

Real time underlying inflation gauges for monetary policy makers*

Marlene Amstad and Simon M. Potter

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Abstract

Central banks analyze a wide range of data to obtain better measures of underlying inflationary pressures. Recently, factors models have been used to statistically formalize this procedure. This paper complements the existing literature by developing a measure of underlying inflation (UIG) that can be updated at a daily frequency and that is not sensitive to data revisions or seasonal adjustment revisions. Unlike previous factor approaches in the US, we utilize all of the 211 price series underlying the monthly CPI release in the U.S. We apply these methods to isolate the underlying U.S. inflation movements of relevance for monetary policymakers for both the consumer price index and the personal consumption deflator. We show that the UIG outperforms traditional core type measures.

JEL classification: C13; C33; C43; E31;E37

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“Although it is conceptually easy to survey the prices of individual commodities at any given time, using them to produce a measure appropriate for monetary policy is far from straightforward.” Cecchetti (1997).

1 Introduction

The Consumer Price Index (CPI) and Personal Consumption Expenditure Deflator (PCE) released each month are the two main measures of price inflation for consumers in the U.S. From a monetary policy perspective the “headline” measures of both series are too volatile to be used as a measure for underlying inflation. For example, in September 2005 the headline CPI increased at a 14% annualized rate and in November 2005 it decreased at a 8% annualized rate. Consequently there had been major efforts in measuring inflation pressures and extracting the underlying component out of the monthly inflation releases. The most common approach is to permanently exclude prices of volatile commodity type goods and derived services and usually the resulting measure of inflation is called the core. In the U.S. the core measures of the CPI and PCE exclude the food and energy subcomponents (XFE)¹. Another related approach excludes the goods or services with the largest price movements (both up and down) each month. In the U.S. such trimmed mean and median measures are calculated by the Cleveland and Dallas Federal Reserve Banks². Other approaches weight the CPI sub-components by their volatility contribution instead of completely excluding volatile components.

All of the approaches discussed so far do not take into account the time dimension. For example, energy prices are very volatile but before excluding them from a measure of underlying inflation one should examine how persistent are their changes. Modern computing power and new statistical techniques now make it possible to simultaneously combine information from both cross-sectional dispersion of prices as well as time-series properties of individual prices in a unified framework. The statistical techniques are known as large data factor models and are starting to be widely used by

¹Bryan and Cecchetti (1999) give an overview of different additional components excluded from CPI by different central banks.

²See Bryan, Cecchetti (1994) for fixed trimming and Bryan, Cecchetti, Wiggins (1997) for time varying percentages. Dolmas (2005) describes the construction of the trimmed mean PCE.

Central Banks to complement existing measures of underlying inflation and real activity³. This paper adds to this literature by developing a measure of underlying inflation in the US that can be updated at a daily frequency and that is not sensitive to data revisions or seasonal adjustment procedures. Unlike previous factor approaches in the US we utilize all of the 211 price series underlying the monthly CPI release in the U.S. and use the dynamic factor approach of Forni et. al. (2001) to isolate the different persistence of these price series.⁴

Our new factor based measure of underlying inflation complements the existing measures of core and underlying inflation available to monetary policy makers. An extensive literature on core and underlying inflation comparisons conclude that there is no single core inflation measure which outperforms the others on all criteria⁵. We use our dynamic factor approach to develop underlying measures of inflation for both the CPI and PCE indices, which we name `CPI_UIG` and `PCE_UIG`. As many economic variables affect the inflation process we do not restrict ourselves to price data only. Instead we also allow for a broad range of nominal, real and financial variables to influence the measure of underlying inflation. Our use of daily updates, following Amstad and Fischer (2004), allows us to derive the impact of a particular data release (e.g. unemployment rate or ISM) on underlying inflation and compare the reaction of our measure to that in the nominal and indexed linked treasury market in the U.S. Furthermore we show that the UIG measures outperform traditional cores in terms of forecasting.

The remainder of the paper is organized as follows. Section 2 discusses a range of measures of underlying inflation and relates them to the underlying inflation gauges introduced in this paper. Section 3 describes the data environment used for the real time underlying inflation gauges and gives a non-technical description of the used estimation procedure. A technical de-

³For inflation in the Euro Area see Cristadoro et al. (2001). For inflation in Switzerland the SNB produces DFI (dynamic factor inflation) which is evaluated daily and published monthly, see Amstad, Fischer (2004, 2005a,b). For a quarterly inflation measure in New Zealand see Giannone, Matheson (2006). For GDP in the Euro Area CEPR produces EuroCoin, which is publicly available on a monthly basis (see Altissimo et al. (2001)). For the US there is the Chicago Fed National Activity Index based on the methods of Stock and Watson (1999).

⁴Recently, Reis and Watson (2007) have used dynamic factor models for the disaggregate components of the PCE price index. The underlying source for most of the prices used in the PCE is from the BLS survey used to construct the CPI.

⁵See e.g. Rich and Steindel (2007) and therein given references.

scription is given in the Appendix. In section 4 differences between core concepts and benchmark series are described. Section 5 reports on the practical experience of using the UIG in the briefing process at FRBNY in real time since mid 2005. Section 6 concludes and is followed by the technical appendix.

2 Underlying inflation concepts

In this section we review the concept of underlying inflation. The review motivate our choice of methodology, data set and parameterization of the dynamic factor model. The term “core inflation” is widely used by practitioners as well as in academics to represent an inflation measure that is less volatile than the headline measure. However, there exists no exact and widely accepted definition of underlying inflation. Consider any observed total inflation rate (e.g., CPI, PCE) π_t , we can always decompose it as:

$$\pi_t = \pi_t^* + c_t,$$

1. Underlying rate of inflation π_t^*
2. Deviations from underlying rate, c_t

Some examples used to measure underlying inflation in US are

1. Traditional core: for both CPI and PCE excludes all food and energy goods and services. This exclusion also includes “food away from home”, most other countries just exclude fresh food since “food away from home” is not very volatile.
2. Core ex energy: for both CPI and PCE excludes all energy good and services.
3. Core PCE Market Based: excludes all food and energy goods and services and a number of imputed prices for financial and medical services.
4. Median CPI: inflation is measured as the good or service with median price change, where the median is defined by expenditure shares.
5. Trimmed Mean CPI/PCE: excludes goods and services with the largest price movements. For example, the 8% trimmed mean would exclude good and services whose price movements were in the bottom 8% and top 8%.

6. Model-based approaches which try to derive the core inflation from economic theory. Examples are Quah and Vahey (1995) and forecasts from Gordon “triangle” type models less “exogenous” variables. The triangle model is a common approach to modeling inflation in the Federal Reserve System (see Rudd and Whelan 2007).
7. Unobserved Component Models. These are time series methods that attempt to extract a persistent component of inflation. Simple univariate examples are the Exponential Smoothed Inflation of Cogley (2002) and model of Stock and Watson (2007). More complex multivariate examples are the Chicago Fed National Activity Index and the model presented in this paper.
8. Measures from financial markets and surveys of inflation expectations.

We take the stand of a policy oriented concept and define underlying inflation as “an inflation measure free of aspects, which should not affect policy maker’s decision”. We can express this feature mathematically as

$$E_t [\pi_{t+h}] \longrightarrow E_t [\pi_{t+h}^*] \text{ as } h \text{ increases.}$$

That is, the policy maker is reacting to changes in underlying inflation such that actual inflation converges to it in expectation. Note that if $E_t [\pi_{t+h}^*]$ satisfies the above property then it implies $E_t [c_{t+h}] \longrightarrow 0$. Thus, any successful measure of underlying inflation should capture a long-run, persistent component in inflation at the horizon of interest to policy makers. This is different from the measure simply being a less volatile inflation series.

2.1 Exclusion measures of underlying inflation

Traditional core inflation indicator became popular in the 1970s as headline inflation was influenced severely by the oil price shocks. This experience triggered the construction of a variety of different “CPI ex some subcomponent” gauges, either in the form of excluding always the same subcomponents (as in the ex food ex energy approach, XFE) or time varying subcomponents (as in the trimmed mean approach, TM). However, the concept of reaching a smoother signal by excluding volatile components suffers from some disadvantages. (i) In the XFE approach the specific subcomponent to be removed can only be determined in a backward looking manner after the

“noise” showed up. (ii) In the TM approach the subcomponents to be excluded are determined by a technical criterion: usually the cut-off percentage (whether symmetrically or not) is fixed by minimizing the RMSE of a trend inflation forecast - for example, defined as 36 month moving average. However, by excluding components and following only the stable ones one risks removing not only volatility but also early signals of changes in the inflation process, which tend to catch up in the tails of the price change distribution. Therefore, even though the average forecast error might be low in a excluding approach, the core gauge might still be lagging at turning points. Related to that, the core measures based on the exclusion of CPI subcomponents were recently confronted with increasing criticism⁶. Supposed that the oil price increase of the recent years is to be considered as a signal in price trend⁷ and not as temporary outliers. In this case excluding the direct effects of oil would be misleading or at least produce a lagged inflation signal. This demonstrates the need for underlying measures which are able to smooth short term volatility in inflation without neglecting potentially informative price changes.

2.2 Time series models of underlying inflation

One of the most prominent differences between XFE-,TM approaches and time series model based approaches is that the later is not limited to CPI and a few subcomponents. As Bernanke and Boivin (2003) argue monetary policy needs to make its choices in a "data-rich environment". Furthermore Stock and Watson (1999) showed that taking into account a broad information set can improve forecasting. Therefore, it is stated by several authors (including Gali (2001)) that from a policy maker's perspective it would be beneficial to have a comprehensive measure which extracts and summarizes the inflation relevant information from a broader data set.

One traditional approach based on Gordon (1982) is to estimate a backward looking Phillips curve type model with additional covariates to capture exogenous pricing pressures such as energy. Underlying measures can then be produced by setting the future value of exogenous covariates and gener-

⁶In particular critics argue along the line that the XFE and TM approach exclude inflation by definition as they seem to follow an approach of “without the items that are going up in price, there is no inflation”.

⁷E.g., as a result that oil prices are driven mostly by long term demand than short term supply disruptions.

ating forecasts from the model. For example, one could use future prices on energy.

A criticism of these traditional approaches is that they are very sensitive to the exact specification chosen. We investigate the use of a new statistical technique, dynamic factor modeling (DFM) that allows us to extract information from a very large data set. The first source of additional data is the inflation release itself. In the various exclusion measures specific detail on some individual goods and service prices is used to generate the underlying measure. DFM techniques allow us to use all the detail in the monthly US CPI inflation report. Further, the DFM techniques we use explicitly consider whether a large movement in a particular price is likely to persist or not. If the price move is likely to persist it will influence the estimate of underlying inflation. In contrast traditional exclusion measures will initially ignore the large price movement.

There are many other time series which are potentially of interest to be included to determine underlying inflation. Particularly, there is information about the future price pressure incorporated in real variables. Slack in product and labor market are well-known possible driving factors of inflation. However, in evaluating core measures this information has gone unused so far, as XFE and TM gauges rely on CPI and subcomponents only. Further, standard Phillips curve models rely on one measure of slack and are vulnerable to specification errors in this regard. The DFM approach allows summarizing a broad information set with regard to price pressure in a formal and systematic way (see Stock and Watson 1999). The correlations between the variables are considered without imposing any restriction on sign or extent. This differs with strong assumptions often made e.g., in SVAR-models.

2.3 Measures of underlying inflation and inflation targets

A growing number of countries establish their monetary policy more or less explicitly according an inflation target. In these countries the information on the inflation targeting regime is useful for constructing the measure of underlying inflation. In particular if the country has a point target then the average of the underlying measure should be at this point target. A feature of the DFM technique we use is that it does not directly provide an estimate of the average of the underlying measure. Thus, in countries with inflation

targets the target can be used as the average. The US does not have an inflation target but we will assume implicitly that the target is close to the recent average of inflation in the US in our estimation.

