WORKING PAPERS
RESEARCH DEPARTMENT

WORKING PAPER NO. 08-9
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May 2008

RESEARCH DEPARTMENT, FEDERAL RESERVE BANK OF PHILADELPHIA
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Abstract

Two rationales offered for policymakers' focus on core measures of inflation as a guide to underlying inflation are that core inflation omits food and energy prices, which are thought to be more volatile than other components, and that core inflation is thought to be a better predictor of total inflation over time horizons of import to policymakers. Our investigation finds little support for either rationale. We find that food and energy prices are not the most volatile components of inflation and that depending on which inflation measure is used, core inflation is not necessarily the best predictor of total inflation. However, we do find that combining CPI and PCE inflation measures can lead to statistically significant more accurate forecasts of each inflation measure, suggesting that each measure includes independent information that can be exploited to yield better forecasts.

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This paper updates and expands on N.N.K. Khettry and L.J. Mester, "Core Inflation as a Predictor of Total Inflation," *Research Rap Special Report*, Federal Reserve Bank of Philadelphia, April 26, 2006, and revised mimeo, April 30, 2007.

We thank Tom Stark for helpful comments and suggestions on comparing the accuracy of different forecast models and Sally Burke for editorial assistance.

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. However, in October 2007, the FOMC began releasing projections of total PCE inflation along with core PCE inflation.

One 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.[3] Another related rationale that would favor core inflation over total inflation would be 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.

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[1] The CPI is released by the U.S. Department of Labor's Bureau of Labor Statistics and is available on the BLS website at www.bls.gov/cpi. The PCE price index is released by the Bureau of Economic Analysis 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.

This paper seeks evidence on these rationales and more generally on which measures of consumer price inflation yield better predictions of future inflation. Section 1 of the paper reviews the differences between the PCE and CPI. Monthly changes in the CPI are more variable than changes in the PCE price index, but both inflation measures can be quite volatile. Section 2 looks at the volatility of the subcomponents of both measures and describes the most popular candidates for underlying inflation, comparing their volatility to that of the corresponding total inflation measure. Section 3 compares the accuracy of forecasts using the common measures of underlying inflation with forecasts using only the total inflation measure itself. For these comparisons, we update and extend to additional inflation measures the analysis of Blinder and Reis (2005), which found that current core CPI inflation (i.e., CPI less food and energy) is a better predictor of future total CPI inflation than is current total CPI inflation itself. The additional measures of inflation we examine include CPI inflation less energy, monthly personal consumption expenditures (PCE) inflation, monthly core PCE inflation, the Federal Reserve Bank of Cleveland's weighted median CPI, and the Federal Reserve Bank of Dallas's trimmed-mean PCE. As in Blinder and Reis (2005), we present root-mean-squared forecast errors (RMSEs) for the various forecasting models to compare their out-of-sample forecasting accuracy, but unlike Blinder and Reis, we perform tests to determine whether differences in MSEs across the models are statistically significant. Section 4 goes beyond the analysis of Blinder and Reis (2005) by 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 baseline 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 baseline forecasting model. Section 5 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 6 compares our results with other results in the literature, and Section 7 summarizes our findings.

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[3] See Motley (1997) for further discussion.

We find that core inflation, which omits food and energy prices, is less volatile than total inflation, but the reduced volatility comes from omitting the energy components. Several components of the CPI exhibit higher volatility than food prices. And an index that omits food and energy prices demonstrates slightly more volatility than a measure that omits only the energy components and retains the food components. We find that core CPI outperforms total CPI as a predictor of total CPI inflation as indicated by root-mean-squared errors (RMSEs), but there is not a statistically significant improvement in forecast accuracy. The same is true for CPI less energy. Contrary to what is often posited, total PCE inflation outperforms core PCE inflation as a predictor of total PCE inflation as indicated by RMSEs, although the difference is not statistically significant. Perhaps not surprisingly, we find that using final revised data as opposed to preliminary data can yield statistically significant better forecasts. More surprising, we find that while this is true for forecast horizons up to one year, it is not necessarily true for longer horizons.

Perhaps most important, we find that including PCE inflation when forecasting CPI inflation and including CPI inflation when forecasting PCE inflation significantly improves the accuracy of the forecasting model for horizons up to one year. This suggests that each measure of inflation provides independent information that can be exploited to yield statistically significantly more accurate forecasts.

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

While the CPI and the PCE price index both attempt to measure inflation at the consumer level, there are several important differences in their construction. The major differences include the scope of the two indexes, 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. To calculate the CPI, the Bureau of Labor Statistics (BLS) collects price data in 87 urban areas, surveying approximately 50,000 housing units and approximately 23,000 retail establishments.[4] Prices, including directly associated taxes, are collected for a 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.

To 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.[5] 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. Finally, except to update the seasonal adjustment factors, the BLS does not revise the CPI.

The U.S. Department of Commerce's Bureau of Economic Analysis (BEA) publishes the second standard measure of consumer inflation in the U.S, the price index for personal consumption expenditures (PCE). Like the CPI, the PCE proxies the price level faced by consumers. The PCE index, however, 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. 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. For example, the BEA uses the producer price index for the cost of physicians' services, and it imputes the value of financial

[4] 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.

[5] Appendix Table A.1 lists the weights or "relative importance" for various components and special groupings of goods and services of the CPI in December 2006; these weights are based on the Consumer Expenditure Surveys from 2003 and 2004. See www.bls.gov/cex/ for a description of the Consumer Expenditure Survey.

services for which customers are not charged, such as free checking, by combining data on employment in financial institutions with interest rate revenues net of expenditures.[6]

Because the components of the two major price indexes are different, the weights on the components in the two indexes are necessarily different.[7] But another reason the weights differ is that the CPI is a fixed-weight index, whereas the PCE price index is a chain-weight index. This means that the CPI is a sum of price components weighted by consumer expenditure shares that are determined in an initial period. 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, which is never revised, the PCE price index undergoes continual revision.

