weighted	2.056	1.387	0.802	0.560	RMSE
	Median CPI	0.067	0.823	2.016 *	1.465	GW Stat
5.	Cleveland Fed Trimmed	2.189	1.419	0.836	0.570	RMSE
	Mean CPI	−0.966	0.863	1.429	1.581	GW Stat
Alternative Models with Total Inflation as an Independent Variable						
6.	Core CPI,	2.088	1.568	0.986	0.701	RMSE
	Total CPI	−1.370	−1.187	0.253	−0.194	GW Stat
7.	CPI Less Energy,	2.153	1.572	0.884	0.581	RMSE
	Total CPI	−1.780 ††	−0.823	1.130	1.307	GW Stat
8.	Cleveland Fed Weighted	2.155	1.569	0.870	0.596	RMSE
	Median CPI,	−1.684 ††	−0.734	1.689 **	1.782 **	GW Stat
	Total CPI					
9.	Cleveland Fed Trimmed	2.226	1.578	0.861	0.622	RMSE
	Mean CPI,	−1.435	−0.822	1.353	1.382	GW Stat
	Total CPI					

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_t$, where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated by starting with data from the window August 1987 through December 1995.

* Alternative model is more accurate (i.e., has a significantly lower MSE) than the baseline total inflation model at the 5 percent level of significance.
** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.
† Baseline total inflation model is more accurate than alternative model at 5 percent level of significance.
†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.

Table 1b

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Baseline Model

Dependent Variable: Total PCE

Independent Variables	6 months	12 months	24 months	36 months	
	Forecasting horizon				
Baseline Model					
1. Total PCE	1.538	1.168	0.956	0.712	RMSE
Alternative Models without Total Inflation as an Independent Variable					
2. Core PCE	1.568	1.219	0.962	0.676	RMSE
	−0.794	−0.651	−0.137	1.027	GW Stat
3. PCE Less Energy	1.633	1.253	0.975	0.666	RMSE
	−1.219	−0.992	−0.478	1.359	GW Stat
Alternative Models with Total Inflation as an Independent Variable					
4. Dallas Fed Trimmed-	1.567	1.164	0.834	0.610	RMSE
Mean PCE	−0.520	0.067	1.363	1.416	GW Stat
5. Core PCE,	1.575	1.262	1.011	0.724	RMSE
Total PCE	−1.306	−1.558	−1.218	−0.281	GW Stat
6. PCE Less Energy,	1.635	1.296	1.015	0.711	RMSE
Total PCE	−1.587	−1.723 ††	−1.134	0.023	GW Stat
7. Dallas Fed Trimmed-	1.624	1.261	0.924	0.654	RMSE
Mean PCE,	−1.981 †	−1.299	0.650	1.254	GW Stat
Total PCE					

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_{t,}$ where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated by starting with data from the window August 1987 through December 1995.

* Alternative model is more accurate (i.e., has a significantly lower MSE) than the baseline total inflation model at the 5 percent level of significance.
** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.
† Baseline total inflation model is more accurate than alternative model at 5 percent level of significance.
†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.

Table 2

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Inflation Using Real-Time Data Series

Independent Variable	**Forecasting horizon**			
	2 quarters	4 quarters	8 quarters	12 quarters
Final PCE data model				
2010Q4 vintage	1.173	0.871	0.711	0.650
Real-time vintage PCE data model				
Rolling real-time vintages	1.194	0.887	0.746	0.703
Giacomini-White test statistic	−1.71 †	−1.06	−0.92	−0.95

† Model using final data is more accurate (i.e., has a significantly lower MSE) than alternative model using real-time data at 5 percent level of significance.
†† Model using final data is more accurate (i.e., has a significantly lower MSE) than alternative model using real-time data at 10 percent level of significance.