2.4 Financial market and survey measures of underlying inflation

Financial markets now produce measures of expected inflation at various horizons from the difference in yields between nominal debt and debt indexed to an inflation measure. One approach would be to take the expected inflation at the policy horizon from financial market as a measure of underlying inflation. These measures are available at the daily or higher frequency. In addition, there are various surveys of professional economic forecasters and consumers that generate additional information on expected inflation. We view these measures as a useful benchmark for a central banks own measure of underlying inflation. For various technical reasons one would not expect these measures of expectations to be equal to the central bank’s measure of underlying inflation. But one would expect that the changes would be highly positively correlated with the underlying measure used by the central bank. Further, the volatility of these measures relative to the central bank’s underlying measure would be of interest.

3 Underlying inflation gauge (UIG)

We use dynamic factor modelling techniques to estimate underlying inflation. We call our estimate the “Underlying Inflation Gauge” (UIG). The UIG is set up as a monthly model which is updated daily as proposed in Amstad and Fischer (2004) for Swiss data. The monthly basis is motivated by monthly frequency of inflation reports in the U.S. The daily updates allow us to give a daily estimation of monthly underlying inflation. This allows us to follow the inflation process closer and especially allows monetary policy makers to assess movements in inflation expectations in financial markets.

3.1 Data

Based on substantial previous work on structural breaks in the US inflation process (see Clark (2004) for a comprehensive evaluation) we limit our

analysis to the period starting in January 1993. For similar reasons OECD (2005) divides the sample for a multi-country study in 1984-1995 and 1996-2004. Additionally in a data rich environment approach – and a methodology which asks for balanced data set at the start - we had to compromise between long and many time series. Within this limits we choose the start date to minimize the risk of structural breaks. Starting before 1993 would have limited significantly the considered information breadth.

We used two broad data sets from the following broad categories: (i) good and services prices (CPI, PPI); (ii) labor market, money, produced surveys, and financial variables (FX, credit, stocks, commodities, high yield bonds, gov.bonds). We abstain from including every indicator available, since recent research on factor models (see Boivin and Ng(2003)) shows this does not come without risks. Figures 1a and 1b give more information on the current data set used.

In order to derive a signal for monetary policy makers, stability of the most current estimates becomes an important issue. Therefore, nearly all of the data we have chosen is not subject to revision. Following Amstad and Fischer (2004) we use only non-seasonally adjusted data and apply filters within the estimation to generate a seasonally adjusted estimate of underlying inflation. The main reasons for this choice is that it prevents revisions in our measure of underlying inflation being driven by concurrent seasonal adjustment procedures.

As standard in the literature prior to the estimation we transformed the data to induce stationary. Afterwards we demean and normalize the series, as otherwise more volatile series would get a higher weighting than less volatile ones in the estimation. As we discussed above we need to assign an average value to our underlying measure. We use 2.25 for the CPI and 1.75 for the PCE. These numbers were very close to the average inflation since 1993 when we started the project end of 2004.

3.2 Estimation procedure

We follow the approach of Forni, Hallin Lippi and Reichlin (2000) - who extended the original work of Brillinger (1981) to large data sets. The advantage for us of this approach is that it allows us to investigate lead/lag relationships more directly and specify a policy relevant horizon. Technically

this is accomplished by working in the frequency domain. The precise estimation procedure follows Cristadoro et. al (2001) and the technical details are given in the appendix. Here we describe the methods informally in the time domain.

We assume that the N variables in the panel, $x_t = (x_{1t}, x_{2t}, \dots, x_{Nt})'$, are measured with error and that they can be decomposed into the sum of two components: the signal x_{it}^* and the idiosyncratic error e_{it} specific to variable i is specified as

$$x_{it} = x_{it}^* + e_{it}$$

Recall the definition of underlying inflation from section 2. We can think of the common signal component and individual idiosyncratic error as also being present in forecasts of x_{it} :

$$E_t[x_{it+h}] = E_t[x_{it+h}^*] + E_t[e_{it+h}].$$

The DFM approach effectively extracts the common components across variables $E_t[x_{it+h}^*]$ at different horizons with the further restriction that the individual common components are related across horizons. We call these restricted common components, the dynamic factors.

Recall the definition of underlying inflation from section 2. Let $\{F_{kt}\}$ represent the q dynamic factors then the UIG measure of underlying inflation is obtained by:

$$\pi_t^* = \bar{\pi} + \sum_{k=1}^q \sum_{\ell=0}^p \widehat{\beta}_{k\ell} F_{kt-\ell}, \quad (1)$$

where $\{\widehat{\beta}_{k\ell}\}$ are the estimated regression coefficients from the regression of $(\pi_t - \bar{\pi})$ on the contemporaneous and p lags of the q dynamic factors. Here, $\bar{\pi}$ is the fixed average of the underlying inflation rate. Thus, we produce the UIG for both the CPI and PCE using the same set of factors. We now consider the relevant horizons for constructing the common components and the choice of the number of dynamic factors.

3.2.1 Horizons of interest

We want the UIG to be useful for monetary policy makers. This immediately suggests that we should not look for common components at short horizons

since there is little policy makers can do about these fluctuations in inflation. Lags in monetary transmission mechanisms suggest that inflation at least up to a year is relatively insensitive to small unexpected changes in current monetary policy. Hence, if monetary policy has been achieving its objective of price stability with well anchored inflation expectations, the effects of current movements in monetary policy will be on expected inflation at horizons more than 12 months. Thus, we focus on horizons of 12 months and more to extract the common components. In practice, the estimation is done directly in the frequency domain, as described in the Appendix.

3.2.2 Number of dynamic factors

Our final specification choice is the number of dynamic factors. Different papers find that much of the variance in U.S. macroeconomic variables is explained by two shocks. Giannone, Reichlin, Sala (2004) show these findings in large- n factor models for 1970-2003 and Sims/Sargent (1977) for a small- n frequency domain factor analysis for 1950-1970. Watson (2004) notes that the good fit of the two-factor model seems a remarkably stable feature of postwar U.S. data. Hence, in most dynamic factor model applications q (the number of dynamic factors) is set to two.

Often it is claimed that one factor explains much of the variance of the real variables, while the second factor represents nominal prices. Our choice of the number of factors is not driven by this consideration. Our aim is to incorporate the lowest number of factors needed to represent our data environment properly, without attempting to label these factors. In contrast, in an innovative paper Reis and Watson (2007) use restrictions on the factors to find a measure of the numeraire.

We start by restricting our analysis to price data only. Figures 2a and 2b show the UIG for CPI and PCE assuming 1 and 2 dynamic factors. As can be seen there is little difference between the UIG with 1 or 2 factors. Further, the movements in the UIG are very smooth. We investigated the smoothness further by the following experiment: take a monthly CPI release and scale up all the 211 time series by a fixed amount. The result of the experiment was a big upward movement in the UIG.

Figures 3a and b show the UIG for CPI and PCE assuming different numbers of dynamic factors $q = 1$ to 8 for the whole dataset. Three findings are noteworthy. First, the UIG now shows large cyclical fluctuations. Second,

the UIG under the assumption of a single dynamic factor while similar to the case with additional factors, does show different dynamics particularly from 2000 onwards. Third, the change produced allowing more than two dynamic factors is limited, consistent with findings in the above mentioned papers. Based on these results, the previous finding and the desire to capture any common movement in prices alone, we set the number of dynamic factors to two.

3.2.3 Related approaches

From a methodological point of view DFM-gauges are in the same class as the CFNAI for US-GDP and Cristadoro et.al. for the Euro zone inflation. The CFNAI relies on the methodology proposed by Stock, Watson (1999) which lies also at the core of FHLR (2000, 2001) we are using here. However in FHLR (2000, 2001) special attention is given to the smoothing in the frequency domain, a reduced correlation between idiosyncratic and common is allowed and a specific procedure (Altissimo et. al. (2001), see Appendix) is used to reduce the end of sample problem. We follow the approach of Cristadoro et al. (2001) which introduced a core indicator for the Euro zone. Besides the application to US-CPI and PCE, we also differ in using seasonal unadjusted data to ensure that the estimation is not affected by a seasonal adjustment method. We take care of the seasonality by cutting off the seasonal frequencies of the UIG within the factor estimation instead of using seasonally adjusted data at the initial step of the analysis. In contrast to the Dynamic Factor Inflation gauge (DFI) for Switzerland (Amstad, Fischer, 2004) we focus on data that is mostly unrevised and we set the mean of the factor ex ante.

4 Comparing measures of underlying inflation

In the following we compare CPI and PCE based UIG measures using the ex food energy (XFE), trimmed mean (TM), median (MED) and above described factor model based approach.

4.1 General features of underlying measures

We start by providing time series plots of the same measure of underlying inflation for different price indices. As shown in Figures 4a to 4c, the underlying measures seem most closely related to methodology used to produce the underlying rate rather than the price index. In Figures 5a and b we show the various underlying measures for each price index. Now it can be seen that the differences are substantial depending on the underlying concept used. Tables 1 to 2b present the standard deviations and correlations between the various measures for different price indices where with the exception of the UIG measures we use 12 month rates of inflation.

As expected the UIG provide the smoothest signal as can be seen in Figures 4a to 4c. Despite this extra smoothness the standard deviation of UIG is similar to other underlying measures (see Table 1). Thus, the XFE-measures and to less extent also the TM-approach provides a signal with remaining high frequency volatility, which leaves it to the policy makers to decide whether an actual change should be considered as a change in trend or not.

The correlations between the various underlying measures and total inflation shown in Tables 2a and 2b show an interesting pattern. The UIG has almost no correlation with the other underlying measures of CPI but has reasonably high correlation with the 12 month CPI inflation rate. For the PCE the UIG is more correlated with traditional measures. In both cases it is clear that the UIG is producing a different signal. This finding is confirmed by a principal component analysis on CPI and cores including UIG as shown in Table 2c. The traditional core measures are arranged in a first factor, while UIG and CPI are identified as a combined second factor which is orthogonal to the information of the traditional cores.

Although there are clear differences between the CPI and PCE UIG that can be seen in the time series plots, they are highly correlated with each other as can be seen in Table 2d. This is also true if we restrict the data set for extracting factors to prices only. Thus, to save space we will focus more on the CPI-UIG since it has the advantage that the CPI is only subject to minor revisions whereas the PCE experiences major revisions.

4.2 Time series features of underlying inflation measures

Different measures of underlying inflation raise the issue of what to do when the different underlying measures send different signals to policy makers. In the following we highlight phases during which underlying inflation measures differed and discuss the reasons behind these differences. In that we give special emphasis to differing recognition time of turning points. We start by analyzing some of the possible sources of the differences in the measures. We then turn to a statistical analysis of the different underlying inflation measures with respect to future inflation.

4.2.1 Differences in underlying measures over recent history

Differences in the reaction to import (including oil) prices and state of the business cycle explain to a great extent differences in underlying measures over time. This is best reflected in the phase from mid to end of the 1990s; a phase characterized by conflicting signals for underlying inflation as import prices diminished but economic growth was generally strong. XFE as well as TM gauges signaled diminishing underlying inflation (see Figure 5a). Neither catch the increasing tightness in labor and product markets, leaving room for declining import prices to put downward pressure on XFE and TM. In contrary the UIG is less responsive to import prices and more responsive to the high level of activity suggesting more stable inflation pressure.

The underlying measures also differ in their reaction to the 2001 recession. The UIG turns down in late 2000 with the worsening of labor market conditions and the decline in manufacturing sentiment. The other measures keep on increasing through the recession year.

4.2.2 Underlying inflation as an attractor to inflation

The basic reason for developing underlying measures of inflation is that they should produce better forecasts of future inflation than the headline measure. Following Cogley (2002) and others we evaluate in sample the horizon at which the deviation of the underlying from total inflation correctly predicts the future behavior of total inflation. Let π_{mt} be the measure of underlying inflation, then we run the following regressions for horizons of 1 month to 24

months.

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi_{mt}) + u_{t+h} \quad (2)$$

An ideal measure of underlying inflation for horizon h would have $\alpha_h = 0$ (unbiased) and $\beta_h = -1$ and explain a substantial amount of the future variation in inflation. If β_h were negative but less than one in absolute value, the measured deviation would overstate the magnitude of subsequent changes in inflation, and thus would also overstate the magnitude of current transients. Similarly, if β_h were negative but greater than one in absolute value, the measured core deviation would understate the magnitude of current transients.