Despite the differences in the two indexes, the inflation rates computed from the CPI and the PCE follow similar patterns. The correlation in the 12-month change in the two indexes from August 1987 to December 2006 is 0.96. On a year-over-year basis, the PCE index generally registers lower inflation than the CPI (Figure 1). (The average 12-month change from August 1987 to December 2006 was 3.1 percent for the CPI and 2.6 percent for the PCE.[8]) The gap, however, has varied significantly in different time periods, suggesting that the two indexes may convey independent information about the underlying rate of inflation. (We investigate this possibility below.)

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[6] See Clark (1999).

[7] Appendix Table A.2 lists the weights or "relative importance" for various components of the PCE price index in December 2006.

[8] With the effect of compounding, the CPI increased almost 16 percentage points more than the PCE index over this nearly 20-year period.

2. Volatility in the CPI and the PCE Price Indexes and the Search for the Underlying Inflation Rate

The CPI is more volatile than the PCE. Between 1987 and December 2006, the standard deviation of the monthly change in the CPI was 0.22 percentage point and in the PCE, it was 0.17. In both cases, the standard deviation is over 80 percent of the average annualized monthly increase, which suggests considerable volatility in the indexes. As pointed out by Stock and Watson (2007), among others, inflation volatility in the period since 1984 has been lower than in the 1970-1983 period. This is similar to the decline in volatility of many measures of real economic activity since 1984, a period that has been called the "Great Moderation." But as shown in Figure 2, the volatility of both the CPI and the PCE inflation series has increased since the 1990s. Between August 1987 and July 1997, the standard deviation of the monthly change in the CPI was 0.16 and in the PCE, it was 0.14. Between August 1997 and December 2006, these standard deviations increased to 0.26 for the CPI and 0.20 for the PCE.

Some of the components of the two major inflation indexes are considerably more volatile than the overall indexes themselves. The high volatility of some components might reflect large relative price changes, which are unrelated to trend inflation. If so, total inflation, which includes these components, could give false signals about underlying trend inflation. Food and energy prices are often singled out as especially volatile. But do these components exhibit more volatility?[9]

Tables 1a and 1b present the monthly volatility of inflation over the period August 1987 through December 2006 as measured by total CPI, total PCE, their major components, and some special indexes. In both the CPI and PCE, the energy component has been the most volatile, with a standard deviation more than 10 times higher than the standard deviation of the overall CPI and nearly 14 times higher than the standard deviation of the overall PCE price index. This is consistent with Blinder and Reis's (2005) finding that the real price of oil from 1970 to 2004 has shown no upward trend and that oil-price shocks over this period have tended to reverse themselves. Other highly volatile components include transportation, apparel, and commodities. Food prices, which are often assumed to be especially volatile,

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[9] We thank Joel Naroff of Naroff Economic Advisors for suggesting we examine this issue.

are only slightly more volatile than the overall CPI or PCE.

The volatility of the monthly inflation numbers makes it difficult for policymakers to determine the underlying rate of inflation and for forecasters to accurately predict future inflation. Faced with these issues, economists have developed less volatile measures of inflation to try to capture the underlying inflation rate. In recent years, the statements following the Federal Open Market Committee meetings have reflected the Fed's focus on these less volatile measures of inflation. The statements have referred variously to "core inflation" (December 13, 2005), "underlying inflation" (November 1, 2005), or both (August 9, 2005).

2.1. Eliminating a Consistent Set of Components from the Total Inflation Measures

The major efforts to date for defining a less volatile measure of inflation have concentrated on eliminating certain components from the overall measure that are thought to be particularly volatile. The remaining subset of components is then re-weighted to get a more stable measure of inflation. The most frequently used measures of this type are the CPI less food and energy or the PCE less food and energy. In fact, these measures are referred to as "core inflation." In December 2006, expenditures on food accounted for 13.9 percent of the expenditures on all items in the CPI bundle and in the PCE bundle. Expenditures on energy accounted for 8.7 percent of the CPI bundle and 5.5 of the PCE bundle. These items are removed to create the "all items less food and energy" grouping – i.e., core CPI and core PCE – which accounted for 77.4 percent of the total CPI bundle and 80.7 percent of the PCE bundle.

Deleting volatile components, however, does not necessarily result in an index that is less volatile than the whole because of potentially offsetting co-movements among the components. For example, excluding food and energy from the CPI yields an index with less month-to-month variation than that of the total CPI (exhibiting about 0.54 times as much volatility as the overall index: see Table 1a). In contrast, excluding only food from the CPI results in an index that shows more volatility than the total CPI, even though food is (slightly) more volatile than the total CPI.[10] Excluding energy alone from the

[10] There might be other reasons to omit food prices, e.g., some food prices are regulated prices rather than market prices.

CPI yields an index with slightly less volatility than the core and about half as much volatility as that of the total CPI. These results suggest that in addition to core inflation, looking at inflation less energy might be of interest for those trying to obtain a measure or predictor of underlying inflation.

Looking at more finely disaggregated components of the CPI, Clark (2001) also finds that the CPI less energy is less volatile than the CPI. He argues that it is reasonable not to exclude food prices in a measure of underlying inflation for two reasons. First, inflation in the "food away from home" subcomponent of the CPI is very stable: Clark reports that its volatility from 1967 to 1997 was 3.7 percent (as measured by the standard deviation of annualized monthly changes in the level). Second, the relative importance and the volatility of the "food at home" subcomponent have declined over the past 30 years. In Section 3 below, we include CPI less energy and PCE less energy as candidates for the best predictors of total inflation.

2.2. Eliminating a Changing Set of Components from the Total Inflation Measures

The measures discussed so far eliminate the traditionally more volatile components of the CPI or PCE each month to estimate the underlying inflation rate. A second methodology eliminates a certain percentage of the components with the greatest increases or the smallest increases (greatest decreases) in a given month. This methodology potentially uses a different set of components each month to measure the underlying inflation rate. There are two commonly cited measures of this type: the median CPI and the trimmed-mean PCE.