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Appendix. Combining Measures from Both the CPI and the PCE to Predict Total Inflation

Another possibility for forecasting total CPI or total PCE inflation is combining these two standard measures or similar components of these measures to forecast each of the total inflation series. A straightforward way to combine the two standard measures in the forecasting exercise is to include both of the standard measures or their components in the forecasting equations. A second way is to use a dynamic factor model to estimate the underlying inflation rate reflected in each of the standard series. The latent dynamic factor can then be used to forecast total CPI or total PCE. We compare forecasts using both of these methods with the forecasts derived from our univariate baseline models with total CPI or total PCE as the only right-hand-side variable.

A.1. Including Both CPI and PCE Measures in the Forecast Models

Tables A.1a and A.1b present the results for our models that combine CPI and PCE measures in forecasts of total CPI or total PCE inflation. As shown in Table A.1a, for the CPI, none of the alternative models that contain measures of both CPI and PCE inflation produce forecasts that are statistically significantly more accurate than the baseline model. However, in two cases the baseline model produces statistically significantly more accurate forecasts than an alternative model. As shown in Table A.1b, for the PCE, the RMSEs of most of the forecasts from the alternative models that contain measures of both CPI and PCE inflation are larger than the RMSEs of the forecast from the baseline model, although in no case is the difference statistically significant.

A.2. Dynamic Latent Factor Models

Some recent studies have used large dynamic factor models that include besides price series, real variables, financial variables, and monetary variables and use the estimated dynamic factors to predict future inflation (Cristadoro, et al., 2005, and Amstad and Potter, 2007).[19] We limit our dynamic factor

[19] Velde (2006) also uses a latent factor model to estimate the underlying rate of inflation. Rather than selecting a subset of the components to estimate the underlying rate, he estimates a latent dynamic factor from the components of the CPI. The theory is that each of the components reflects the underlying inflation to a different degree and also has an idiosyncratic component. The degree to which any component reflects the underlying rate of inflation is not related to its weight in expenditure surveys.

model to include only the price series because our goal is to investigate forecasting models that use only past changes in the price indexes or their components to forecast total inflation.[20]

To estimate the underlying rate of inflation, we use a variant of the dynamic factor model developed by Stock and Watson (1989, 1991). The unobserved underlying rate of inflation is assumed to be reflected to varying degrees in the observed measures of inflation (CPI or PCE).

For each of the observed variables, π_i, there is a measurement equation:

$$\pi_{it} = \alpha_i + \beta_i\rho_t + u_t\,. \tag{A.1}$$

We assume the unobserved underlying rate of inflation, ρ, follows an AR(2) process:

$$\rho_t = \gamma + \delta_1\rho_{t-1} + \delta_2\rho_{t-2} + \varepsilon_t\,, \tag{A.2}$$

where,

π_{it} = the log difference in the observed price indexes, CPI and PCE,

and

ρ_t = the log difference in the underlying price index, the latent factor estimated in the model.

The error terms u_t and ε_t are modeled as AR processes of varying length to produce a model that generates a single smooth dynamic factor. We estimate the system of equations (A.1) and (A.2) by maximum likelihood using the Kalman filter. In addition to estimating a latent factor for total CPI and total PCE, we use equations (A.1) and (A.2) to estimate a latent factor for CPI less food and energy and PCE less food and energy, and a latent factor for CPI less energy and PCE less energy.[21]

[20] A recent paper by Reis and Watson (2010) also estimates a common component in many price series, but it differs from our analysis and the other dynamic factor models because the common component is constrained to have an equiproportional effect on all prices. The factor estimated in their model is not designed to help forecast total inflation.