The results of the analysis are shown in Table 3. Only the $h=24$ results are given. The median as well as UIG are significantly biased. In the case of the UIG this is just the result of our decision to fix the long run average of UIG to 2.25 and could be removed by assuming the actual long run mean of the CPI. In contrast with the results shown here, Rich and Steindel (2007) find that CPI, CPI_XFE and CPI_MED are biased. This illustrates that these findings may vary depending on the sample and the forecast horizon. Concerning the behavior of β_h we find in accordance with Rich and Steindel (2007) that most of the cores fulfill the $\beta_h = -1$ hypothesis. Figure 6 shows that the in sample fit is worst for the CPI_XFE. The other measures reach similar results with UIG reaching slightly higher R^2 values than the other measures. One could argue that the benchmark for a underlying inflation gauge should not be CPI itself but a smoother CPI trend. Following Clark (2001) and Rich and Steindel (2007) we investigate the ability of the gauges to track the trend rate of inflation. The inflation trend is defined as the Baxter-King (1999) band-pass filter that eliminates all periods less than 32 quarters. We drop two years of data from the beginning and end of the band-pass filtered series because they are relatively poorly estimated. Table 4 shows that the UIG tracks the trend inflation significantly more closely than CPI_XFE, CPI_MED and CPI_TM. However, all these regressions only give information on in sample “forecast” performance, we now turn to a pseudo out of sample forecast evaluation.

4.3 Forecasting inflation

Another way to compare underlying inflation measures is to investigate their ability to forecast inflation in real time. It is often argued that a forecasting

exercise will be able to reveal the best underlying inflation measure. However several aspects of such comparisons are tricky particular in producing underlying measures of use for policy makers. The most difficult aspect is the appropriate loss function to measure forecast accuracy. The standard approach is to use a quadratic loss function for deviations of forecast from the actual. This does not depend on the loss for the policy maker of the actual inflation rate relative to their desired levels. Consider the following example:

- For total inflation between 1% and 3% the RMSE at 12 months for underlying measure A is 1%, for measure B it is 1.1%.
- For total inflation outside of 1% and 3% the RMSE at 12 months for underlying measure A is 2%, for measure B it is 1.2%.

If the policy maker uses measure A they will be slow to recognize turning points in inflation. If the policy maker uses measure B they will be quicker to recognize turning points in inflation. Suppose the policy maker successfully uses measure B to conduct monetary policy so that total inflation is rarely outside of 1% to 3%, then a forecast evaluation would favor measure A if the fraction of time that actual inflation was outside 1% to 3% was less than 1/10.

Other practical issues involve the choice of forecasting sample. Long time horizons can be problematic since they might cover different inflation regimes. Furthermore as most industrialized countries have successfully lowered their inflation rates the signal with the least variation (e.g. a constant) might have an advantage compared to signals generated from earlier periods with more fluctuation in inflation. In general the forecasting exercises are “pseudo” real time in the sense that estimation is conducting using data only up to the forecast origin. In practice the actual data used might have been revised subsequently. In our case the UIG is constructed from data that is either not revised or only revised slightly (some PPI prices). We focus on the CPI since its revisions are very minor (seasonal adjustment and correction of small technical mistakes).

Table 5a gives the result of a forecasting exercise based on equation 2⁸ in 4.2.2. which spans three different samples through 2007.M3: (a) a post 2000 sample: a time range that could be considered as one inflation regime, (b) a post 2002 sample, which captures the upward trend in CPI as well as (c) a post 2004 sample, which covers the flattening out of the CPI. The results show that for all but one sample UIG exhibits the significantly lowest RMSE on 1 and 2 year horizon and no significant difference to the lowest RMSE on the 3 year horizon. The additional usage of real and financial information seems to improve predicting inflation on different time horizons as well as different CPI phases (u-shaped, upward sloped or flattening out). Further noteworthy is that the most often cited core inflation measure CPI_XFE reaches over all the worst performance. Among the traditional core measures the CPI_Median performs best up to 2002, but fails to detect the decreasing inflation pressure in 2006.

The three panels of table 5b give a different perspective on forecasting performance based on the equation:

$$\sum_{h=1}^H \pi_{t+h} = \alpha_H + \varphi_H(L)\pi_t + \beta_H\pi_{mt}, \quad (3)$$

which is similar to the forecast evaluation used in Stock and Watson (2002a). We consider three cases for the autoregressive operation $\varphi_H(L)$: random walk (i.e., $\varphi_H(L) = 0$), autoregression of order 3 and autoregression of order 6. We present the results in terms of relative RMSE and it can be seen that the best performers at horizons of 12 to 24 months tend to be the UIG and the trimmed mean. We also included a simple average of these two measures as another measure of underlying inflation. This average tends to out-perform the individual measures. Further, it is clear that adding autoregressive dynamics does little to improve the forecasting performance.

5 Experience with the UIG through July 2007

The CPI_UIG has been produced on a daily basis since July 2005. Since then as can be seen in figure 5a it has shown an almost flat, slight downward

⁸To ensure comparability we use the same setting as in the paper of Rich and Steindel (2007), which compares forecast performance of traditional core measures. The same regression model has been used in studies such as Clark (2001), Hogan, Johnson and Laffèche (2001), Cutler (2001) and Cogley (2002).

trend until mid of 2006 but stayed above all the other underlying measures. As can be seen in Figure 5a the XFE, TM and especially MED measures have all increased substantially towards the higher UIG level from mid 2005 through mid 2006. While UIG suggests a higher but slightly decreasing inflation pressure since mid 2005 the traditional cores signaled lower but increasing inflation until mid 2006 (XFE, TM) or end 2006 (Median) and only afterwards a decreasing inflation. Many of the more traditional core measures appeared to have been driven by the cost of shelter component of the CPI, especially owners equivalent rent. The UIG tends to view this component as more of a lagging indicator rather than leading indicator of prices pressures. This partly accounts for its early recognition of the drop in inflation pressures in 2001.

A recent exercise was conducted to examine the role of owners equivalent rent (OER) in the acceleration of the XFE, TM and MED underlying measures. Instead of using the CPI as the predictor in the factor regression in section 3.2 we used the CPI excluding OER. The dynamics of the UIG were almost identical but it did show more acceleration of inflation in 2005 than the standard UIG and currently is registering more inflationary pressure (see Figure 7). Thus, contrary to a standard exclusion analysis, we find higher underlying inflation in the recent period using a measure of inflation that excludes OER. This partly explains why the UIG has fallen by less than some traditional core measures in the spring of 2007.

In addition to the UIG itself forecasts of inflation at various horizons of interest are produced. First a short term forecast of average inflation over the next two years, then a medium term forecast of two to three years and finally a three to five year horizon forecasts. These forecasts from the CPI_UIG are compared to the expected inflation derived from financial markets at the same horizons. The standard daily output is shown in Figure 8. This also includes some short run monthly forecasts The daily inflation forecasts derived from financial markets is compared to the daily UIG to identify phases in which market participants reaction to news is different than that implied by the UIG.

The lack of movement in the UIG forecast at longer horizons caused us to experiment as discussed above in section 3.2.2. In these experiments we artificially introduced a common factor into the 211 prices in the CPI release. This did produce a large movement in the UIG. One interpretation of the smoothness in the UIG is that long-term inflation expectations are well-anchored and that much of the movement in individual prices is unrelated

to any “inflation trend.” Support for this viewpoint comes from the behavior of expected inflation derived from financial markets. Although they have clearly been more volatile than the forecasts from the UIG, they do not show any sustained increase over the last two years. This is in contrast to the other underlying measures.

6 Conclusions

This paper has presented a new application of dynamic factor methods to US inflation. We add to the existing literature on U.S. inflation by using a carefully chosen data set with an overweighting of price data. Although in the period we examine the influence of individual price movements on underlying inflation is not large, their presence is useful to capture any future unanchoring of overall inflation expectations. The underlying measure of inflation produced by our methods adds information over existing measures. In addition we are able to calculate it on a daily basis, allowing us to compare its movements to those of inflation expectations derived from financial markets.

References

- [1] Alesina, Alberto, Olivier Blanchard, Jordi Gali, Francesco Giavazzi and Harald Uhlig (2001), "Defining a Macroeconomic Framework for the Euro Area - Monitoring the European Central Bank", 3, CEPR 2001.
- [2] Altissimo, Filippo, Antonio Bassanetti, Riccardo Cristadoro, Mario Forni, Marc Hallin, Marco Lippi, Lucrezia Reichlin, Giovanni Veronese (2001) 'Real Time Coincident Indicator of the Euro Area Business Cycle,' CEPR Discussion Paper #3108.
- [3] Amstad, Marlene, and Andreas M. Fischer (2004) 'Sequential Information Flow and Real-Time Diagnosis of Swiss Inflation: Intra-monthly DCF Estimates for a Low Inflation Environment,' CEPR Discussion Paper #4627.
- [4] Amstad, Marlene, and Andreas M. Fischer (2005a) 'Shock Identification of Macroeconomic Forecasts based on Daily Panels', FRBNY staff paper 206 .
- [5] Amstad, Marlene, and Andreas M. Fischer (2005b) 'Time-Varying Pass-Through from Import Prices to Consumer Prices: Evidence from an Event Study with Real-Time Data', CEPR Discussion Paper #5395.
- [6] Balke, Nathan S., and Mark A. Wynne (1996), "An equilibrium analysis of relative price changes and inflation," Federal Reserve Bank of Dallas Research Paper 9609.
- [7] Bernanke, B.S. and Boivin, J. (2003) 'Monetary policy in a data rich environment', Journal of Monetary Economics vol. 50, pp. 525-546.
- [8] Bowley, A. L. (1928), "Notes on index numbers," Economic Journal, 38, 216-137.
- [9] Brillinger, D.R. (1981), 'Time Series : Data Analysis and Theory', Holden-Day, San Francisco
- [10] Bryan, Michael F., and Christopher J. Pike (1991), "Median price changes: an alternative approach to measuring current monetary inflation," Federal Reserve Bank of Cleveland Economic Commentary, December 1.

- [11] Bryan, Michael F. and Stephen G. Cecchetti (1994), ‘Measuring Core Inflation’ in: N.G. Mankiw, *Monetary Policy*, 195–215, Chicago: University of Chicago Press.
- [12] Bryan, Michael F. and Stephen G. Cecchetti (1996), “Inflation and the distribution of price changes,” NBER Working Paper No. 5793.
- [13] Bryan, Michael F., Stephen G. Cecchetti and Rodney L. Wiggins (1997) ‘Efficient Inflation Estimation’, NBER Working Paper Nr. 6183.
- [14] Boivin, J. and S. Ng (2003), ‘Are more data always better for factor analysis?’ NBER Working Paper No. W9829
- [15] Castelnuovo, Efram, Sergio Nicoletti-Altimari and Diego Rodriguez-Palenzuela (2003) ‘Definition of price stability, range and point inflation targets: the anchoring of long-term inflation expectations’, ECB working paper No. 273.
- [16] Cecchetti, S.G. (1995), ‘Inflation Indicators and Inflation Policy,’ NBER *Macroeconomics Annual*, 191-219.
- [17] Cecchetti (1997), “Measuring Short-Run Inflation for Central Bankers” *Review*, Federal Reserve Bank of St. Louis.
- [18] Clark, Todd E. (2001), ‘Comparing Measures of Core Inflation’, *Federal Reserve Bank of Kansas City Economic Review*, v. 86, No.2, pp.5-31.
- [19] Clark, Todd E.. (2004), ‘An Evaluation of the Decline in Goods Inflation’, *Federal Reserve Bank of Kansas City Economic Review*, *Economic Review*.
- [20] Cogley, Timothy E. (2002), ‘A Simple Adaptive Measure of Core Inflation’, *Journal of Money, Credit and Banking*, Vol. 34. No.1, February, pp.94-113.
- [21] Cutler, Joanne (2001), ‘Core inflation in the U.K.’, Bank of England, *External MPC Unit Discussion Paper No.3*, March.
- [22] Cristadoro, R., M. Forni, L. Reichlin, and G. Veronese (2001) ‘A Core Inflation Index for the Euro Area,’ *CEPR Discussion Paper #3097*.