The Federal Reserve Bank of Cleveland computes a monthly inflation measure called the weighted median CPI.[11] The weighted median CPI eliminates the most volatile components of CPI each month regardless of sector. To compute this measure each month, the Cleveland Fed first multiples the monthly change in each of the 41 components of the CPI published by the BLS by an updated measure of the component's relative importance in the total CPI. This measure of relative importance has been

[11] 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.

updated according to the formula (as given in Smith, 2004):

$$RI_{t+1}^{i} = RI_{t}^{i}\left(\frac{1+\pi_t^i}{1+\pi_t}\right), \tag{1}$$

where i is the CPI component, π_t^i is inflation in that component, and π_t is total CPI inflation. These weighted changes are then arranged by size, and the median of these price changes is selected. Half of the expenditures in the month are on components whose price changes are smaller than this component's, and half of the expenditures in the month are on components whose price changes are greater than this component's.

The Dallas Fed computes a trimmed-mean PCE inflation measure based on the component price changes and associated weights as published by the BEA. Like the Cleveland Fed's index, the price changes are ordered from lowest to highest, and 19.4 percent of the weight from the lower tail and 25.4 percent of the higher tail are excluded. Then a weighted average of the remaining components is computed. (The amount trimmed from the lower and upper tails is based on historical data and are determined by what results in the best fit between the trimmed-mean measure of inflation and the core PCE inflation rate.)[12]

The Cleveland Fed's median CPI and the Dallas Fed's trimmed-mean PCE are available monthly on the respective Reserve Bank's website.

3. 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 exists a sizable literature that investigates the prediction of total inflation by various measures of underlying inflation. Cogley (2002) discusses the rationales behind various measures

[12] See the Dallas Fed's website at www.dallasfed.org/data/pce/descr.html.

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 inflation variables as predictors. This choice 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.[13] It is also supported by Stock and Watson (2007)'s 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.)

Our evaluation of inflation forecasts extends the work of Blinder and Reis (2005), who examine whether core or total inflation is a better predictor of future inflation. Four differences between our work and theirs are: (1) we update the sample period – Blinder and Reis's sample ended in March 2005 and ours ends in December 2006; (2) we investigate a richer set of monthly inflation measures: While Blinder and Reis investigate the predictability of total CPI inflation using core CPI inflation, we look at the predictability of total CPI inflation using core CPI, CPI less energy, and the Cleveland Fed's weighted median CPI; and we look at the predictability of total PCE inflation using core PCE, PCE less energy, and the Dallas Fed's trimmed-mean PCE;[14] (3) we estimate models that combine CPI and PCE measures of inflation; and (4) we examine the effects of using real-time data on our results.

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

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

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,

[13] 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.

[14] We thank the BEA for generously sharing with us the monthly data series of PCE less energy.

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

As in Blinder and Reis, 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.[15]

The parameters of each of the models are estimated using data from August 1987 to December 1995. We report the root-mean-squared errors (RMSEs) of the out-of sample forecasts for each of the models from January 1996 through December 2006. 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 fixed window (August 1987 to December 1995). 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. 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.

[15] 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.

Tables 2a and 2b 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. The first number in each row represents the out-of sample RMSE of the forecasts. Our results are similar to Blinder and Reis's (2005) in that we find that core CPI inflation is a better predictor of future total CPI inflation than total CPI inflation itself: i.e., we find that the model that uses core CPI as a right-hand-side variable in the forecasting regression leads to smaller out-of-sample RMSEs than the model that uses total CPI as the sole right-hand-side variable. We also find that the model with CPI less energy, and the model with core CPI and total CPI have lower RMSEs than the baseline total inflation model. (See Table 2a, first four rows.) However, the models with the Cleveland Fed's weighted median CPI and the model with the CPI less energy combined with the total CPI have higher RMSEs than the baseline total CPI model for every forecast horizon we tested.

For the PCE, the results were more uniform. All of the alternative models in Table 2b have higher RMSEs than the baseline total PCE inflation model, with one exception: the model containing both core PCE and total PCE for the 12-month forecast horizon had a very similar RMSE to that of the baseline model.

Note, though, that a lower RMSE does not guarantee a forecast that is statistically significantly more accurate. The Giacomini-White (GW) statistics presented in Tables 2a and 2b test the accuracy of our alternative forecasting models relative to the baseline models with total inflation alone as right-hand-side variable. These statistics indicate that for both the CPI and the PCE, forecasts from the baseline total inflation models for the 6-month and 12-month horizons are statistically significantly more accurate (i.e., have significantly lower MSEs) than some of the alternative models at the 5 percent and 10 percent level of significance. Forecasting total CPI using just total CPI statistically significantly outperforms forecasting total CPI with the Cleveland weighted median and total CPI. Forecasting total PCE using just total PCE statistically significantly outperforms forecasting total PCE with the Dallas trimmed-mean and total PCE or forecasting it with PCE less energy and total PCE. Even though these recent candidates for measures of underlying inflation are less volatile than the total inflation measures, they tend to produce statistically less accurate forecasts of the total inflation measures, at least over horizons up to one year. There is no case in Tables 2a and 2b in which the alternative model produces a statistically significantly more accurate forecast than the baseline total inflation model.

In summary, the results reported in Tables 2a and 2b suggest that the commonly used measures of underlying inflation by themselves are not significantly more reliable predictors of their respective total measure than total inflation itself.

4. 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 standard measures or their components in the forecasting equations. A second way to combine CPI or PCE (or their components) 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.

4.1. Including Both CPI and PCE Measures in the Forecast Models

Tables 3a and 3b 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 3a, for the CPI, the baseline model is never statistically significantly more accurate than any of the alternative models that include measures of both the CPI and the PCE inflation. As shown in Table 3b, for the PCE, the baseline model is statistically significantly more accurate than the alternative model in only one case: the 6-month forecasting model with both standard measures less energy and both total inflation measures as predictors.

Among our alternative models, those models that combine both total CPI and total PCE inflation are more accurate at the 5 or 10 percent level of significance than our baseline models for CPI and PCE.

In summary, including total PCE in the baseline model for the CPI and vice versa significantly improves the accuracy of the baseline forecasting model for each of the standard inflation measures up to a one-year horizon. Thus, the two measures of inflation include independent information that can be exploited to yield statistically significantly better forecasts of each inflation measure.

4.2. 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).[16] We limit our dynamic factor 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. A recent paper by Reis and Watson (2007) 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.

