Marlene Amstad, Simon Potter, and Robert Rich

The New York Fed Staff Underlying Inflation Gauge (UIG)

- Monetary policymakers and others would benefit from a smooth, broad based, real-time measure of underlying inflation.
- The authors introduce the New York Fed Staff Underlying Inflation Gauge (UIG), explain its construction and review the experience of the Federal Reserve Bank of New York with daily, real-time updates of the UIG, made internally since 2005.
- The UIG includes a wide range of nominal, real, and financial variables in addition to prices and focuses on the persistent common component of monthly inflation.
- The UIG proved especially useful in detecting turning points in trend inflation and has shown higher forecast accuracy compared with core inflation measures.

1. Introduction

The two most widely followed measures of consumer price inflation in the United States are the consumer price index (CPI) and the personal consumption expenditures (PCE) deflator, both released monthly. Yet for many observers—including monetary policymakers and market participants—the "headline" readings of both series are too volatile to provide a reliable measure of the trend in inflation even after some averaging of the series. Indeed, the series can fluctuate quite dramatically: the headline twelve-month change in the CPI was 5.6 percent in July 2008, fell to zero in December of the same year, and then reached a low of –2.1 percent in July 2009.

Not surprisingly, the volatility of the two leading measures has prompted a large and ongoing research effort to extract the long-run, or persistent, component of aggregate inflation from the monthly data releases. Approaches to estimating this component—termed "underlying inflation"—have varied, both in their methodology and in the data set used.

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Work on the UIG began in 2004-05 when Amstad, on leave from the Swiss National Bank, was a Federal Reserve Bank of New York resident visiting scholar, and it continued during periodic follow-up visits. An earlier version of this article was published as "Real-Time Underlying Inflation Gauges for Monetary Policymakers," Federal Reserve Bank of New York Staff Reports, no. 420 (2009). The authors' work draws from a prior experience developing a similar gauge for Switzerland (Amstad and Fischer 2009a, 2009b) and builds on code developed by Ricardo Cristadoro, Mario Forni, Domenico Giannone, Marc Hallin, Marco Lippi, Lucrezia Reichlin, and Giovanni Veronese (see Cristadoro et al. [2005]).

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One well-established approach to estimating underlying inflation is to construct measures of "core" inflation. This approach assumes that transitory changes in the aggregate price index are linked to the volatility of its subcomponents. Consequently, core inflation measures are generally designed to remove the most volatile price changes associated either with the same specific goods and services, or with those goods and services displaying the largest price increases and decreases in a particular month. The former strategy underlies the "ex-food and energy" measure—which removes the impact of food and energy prices on inflation. The latter strategy motivates the trimmed mean and median measures.[1] Although such adjustments may seem reasonable, researchers have identified various limitations in the core inflation measures.[2] One well-known limitation of these measures is that they assume that the source of transitory movements in aggregate inflation remains constant over time. In addition, they focus exclusively on the cross-sectional dimension of the data and therefore neglect potentially useful information in movements of the data over time. Further, core inflation measures can only be updated monthly, which might be too infrequent during periods when there is heightened uncertainty about movements in trend inflation. There are also reasons to question the reliability and timeliness of these measures as a gauge of underlying inflation.[3]

Another common approach to estimating underlying inflation is to use model-based techniques. This approach can involve statistical smoothing methods whose complexity can vary widely. It can also involve the estimation of Phillips curve models and structural vector autoregression (SVAR) models. However, as with the core inflation measures, researchers have raised concerns about the model-based measures—in this case, because of their near-exclusive reliance on price data, sensitivity to particular specifications, or strong model restrictions.

Recognizing the limitations of commonly used measures of underlying inflation, we present the New York Fed Staff Underlying Inflation Gauge (UIG). This measure of underlying inflation for the CPI and PCE deflator provides a complement to existing measures and aims to add value by helping to detect turning points in trend inflation. This article describes the development of the UIG, explains its construction, and reviews the experience of the Federal Reserve Bank of New York with daily, real-time updates of the UIG, made internally since 2005. We note that the New York Fed is preparing to publish monthly updates of the UIG for CPI inflation starting later in 2017.

The design of the UIG is based on the premise that movements in underlying inflation are accompanied by related persistent changes in other economic and financial series. Specifically, the UIG is defined as *the persistent common component of monthly inflation*. Consequently, we examine a large data set and apply modern statistical techniques to extract a small number of "factors" that capture the common fluctuations in the series. The data set includes disaggregated price data as well as a wide range of nominal, real, and financial variables. The statistical techniques, known as dynamic factor models, provide a very tractable framework in which to use large information sets, with the extracted factors serving as the basis to construct the UIG.