- [23] Dolmas, Jim (2005). "Trimmed Mean PCE Inflation". Federal Reserve Bank of Dallas, Working Paper 0506.
- [24] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2000) 'The generalized factor model: identification and estimation', *The Review of Economics and Statistics* vol. 82, pp. 540-554.
- [25] Gali, Jordi (2002), 'New Perspectives on Monetary Policy, Inflation and the Business Cycle', CEPR Discussion Paper #3210.
- [26] Gavin, William T. and Kevin L. Kliesen (2006), 'Forecasting Inflation and Output: Comparing Data-Rich Models with Simple Rules', Federal Reserve Bank of St. Louis, Working Paper 2006-054A.
- [27] Giannone, Domenico, Lucrezia Reichlin, and Luca Sala (2004) 'Monetary Policy in Real Time', NBER Macroeconomics Annual, Mark Gertler and Ken Rogoff Editors, MIT Press (forthcoming).
- [28] Giannone, Domenico and Troy Matheson (2006), 'A new core inflation indicator for New Zealand', RBNZ Discussion Paper Series.
- [29] Gordon, R.J. (1982), 'Price inertia and policy ineffectiveness in the United States, 1890-1980, *Journal of Political Economy*, 90, (6), December, pp.1087-1117.
- [30] Hogan, Seamus, Marianne Johnson and Thérèse Laffèche (2001), 'Core Inflation', Technical Report 89, January, Bank of Canada.
- [31] Mishkin, Frederic S. and Klaus Schmidt-Hebbel (2001), 'One Decade of Inflation Targeting in the World: What Do We Know and What Do We Need to Know?', NBER Working Paper No. W8397.
- [32] OECD(2005), *Economic Outlook*.
- [33] Quah, Danny and Shaun P. Vahey (1995) 'Measuring Core Inflation', *Economic Journal* 105(432): 1130–1144.
- [34] Rich, Robert and Charles Steindel (2007), 'A Comparison of Core Inflation', Federal Reserve Bank of New York Economic Policy Review forthcoming.

- [35] Reis, Ricardo and Mark W. Watson (2007), 'Measuring Changes in the Numeraire', mimeo.
- [36] Rudd, Jeremy and Karl Whelan (2007), 'Modelling inflation dynamics: a critical review of recent research', *Journal of Money, Credit and Banking*
- [37] Sargent and Sims(1977): 'Business Cycle Modeling Without Pretending to Have Too Much a Priori Economic Theory,' in: *New Methods in Business Cycle Research: Proceedings From a Conference*, Federal Reserve Bank of Minneapolis, October, 1977, p. 45–109. (FRB Mpls Working paper No. 55, Mar, 1976, Rev. Jan, 1977).
- [38] Stock, J.H. and M.W. Watson (1999), 'Forecasting Inflation', *Journal of Monetary Economics*.
- [39] Stock, J.H. and M.W. Watson (2002a) 'Macroeconomic Forecasting Using Diffusion Indexes', *Journal of Business and Economic Statistics* vol. 20, pp. 147-162.
- [40] Stock, J.H. and M.W. Watson (2002b), 'Forecasting using principal components from a large number of predictors', *Journal of the American Statistical Association*, 97, pp. 1167—1179.
- [41] Stock, J.H. and M.W. Watson (2007), "Is inflation harder to forecast?" *Journal of Money, Credit and Banking*,
- [42] Vining, Daniel R., Jr., and Thomas C. Elwertowski (1976), "The relationship between relative prices and the general price level," *American Economic Review*, 66, 699-708.
- [43] Watson (2004), 'Comment on Giannone, Reichlin and Sala's "Monetary Policy in Real Time"', June 2004.
- [44] Wynne, Mark A. (1997), "Commentary," *Federal Reserve Bank of St. Louis Economic Review*, 79, 161-167.
- [45] Wynne, Mark A. (1998), "Measures of core inflation for the ECB," unpublished manuscript, European Central Bank.

Appendix

Technical description

The estimation procedure follows Altissimo et al.(2001). The methodology is based on the Generalized Dynamic Factor Model as developed by Forni, Hallin, Lippi and Reichlin (2000, 2001), hereafter FHLR. The FHLR approach generalizes the traditional dynamic factor models (Sargent and Sims (1977) for large panels using a generalization of the approximate factor models. In contrast to Stock and Watson (1999, 2002) the FHLR approach does not focus on estimation and forecast of the unsmoothed inflation series but on the estimation and forecast of inflation which is cleaned (or smoothed) in cross sectional (measurement errors, local or sectoral shocks) and time dimension.

The model

We assume a panel of $i = 1, \dots, N$ time series, $x_{it} = (x_{1t}, x_{2t}, \dots, x_{Nt})'$, which are realizations of a zero mean, wide-sense stationary process and thought of as an element from an infinite sequence. As in the traditional dynamic factor approach each time series is assumed to be measured with error and can be decomposed into the sum of two unobservable orthogonal components:

$$x_{it} = \chi_{it} + \xi_{it} = \mathbf{b}_i(L)\mathbf{u}_t + \xi_{it} = \sum_{j=1}^q b_{ij}(L)u_{jt} + \xi_{it} \quad (1)$$

where χ_{it} is the common component, driven by q dynamic common shocks $\mathbf{u}_t = (u_{1t}, \dots, u_{qt})$ with non-singular spectral density matrix and ξ_{it} is the idiosyncratic component (reflecting measurement errors and local shocks). $\mathbf{b}_i(L)$ is a vector of lag polynomials of order s and considers the factor dynamics. ξ_{it} is orthogonal to the common shocks \mathbf{u}_{t-k} for all k and i . The traditional dynamic factor model assumes mutual orthogonality of the idiosyncratic components ξ_{it} . This is quite a strict assumption especially for $N \rightarrow \infty$, as it ignores local shocks, which affect only a small subset but more than only

one variable. Forni et al. (2000) proposed the generalized dynamic factor model which, as the main difference to the above mentioned traditional dynamic factor models, eases this assumption and allows for limited dynamic cross-correlation. As orthogonality can not serve anymore as a theoretical distinction between χ_{it} and ξ_{it} the following assumptions are needed:

1. (I) The q -dimensional vector process $\{(u_{1t} \ u_{2t} \dots u_{qt})', t \in \mathbb{Z}\}$ is orthonormal white noise. That is, $E(u_{jt}) = 0$; $var(u_{jt}) = 1$ for any j and t ; $u_{jt} \perp u_{jt-k}$ for any j, t and $k \neq 0$; $u_{jt} \perp u_{st-k}$ for any $s \neq j, t$ and k .
 (II) $\xi = \{\xi_{it}, i \in \mathbb{N}, t \in \mathbb{Z}\}$ is a double sequence such that, firstly, $\xi_n = \{(\xi_{1t} \ \xi_{2t} \ \dots \ \xi_{nt})', t \in \mathbb{Z}\}$ is a zero-mean stationary vector process for any n , and, secondly, for any i, j, t , and k ; $\xi_{it} \perp u_{jt-k}$ for any i, j, t , and k ;
 (III) the filters $b_{ij}(L)$ are one-sided in L and their coefficients are square summable.
2. For any $i \in \mathbb{N}$, there exists a real $c_i > 0$ such that $\sigma_{ii}(\theta) \leq c_i$ for any $\theta \in [-\pi, \pi]$, with $\sigma_{ii}(\theta)$ the entries of the spectral density matrix $\Sigma_n(\theta)$ of the vector process x_{nt} .
3. The first idiosyncratic dynamic eigenvalue λ_{n1}^ξ is uniformly bounded. That is, there exists a real Λ such that $\lambda_{n1}^\xi(\theta) \leq \Lambda$ for any $\theta \in [-\pi, \pi]$ and any $n \in \mathbb{N}$.
4. The first q common dynamic eigenvalues diverge almost everywhere in $[-\pi, \pi]$. That is, $\lim_{n \rightarrow \infty} \lambda_{nj}^x(\theta) = \infty$ for $j \leq q$, a.e. in $[-\pi, \pi]$, with λ_{nj}^x the dynamic eigenvalues of the spectral density matrix $\Sigma_n^x(\theta)$ of the vector process χ_{nt} .

Under the assumptions 1-4 model (1) is a generalized dynamic factor model.

Estimation and Forecasting Procedure

Our estimation and forecasting procedure follows Altissimo et al. (2001). We begin with the estimation of the spectral density matrices of the common (and the idiosyncratic) using the above described method of generalized dynamic principal components of Forni et al. (2000).

$$\widehat{\Sigma}_\chi(\theta) = \mathbf{U}(\theta)\mathbf{\Lambda}(\theta)\widetilde{\mathbf{U}}(\theta) \quad (2)$$

where $\mathbf{\Lambda}(\theta)$ is the diagonal matrix $\lambda_1(\theta), \dots, \lambda_q(\theta)$ and $\mathbf{U}(\theta)$ is the matrix of eigenvectors.

Using the Inverse Fourier Transformation to the frequency band $[-\theta, \theta]$, with $\theta = \frac{2\pi}{12}$ we get an estimate of the covariance matrix of χ at lower frequencies

$$\Gamma_{\chi^L}(k) = \frac{2\pi}{2H+1} \sum_{h=-H}^H \widehat{\Sigma}_\chi(\theta_h) e^{i\theta_h k} \quad (3)$$

with H defined by the conditions $\theta_H \leq 2\pi/12$ and $\theta_{H+1} > 2\pi/12$.

Next, we use this covariance matrix to estimate the static factors by generalized principal components and to estimate and forecast χ_t by

$$\widehat{\chi}_{t+h} = \Gamma_\chi(h)\mathbf{V}(\mathbf{V}'\Gamma_\chi\mathbf{V})^{-1}\mathbf{V}'x_t \quad (4)$$

with \mathbf{V} the matrix of generalized eigenvectors. In FHLR (2001b) it is shown that as both n and T got to ∞ at a suitable rate, $\widehat{\chi}_t$ converges in probability to χ_t and $\widehat{\chi}_{t+h}$ converges to the theoretical projection of χ_{t+h} on contemporaneous and past values of (u_{1t}, \dots, u_{qt}) . We work with two dynamic factors and twelve static factors.

In the last step, we estimate the common component at low frequency by using the static factors. This last step involves performing a projection of the common component at low frequency on the leads and lags of the estimated static factors. Our estimate of the common cyclical component is then

$$\widehat{\chi}_{t+h}^L = \mathbf{R}\mathbf{W}(\mathbf{W}'\mathbf{M}\mathbf{W})^{-1}\mathbf{W}'\mathbf{X}_t \quad (5)$$

with \mathbf{M} the sample covariance matrix of $\mathbf{X}_t = (x'_{t+m} \dots x'_t \dots x'_{t-m})'$, \mathbf{W} the diagonal matrix with the generalized eigenvectors and \mathbf{R} the lead and lag of variance matrices of the common component at low frequencies.

To generate the forecasts, we apply the shifting procedure for the covariance matrix by Altissimo *et al.* (2001). This means we first expand the data set using the shifting procedure in Altissimo *et al.* (2001) and then estimate the common components on data up to the forecast period, $t+h$.⁹ An

⁹The forecasting approach of Stock and Watson (2002) instead estimates first the common factors with data up to t and then uses the estimated factors in a separate regression

important step in our forecasting procedure is to apply the band-pass filter before projecting. Our decision to work with the low frequency component with cutoff $2\pi/12$ introduces a smoothed common. For the forecasts, this implies that the idiosyncratic component should not have a large influence on the forecasts. We therefore interpret that changes in the forecast can be attributed to new information from the data release and not to measurement error.