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:

$$\pi_{it} = \alpha_i + \beta_i\rho_t + u_t\,. \tag{5}$$

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

$$\rho_t = \gamma + \delta_1\rho_{t-1} + \delta_2\rho_{t-2} + \varepsilon_t\,, \tag{6}$$

where,

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

[16] 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

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 (5) and (6) by maximum likelihood using the Kalman filter. In addition to estimating a latent factor for total CPI and total PCE, we use equations (5) and (6) to a estimate 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.

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 (5) and (6).[17] 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 models were specified and estimated with data from 1985 to 1995, and the latent factors were then forecasted through 2006. Table 4 shows the estimated yearly inflation rate for the two total series based on the different trends imposed on the latent factor, and the actual inflation rates as given by the BLS and BEA data series.

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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.

[17] 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.

Tables 5a and 5b show the standard deviations of the latent factor inflation rates for the total rates and the total less food and energy and total less energy components. As shown, except for total PCE, the latent factors we have estimated 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 6a and 6b). As shown in Table 6a, for the CPI, our latent factor alone and in combination with the total CPI produces a more accurate forecast of total CPI inflation over the 6-month and 12-month time horizons than forecasting using total CPI inflation alone. As shown in Table 6b, for the PCE, the results for the latent factor models were not as positive. Over the 6-month and 12-month horizons, our baseline model forecasts total PCE more accurately than the model with the latent factor alone.[18] Only when the latent factor is combined with total PCE inflation does the alternative model outperform our baseline model (at the 6-month and 12-month horizons).

Comparing the results in Tables 3a and 3b with those in Table 6a and 6b indicates that including both total CPI and PCE in the forecast models does at least as well in forecasting total inflation over horizons up to one year as does an estimated latent factor based on combining the two standard inflation series.

5. 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 for two reasons. First, when testing potential models, we select a sample period for model estimation, usually by splitting our whole sample into two identically sized samples. The early sample is used for model estimation and the latter for testing forecasting accuracy. If there were significant benchmark revisions of the data, then our model estimation using a revised series does

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[18] The same is true for the model that includes the latent factor less energy and total PCE inflation for the 6-month horizon.

not resemble the true forecasting experience encountered by policymakers and other forecasters. The model should be built with data known at implementation time. Second, if we used a revised series in our accuracy test, then we are assuming that forecasters know exactly what the final revised data will be during each forecast. But this is incorrect because when forecasts are made in practice, they are based on the data in the hands of the forecaster at the time he makes his forecast, rather than the final revised data. A true test of a forecasting model should include conditions present at the time the model would have been implemented.

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").[19] 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.

5.1 Forecasting Model

Using the same model formulation and an in-sample range similar to that in our previous exercises, we used the 1996Q2 vintage to construct a PCE inflation series (hereafter referred to as the 1996Q2 PCE inflation vintage) to emulate the data forecasters had available to estimate the forecast model. The in-sample period runs from 1987Q3 to 1996Q1. For a baseline of comparison, we computed a "final revision" series using our most up-to-date vintage of PCE inflation (hereafter referred to as the 2007Q2 PCE inflation vintage).

We estimate the two regressions, one for the 1996Q2 vintage and one for the 2007Q2 vintage, as

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

follows:

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

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 vintages over four different forecasting horizons: h = 2 quarters, 4 quarters, 8 quarters, and 12 quarters (quarterly equivalents to our monthly horizons used earlier).

Using the two model estimations, we calculated forecasts for the out-of-sample period of 1996Q2 to 2006Q4. For the 1996Q2 vintage model out-of-sample forecast, we created a rolling series to emulate what forecasters had available to them during each quarterly forecast. We accomplished this by calculating the 4-quarter growth rate for the real-time PCE index, $x_{t-4,t,}$ using the vintage series available to forecasters during the quarter in question and incrementing forward in vintages with each subsequent quarter. In the end, we were left with a series containing PCE estimates based on preliminary data. For the 2007Q2 vintage model out-of-sample forecast, we used the 2007Q2 vintage of PCE inflation.

For each model over the 4 forecasting horizons, we calculate RMSEs to evaluate forecasting errors and the Giacomini-White statistic to compare our real-time forecasting model (1996Q2 vintage with rolling real-time series) with the baseline model (2007Q2 vintage).

5.2 Results

Table 7 shows the results for this set of regressions. The real-time PCE forecasting model had larger RMSEs in the 2-, 4-, and 8-quarter forecasting horizons, but had a smaller RMSE than the final data model for the 12-quarter horizon. The Giacomini-White statistic indicates that the final-data model is a statistically significantly more accurate forecasting model than the real-time model for the 2-quarter and 4-quarter horizons (at the 10 percent and 5 percent levels, respectively). Over the other forecasting horizons neither model is statistically better. Thus, revisions to PCE inflation do not necessarily improve forecasting effectiveness; it depends on forecast horizon.

6. 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), and Smith (2004), 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, which differs slightly from ours, is:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi_t^{ALT}) + \varepsilon_{t+h} \qquad (9)$$

where π_{t+h} is the annualized h-quarter-ahead inflation rate with h corresponding to the forecasting horizon, π_t is the current annualized quarterly inflation rate, and π_t^{ALT} is the current annualized alternative inflation rate. They do not look at total inflation's ability to predict future total inflation as we do (following Blinder and Reis), but they do look at the out-of-sample RMSEs of forecasts of total inflation using various alternative measures of inflation. They do not test whether the difference in RMSEs are statistically significant.

Rich and Steindel 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. Our out-of-sample prediction results for the PCE and its alternatives are consistent with those of Rich and Steindel: there is no clear best performer. But our results for the CPI differ. We find that the CPI less food and energy is a better forecaster of total CPI than is CPI less energy at all forecasting horizons, and we find that both of these are clearly superior to the weighted median CPI.[20] In contrast, Rich and Steindel find that the weighted median gives the best forecast performance at longer forecast horizons.

