Federal Reserve Bank of New York
Staff Reports

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Staff Report no. 420
December 2009

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

Abstract

Central banks analyze a wide range of data to obtain better measures of underlying inflationary pressures. Factor models have widely been used to formalize this procedure. Using a dynamic factor model this paper develops a measure of underlying inflation (UIG) at time horizons of relevance for monetary policymakers for both CPI and PCE. The UIG uses a broad data set allowing for high-frequency updates on underlying inflation. The paper complements the existing literature on U.S. "core" measures by illustrating how UIG is used and interpreted in real time since late 2005.

Key words: inflation, dynamic factor models, core inflation, monetary policy, forecasting

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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 even with appropriate averaging. As recently as July 2008 the headline 12 month change was almost 6% but fell to zero in December of the same year and reached a low of around -2% in July 2009. Consequently there have been a number of 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 are published by the statistical agencies that exclude the food and energy subcomponents [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 Banks[2]. Other approaches weight the CPI subcomponents by their volatility contribution instead of completely excluding volatile components.

All of the approaches discussed so far do not take into directly account for 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 make it possible to simultaneously combine information from both cross-sectional dispersion of prices as well as time-series properties

[1] Bryan and Cecchetti (1999) give an overview of different additional components excluded from CPI by different central banks. In the 2009 comprehensive revisions of the national income accounts the definition of core PCE was changed to incorporate restuarant prices. We use the old definition of core PCE in this paper.

[2] See 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.

of individual prices in a unified framework. The statistical techniques are known as large data factor models and are widely used by Central Banks to complement existing measures of underlying inflation and real activity[3].

Our new factor based measure of underlying inflation complements the existing measures of core and underlying inflation available to monetary policymakers. We use the large data factor approach of Forni et. al. (2001) to develop underlying measures of inflation for both the CPI and PCE indices.[4]. Unlike previous factor approaches in the US we utilize all of the 211 non-seasonally adjusted price series formed in constructing the overall CPI[5]. Furthermore we do not restrict ourselves to price data only, as many economic variables may affect the inflation process. Instead we also allow for a broad range of nominal, real and financial variables to influence the measure of underlying inflation.

An extensive literature on core and underlying inflation comparisons conclude that there is no single core inflation measure which outperforms the others on all criteria[6]. However, the criteria most policymakers focus on is whether an underlying inflation measure is able to track and forecast inflation. We find that the UIG outperforms traditional cores in terms of tracking trend inflation as well as in terms of forecasting over different time periods (increasing, decreasing inflation as well as spanning a whole inflation cycle). Another extensive literature examines whether measures of real activity improve inflation forecasts. Stock and Watson (2008) find that recently a simple random walk specification (i.e., using the most recently observed annual change in inflation to forecast future inflation) is at least as accurate as most

[3]For 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 and Fischer (2009a and 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 method of Stock and Watson (1999).

[4]Charts and tables are given for both inflation series. We always label the factor model for the PCE as PCE_UIG.

[5]Recently, Reis and Watson (2007, update references) 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.

[6]See for example, Rich and Steindel (2007) and therein given references. More recently, Stock and Watson (2008) gave a comprehensive analysis supporting this assessment including a number of models that use output gaps.

forecasting models that use measures of real activity confirming the earlier result of Atkeson and Ohanion (2001). We find that the UIG outperforms such random walk specification in a pseudo out of sample forecasting exercise and in a genuine out of sample forecast exercise from November 2006 to April 2009.[7]

UIG can be used for further purposes, besides forecasting inflation. Following Amstad and Fischer (2009a and b), it can be updated on a daily basis allowing the derivation of the impact of a particular data release (e.g. unemployment rate or ISM) on underlying inflation. For example, the daily forecasts of UIG can be compared to the information on inflation expectations derived from nominal and indexed linked treasury market in the U.S.The use of factor models in real time is sometimes criticized for its lack of stability. We show that revisions of UIG tend to be minor in normal times and do not affect its use in real time policy analysis but we do find evidence that the ease of the identification of the number of factors used in the construction of the UIG varies through time. Further, the two-sided nature of the UIG means that in non-normal times, for example the path of inflation and the US economy in 2008, there can be large revisions in its assessment of underlying inflation.

The remainder of the paper is organized as follows. Section 2 discusses a range of measures of underlying inflation and relates them to the data rich approach of 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 estimation procedure and a rational for our chosen parametrization. In section 4 the UIG is compared to traditional core concepts based on descriptive measures as well as a forecasting exercise. The UIG was first constructed during 2005 and has been updated usually at a daily frequency. Through-out the paper we add some discussion of the real-time modeling experience with the UIG. Based on this real time experience we conclude that UIG adds value on traditional core measures for monetary policymakers.

[7] This is a genuine forecast comparison exercise since the UIG forecasts were produced in real time as part of the forecasting process at FRBNY.

2 Underlying inflation concepts

In this section we review the concept of underlying inflation. We emphasize the difference of excluding versus broad data approaches. The review motivates our definition/measurement of underlying inflation, choice of methodology, data set and parameterization of the dynamic factor model.

2.1 Defining/measure underlying inflation

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 food and energy goods and services. This excludes also "food away from home" in the CPI, most other countries just exclude fresh food since "food away from home" is not very volatile. We will indicate these measures by the extension XFE.

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%. We will indicate these measures by the extension TM.

6. Model-based approaches which try to derive the core inflation from economic theory. The leading examples are forecasts from Gordon (1982) "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 the model of Stock and Watson (2007). More complex multivariate examples are the Chicago Fed National Activity Index for gdp and the model for inflation presented in this paper.

8. Measures from financial markets and surveys of inflation expectations.

In this paper underlying inflation is defined/measured differently. We explicitly take the stand of a policy oriented concept and define underlying inflation as "an inflation measure free of aspects, which should not affect policymaker's decision". We can express this feature mathematically as

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

That is, the policymaker is reacting to changes in underlying inflation such that actual inflation converges to underlying inflation in expectation. Note that if expectation of underlying inflation $E_t\left[\pi^*_{t+h}\right]$ satisfies the above property then it implies that the transitory component converges to zero in expectation as the horizon extends $E_t\left[c_{t+h}\right] \longrightarrow 0$. Thus, any successful measure of underlying inflation should capture a persistent component in inflation at the horizon of interest to policymakers. This can be very different from a measure simply being a less volatile inflation series.

2.2 Exclusion measures of underlying inflation

Traditional core inflation indicators became popular in the 1970s as headline inflation was influenced by large oil price movments. 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 and energy approach) or time varying subcomponents (as in the trimmed mean approach). However, the concept of reaching a smoother signal by excluding volatile components suffers from some disadvantages. (i) In the ex food and energy approach the specific subcomponent to be removed can only be determined in a backward looking manner after the "noise" has appeared in the inflation release. Rich and Steindel (2007) conclude in their comprehensive comparison of core measures, that the fact that no single core measures outperforms the others over different sample ranges is due to the fact that there is too much variability in the nature and sources of transitory price movements to be captured effectively through the desiging of any individual measure. (ii) In the trimmed mean 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 are confronted with recurring criticism[8]. For example, many analysts argued that the sustained oil price increase until mid 2008 should be considered as a signal in price trend[9] and not as temporary outlier. 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.

2.3 Data rich time series models of underlying inflation

One of the most prominent differences between the exclusion measures (ex food, ex energy, trimmed mean) and time series model based approaches is

[8]In particular critics argue along the line that the ex food and energy and trimmed mean approaches 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".

[9]This was based on the view that the oil price increase was driven mostly by long-term supply and demand consideration rather than short term supply disruptions – the traditional reason to exclude oil prices.

that the later is not limited to CPI and few of its subcomponents. Simplicity is a main advantage of the exclusion approach and as shown by Atkeson and Ohanion (2001) the performance can be very similar or even better than more complicated approaches. However from a policy as well as a from a forecasting perspective there are several reasons why the approach of adding information instead of excluding information to measure underlying trend inflation is beneficial. As argued in Bernanke and Boivin (2003), monetary policymaking uses in a "data-rich environment". Furthermore Stock and Watson (1999, 2008) showed that taking into account a broad information set can improve forecasting in certain time periods. Therefore, it is stated by several authors (including Gali (2001)) that from a policymaker'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 broad data 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 generating 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 (see Stock and Watson 2008).

We investigate the use of large data factor modeling, which has three main advantages: broad data approach, flexibility and smoothness.
First, it allows summarizing a very broad information set with regard to price pressure in a formal and systematic way. 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 excluded to generate the underlying measure. Large data factor techniques allow us to use all the detail in the monthly US CPI inflation report. 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 and financial variables. For example, slack or tightness in product and labor market are well-known possible driving factors of inflation. However, in calculating core measures this information is little used so far. Further, standard Phillips curve models rely on one measure of slack and are vulnerable to specification errors in this regard. Second, the dynamic factor approach allows to extract information from a very large data in a flexible way. 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 Structural VAR-models and Phillips curve based models. Third, the dynamic factor model explicitly evaluates 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 and only incorporate it at a later date if it turns out to correlate with underlying inflation.