End of sample procedure

To consider the most up to date information of daily available information we use a data set which is unbalanced at the end. Therefore some series end in T , others in $T + 1, \dots, T + w$. To treat the end-of-sample unbalance and forecast we use the methodology of Altissimo et al. (2001) and Cristadoro et al (2005) by reordering the variables $x_{i,t}$ in a way that

$$x_{i,t}^* = (x_{i,t}^1 \ x_{i,t}^2 \ \dots \ x_{i,t}^w) \quad (6)$$

where $x_{i,t}^j, j = 1, \dots, w$ groups variables along the same last available observation $T + j - 1$. In the same way the covariance matrix is partitioned as follows

$$\widehat{\Gamma}^*(k) = \begin{pmatrix} \widehat{\Gamma}^{11}(k) & \widehat{\Gamma}^{12}(k) & \cdot & \widehat{\Gamma}^{1w}(k) \\ \widehat{\Gamma}^{21}(k) & \widehat{\Gamma}^{22}(k) & \cdot & \widehat{\Gamma}^{2w}(k) \\ \cdot & \cdot & \cdot & \cdot \\ \widehat{\Gamma}^{w1}(k) & \widehat{\Gamma}^{w2}(k) & \cdot & \widehat{\Gamma}^{ww}(k) \end{pmatrix} \quad (7)$$

and accordingly for the covariance matrix of the common $\widehat{\Gamma}_\chi^*(k)$ and the covariance matrix of the idiosyncratic $\widehat{\Gamma}_\xi^*(k)$ ¹⁰ as well. After shifting the variables in such a way to retain, for each one of them, only the most updated observation, the generalized principal components is computed for the

to forecast inflation for $t + h$. An alternative forecasting procedure based on the Kalman filter is proposed by Giannone *et al.* (2004).

¹⁰ $\widehat{\Gamma}_\xi^*(k)$ is diagonal and therefore the realigned $\widehat{\Gamma}_\xi^*(k)$ equals the original $\widehat{\Gamma}_\xi(k)$.

realigned vector $\widehat{\Gamma}_\xi^*(k)$ to get the forecasts. The final step is to restore the original alignment. The procedure is describes in greater detail in Cristadoro et al. (2005).