[21] To reduce the number of parameters to be estimated, it is common in factor analysis models to use a zero mean of the observed variables (π_i). This eliminates the need to estimate α_i and γ in equations (A.1) and (A.2). We also scale each of the price series in our latent factor models by dividing by the standard deviation of the log difference over the period used for the estimation. This is not necessary to identify the model, but it scales the data and the parameters and helps in the optimization process. It also produces a latent factor, ρ, with no trend, so we need to reintroduce a trend in the underlying rate after the estimation. We calculate the trend in two ways. First, we set the trend equal to the average change in the CPI measure. This version of the latent factor is used to compare it to the overall CPI. Second, we set the trend equal to the average change in the PCE measure. This version of the latent factor is used to compare it to overall PCE. The use of different trends helps us compare the average change of the latent factor to the change in the respective measured series. It does not, however, affect the forecast accuracy of the latent factor, since the trend in each case is simply a constant rate of change. The model specification (i.e., lag lengths of u_t and e_t) was determined using data from 1985-2010 and the latent factor is re-estimated each period using rolling regressions from 1996 through 2010. Except for total PCE, the estimated latent factors are less volatile than the corresponding CPI or PCE measures.

We use the same forecast models described above to compare the predictive power of this new measure of underlying inflation to the predictive power of total inflation alone (Tables A.2a and A.2b). As shown, none of the models that include the latent factor produce statistically significantly more accurate forecasts of total CPI or of total PCE than the baseline model, and in one case, a model with the latent factor does significantly worse.

Thus, neither including both standard indexes in the forecasting model nor including a latent factor based on combining the two standard indexes yields more accurate forecasts than the baseline models. These results suggest that while the two measures of inflation differ in the way they are constructed, they do not seem to include independent information that can be exploited to yield statistically significantly better forecasts of each inflation measure.[22]

[22] We repeated our analysis based on a forecasting equation that is estimated using data from August 1987 through December 1996 rather than the rolling regressions. In some cases including both CPI and PCE yielded significantly better forecasts but in other cases, the forecasts were less accurate.

Table A.1a

Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI Using both CPI and PCE Measures and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Baseline Model

Dependent Variable: Total CPI

Independent Variables	Forecasting horizon 6 months	12 months	24 months	36 months	
Baseline Model					
1. Total CPI	2.062	1.520	0.999	0.685	RMSE
Alternative Models without Total Inflation as an Independent Variable					
2. Core CPI, Core PCE	2.062	1.508	1.070	0.566	RMSE
	0.000	0.061	−0.937	1.210	GW Stat
3. CPI Less Energy, PCE Less Energy	2.180	1.546	1.041	0.566	RMSE
	−0.701	−0.136	−0.553	1.135	GW Stat
Alternative Models with Total Inflation as an Independent Variable					
4. Total CPI, Total PCE	2.101	1.603	1.071	0.657	RMSE
	−0.739	−1.015	−0.797	0.256	GW Stat
5. Core CPI, Core PCE, Total CPI, Total PCE	2.132	1.742	1.122	0.647	RMSE
	−1.282	−2.183 †	−1.878 ††	0.543	GW Stat
6. CPI Less Energy, PCE Less Energy, Total CPI, Total PCE	2.111	1.633	1.088	0.571	RMSE
	−0.625	−1.307	−0.987	1.037	GW Stat

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_{t,}$ where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated starting with data from the window August 1987 through December 1995.

* Alternative model is more accurate (i.e., has a significantly lower MSE) than the baseline total inflation model at the 5 percent level of significance.
** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.

† Baseline total inflation model is more accurate than alternative model at 5 percent level of significance.
†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.

Table A.1b

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Using both CPI and PCE Measures and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Baseline Model

Dependent Variable: Total PCE

	Independent Variables	Forecasting horizon: 6 months	12 months	24 months	36 months	
Baseline Model						
1.	Total PCE	1.538	1.168	0.956	0.712	RMSE
Alternative Models without Total Inflation as an Independent Variable						
2.	Core CPI, Core PCE	1.568	1.225	1.020	0.697	RMSE
		−0.834	−0.982	−0.945	0.340	GW Stat
3.	CPI Less Energy,	1.632	1.222	0.977	0.678	RMSE
	PCE Less Energy	−1.358	−1.023	−0.295	0.676	GW Stat
Alternative Models with Total Inflation as an Independent Variable						
4.	Total CPI, Total PCE	1.543	1.218	0.972	0.744	RMSE
		−0.067	−0.395	−0.367	−0.576	GW Stat
5.	Core CPI, Core PCE	1.590	1.349	1.050	0.781	RMSE
	Total CPI, Total PCE	−0.747	−1.519	−1.342	−1.142	GW Stat
6.	CPI Less Energy,	1.576	1.277	1.001	0.709	RMSE
	PCE Less Energy,	−0.493	−1.047	−0.592	0.058	GW Stat
	Total CPI, Total PCE					

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_t,$ where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated starting with data from the window August 1987 through December 1995.