Clark (2001) estimates the same model as Rich and Steindel, which differs slightly from ours, using CPI and its less volatile alternatives; he does not study the PCE. He compares the in-sample forecasting performance using regression R-squared goodness-of-fit measures; he does not compute out-of-sample RMSEs.[21] He runs regressions using two different sample periods (1967-2000 and 1985-2000) and two forecasting horizons (12 months and 24 months). With the longer sample, he finds that only CPI less energy has statistically significant predictive power of total CPI at the 12-month forecasting horizon. It is also the best predictor at the 24-month forecasting horizon, but the trimmed-mean CPI and median CPI are also statistically significant predictors at this forecasting horizon. All alternative CPI measures are found to be statistically significant in the shorter sample regressions. The CPI less energy is the best forecaster at the 12-month forecasting horizon, while the median CPI is the best at the 24-month forecasting horizon.

Clark's shorter sample period is closest to the sample period we studied, and our findings are consistent with Clark's in that the in-sample standard error for the 12-month forecasting horizon is the smallest when the CPI less energy is used. However, we find that CPI less energy continues to show the lowest RMSE when the forecasting horizon is extended to 24 months. In contrast, Clark finds that the

[20] In addition to using a different forecasting model and sample period, we measure total inflation by the monthly 12-month percentage change, while Rich and Steindel use the quarterly percentage change.

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

median CPI is the best in this case. Additionally, Clark's overall results for the short sample suggest that core CPI is the weakest of all the candidates in terms of predictive power; we find that it is the strongest when judged by RMSE.

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 of the form,

$$\pi_{t,t+h} = x_{t-1,t} + \beta x_{t-2,t-1} + \beta^2 x_{t-3,t-2} + \ldots + \beta^{24} x_{t-25,t-24} + \varepsilon_{t+h} \tag{10}$$

where π_{t+h} is the annualized h-quarter-ahead inflation rate with h corresponding to the forecasting horizon, x is the alternative inflation rate for the specified month in the past, and the β coefficients sum to one. Smith finds that the median CPI outperforms the CPI, the trimmed-mean CPI, and the core CPI as a predictor of future CPI.[22] She also finds that median PCE outperforms the PCE and the core PCE as a predictor of future PCE.

7. 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. This actually produces a series that demonstrates slightly more volatility than a measure that omits only the energy components and retains the food components.

[22] 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.

We find that since August 1987, core CPI inflation (i.e., total CPI less food and energy) performs better (as indicated by root-mean-squared error) as an out-of-sample predictor of total CPI inflation than the total CPI, and the Cleveland Fed's weighted median CPI; core CPI and the CPI less energy perform nearly equally as well. This suggests that even if policymakers have total CPI inflation in their loss function, they might want to focus on core CPI inflation as an indicator of underlying inflation rather than total CPI inflation over short time horizons. We note, however, that in most cases, the improvement in forecast accuracy is not statistically significant.

Based on our results, we cannot reach a similar conclusion for the PCE, because contrary to what is often posited, and in contrast to the CPI, we find that total PCE inflation outperforms core PCE inflation as a predictor of total PCE inflation (as indicated by RMSEs), although the difference is not statistically significant.

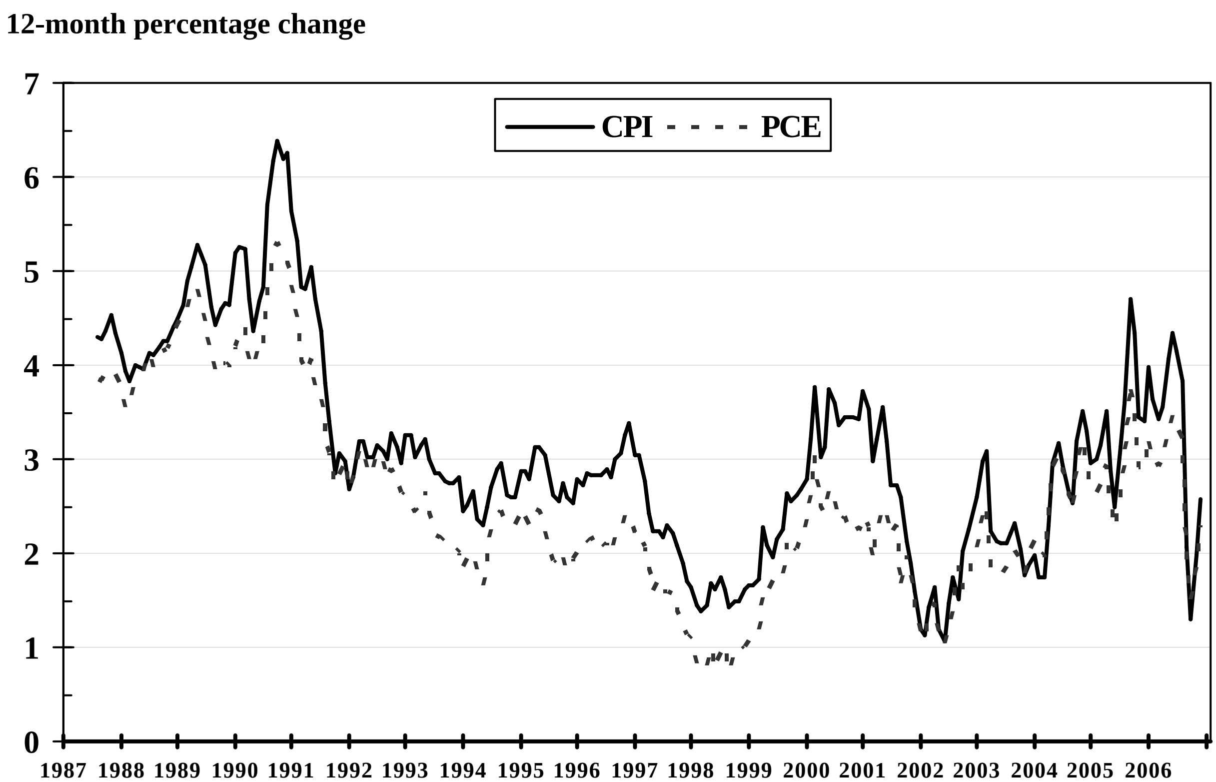
Perhaps not surprisingly, we find that revised data can yield statistically significantly better forecasts than preliminary data. More surprising, we found this to be true at forecast horizons up to one year, but not necessarily at longer forecast horizons.