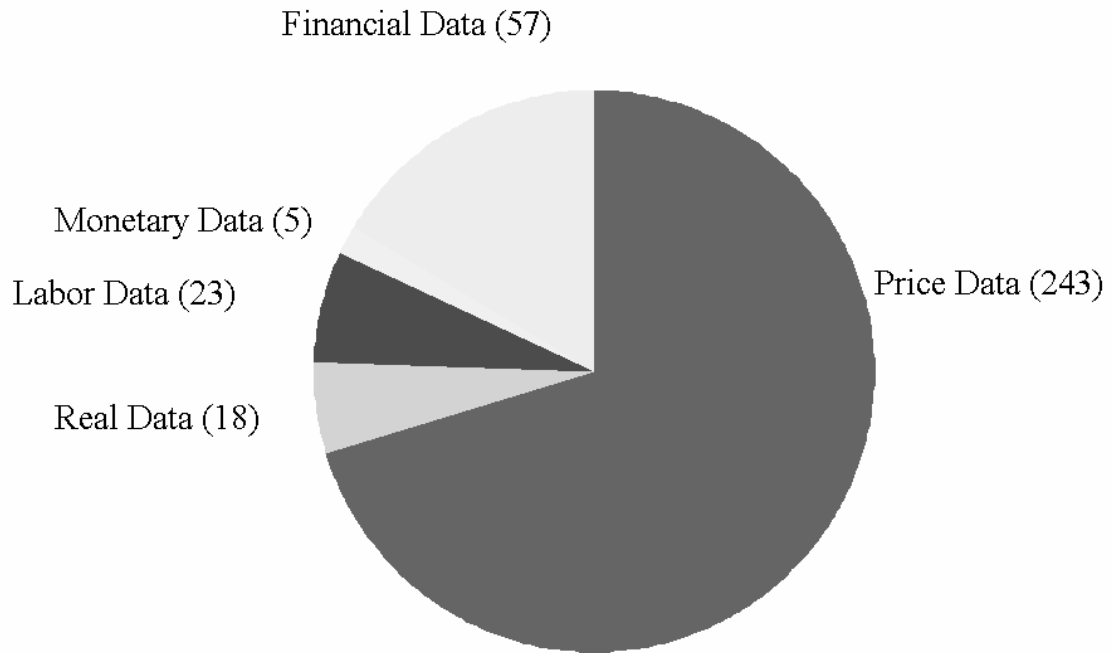


Figure 1a: Breakdown of UIG Series by Type

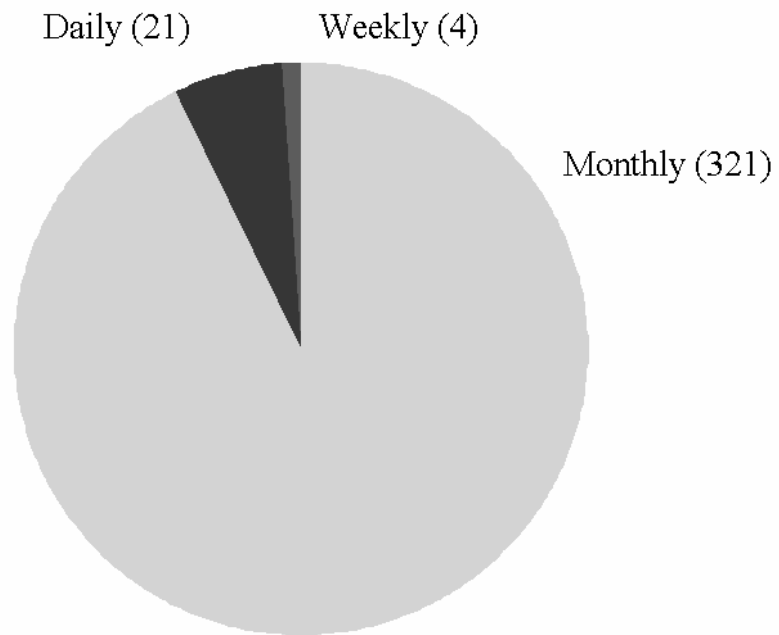


Figure 1b: Breakdown of UIG Series by Type

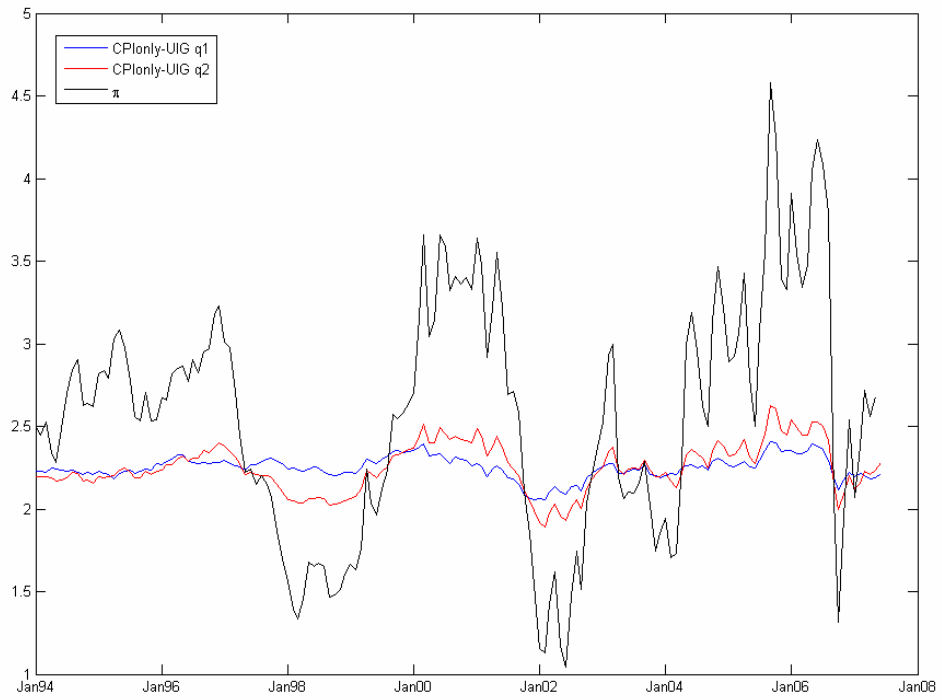


Figure 2a: CPI_UIG_Prices Only

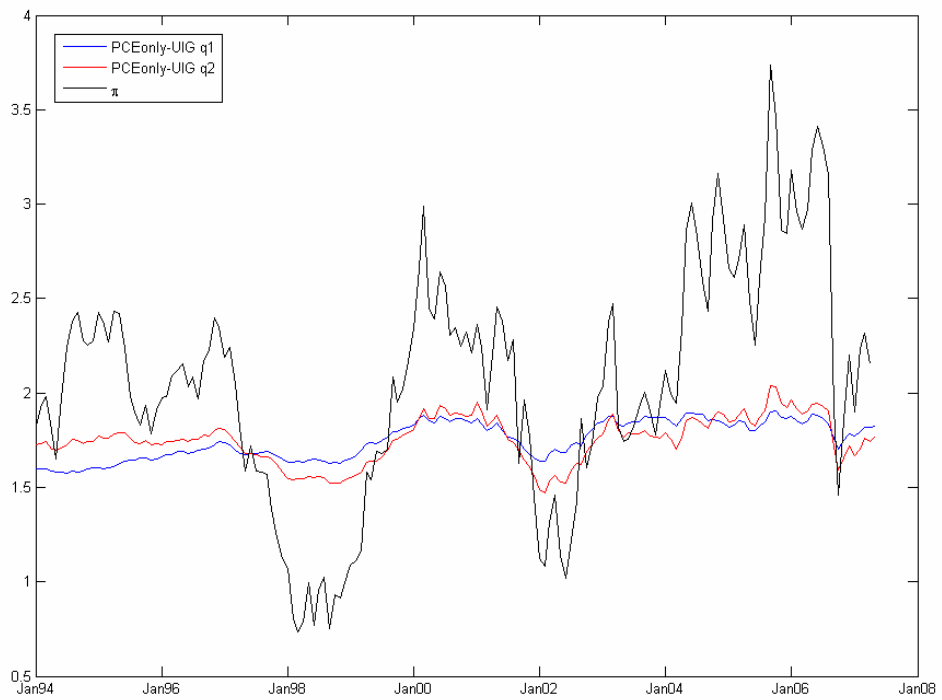


Figure 2b: PCE_UIG_Prices Only

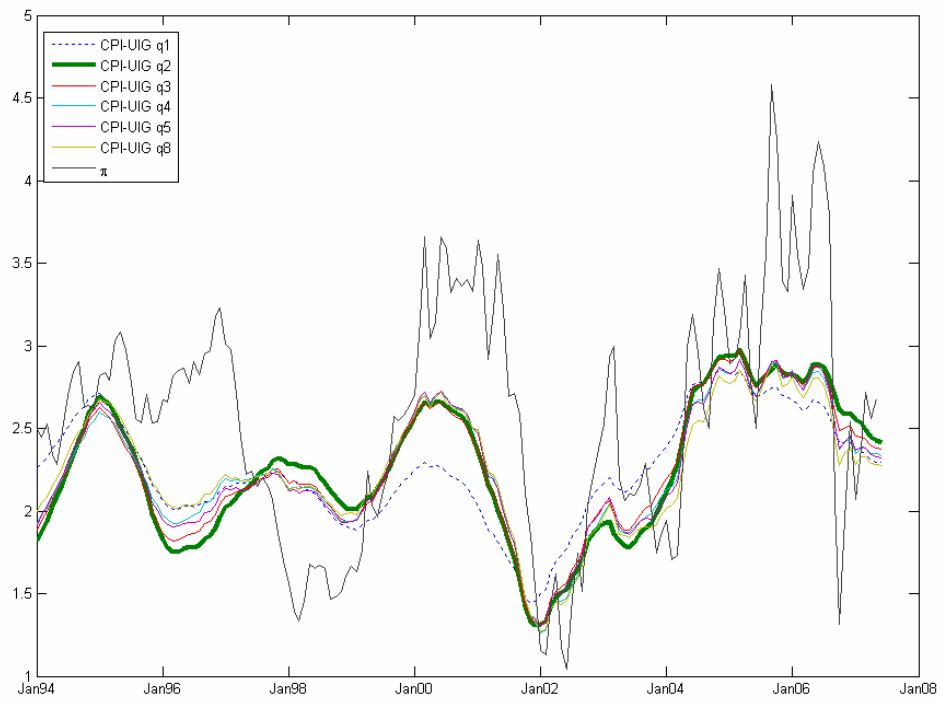


Figure 3a: CPI_UG for different numbers of factors

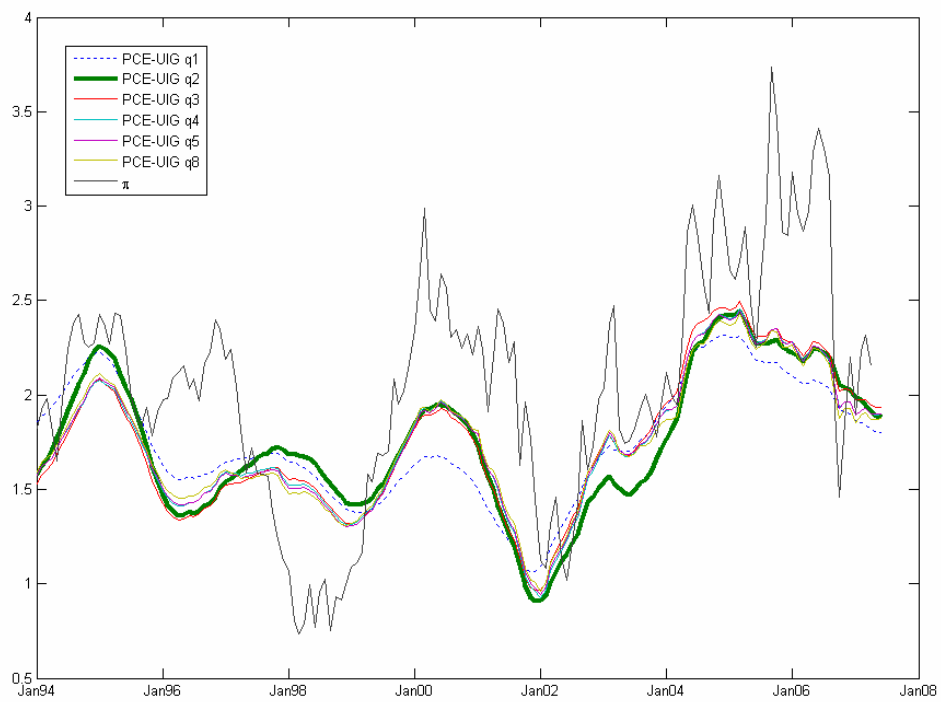


Figure 3b: PCE_UG for different numbers of factors

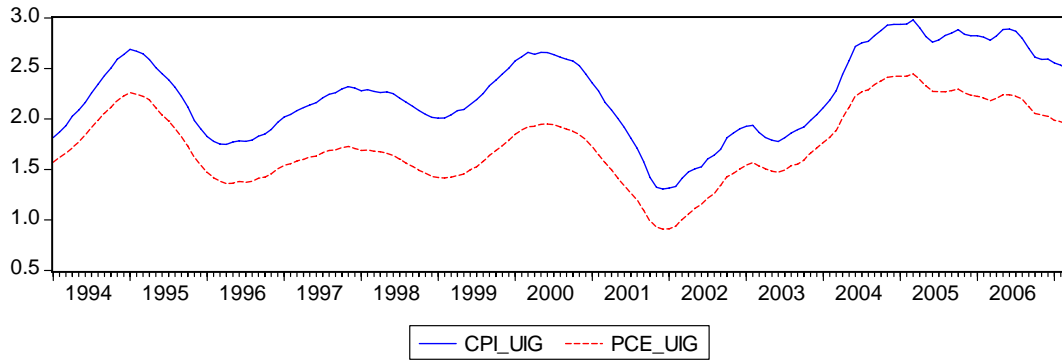
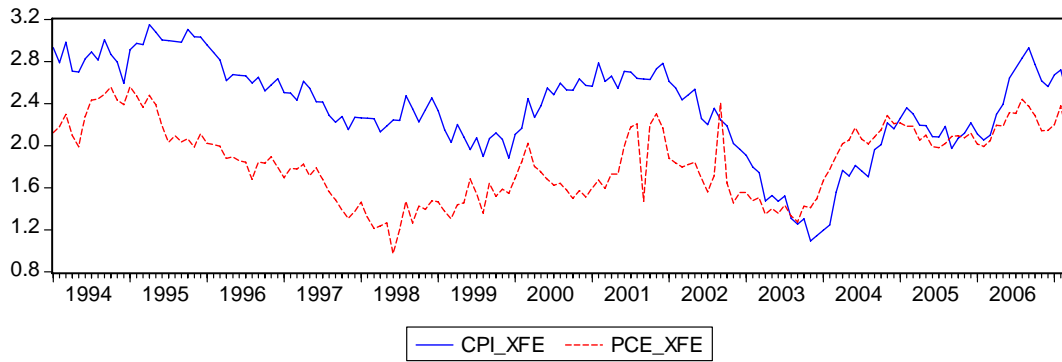
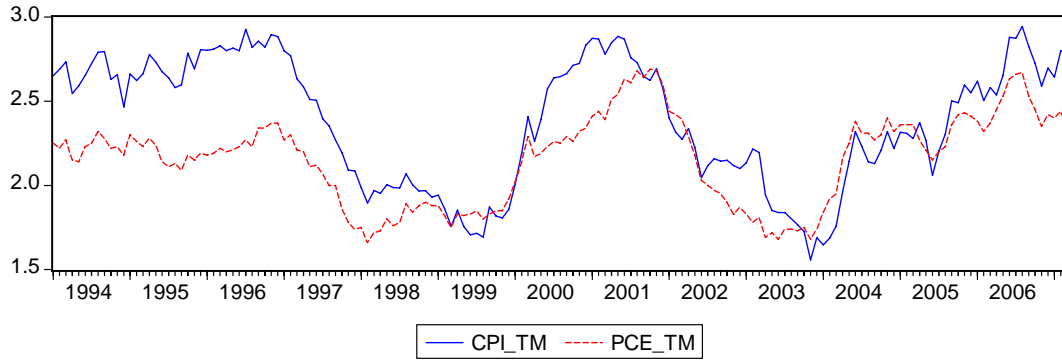