3 Underlying inflation gauge (UIG)

3.1 Data

Based on substantial previous work on structural breaks in the US inflation process (see Clark (2004, see also Stock and Watson (2008)) 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 time length of the study and the range of time series we can use. 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, producer surveys, and financial variables (FX, credit, stocks, commodities, high yield bonds, gov.bonds). We abstain from including every indicator available, since research on factor models (see Boivin and Ng (2006)) shows this does not come without risks. Our approach is to include the variables which are regularly followed by FRBNY staff in their economic assessment. This procedure allows to profit from their long term experience and assures some stability of the set of variables, while the time varying weight of an individual series is determined by the factor model. Figures 1a and 1b give more information on the current data set used and Appendix B (available at URL) gives a detailed listing of the variables and transformations.

In order to derive a signal for monetary policymakers, stability of the most current estimates becomes an important issue. Therefore, nearly all of the data we have chosen is not subject to revision. This implies that we reply heavily on survey data for real activity and do not use more traditional measures based on the National Income and Product Accounts. Another advantage is that survey data is usually released more quickly than expenditure and production data. Following Amstad and Fischer (2009a and b) 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 is standard in the factor literature prior to the estimation we transformed the data to induce stationary and standardize each series so it has zero mean and unit variance. The standardization requires us to assign an average value for the underlying measure derived from the analysis. 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[10]. By the middle of 2008 this centering of the UIG was producing downward bias in the estimates of underlying inflation relative to the average of CPI inflation since 1993. No changes were made in the centering since our focus is on the "inflation gap" (Cogley et al 2009), the deviation of inflation from the central bank's price stability objective and there is no evidence of any change in this objective. Of course since the summer of 2008, CPI inflation has been negative reducing considerably this bais.

UIG is set up as a monthly model of inflation which is updated daily as proposed in Amstad and Fischer (2004, 2009) 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 policymakers to assess movements in inflation expectations in financial markets.

[10] 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 dynamic factor model 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 inflation objective is close to the recent average of inflation in the US in our estimation.

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 an appendix. Here we describe the methods informally.

We assume that the N (transformed and standardized) variables in the panel, $x_t = (x_{1t}, x_{2t}, \cdots, x_{Nt})'$ can be decomposed into the sum of two components: the underlying signal x^*_{it} and a variable specific comoonent e_{it}:

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

Recall the definition of underlying inflation from section 2. For forecasts of the future value of the variable we have:

$$E_t[x_{it+h}] = E_t[x^*_{it+h}] + E_t[e_{it+h}],$$

where the underly signal is chosen so that at horizon h and higher the forecast of the variable specific component is approximately zero. Our estimation approach effectively extracts the common components across variables $E_t[x^*_{it+h}]$ at horizons of h. We call these common components, the dynamic factors. Let $\{F_{kt}\}$ represent the dynamic factors, then the UIG measure of underlying inflation is obtained by:

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

where $\{\widehat{\beta}_{k\ell}\}$ are the estimated regression coefficients from the regression of $(\pi_t - \overline{\pi})$ on the contemporaneous and p lags of the q dynamic factors. Here, $\overline{\pi}$ is the fixed average of the underlying inflation rate. 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 UIG to be useful for monetary policymakers. This immediately suggests that we should not look for common components at short horizons since there is little policymakers 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 technical appendix.

3.2.2 Number of factors

Our final specification choice is the number of factors. Different papers find that much of the variance in U.S. macroeconomic variables is explained by two factors. Giannone, Reichlin, Sala (2004) show these findings for factor models with hundreds of variables for 1970-2003 and Sims/Sargent (1977) for a relatively small set of variables using 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 large data factor model applications q (the number of 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 from the CPI only. One would expect these series to be driven by one single factor. Figures 2.a and 2.b show the estimates for the UIG for CPI and PCE assuming 1 and 2 dynamic factors along with the 12 month change in the relevant price index. As can be seen there is little difference between the two estimates. Further, the movements in the estimates are very smooth when we consider only frequencies of 12 months or longer with the exception of the movements in 2008. We investigated the smoothness earlier in the construction of the UIG by the following experiment in 2005: 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 showing that the methods could capture a common movement in all the individual price series. It should be noted that if we include all frequencies in the estimation of the UIG then as would be expected there is a very close correspondence between the movements in total inflation and the UIG.

Figures 3.a and 3.b show the UIG for a range of total factors from 1 to 8 where we add the non-CPI variables in our dataset for data through April 2009. Three findings are noteworthy. First, the estimates now show larger cyclical fluctuations although they do not capture the large increase in inflation in the first half of 2008. Second, until the addition of the last year of data there was very little difference between the estimates with the number of factors at least equal to 2 but as we have added data over the last year there is evidence of additional dynamics not captured by two factors alone. In addition to the divergence in 2008 the newly estimated factors now show greater divergence in the mid-1990s suggesting that additional non-zero loadings.

4 Comparing measures of underlying inflation

In the following we compare the traditional core, trimmed mean, median and above described UIG approach for CPI as well as for PCE. After commenting general statistical differences we turn to the time series features of underlying inflation measures and compare their ability to track as well as to forecast inflation.

4.1 General statistical features/properties

We find four general statistical differences in the underlying measures considered.

First, the general behavior of the different measures is mainly driven by the choice of the underlying inflation concept and less whether it is based on CPI or PCE. 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.

Second, even though. (volatility across all frequencies) is similar for all underlying measures considered with the exception of the prices only UIG measures (see Table 2), UIG has the most low frequency variation as would be expected given its focus on cycles over at least 12 months (see Figure 4a to 4c). Thus, the traditional core measures and to less extent also the trimmed mean approach provides a signal with some remaining high frequency volatility, which leaves it to the policymakers to decide whether an actual change should be considered as a change in trend or not. On contrary a change in UIG can be interpreted with more confidence as an actual change in underlying inflation.

Third, UIG is closly related to CPI and at the same time is able to provide additional information to the policymaker that is not included in traditional core measures. This is illustrated in the correlations between the various underlying measures and total inflation shown in Tables 3a-c which show an interesting pattern. The UIG has almost no correlation with the other underlying measures of CPI but still has a 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 simple principal component analysis on CPI and underlying measurues including UIG as shown in Table 4. 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.

Fourth, although there are clear differences between the CPI and PCE UIG, they are highly correlated with each other as can be seen in Table 2c. 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 UIG based on CPI since it has the advantage that the CPI is only subject to very minor and rare revisions whereas the PCE experiences major revisions.

4.2 Forecast Performance

The basic reason for developing underlying measures of inflation is that they should produce better forecasts of future inflation than considering the headline measure alone. For policymakers it is of particular interest that the forecast exercise reflects a realistic setting. Following Cogley (2002) and others we evaluate the performance of the various measures by examining the predictive power of the contemporaneous deviation of the underlying measure from total inflation to predict the future behavior of total inflation. Let π_{mt} be the measure of underlying inflation, then we run the following regressions for horizon h.

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

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. This specification nests the model of Atkeson and Ohanion (2001) when $\alpha_h = \beta_h = 0$.

When this regression is estimated in sample the main interest is in testing the properties of unbiasedness and accurate assessment of the size of the transitory deviation in inflation. Rich and Steindel (2007) find that over a long sample period the property of unbiasedness can be rejected but there is less evidence against the hypothesis of accurate assessment of the deviation ($\beta_h = -1$). In our shorter sample we are unable to reject any of the hypotheses. However, it should be noted that the test for unbiasedness of the UIG suffers from pre-test bias as the UIG must be centered separately from the estimation of the factors. Further, while in sample it is always possible to reject the model of Atkeson and Ohanion this does not provide information about the out of sample performance.

Thus, we now investigate the relative performance of underlying inflation measures in 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 policymakers. Therefore we want to add some remarks as a note of caution before we run the usual forecasting exercise in the broadly accepted setting of Rich and Steindel (2007).

The most difficult aspect - which should be considered in the interpretation of forecasting results - 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 policymaker of the actual inflation rate relative to their desired levels. Consider the following example:

- case 1: 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.

- case 2: 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 policymaker uses measure A they will be slow to recognize turning points in inflation. If the policymaker uses measure B they will be quicker to recognize turning points in inflation. Suppose the policymaker 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.

Besides a cautious interpretation of the results, it is an important practical issue to find an appropriate setting for the forecasting exercise. This involves the choice of forecasting sample. Long time periods 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. Therefore it is important to run the exercise over a sample with significant variation in inflation. The path of inflation in the US since 2000 satisfies this need for significant variation.

Finally, often the forecasting exercises are "pseudo" real time in the sense that estimation is conducted 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) but unlike more traditional exclusion measures, future data can produce reassessments of the the past.. We focus only the CPI since its revisions are very minor (correction of small technical mistakes) and thus the forecast target and the underlying measures used for comparison are based on real time data.[11]

[11] Because we focus at the 12 month horizon there is no meaningful difference between seasonally adjusted and non-seasonally adjusted measures.