Importantly, we find that statistically significantly better forecasts are obtained when information from both inflation measures, CPI and PCE, are used when forecasting the other measure. Thus, there is independent information in each measure that can be exploited to yield significantly better forecasts.

Finally, we note that the results on 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 MSEs across our forecasting models were not statistically significant. Combining information from the CPI and PCE seems to hold the most promise of improved forecasts.

Figure 1

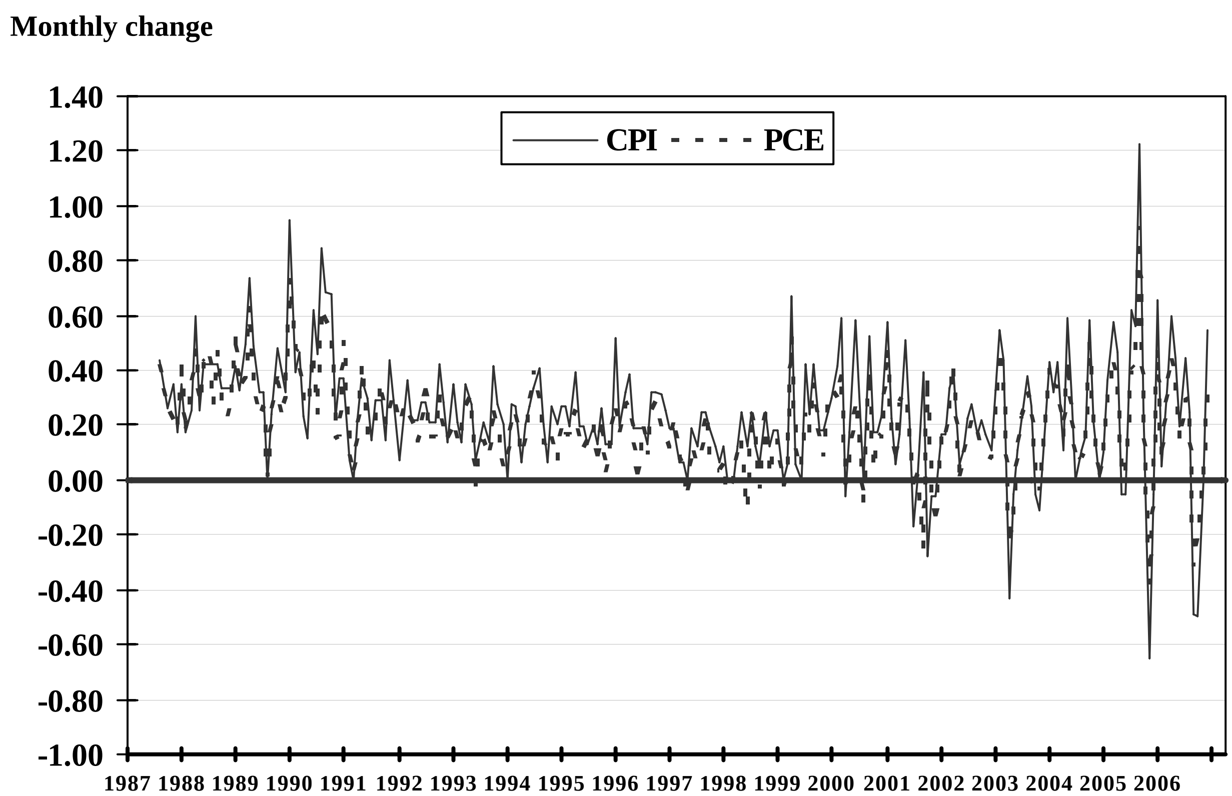
12-Month Change in the CPI and PCE



Monthly data, August 1987 – December 2006
Source: BLS, BEA, and Haver Analytics

Figure 2

Monthly Change in the CPI and PCE



Monthly data, August 1987 – December 2006
Source: BLS, BEA, and Haver Analytics

Table 1a
Monthly Volatility in Inflation as Measured by CPI and Its Components

	Average Monthly Change %	Standard Deviation	Ratio of Standard Deviation of Component to Standard Deviation of Overall Index
CPI-U: All Items	0.249	0.219	1.000
Major Components			
CPI-U: Food	0.236	0.250	1.142
CPI-U: Energy	0.352	2.308	10.539
CPI-U: Food and Beverages	0.237	0.229	1.046
CPI-U: Housing	0.254	0.148	0.676
CPI-U: Apparel	0.037	0.489	2.233
CPI-U: Transportation	0.225	0.974	4.447
CPI-U: Medical Care	0.413	0.173	0.790
CPI-U: Other Goods and Services	0.402	0.506	2.311
CPI-U: Commodities	0.177	0.463	2.114
CPI-U: Services	0.301	0.123	0.562
Special Indexes			
CPI-U: All Items Less Food and Energy	0.243	0.119	0.543
CPI-U: All Items Less Food	0.251	0.242	1.105
CPI-U: All Items Less Energy	0.242	0.112	0.511

Note. Standard deviation of monthly percentage changes in each index from August 1987 through December 2006

Table 1b
Monthly Volatility in Inflation as Measured by the PCE Price Index and Its Components

	Average Monthly Change %	Standard Deviation	Ratio of Standard Deviation of Component to Standard Deviation of Overall Index
PCE: All Items	0.208	0.175	1.000
Major Components			
PCE: Food	0.209	0.184	1.051
PCE: Energy goods and services	0.359	2.441	13.966
PCE: Housing	0.271	0.114	0.653
PCE: Clothing and shoes	−0.036	0.547	3.132
PCE: Transportation	0.251	0.461	2.640
PCE: Medical care	0.341	0.177	1.015
PCE: Durable goods	−0.057	0.254	1.452
PCE: Nondurable goods	0.190	0.470	2.691
PCE: Services	0.276	0.146	0.834
Special Indexes			
PCE: All Items Less Food and Energy	0.201	0.135	0.771
PCE: All Items Less Energy	0.202	0.126	0.723

Note. Standard deviation of monthly percentage changes in each index from August 1987 through December 2006.