Figure 4a-c: Comparing different underlying inflation gauges for CPI and PCE

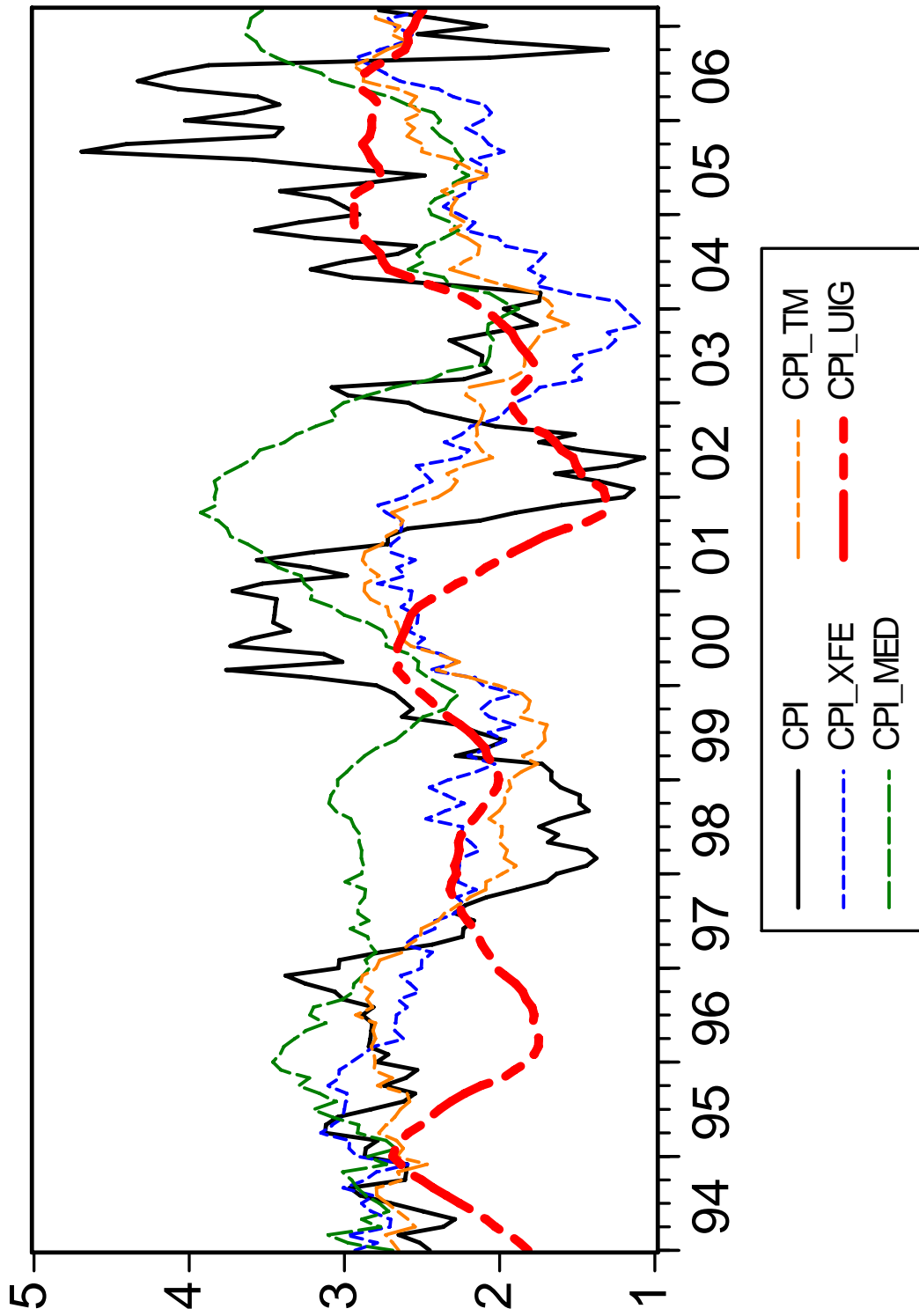


Figure 5a: Different underlying inflation gauges for CPI

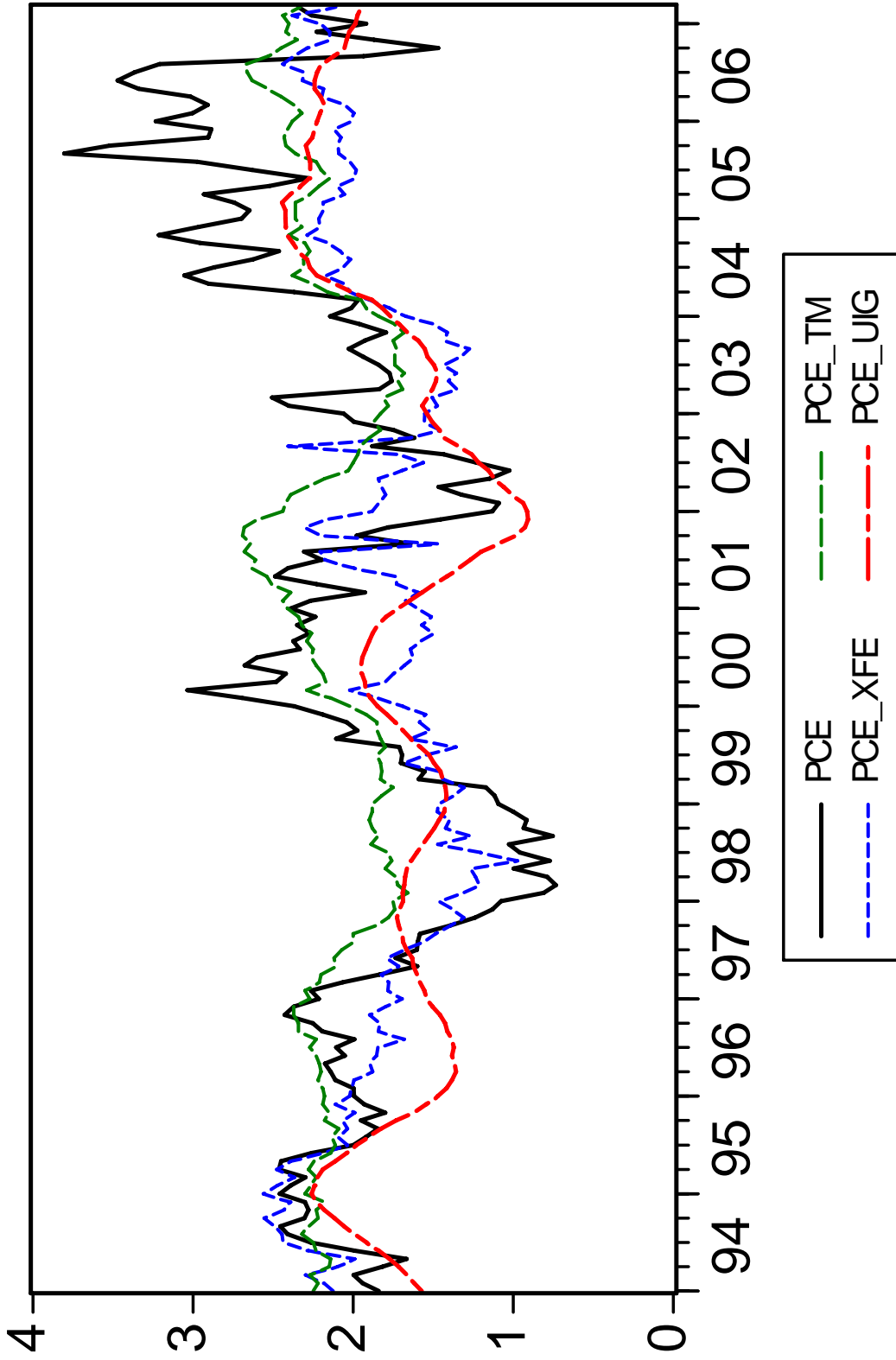


Figure 5b: Different underlying inflation gauges for PCE

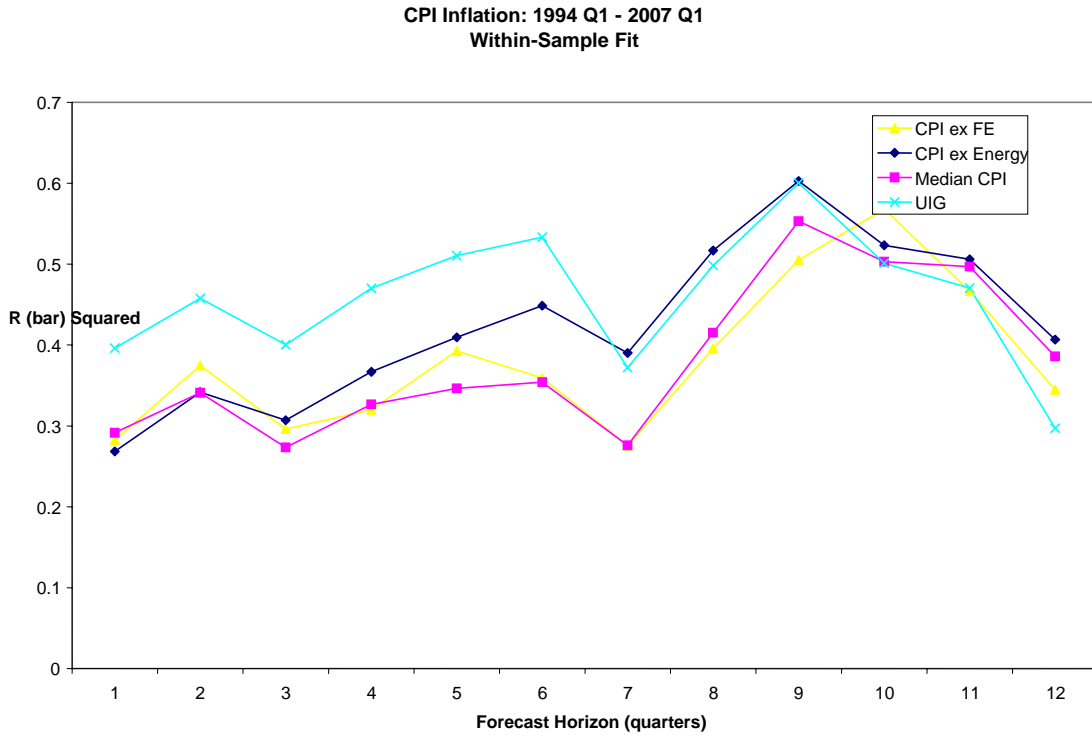


Figure 6: CPI Inflation 1994.1-2007.1, Within Sample Fit

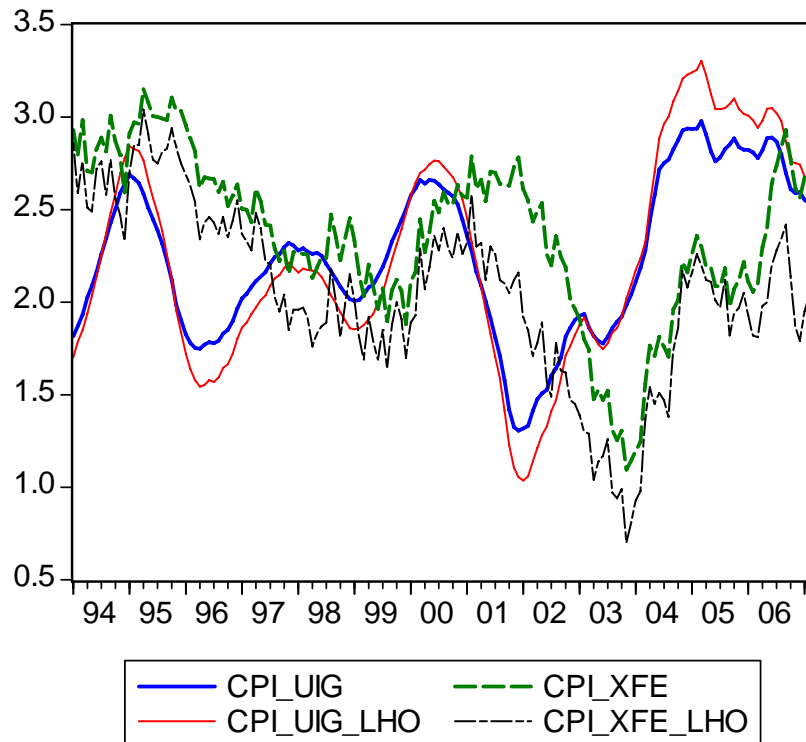


Figure 7: UIG and XFE with and w/o homeowners' equivalent rent

| | CPI | CPI UIG | CPI_Ponly UIG | CPI_XFE | CPI_TM | CPI_Med |
|------|------|---------|---------------|---------|--------|---------|
| S.D. | 0.74 | 0.42 | 0.15 | 0.44 | 0.38 | 0.47 |

| | PCE | PCE UIG | PCE_Ponly UIG | PCE_XFE | PCE_TM |
|------|------|---------|---------------|---------|--------|
| S.D. | 0.63 | 0.37 | 0.12 | 0.36 | 0.27 |

Table 1: CPI and PCE Standard Deviation

| | CPI UIG | CPI | CPI_XFE | CPI_TM | CPI_Med |
|---------|---------|-------|---------|--------|---------|
| CPI UIG | 1.00 | | | | |
| CPI | 0.58 | 1.00 | | | |
| CPI_XFE | -0.03 | 0.19 | 1.00 | | |
| CPI_TM | 0.08 | 0.55 | 0.80 | 1.00 | |
| CPI_MED | -0.50 | -0.24 | 0.67 | 0.52 | 1.00 |

Table 2a: CPI Correlations

| | PCE UIG | PCE | PCE_XFE | PCE_TM |
|---------|---------|-------|---------|--------|
| PCE UIG | 1.000 | | | |
| PCE | 0.668 | 1.000 | | |
| PCE_XFE | 0.471 | 0.590 | 1.000 | |
| PCE_TM | 0.214 | 0.572 | 0.717 | 1.000 |

Table 2b: PCE Correlations

| | PCA1 | PCA2 | PCA3 | PCA4 | PCA5 |
|------------------|-------|-------|-------|-------|-------|
| CPI | -0.20 | 0.63 | 0.54 | 0.19 | 0.49 |
| CPI UIG | 0.07 | 0.64 | -0.69 | 0.31 | -0.14 |
| CPI_XFE | -0.60 | -0.01 | -0.40 | -0.55 | 0.42 |
| CPI_TM | -0.59 | 0.20 | 0.24 | -0.09 | -0.74 |
| CPI_MED | -0.49 | -0.40 | -0.12 | 0.75 | 0.16 |
| Eigenvalue | 2.42 | 1.91 | 0.42 | 0.18 | 0.08 |
| Variance Prop. | 0.48 | 0.38 | 0.08 | 0.04 | 0.02 |
| Cumulative Prop. | 0.48 | 0.87 | 0.95 | 0.98 | 1.00 |

Table 2c: Principal Component Analysis on CPI cores and UIG

| | CPI UIG | CPI UIG_PricesOnly | PCE UIG | PCE UIG_PricesOnly |
|--------------------|---------|--------------------|---------|--------------------|
| CPI UIG | 1.00 | | | |
| CPI UIG_PricesOnly | 0.57 | 1.00 | | |
| PCE UIG | 0.96 | 0.52 | 1.00 | |
| PCE UIG_PricesOnly | 0.60 | 0.94 | 0.62 | 1.00 |

Table 2d: UIG correlations

| Core Inflation Measure | α (Ho: $\alpha = 0$) | β (Ho: $\beta = -1$) | Ho: $\alpha = 0$ and $\beta = -1$ |
|--------------------------------------|---------------------------------|--------------------------------|-----------------------------------|
| CPI ex food and energy (St. Err.) | -0.44946 (0.43836) | -0.7671* (0.09149) | 9.00641 p-value = 0.01107 |
| Median CPI (St. Err.) | -0.99236* (0.46355) | -0.95322 (0.07598) | 5.20153 p-value = 0.07422 |
| Trimmed Mean CPI (St. Err.) | -0.66101 (0.49293) | -0.8774 (0.08673) | 3.09085 p-value = 0.21322 |
| UIG (St. Err.) | 0.54825* (0.25764) | -0.97868 (0.12335) | 5.5629 p-value = 0.06195 |

* Significant at the 5 percent level

** Significant at the 1 percent level

Table 3: Unbiasedness Test, $h=24$ months

| | RMSE ^a |
|------------------------|-------------------|
| CPI ex food and energy | 1.19 |
| Median CPI | 1.01 |
| Trimmed Mean CPI | 0.70 |
| UIG | 0.53 |

$$a) RMSE^{core} = \sqrt{\sum(\pi_t^{trend} - \pi_t^{core})^2/T}, \quad t = 1, \dots, T$$

- π^{trend} : Baxter-King band pass filter eliminating periods less than 32 quarters

- sample: 1996-2005

Table 4: Accuracy with which underlying inflation gauges track trend inflation,

*Out of sample performance for annual inflation through 2007.M5
(estimation sample starts in 1994M1)*

Post 2000 sample ("u-shaped CPI phase")

| | <i>h=12</i> | <i>h=24</i> | <i>h=36</i> |
|------------|----------------|----------------|----------------|
| UIG | 3.53926 | 3.87967 | 4.06869 |
| CPI_XFE | 3.70231 * | 4.20956 * | 4.07291 |
| CPI_TM | 3.66568 | 3.92719 | 4.06263 * |
| CPI_Median | 3.72645 * | 4.04599 | 4.01214 |

Post 2002 sample ("increasing CPI phase")

| | <i>h=12</i> | <i>h=24</i> | <i>h=36</i> |
|------------|----------------|----------------|----------------|
| UIG | 3.91628 | 4.50258 | 4.86761 ** |
| CPI_XFE | 4.08548 ** | 4.79496 | 4.89527 * |
| CPI_TM | 4.06532 * | 4.46634 | 4.89368 ** |
| CPI_Median | 4.1414 * | 4.51356 | 4.82686 |