Table 5 gives the result of a forecasting exercise based on a predictive version of equation 2 [12]

$$\widehat{\pi}_{t+h} = \pi_t + \widehat{\alpha}_{h,t} + \widehat{\beta}_{h,t}(\pi_t - \pi_{mt}),$$

where .$\widehat{\alpha}_{h,t}, \widehat{\beta}_{h,t}$ are the estimated regression coefficients using data through time t. To allow for the sensitivity of forecast comparisons to sample periods above we consider a number of different sample periods through April 2009: (a) a post 2000 sample: a time range that could be considered as more than one inflation cycle, spanning up as well as down phases in CPI, (b) a post 2002 sample, which captures one cycle (c) a post 2005 sample, which covers a phase of increased CPI volatility while the overall. Finally, for comparison purposes we also consider a sample from 2001 to 2007 that exactly matches one in Stock and Watson (2008). We compare the forecast performance of the UIG to the traditional core, trimmed mean and the prior 12 month change in CPI in Table 5. We also include a prices only version of the UIG in the comparison.The results show that UIG out performs the other measures in forecasting headline CPI. Further, the 12 month change in total CPI has very similar forecast performance to the traditional underlying inflation measures. In most cases the improvement in forecast performance is statistically significant, although these results are the weakest for the Stock and Watson sample. Of course the estimate of the UIG used in this forecasting equation has the advantage of being derived from a process that uses information from future values of the dataset used in its construction. One approach to assessing the significance of this advantage would be to re-estimate the whole UIG at each time period. Such a procedure would not be necessary if the revisions to past UIG estimates where small as new data was added.

This issue was examined for a 18 month period from November 2005 to April 2007. We examined the revisions in each of the monthly estimates of the UIG over 240 wordays (approximately one year). The results of this exercise are contained in figure 6a for the absolute size of the change and figure 6b for the raw change. They show that the largest changes in the estimate of the UIG for a month usually occur within the first month. The source of this change is the publication of the monthy CPI report. After that the

[12] To ensure comparibility 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 Laflèche (2001), Cutler (2001) and Cogley (2002).

mean revision tends to converge more slowly to zero than the median. This likely reflects the sustained period of CPI inflation over 3% in the evaluation period – an ex ante unlikely event given our chosen centering of 2.25% and the volatility of the CPI from 1993-2005.

These results on the size of revisions in the estimate of the UIG were completed in the summer of 2008. Since then with the large drop in the CPI and the deep recession in the US, the revisions have been considerably larger. Since November 2005 real time forecasts from the UIG have been produced each day. These forecasts are produced directly from the statistical model underpinning the UIG rather than from prediction models based on equation 2. The original motivation was to compare any changes in the these forecasts with movements in inflation expectations from financial markets. The real time forecasts were produced for a range of horizons. Figure 7 shows a standard chart comparing forecasts of inflation over 2, 2-3 and 3-5 years with inflation expectations derived from financial markets. The figure also gives current forecasts from the UIG at shorter horizons. The forecasts for the one year horizon were used in a genuine out of sample forecast comparison to forecast based on the prior 12 month change in the CPI and core CPI. The target variables were both the CPI and the core CPI. The results are contained in Table 6 for sample from November 2006 to April 2009. Again the UIG outperforms these more traditional measures of underlying inflation.

Finally, we examine in more detail the changes in the estimated path of the UIG since 1995 for last two months of 2008 and the first month of 2009. For each month we show the path of the UIG after the the release of the CPI in the prior month (i.e., the CPI for two months earlier), the release of the employment situation for the prior month and finally the release of the CPI for the prior month. The results are contained in Figures 8a to c. The results for November indicate little sensitivity to the CPI or employment sitiation for October 2008. In December 2008 it can be seen that the November CPI had a large effect on the current value and previous 24 month of estimates for the UIG. Finally, the December 2008 employment situation produced a massive move in the current estimate (ie., January 2009) of the UIG and significantly revised its whole history. The effect on the two year forecast of CPI can be seen in figure 7.

5 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. 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.

UIG is able to inflation at a frequency of relevance to policymakers, very closely. The smoothness of UIG gives the policy maker a clear indication of which CPI movements and developments in the economy are to be considered as important Furthermore, UIG is closely related to headline inflation and at the same time adds information on underlying inflation over what is included in the traditional core measures. Therefore UIG can be used in addition to other core measures more in a complementary than a substitutive way. Moreover, in a competitive horse race setting of forecasting head line inflation UIG significantly outperforms traditional core measures and for different regimes (whole cycle, up and downward sloped) of headline inflation.

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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) as well as time dimension.

The model

We assume a panel of $i = 1, ..N$ time series, $x_{it} = (x_{1t}, x_{2t}, \cdots, x_{Nt})'$, 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:

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

where χ_{it} is the common component, driven by q dynamic common shocks $\mathbf{u_t} = (u_{1t}, .., u_{qt})$ with non-singular spectral density matrix and ξ_{it} is the idiosyncratic component (reflecting measurement erros 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 $N \to \infty$, 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 allowes 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 $\{(u_{1t}\ u_{2t} \cdots u_{qt})', t \in \mathbb{Z}\}$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) $\boldsymbol{\xi} = \{\xi_{it}, i \in \mathbb{N}, t \in \mathbb{Z}\}$ is a double sequence such that, firstly, $\boldsymbol{\xi}_n = \{(\xi_{1t}\ \ \xi_{2t}\ ...\xi_{nt})', t \in \mathbb{Z}\}$ is a zero-mean stationary vector process for any n, and, secondly, for and $\xi_{it} \perp u_{jt-k}$ 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 $\lambda_{n1}^{\xi}$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, $\underset{n \to \infty}{lim} \lambda_{nj}^{\chi}(\theta) = \infty$ for $j \leq q$, a.e. in $[-\pi, \pi]$, with λ_{nj}^{χ} the dynamic eigenvalues of the spectral density matrix $\Sigma_n^{\chi}(\theta)$ 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 of the density matrices of the common (and the idiosyncratic) using the above described method of generalized dynamic principal components of Forni et al. (2000).

$$\widehat{\boldsymbol{\Sigma}}_{\chi}(\theta) = \mathbf{U}(\theta)\boldsymbol{\Lambda}(\theta)\tilde{\mathbf{U}}(\theta) \tag{2}$$

where $\mathbf{\Lambda}(\theta)$ is the diagonal matrix $\lambda_1(\theta), ..., \lambda_q(\theta)$ 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

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

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

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

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 $(u_{1t}, .., u_{qt})$. 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

$$\widehat{\boldsymbol{\chi}}_{t+h}^{L} = \mathbf{RW}(\mathbf{W}'\mathbf{MW})^{-1}\mathbf{W}'\mathbf{X}_t \tag{5}$$

with $\mathbf{M}$ the sample covariance matrix of $\mathbf{X}_t = (x'_{t+m}...x'_t...x'_{t-m})'$, $\mathbf{W}$ 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, $t+h$.[13]. An important step in our forecasting procedure is to apply the band-pass filter

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

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,..,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

$$x^*_{i,t} = (x^1_{i,t}\ x^2_{i,t}\ ...\ x^w_{i,t}) \tag{6}$$

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

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

and accordingly for the covariance matrix of the common $\widehat{\Gamma}^*_\chi(k)$ and the covariance matrix of the idiosyncratic $\widehat{\Gamma}^*_\xi(k)$[14] 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 realigned vector $\widehat{\Gamma}^*_\xi(k)$ to get the forecasts. The final step is to restore the original alignement. The procedure is decribes in greater detail in Cristadoro et al. (2005).