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****** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.

† Baseline total inflation model is more accurate than alternative model at 5 percent level of significance.
†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.

Table A.2a

Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Baseline Inflation Model

Dependent Variable: Total CPI

Independent Variables	**Forecasting horizon** 6 months	12 months	24 months	36 months	
Baseline Model					
1. Total CPI	2.062	1.520	0.999	0.685	RMSE
Alternative Models without Total Inflation as an Independent Variable					
2. Latent Core	1.951	1.497	1.640	1.543	RMSE
	1.092	0.110	−1.188	−1.097	GW Stat
3. Latent Less Energy	1.981	1.468	1.413	1.548	RMSE
	0.722	0.258	−1.337	−1.134	GW Stat
4. Latent Total	2.060	1.528	1.327	1.111	RMSE
	0.016	−0.040	−1.177	−1.178	GW Stat
Alternative Models with Total Inflation as an Independent Variable					
5. Latent Core,	2.037	1.602	1.491	1.538	RMSE
Total CPI	0.340	−0.951	−1.144	−1.101	GW Stat
6. Latent Less Energy,	2.009	1.611	1.426	1.473	RMSE
Total CPI	0.645	−1.430	−1.391	−1.135	GW Stat
7. Latent Total,	2.167	1.601	1.228	1.055	RMSE
Total CPI	−1.670 ††	−1.600	−1.254	−1.220	GW Stat

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_{t,}$ where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated starting with data from the window August 1987 through December 1995.

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****** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.

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†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.

Table A.2b

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model

Dependent Variable: Total PCE

	Independent Variables	Forecasting horizon: 6 months	12 months	24 months	36 months	
Baseline Model						
1.	Total PCE	1.538	1.168	0.956	0.712	RMSE
Alternative Models without Total Inflation as an Independent Variable						
2.	Latent Core	1.501	1.218	1.496	1.593	RMSE
		0.689	−0.443	−1.005	−1.054	GW Stat
3.	Latent Less Energy	1.539	1.211	1.270	1.540	RMSE
		−0.002	−0.526	−1.031	−1.067	GW Stat
4.	Latent Total	1.591	1.279	1.225	1.130	RMSE
		−1.091	−1.095	−0.945	−1.054	GW Stat
Alternative Models with Total Inflation as an Independent Variable						
5.	Latent Core,	1.562	1.245	1.328	1.500	RMSE
	Total PCE	−0.725	−1.396	−1.252	−1.092	GW Stat
6.	Latent Less Energy,	1.563	1.296	1.350	1.392	RMSE
	Total PCE	−0.354	−1.306	−1.462	−1.171	GW Stat
7.	Latent Total,	1.609	1.274	1.156	1.070	RMSE
	Total PCE	−1.038	−1.247	−1.317	−1.316	GW Stat

Note. The forecasting equation is of the form $\pi_{t,t+h} = \alpha + \beta x_{t-12,t} + \varepsilon_{t,}$ where $\pi_{t,t+h}$ is future total inflation over time horizon t to t+h, and $x_{t-12,t}$ is either the 12-month change in core inflation, in total inflation, or both in the multivariate case. The out-of-sample root mean squared errors are those of forecasts from January 1996 through October 2010 generated from fixed-window rolling regressions estimated starting with data from the window August 1987 through December 1995.

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** Alternative model is more accurate than the baseline total inflation model at the 10 percent level of significance.

† Baseline total inflation model is more accurate than alternative model at 5 percent level of significance.
†† Baseline total inflation model is more accurate than alternative model at 10 percent level of significance.