Table 2a

Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI Using only Measures from the Respective Indexes (January 1996 through December 2006) and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model

Dependent Variable: Total CPI

Independent Variables	**Forecasting horizon** 6 months	12 months	24 months	36 months		
Total CPI	1.252	1.008	0.843	0.661	RMSE	Baseline model
Core CPI	1.224	0.958	0.791	0.570	RMSE	
	0.23	0.39	0.30	0.57	GW Stat	
Core CPI, Total CPI	1.180	0.989	0.807	0.608	RMSE	
	0.80	1.56	0.89	0.90	GW Stat	
CPI Less Energy	1.221	0.967	0.792	0.583	RMSE	
	0.26	0.33	0.33	0.55	GW Stat	
CPI Less Energy,	1.843	1.150	0.872	0.598	RMSE	
Total CPI	−2.02††	−0.70	−0.13	0.38	GW Stat	
Cleveland Fed	1.438	1.184	0.927	0.654	RMSE	
Weighted Median CPI	−1.59	−1.47	−0.69	−0.07	GW Stat	
Cleveland Fed	2.098	1.482	0.984	0.683	RMSE	
Weighted Median CPI, Total CPI	−2.77††	−2.03††	−0.91	−0.23	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 December 2006 generated from forecasts estimated using data from August 1987 through December 1995.

†† 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 2b

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Using only Measures from the Respective Indexes (January 1996 through December 2006) 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		
Total PCE	0.920	0.740	0.726	0.661	RMSE	Baseline model
Core PCE	0.998	0.824	0.869	0.874	RMSE	
	−0.71	−0.68	−0.82	−1.26	GW Stat	
Core PCE, Total PCE	1.006	0.730	0.796	0.838	RMSE	
	−0.77	0.16	−0.59	−1.23	GW Stat	
PCE Less Energy	0.938	0.774	0.772	0.732	RMSE	
	−0.22	−0.38	−0.39	−0.69	GW Stat	
PCE Less Energy,	1.270	0.819	0.798	0.750	RMSE	
Total PCE	−2.02††	−0.73	−0.51	−0.75	GW Stat	
Dallas Fed Trimmed-	0.979	0.833	0.787	0.700	RMSE	
Mean PCE	−0.87	−1.15	−0.52	−0.37	GW Stat	
Dallas Fed Trimmed-	1.623	1.345	1.078	0.962	RMSE	
Mean PCE, Total PCE	−3.21††	−2.42††	−1.24	−1.03	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 December 2006 generated from forecasts estimated using data from August 1987 through December 1995.

†† 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 3a

**Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI Using both CPI and PCE Measures (January 1996 through December 2006)
and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model**

Dependent Variable: Total CPI

Independent Variables	**Forecasting horizon** 6 months	12 months	24 months	36 months		
Total CPI	1.252	1.008	0.843	0.661	RMSE	Baseline model
Total CPI, Total PCE	1.081	0.762	0.638	0.508	RMSE	
	2.16**	1.76*	1.10	0.90	DW Stat	
Core CPI, Core PCE	1.075	0.738	0.620	0.559	RMSE	
	1.46	1.61	1.08	0.62	DW Stat	
Core CPI, Core PCE	1.227	0.970	0.825	0.650	RMSE	
Total CPI, Total PCE	0.19	0.36	0.12	0.07	DW Stat	
CPI Less Energy,	1.081	0.766	0.614	0.494	RMSE	
PCE Less Energy	1.50	1.56	1.17	1.00	DW Stat	
CPI Less Energy,	1.461	0.805	0.622	0.529	RMSE	
PCE Less Energy,	−1.00	1.23	1.14	0.79	DW 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 December 2006 generated from forecasts estimated using data from 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 3b

**Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Using both CPI and PCE Measures (January 1996 through December 2006)
and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model**

Dependent Variable: Total PCE

Forecasting horizon

Independent Variables	6 months	12 months	24 months	36 months		
Total PCE	0.920	0.740	0.726	0.661	RMSE	Baseline model
Total CPI, Total PCE	0.843	0.641	0.619	0.612	RMSE	
	2.04**	2.10**	1.37	0.65	DW Stat	
Core CPI, Core PCE	0.923	0.724	0.696	0.753	RMSE	
	−0.03	0.19	0.39	−1.14	DW Stat	
Core CPI, Core PCE	1.127	0.706	0.713	0.779	RMSE	
Total CPI, Total PCE	−1.56	0.76	0.16	−1.13	DW Stat	
CPI Less Energy,	0.894	0.720	0.644	0.635	RMSE	
PCE Less Energy	0.35	0.28	1.30	0.63	DW Stat	
CPI Less Energy,	1.328	0.752	0.629	0.612	RMSE	
PCE Less Energy,	−2.18††	−0.14	1.39	0.63	DW 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 December 2006 generated from forecasts estimated using data from 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 4

The Underlying Rate of Inflation Estimated from the Dynamic Factor Model 1987-2006 (Latent Model Combining Total CPI and Total PCE)

Date	Underlying Inflation Rate Based on Trend of CPI	CPI Inflation Rate (Dec/Dec)	Underlying Inflation Rate Based on Trend of PCE	PCE Inflation Rate (Dec/Dec)
1987	4.3	4.3	3.9	3.9
1988	4.4	4.4	4.0	4.3
1989	4.6	4.6	4.2	4.0
1990	6.2	6.3	5.8	5.1
1991	3.0	3.0	2.6	3.0
1992	3.0	3.0	2.5	2.6
1993	2.8	2.8	2.4	2.0
1994	2.6	2.6	2.2	2.3
1995	2.5	2.5	2.1	2.0
1996	3.3	3.4	2.9	2.4
1997	1.7	1.7	1.3	1.1
1998	1.6	1.6	1.2	1.0
1999	2.7	2.7	2.2	2.2
2000	3.4	3.4	2.9	2.2
2001	1.6	1.6	1.2	1.5
2002	2.4	2.4	2.0	2.0
2003	1.9	1.9	1.5	2.0
2004	3.3	3.3	2.9	3.0
2005	3.4	3.4	3.0	2.9
2006	2.6	2.6	2.2	2.3

Table 5a

Monthly Volatility in Inflation as Measured by the Latent Indexes (CPI Trended)

	Average Monthly Change %	Standard Deviation	Ratio of Standard Deviation to Standard Deviation of Corresponding Measure from CPI
Latent: Total	0.248	0.214	0.979
Latent: Total Less Food and Energy (Core)	0.242	0.114	0.962
Latent: Total Less Energy	0.240	0.103	0.923

Standard deviation of monthly percentage changes in each index, from August 1987 through December 2006 based on a model estimated from 1985 to 1995.