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

Figure 1a: Breakdown of UIG Series by Frequency

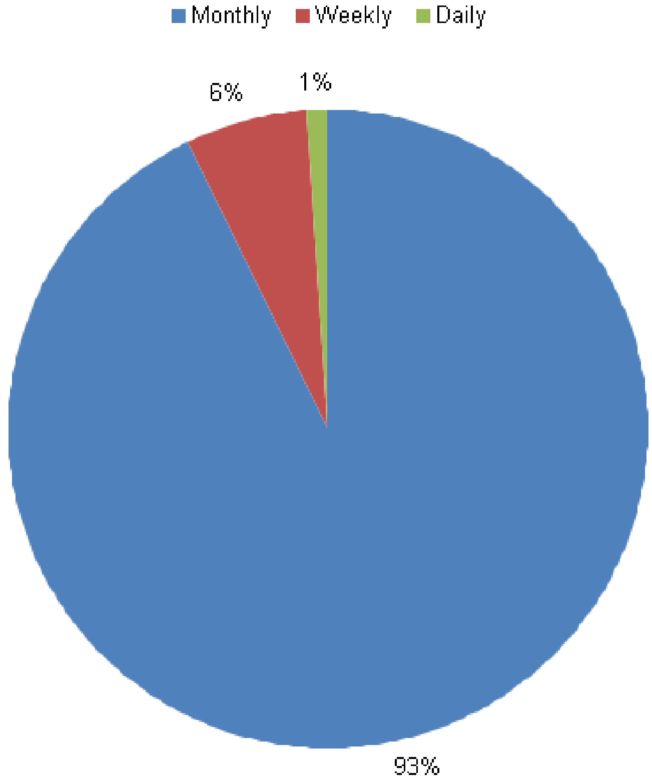


Figure 1b: Breakdown of UIG Series by Type

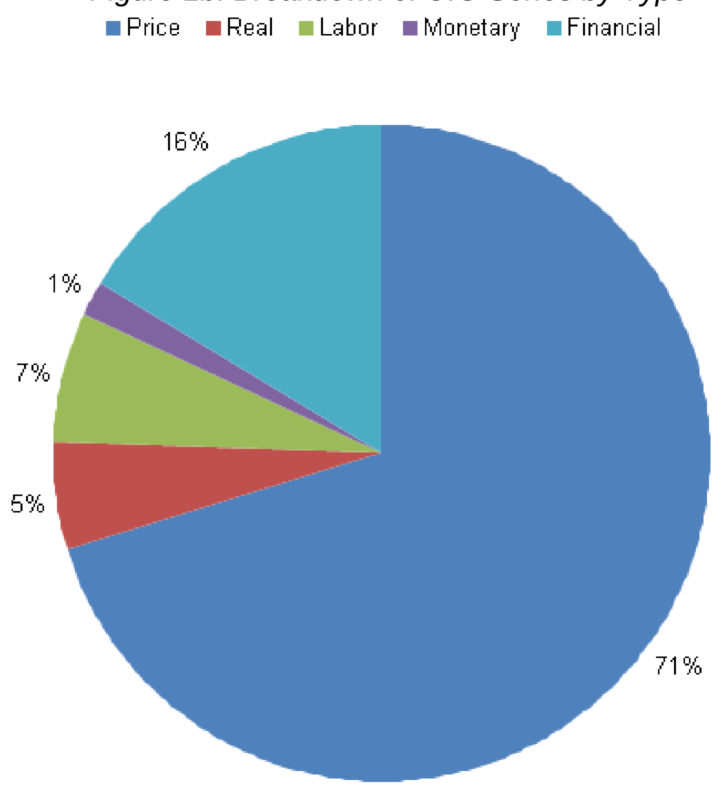


Figure 2a: CPI_UIG_Prices Only

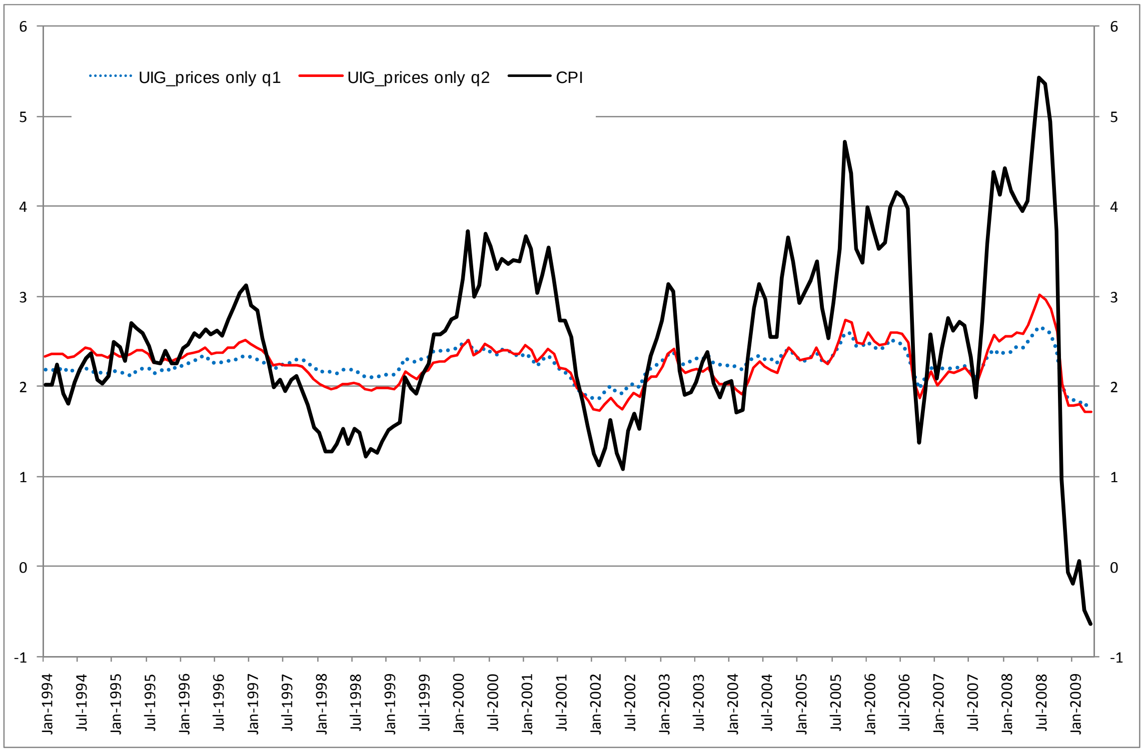


Figure 2b: PCE_UIG__Prices Only

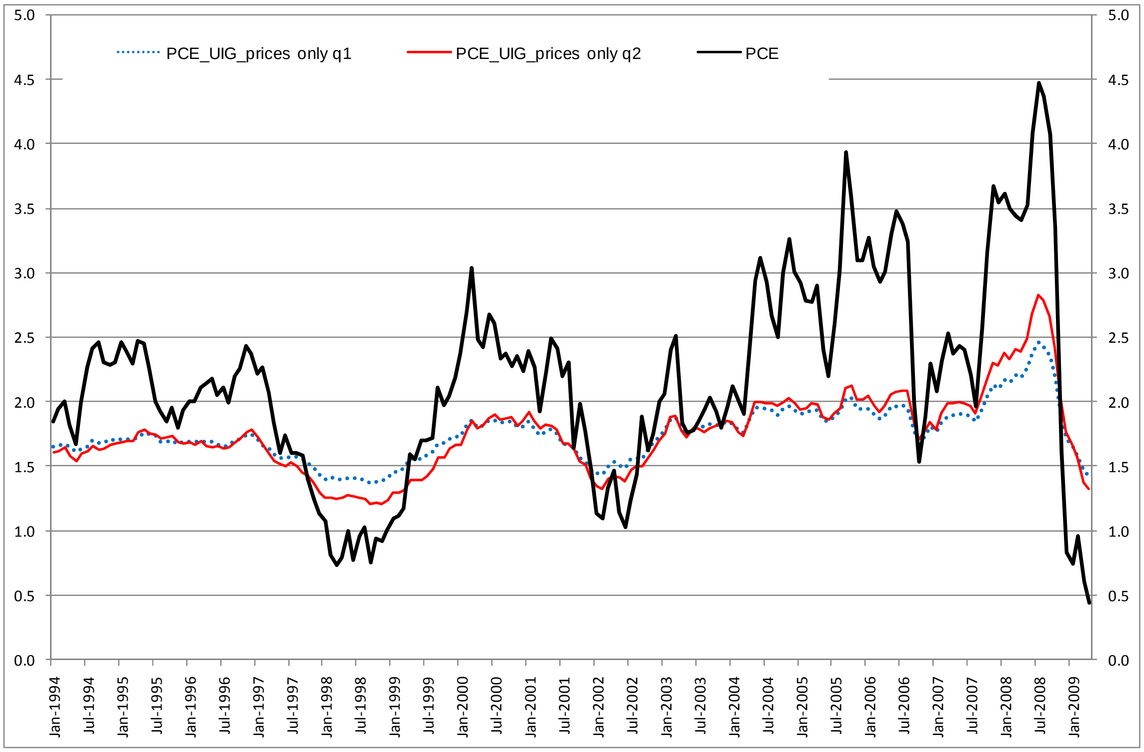


Figure 3a: CPI_UIG for a Different Number of Factors

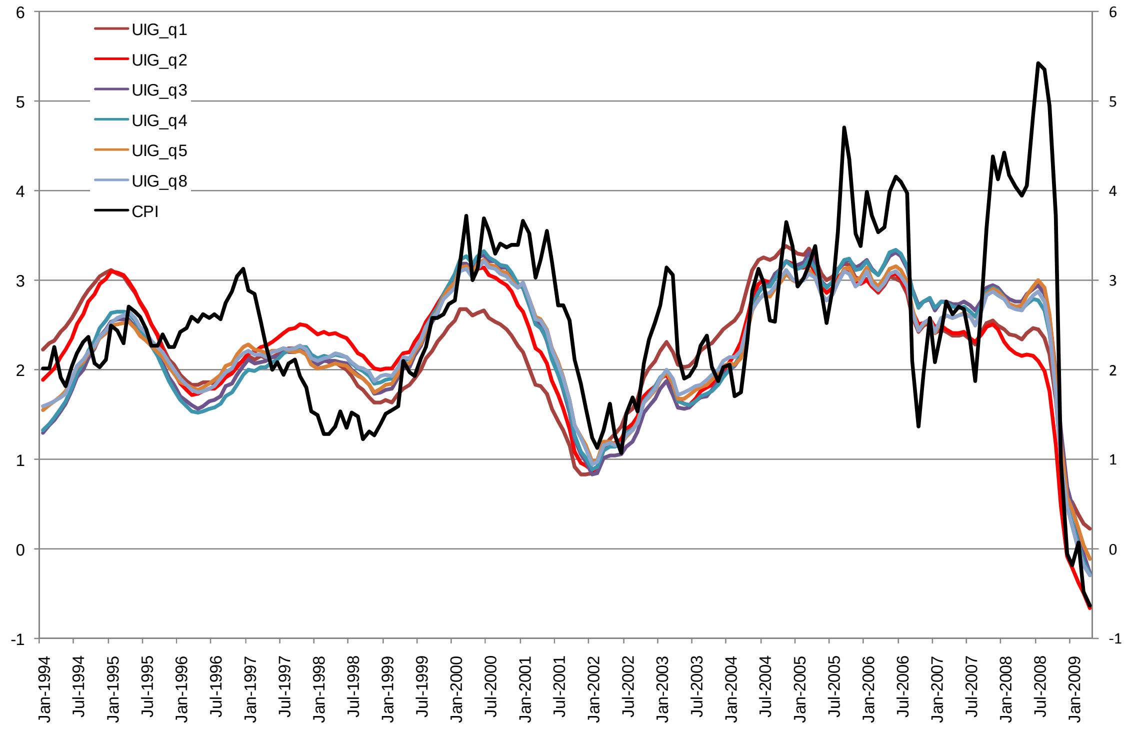