Post 2004 sample ("flattening CPI phase")

| | <i>h=12</i> | <i>h=24</i> | <i>h=36</i> |
|------------|----------------|----------------|----------------|
| UIG | 4.60513 | 4.14966 | 3.22125 |
| CPI_XFE | 4.66432 | 4.52173 | 3.06548 |
| CPI_TM | 4.80135 ** | 4.29878 ** | 3.65378 |
| CPI_Median | 4.86948 ** | 4.45857 ** | 3.75577 |

bold: lowest RMSE; italic: highest RMSE

* 5 % significant level

** 1 % significant level

Diebold-Mariano test of the null hypothesis of equal RMSE against the alternative hypothesis that RMSE of UIG is lower. Test statistics uses the Newey-West covariance matrix estimator

Table 5a: Out of sample performance in RMSE based on equation 2

Out of sample performance for annual inflation: 2000:01-2007:03 ("u-shaped CPI phase")

(Estimation sample 1994:1-1999:12)

Relative RMSE

| | 6 | 12 | 18 | 24 | 30 | 36 |
|-------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| <i>AR(6) RMSE</i> | <i>0.58</i> | <i>0.85</i> | <i>1.33</i> | <i>1.65</i> | <i>1.69</i> | <i>1.60</i> |
| CPI_UIG | 1.072 | 0.971 | 0.789 | 0.773 | 0.930 | 1.015 |
| CPI_XFE | 1.122 | 1.386 | 1.317 | 1.231 | 1.072 | 0.893 |
| CPI_TM | 0.952 | 0.841 | 0.886 | 1.086 | 1.195 | 0.967 |
| CPI_Med | 0.999 | 0.999 | 0.983 | 0.967 | 0.973 | 0.935 |
| CPI_TM, CPI_UIG | 1.001 | 0.859 | 0.789 | 0.932 | 1.102 | 0.990 |
| CPI_UIG0 | 1.074 | 0.979 | 0.956 | 0.955 | 1.067 | 1.009 |
| CPI_UIG24 | 1.029 | 0.914 | 0.802 | 0.793 | 0.940 | 1.067 |
| CPI_PricesOnly | 1.003 | 1.083 | 1.148 | 1.169 | 1.088 | 0.912 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>AR(3) RMSE</i> | <i>0.29</i> | <i>0.65</i> | <i>1.29</i> | <i>1.66</i> | <i>1.77</i> | <i>1.55</i> |
| CPI_UIG | 1.124 | 0.940 | 0.750 | 0.769 | 0.941 | 1.036 |
| CPI_XFE | 0.965 | 1.203 | 1.149 | 1.177 | 1.154 | 0.893 |
| CPI_TM | 0.893 | 0.755 | 0.761 | 1.024 | 1.295 | 1.062 |
| CPI_Med | 0.979 | 0.974 | 0.956 | 0.959 | 0.996 | 0.961 |
| CPI_TM, CPI_UIG | 1.104 | 0.790 | 0.656 | 0.860 | 1.181 | 1.069 |
| CPI_UIG0 | 1.552 | 0.976 | 0.940 | 0.946 | 1.125 | 1.054 |
| CPI_UIG24 | 1.066 | 0.900 | 0.774 | 0.791 | 0.940 | 1.079 |
| CPI_PricesOnly | 0.945 | 1.063 | 1.131 | 1.165 | 1.119 | 0.925 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>Random Walk RMSE</i> | <i>0.27</i> | <i>0.77</i> | <i>1.25</i> | <i>1.71</i> | <i>1.75</i> | <i>1.26</i> |
| CPI_UIG | 1.131 | 0.906 | 0.714 | 0.776 | 0.942 | 1.071 |
| CPI_XFE | 0.893 | 1.060 | 1.033 | 1.114 | 1.179 | 0.870 |
| CPI_TM | 0.926 | 0.679 | 0.692 | 0.950 | 1.300 | 1.295 |
| CPI_Med | 0.946 | 0.939 | 0.937 | 0.948 | 1.001 | 0.950 |
| CPI_TM, CPI_UIG | 1.165 | 0.754 | 0.587 | 0.799 | 1.193 | 1.272 |
| CPI_UIG0 | 1.599 | 0.960 | 0.930 | 0.935 | 1.141 | 1.140 |
| CPI_UIG24 | 1.087 | 0.882 | 0.757 | 0.807 | 0.939 | 1.110 |
| CPI_PricesOnly | 0.925 | 1.065 | 1.121 | 1.149 | 1.125 | 0.890 |

Table 5b(i): Relative out of sample performance in RMSE 2000-2007 based on equation 3.

Out of sample performance for annual inflation: 2002:01-2007:03 ("increasing CPI phase")

(Estimation sample 1994:1-2001:12)

Relative RMSE

| | 6 | 12 | 18 | 24 | 30 | 36 |
|-------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| <i>AR(6) RMSE</i> | <i>0.69</i> | <i>1.08</i> | <i>1.39</i> | <i>1.51</i> | <i>1.54</i> | <i>1.37</i> |
| CPI_UIG | 0.899 | 0.987 | 0.999 | 0.885 | 0.931 | 0.991 |
| CPI_XFE | 1.084 | 1.182 | 1.159 | 1.076 | 0.996 | 1.011 |
| CPI_TM | 0.975 | 0.952 | 0.985 | 1.025 | 1.028 | 0.978 |
| CPI_Med | 0.944 | 0.937 | 1.074 | 1.009 | 0.976 | 1.027 |
| CPI_TM, CPI_UIG | 0.909 | 0.964 | 0.990 | 0.941 | 0.987 | 0.980 |
| CPI_UIG0 | 0.886 | 0.917 | 1.034 | 1.013 | 0.995 | 1.012 |
| CPI_UIG24 | 0.902 | 0.947 | 0.957 | 0.888 | 0.940 | 1.009 |
| CPI_PricesOnly | 1.006 | 1.035 | 1.048 | 1.023 | 0.999 | 1.043 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>AR(3) RMSE</i> | <i>0.51</i> | <i>1.02</i> | <i>1.35</i> | <i>1.51</i> | <i>1.51</i> | <i>1.36</i> |
| CPI_UIG | 0.691 | 0.890 | 0.937 | 0.886 | 0.932 | 1.010 |
| CPI_XFE | 0.978 | 1.071 | 1.075 | 1.062 | 1.022 | 0.981 |
| CPI_TM | 0.788 | 0.853 | 0.913 | 1.009 | 1.071 | 1.010 |
| CPI_Med | 0.947 | 0.882 | 0.990 | 1.001 | 0.986 | 1.005 |
| CPI_TM, CPI_UIG | 0.665 | 0.861 | 0.915 | 0.929 | 1.023 | 1.013 |
| CPI_UIG0 | 1.038 | 0.915 | 0.973 | 1.005 | 1.006 | 1.000 |
| CPI_UIG24 | 0.742 | 0.884 | 0.920 | 0.887 | 0.939 | 1.027 |
| CPI_PricesOnly | 0.959 | 1.014 | 1.032 | 1.024 | 1.001 | 1.033 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>Random Walk RMSE</i> | <i>0.31</i> | <i>0.95</i> | <i>1.37</i> | <i>1.56</i> | <i>1.48</i> | <i>1.15</i> |
| CPI_UIG | 0.790 | 0.837 | 0.900 | 0.877 | 0.915 | 1.100 |
| CPI_XFE | 0.985 | 0.982 | 1.012 | 1.034 | 1.037 | 0.943 |
| CPI_TM | 0.979 | 0.819 | 0.869 | 0.971 | 1.094 | 1.129 |
| CPI_Med | 1.681 | 0.954 | 0.944 | 0.974 | 0.988 | 1.031 |
| CPI_TM, CPI_UIG | 0.805 | 0.819 | 0.870 | 0.910 | 1.050 | 1.139 |
| CPI_UIG0 | 1.824 | 1.016 | 0.959 | 0.986 | 1.022 | 1.084 |
| CPI_UIG24 | 0.829 | 0.868 | 0.909 | 0.885 | 0.920 | 1.117 |
| CPI_PricesOnly | 1.004 | 1.000 | 1.012 | 1.017 | 1.010 | 0.994 |

Table 5b (ii): Relative out of sample performance in RMSE 2002-2007 based on equation 3

Out of sample performance for annual inflation: 2004:01-2007:03 ("flattening CPI phase")

(Estimation sample 1994:1-2003:12)

Relative RMSE

| | 6 | 12 | 18 | 24 | 30 | 36 |
|-------------------------|-------------|-------------|-------------|-------------|-------------|-------------|
| <i>AR(6) RMSE</i> | <i>0.63</i> | <i>1.12</i> | <i>1.40</i> | <i>1.52</i> | <i>1.55</i> | <i>1.35</i> |
| CPI_UIG | 0.841 | 0.905 | 0.931 | 0.915 | 0.983 | 1.121 |
| CPI_XFE | 1.118 | 1.005 | 0.980 | 0.921 | 0.880 | 0.891 |
| CPI_TM | 1.005 | 0.840 | 0.846 | 0.897 | 0.936 | 0.980 |
| CPI_Med | 0.964 | 0.939 | 0.948 | 0.952 | 0.955 | 0.990 |
| CPI_TM, CPI_UIG | 0.886 | 0.812 | 0.833 | 0.863 | 0.937 | 1.070 |
| CPI_UIG0 | 0.837 | 0.914 | 0.953 | 0.940 | 0.971 | 0.988 |
| CPI_UIG24 | 0.851 | 0.909 | 0.925 | 0.913 | 0.978 | 1.126 |
| CPI_PricesOnly | 1.003 | 0.999 | 1.005 | 1.001 | 1.001 | 1.015 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>AR(3) RMSE</i> | <i>0.52</i> | <i>1.05</i> | <i>1.26</i> | <i>1.48</i> | <i>1.56</i> | <i>1.35</i> |
| CPI_UIG | 0.766 | 0.898 | 0.906 | 0.914 | 0.986 | 1.116 |
| CPI_XFE | 1.012 | 0.975 | 0.946 | 0.925 | 0.908 | 0.912 |
| CPI_TM | 0.872 | 0.865 | 0.854 | 0.910 | 0.961 | 0.999 |
| CPI_Med | 0.951 | 0.970 | 0.961 | 0.965 | 0.977 | 0.996 |
| CPI_TM, CPI_UIG | 0.735 | 0.837 | 0.839 | 0.875 | 0.962 | 1.092 |
| CPI_UIG0 | 0.870 | 0.960 | 0.938 | 0.950 | 0.990 | 0.996 |
| CPI_UIG24 | 0.801 | 0.907 | 0.911 | 0.915 | 0.981 | 1.121 |
| CPI_PricesOnly | 0.996 | 1.003 | 1.000 | 1.000 | 1.005 | 1.019 |
| | 6 | 12 | 18 | 24 | 30 | 36 |
| <i>Random Walk RMSE</i> | <i>0.46</i> | <i>1.08</i> | <i>1.31</i> | <i>1.54</i> | <i>1.56</i> | <i>1.30</i> |
| CPI_UIG | 0.871 | 0.904 | 0.915 | 0.922 | 0.984 | 1.153 |
| CPI_XFE | 0.960 | 0.954 | 0.926 | 0.907 | 0.892 | 0.891 |
| CPI_TM | 0.784 | 0.824 | 0.820 | 0.877 | 0.952 | 1.014 |
| CPI_Med | 0.957 | 0.951 | 0.951 | 0.957 | 0.962 | 0.998 |
| CPI_TM, CPI_UIG | 0.744 | 0.799 | 0.808 | 0.853 | 0.953 | 1.127 |
| CPI_UIG0 | 1.058 | 0.922 | 0.927 | 0.939 | 0.957 | 0.993 |
| CPI_UIG24 | 0.915 | 0.924 | 0.930 | 0.934 | 0.979 | 1.154 |
| CPI_PricesOnly | 1.009 | 1.005 | 1.001 | 1.000 | 1.004 | 1.013 |

Table 5b (iii): Relative out of sample performance in RMSE 2004-2007 based on equation 3