Table 5b

Monthly Volatility in Inflation as Measured by the Latent Indexes (PCE Trended)

	Average Monthly Change %	Standard Deviation	Ratio of Standard Deviation to Standard Deviation of Corresponding Measure from PCE
Latent: Total	0.213	0.214	1.225
Latent: Total Less Food and Energy (Core)	0.201	0.114	0.847
Latent: Total Less Energy	0.202	0.103	0.820

Standard deviation of monthly percentage changes in each index, from August 1987 through December 2006 based on a model estimated from 1985 to 1995.

Table 6a

Out-of-Sample Root Mean Squared Errors of Forecasting Total CPI Using Measures from the Respective Indexes and the Latent Variables (January 1996 through December 2006) and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model

Dependent Variable: Total CPI

Independent Variable	**Forecasting horizon** 6 months	12 months	24 months	36 months		
Total CPI	1.252	1.008	0.843	0.661	RMSE	Baseline model
Latent Total	1.245	0.998	0.836	0.656	RMSE	
	2.52**	1.81*	1.11	0.90	GW Stat	
Latent Total, Total CPI	1.147	0.864	0.721	0.555	RMSE	
	2.37**	1.81*	1.17	1.02	GW Stat	
Latent Core	1.224	0.953	0.793	0.581	RMSE	
	0.21	0.40	0.27	0.48	GW Stat	
Latent Core, Total CPI	1.198	0.948	0.781	0.585	RMSE	
	0.48	1.33	0.70	0.73	GW Stat	
Latent Less Energy	1.136	0.853	0.726	0.583	RMSE	
	0.95	1.04	0.66	0.50	GW Stat	
Latent Less Energy,	1.292	0.903	0.782	0.634	RMSE	
Total CPI	−0.22	0.59	0.31	0.16	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 December 2006 generated from forecasts estimated using data from 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 6b

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Using Measures from the Respective Indexes and the Latent Variables (January 1996 through December 2006) and Giacomini-White Statistics for Differences in Accuracy between Alternative Model and Total Inflation Model

Dependent Variable: Total PCE

Independent Variable	**Forecasting horizon** 6 months	12 months	24 months	36 months		
Total PCE	0.920	0.740	0.726	0.661	RMSE	Baseline model
Latent Total	1.035	0.873	0.808	0.668	RMSE	
	−2.62††	−1.77†	−0.97	−0.12	GW Stat	
Latent Total, Total PCE	0.839	0.636	0.616	0.613	RMSE	
	2.01**	2.09**	1.36	0.62	GW Stat	
Latent Core	1.132	0.972	0.898	0.752	RMSE	
	−1.44	−1.23	−0.70	−0.52	GW Stat	
Latent Core, Total PCE	0.912	0.823	0.846	0.692	RMSE	
	0.22	−1.55	−1.11	−0.31	GW Stat	
Latent Less Energy	0.965	0.806	0.793	0.738	RMSE	
	−0.48	−0.64	−0.48	−0.66	GW Stat	
Latent Less Energy,	1.474	0.893	0.814	0.741	RMSE	
Total PCE	−2.41††	−1.08	−0.56	−0.67	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 December 2006 generated from forecasts estimated using data from 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 7

Out-of-Sample Root Mean Squared Errors of Forecasting Total PCE Inflation Using Real-Time Data Series (GW statistic in parentheses)

Model	**Independent Variable**	**Forecasting horizon**				
		2 quarters	4 quarters	8 quarters	12 quarters	
2007Q2 PCE	2007Q2 PCE	0.842	0.694	0.739	0.695	Final revised data model
1996Q2 PCE	Rolling PCE Series	0.911	0.793	0.756	0.651	Real-time data model
		(−1.66) †	(−2.23) ††	(−0.32)	(0.26)	

†† 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.

Appendix

Table A.1

CPI Relative Importance (Weights) by Expenditure Category and for Special Groupings, as of December 2006 (in percent)

Index	Relative Importance
Total	100.000
Food and beverages	14.992
Food	13.885
Housing	42.691
Household energy	4.368
Apparel	3.726
Transportation	17.249
Motor fuel	4.347
Medical care	6.281
Recreation	5.552
Education and communication	6.034
Other goods and services	3.476
All items	100.000
All items less energy	91.285
All items less food	86.115
All items less food and energy	77.401
Services	59.695
Services less energy services	55.666
Commodities	40.305
Commodities less food	26.420
Commodities less food and energy commodities	21.735
Nondurables	29.183
Nondurables less food	15.299
Energy	8.715
Energy commodities	4.685

Source: U.S. Department of Labor, Bureau of Labor Statistics, www.bls.gov/cpi/cpiri2006.pdf.

Table A.2

PCE Relative Importance (Weights) by Expenditure Category, as of December 2006 (in percent)

Index	Relative Importance
Personal Consumption Expenditures (PCE)	100.000
PCE less energy goods and services	94.529
PCE less food	86.131
PCE less food and energy goods and services	80.660
Food	13.869
Services	59.690
Services less electricity and gas	57.564
Durables	11.283
Nondurables	29.027
Nondurables less food	15.158
Nondurables less gasoline, fuel oil, and other energy goods	25.475
Energy goods and services	5.471
Gasoline, fuel oil, and other energy goods	3.345
Electricity and gas	2.126

Source: Bureau of Economic Analysis, Table 2.3.5U.
Note. Weights were calculated from nominal category totals for December 2006. Exact proportions in the price index are not available due to BEA's chain-weighting methodology. See www.bea.gov/bea/dn/nipaweb/nipa_underlying/SelectTable.asp.

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