Figure 3b:PCE_UIG for a Different Number of Factors

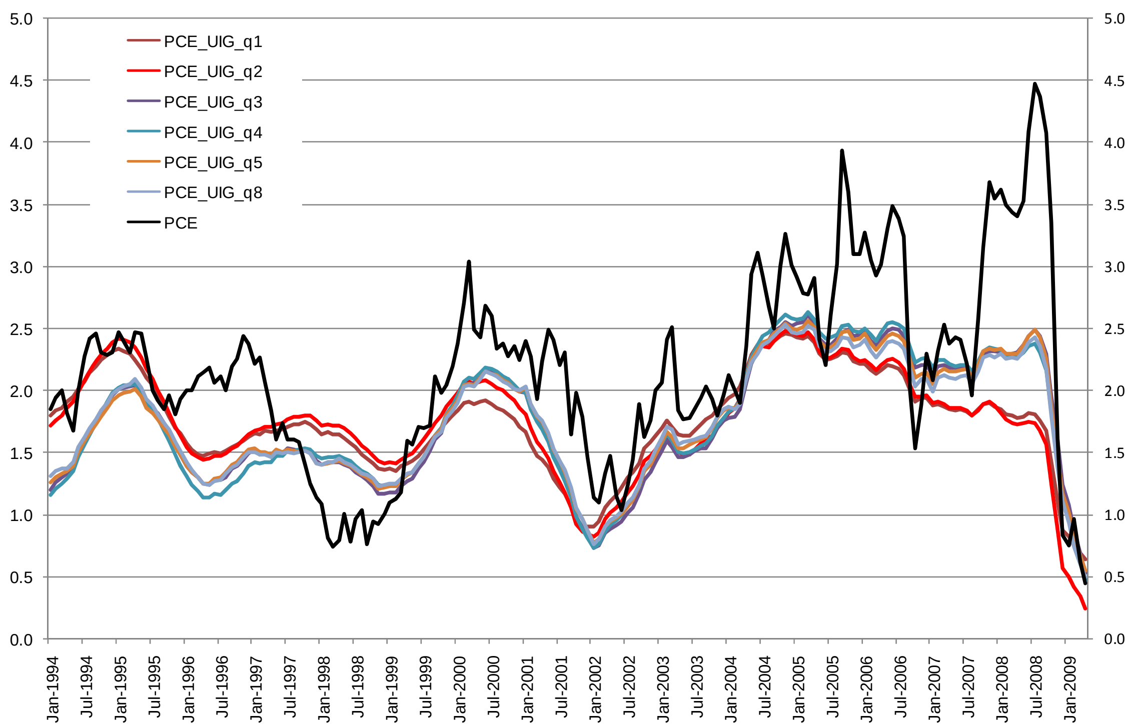


Figure 4a: Traditional Core PCE vs. CPI

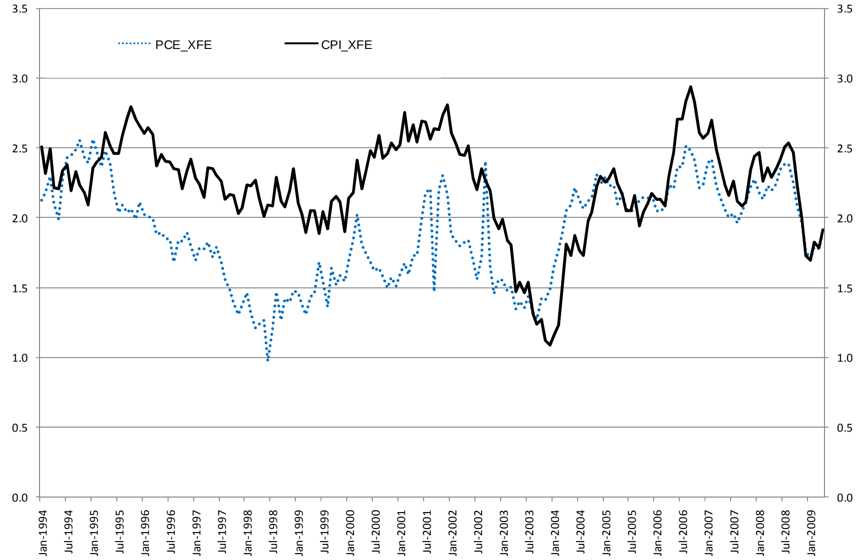


Figure 4b: Trimmed Mean: PCE vs. CPI

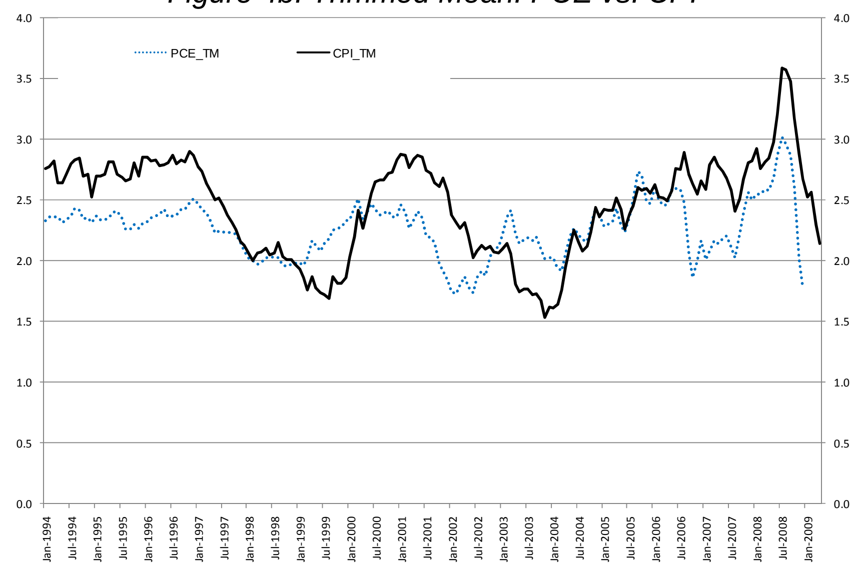


Figure 4c: Underlying Inflation Gauge: PCE vs. CPI

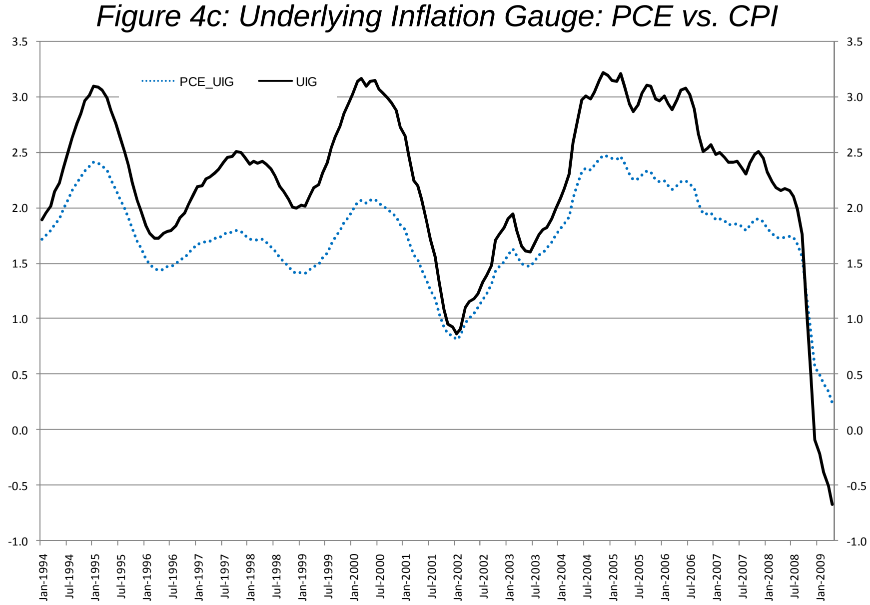


Figure 5a: Different Underlying Inflation Gauges for CPI

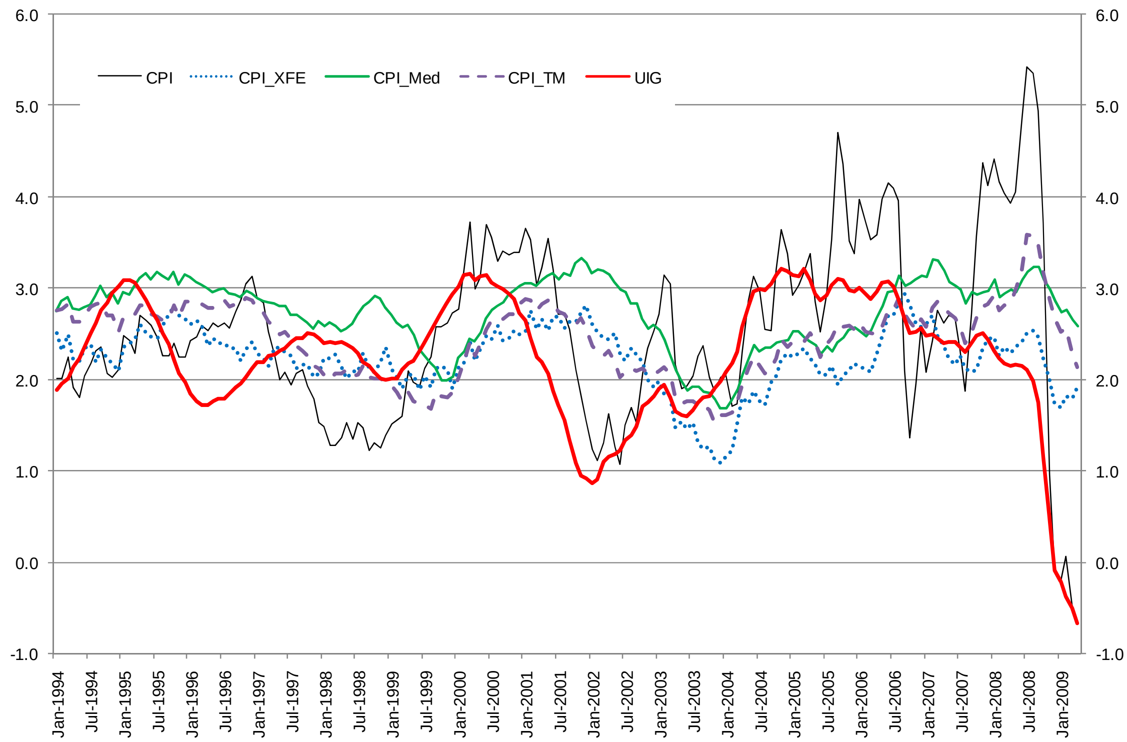


Figure 5b: Different Underlying Inflation Gauges for PCE

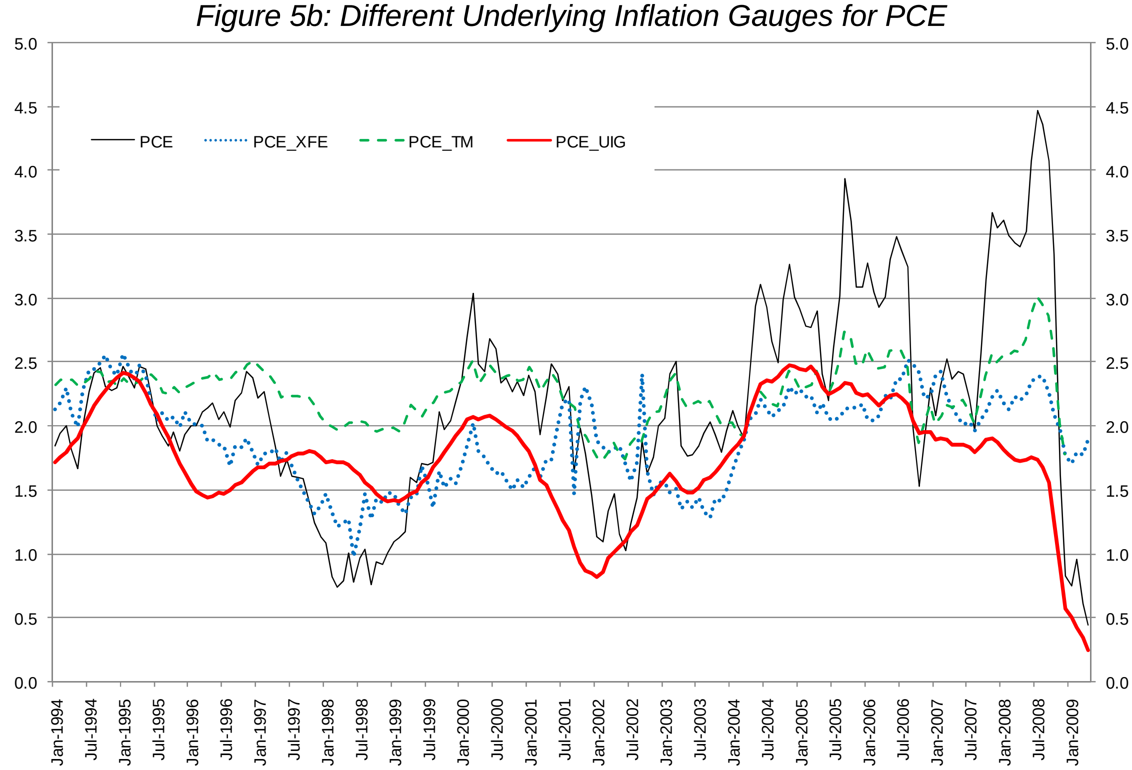


Figure 6: Forecast of Underlying Inflation and TIPS for 2 years, 2-3 years, and 3-5 years

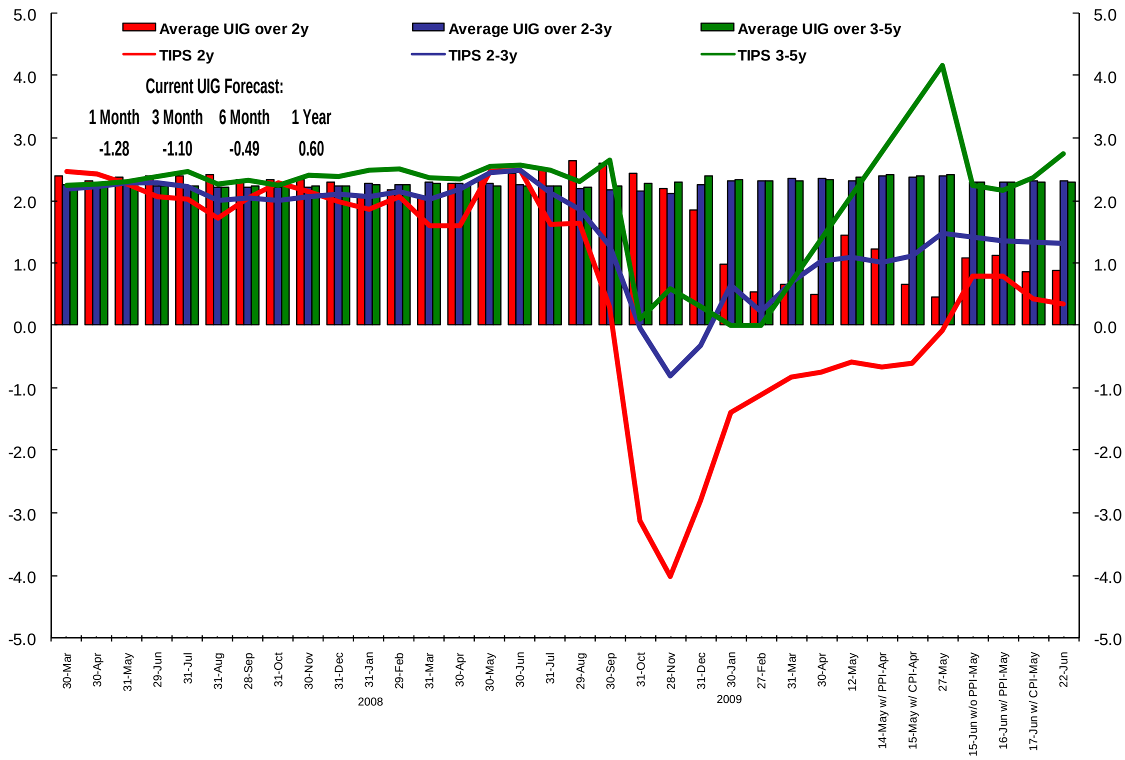


Figure 7a: Absolute Changes in UIG Estimate from First Estimate to One Year (240 workdays) Later

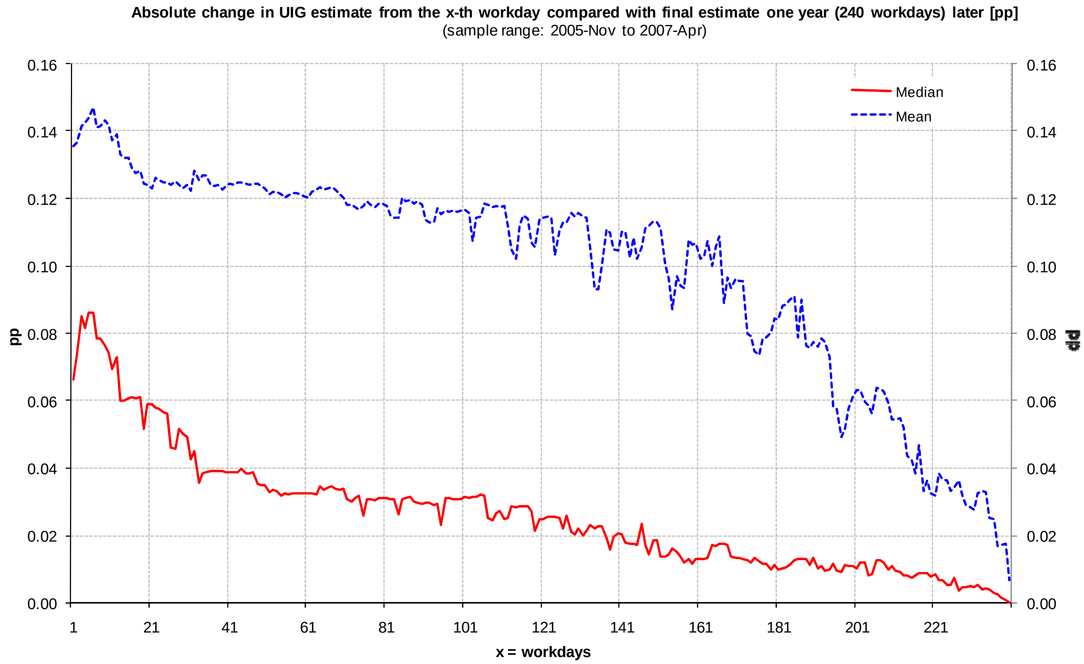


Figure 7b: Changes in UIG Estimate from First Estimate to One Year (240 workdays) Later

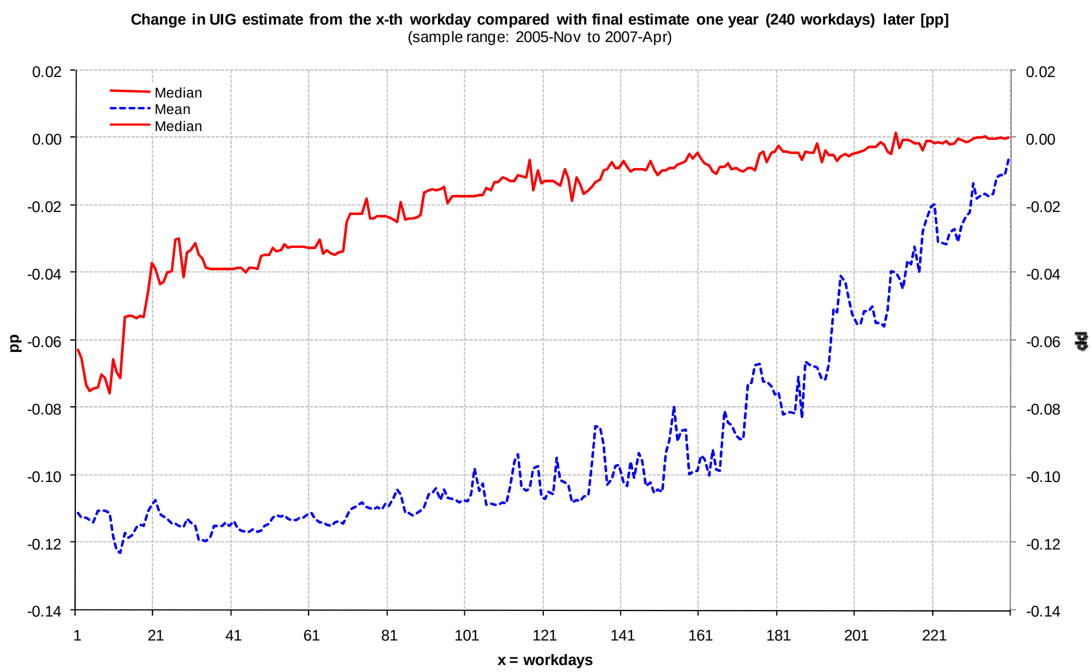
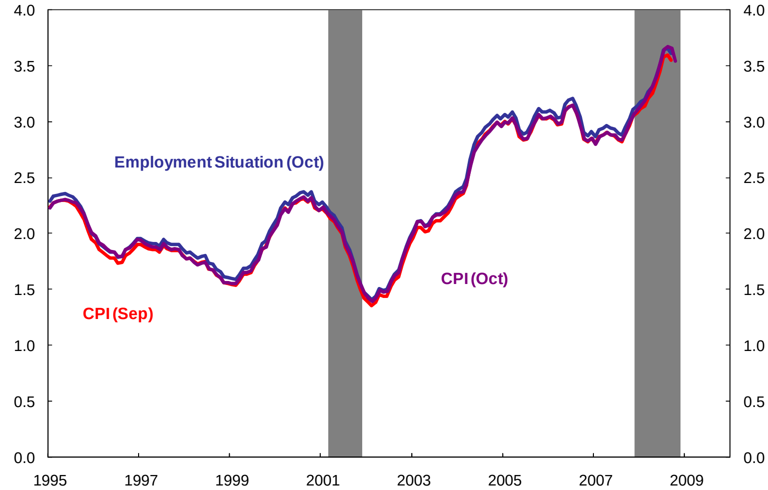
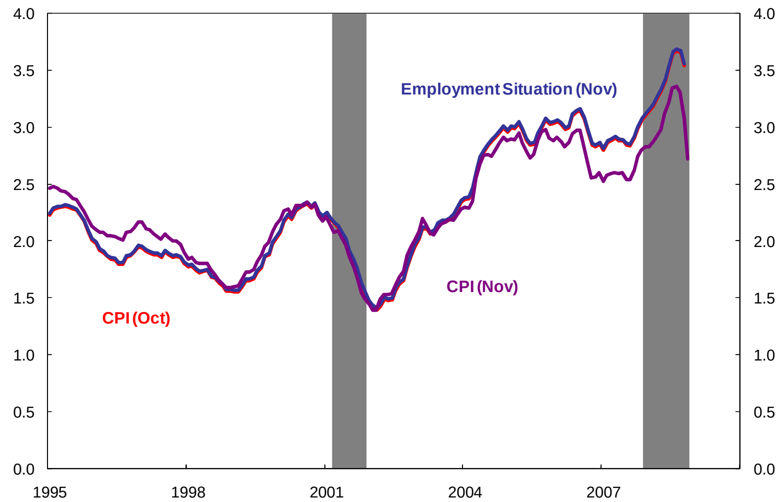


Figure 8a: Change in UIG with Various Economic Indicator Releases November 2008



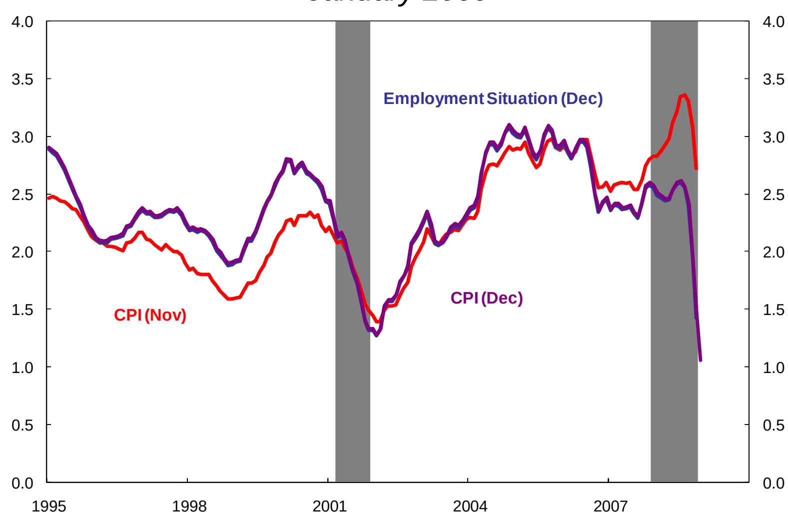
Note: Shading represents NBER recessions.

Figure 8b: Change in UIG with Various Economic Indicator Releases December 2008



Note: Shading represents NBER recessions.

Figure 8c: Change in UIG with Various Economic Indicator Releases January 2009



Note: Shading represents NBER recessions.

Table 1: Example of UIG Inputs

Prices

CPI-U: All Items (NSA, 1982-84=100)
CPI-U: All Items Less Energy (NSA, 1982-84=100)
CPI-U: All Items Less Food (NSA, 1982-84=100)
CPI-U: All Items Less Food & Energy (NSA, 1982-84=100)
CPI-U: All Items Less Medical Care (NSA, 1982-84=100)
CPI-U: All Items Less Shelter (NSA, 1982-84=100)
CPI-U: All Items less Food & Shelter (NSA, 1982-84=100)
CPI-U: All Items less Food, Shelter & Energy (NSA, 1982-84=100)
CPI-U: All Items less Food, Shelter, Energy/Used Cars & Trucks(NSA, 1982-84=100)
CPI-U: Commodities (NSA, 1982-84=100)
CPI-U: Durable Commodities (NSA, 1982-84=100)
CPI-U: Nondurable Commodities (NSA, 1982-84=100)
CPI-U: Services (NSA, 1982-84=100)
CPI-U: Services Less Rent of Shelter (NSA, Dec-82=100)
CPI-U: Transportation Services (NSA, 1982-84=100)
CPI-U: Other Services (NSA, 1982-84=100)
CPI-U: Services Less Medical Care Svcs (NSA, 1982-84=100)
CPI-U: Energy (NSA, 1982-84=100)
CPI-U: Apparel Less Footwear (NSA, 1982-84=100)
CPI-U: Energy Commodities (NSA, 1982-84=100)
CPI-U: Utilities and Public Transportation (NSA, 1982-84=100)
CPI-U: Food & Beverages (NSA, 1982-84=100)
CPI-U: Food (NSA, 1982-84=100)
CPI-U: Food At Home (NSA, 1982-84=100)
CPI-U: Domestically Produced Farm Food (NSA, 1982-84=100)
CPI-U: Cereals & Bakery Products (NSA, 1982-84=100)
CPI-U: Cereals & Cereal Products (NSA, 1982-84=100)
CPI-U: Flour and Prepared Flour Mixes (NSA, 1982-84=100)
CPI-U: Breakfast Cereal (NSA, 1982-84=100)
CPI-U: Rice, Pasta & Cornmeal (NSA, 1982-84=100)
CPI-U: Bakery Products (NSA, 1982-84=100)
CPI-U: White bread (NSA, 1982-84=100)
CPI-U: Bread Other Than White (NSA, 1982-84=100)
CPI-U: Cakes, Cupcakes and Cookies (NSA, 1982-84=100)
CPI-U: Fresh Cakes and Cupcakes (NSA, 1982-84=100)
CPI-U: Cookies (NSA, 1982-84=100)
CPI-U: Other Bakery Products (NSA, 1982-84=100)
CPI-U: Fresh Sweetrolls, Coffeecakes & Doughnuts (NSA, 1982-84=100)
CPI-U: Crackers, Bread & Cracker Products (NSA, 1982-84=100)
CPI-U: Frozen/Refrig Bakery Prdcts/Pies/Tarts/etc (NSA, 1982-84=100)
CPI-U: Meats, Poultry, Fish & Eggs (NSA, 1982-84=100)
CPI-U: Meats, Poultry & Fish (NSA, 1982-84=100)
CPI-U: Meats (NSA, 1982-84=100)
CPI-U: Beef & Veal (NSA, 1982-84=100)
CPI-U: Uncooked Ground Beef (NSA, 1982-84=100)
CPI-U: Pork (NSA, 1982-84=100)
CPI-U: Bacon & Related Products (NSA, 1982-84=100)
CPI-U: Ham (NSA, 1982-84=100)
CPI-U: Ham excluding Canned (NSA, 1982-84=100)
CPI-U: Pork Chops (NSA, 1982-84=100)
CPI-U: Other Meats (NSA, 1982-84=100)
CPI-U: Frankfurters (NSA, 1982-84=100)
CPI-U: Lamb amd Organ Meats (NSA, 1982-84=100)
CPI-U: Poultry (NSA, 1982-84=100)
CPI-U: Fresh Whole Chicken (NSA, 1982-84=100)
CPI-U: Fresh & Frozen Chicken Parts (NSA, 1982-84=100)
CPI-U: Fish & Seafood (NSA, 1982-84=100)
CPI-U: Canned Fish & Seafood (NSA, 1982-84=100)
CPI-U: Frozen Fish & Seafood (NSA, 1982-84=100)
CPI-U: Eggs (NSA, 1982-84=100)
CPI-U: Dairy and Related Products (NSA, 1982-84=100)
CPI-U: Fresh Whole Milk (NSA, 1982-84=100)
CPI-U: Cheese and Related Products (NSA, 1982-84=100)

Real Economy

ISM: Mfg: New Orders Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Production Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Employment Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Vendor Deliveries Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Inventories Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Prices Index (NSA, 50+ = Econ Expand)
ISM: Mfg: Backlog of Orders Index (NSA, 50+=Econ Expand)
ISM: Mfg: New Export Orders Index(NSA, 50+ = Econ Expand)
ISM: Mfg: Imports Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: New Orders Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: Business Activity Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: Employment Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: Supplier Deliveries Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: Inventory Change Index (NSA, 50+ =Econ Expand)
ISM: Nonmfg: Prices Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: Orders Backlog Index (NSA, 50+ = Econ Expand)
ISM: Nonmfg: New Export Orders Index (NSA, 50+=Econ Expand)
ISM: Nonmfg: Imports Index (NSA, 50+ = Econ Expand)

Labor Market

Unemployment Rate: 16-24 Yrs (NSA, %)
Unemployment Rate: 25-34 Yrs (NSA, %)
Unemployment Rate: 35-44 Yrs (NSA, %)
Unemployment Rate: 45-54 Yrs (NSA, %)
Unemployment Rate: 55 Yrs & Over (NSA, %)
Civilian Employment-Population Ratio: 16-24 Yrs (NSA, Ratio)
Civilian Employment-Population Ratio: 25 to 34 Yrs (NSA, Ratio)
Civilian Employment-Population Ratio: 35 to 44 Yrs (NSA, Ratio)
Civilian Employment-Population Ratio: 45 to 54 Yrs (NSA, Ratio)
Civilian Employment-Population Ratio: 55 Yrs & Over (NSA, Ratio)
Average Weeks Unemployed: 16-19 yrs (NSA)
Average Weeks Unemployed: 20-24 yrs (NSA)
Average Weeks Unemployed: 25-34 yrs (NSA)
Average Weeks Unemployed: 35-44 yrs (NSA)
Average Weeks Unemployed: 45-54 yrs (NSA)
Average Weeks Unemployed: 55-64 yrs (NSA)
Average Weeks Unemployed: 65 yrs & over (NSA)
Unemployment (NSA, Thous)
Number Unemployed for less than 5 Weeks (NSA, Thous)
Number Unemployed for 5-14 Weeks (NSA, Thous)
Number Unemployed for 15-26 Weeks (NSA, Thous)
Number Unemployed for 15 Weeks & Over (NSA, Thous)
Unemployment Insurance: Initial Claims (#, NSA)

Money

Money Stock: M1 (NSA, Bil.$)
Money Stock: M2 (NSA, Bil.$)
Adjusted Monetary Base (NSA, Mil.$)
Adjusted Reserves of Depository Institutions (NSA, Mil.$)
Adjusted Nonborrowed Reserves of Depository Institutions (NSA, Mil.$)

Financial Data

Cash Price: Gold Bullion, London Commodity Price, PM Fix (US$/troy Oz)
Gold: London PM Fix (US$/Troy Oz)
Gold Spot ($/oz) NSA
Spot commodity price - West Texas Intermediate crude oil, Cushing OK
Federal funds effective rate
3-month Treasury bill rate coupon equivalent
6-month Treasury bill rate coupon equivalent
1-Year Treasury Bill Yield at Constant Maturity (% p.a.)
5-Year Treasury Note Yield at Constant Maturity (% p.a.)
7-Year Treasury Note Yield at Constant Maturity (% p.a.)
10-Year Treasury Note Yield at Constant Maturity (% p.a.)

Table 2: CPI and PCE Standard Deviation (sample: 1994.M1-2009.M4)

	CPI	UIG	UIG_ prices only	CPI_XFE	CPI_TM	CPI_Med
S.D.	1.00	0.72	0.24	0.35	0.40	0.38

	PCE	PCE_UIG	PCE_UIG_ prices only	PCE_XFE	PCE_TM
S.D.	0.75	0.39	0.30	0.36	0.24

Table 3a: CPI Correlations

	UIG	CPI	CPI_XFE	CPI_TM	CPI_Med
UIG	1.00				
CPI	0.58	1.00			
CPI_XFE	0.13	0.27	1.00		
CPI_TM	0.05	0.50	0.71	1.00	
CPI_MED	-0.18	0.10	0.84	0.78	1.00

Table 3b: PCE Correlations

	PCE_UIG	PCE	PCE_XFE	PCE_TM
PCE_UIG	1.000			
PCE	0.531	1.000		
PCE_XFE	0.435	0.627	1.000	
PCE_TM	0.439	0.922	0.327	1.000

Table 3c: UIG Correlations

	UIG	UIG_prices only	PCE_UIG	PCE_UIG_prices only
UIG	1.00			
UIG_prices only	0.53	1.00		
PCE_UIG	0.95	0.56	1.00	
PCE_UIG_prices only	0.28	0.72	0.40	1.00

Table 4: Principal Component Analysis of UIG on Core Inflation Measures

	PCA1	PCA2	PCA3	PCA4	PCA5
CPI	-0.32	*0.60*	0.53	0.47	0.21
UIG	-0.11	*0.71*	-0.56	-0.40	0.11
CPI_XFE	*-0.55*	-0.11	-0.48	0.51	-0.45
CPI_TM	*-0.56*	-0.04	0.40	-0.59	-0.42
CPI_MED	*-0.53*	-0.35	-0.13	-0.10	0.76
Variance Prop.	0.54	0.31	0.10	0.03	0.02
Cumulative Prop.	0.54	0.86	0.95	0.98	1.00

Table 5: Forecast Performance in RMSE for CPI

Out of sample performance for annual inflation through April 2009
(estimation sample starts in January 1994)

Post 2000 sample ("whole inflation cycle")

	h=12	
UIG	**1.27688**	
UIG_PONLY	1.35412	
CPI_EX_FE	1.52515	**
CPI_TM	*1.66631*	**
CPI_Median	1.63086	**
CPI(t-h)	1.53876	**

Post 2002 sample ("increasing CPI phase")

	h=12	
UIG	**1.34669**	
UIG_PONLY	1.41520	
CPI_EX_FE	1.57310	*
CPI_TM	1.55811	*
CPI_Median	*1.58524*	*
CPI(t-h)	1.54666	*

Post 2005 sample ("flattening CPI phase")

	h=12	
UIG	**1.56511**	
UIG_PONLY	1.73227	*
CPI_EX_FE	1.79400	**
CPI_TM	1.85986	**
CPI_Median	1.87658	**
CPI(t-h)	*1.92714*	**

2001m1-2007m12 ("Stock and Watson (2008)" sample)

	h=12	
UIG	1.06680	
UIG_PONLY	**1.03661**	
CPI_EX_FE	1.25207	
CPI_TM	*1.28516*	*
CPI_Median	1.26806	
CPI(t-h)	1.28260	*

bold: lowest RMSE; *italic: highest RMSE*
* 10 % sigificant level
** 5 % sigificant level
*** 1 % sigificant 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 6: Genuine Out of Sample Forecast Performance

Out of sample performance for annual inflation through April 2009
(estimation sample starts in November 2006)

Forecast Using:	*RMSE for CPI*	*RMSE for Core CPI*
Underlying Inflation Gauge	0.98889	0.12264
12-month change in Core CPI	1.79528	0.45123
12-month change in CPI	2.50494	1.38979