The UIG offers several notable features that build on and extend the work done by other researchers on the estimation of underlying inflation. The framework used here combines information simultaneously from the cross-sectional and the time-series dimensions of the sample in a unified framework. In this regard, our modeling strategy follows that of Cristadoro et al. (2005), who derive a measure of underlying inflation for the euro area. In addition, the UIG uses a real-time framework, entailing daily updates of the model, which was introduced by Amstad and Fischer (2009a, 2009b) in the development of an inflation gauge for Switzerland. Our work also finds parallels with that of Stock and Watson (1999, 2016) and Reis and Watson (2010), who use a dynamic factor model to estimate a common component that they associate with trend inflation. The UIG differs from these last studies, however, by moving beyond the common component to extract its persistent element.

Our analysis offers significant evidence of the UIG's effectiveness in monitoring inflation developments in real time and assessing their implications for the inflation outlook of policymakers and market participants. An essential property of a measure of underlying inflation is the ability to look through

[1] There are also strategies that weight inflation subcomponents inversely by their volatility rather than exclude volatile subcomponents. Going forward, we use the terms "traditional underlying inflation measures" and "core inflation measures" interchangeably. With regard to core inflation measures, our study focuses on the ex-food and energy measure, the trimmed mean, and the median.

[2] For example, see Cecchetti (1997), Cecchetti and Moessner (2008), and Bullard (2011) as well as the references therein for further discussion.

[3] During the recent global financial crisis, the twelve-month change in headline CPI inflation fell to 2.1 percent in July 2009—far below the 1.1 percent value that was the lowest reading during the previous recession in 2001. For the CPI ex-food and energy, however, the lowest twelve-month change during the recent global financial crisis was 0.6 percent—a value that was not reached until October 2010 and was not that far from the low of 1.1 percent observed during the 2001 recession.

A similar concern arises in the case of the PCE deflator during these same episodes. The twelve-month change in headline PCE inflation fell to –1.2 percent in July 2009, again far below the low of 0.6 percent seen during the 2001 recession. Meanwhile, PCE inflation ex-food and energy declined to 1 percent in July 2009, which was only slightly below the low of 1.2 percent during the 2001 recession.

the noise—short-term transitory fluctuations—in headline inflation to identify movements in the trend. We show that in past noncrisis periods, during which trend inflation remained fairly stable, the UIG showed little response to noise in headline inflation. However, when the economy was subject to large and persistent shocks, such as in 2008, the UIG was very responsive to the worsening conditions in the economy and offered a daily signal of the speed and scale of changes in underlying inflation. In particular, we find that the addition of nonprice data was especially important for the UIG to quickly signal the sharp and rapid decline in trend inflation during the global financial crisis. Because the UIG was able to generate this signal in real time, this model feature is particularly useful for decision makers, including policymakers and investors.

Last, how do our findings on the performance of the UIG relate to other researchers' assessments of trend inflation measures? Many studies have concluded that no single measure of underlying inflation consistently outperforms other measures across a range of criteria.[4] Other studies have narrowed their analysis to evaluating the relative performance of select measures in *forecasting* inflation. For example, Atkeson and Ohanian (2001) argue that a simple random walk model (that is, the use of the most recently observed change in inflation to forecast future inflation) is just as accurate as Phillips curve models that incorporate nonprice variables in their specification. Stock and Watson (2008) subsequently find that while Phillips curve models remain useful tools for forecasting inflation, their value is "episodic." That is, Phillips curve models do not offer higher forecast accuracy than a random walk model during times of low volatility, but provide additional predictive content around business cycle turning points.[5] We find that the UIG outperforms core inflation measures as well as a simple random walk model in a pseudo out-of-sample forecast exercise that covers subsamples both before and during the recent global financial crisis. Consequently, we conclude that the UIG adds meaningful value compared with alternative measures in forecasting inflation. We attribute the robustness of the UIG's greater accuracy in this regard to its use of a large data panel and its focus on only the persistent part of the common component of inflation.[6]

[4] See, for example, Rich and Steindel (2007) and the references therein. Stock and Watson (2010) and Wynne (2008) give a comprehensive analysis that also supports this assessment for the United States and Vega and Wynne (2001) for the euro area. Cecchetti (1995) shows evidence that this finding is related to structural breaks in the inflation process.

[5] Liu and Rudebusch (2010) confirm the finding of Stock and Watson (2008) including data for the global financial crisis.

[6] The motivation for the found robustness is supported by Gavin and Kliesen's (2008) evidence that data-rich models significantly improve the forecasts for a variety of real output and inflation indicators.

The remainder of this article is organized as follows. Section 2 discusses a suite of measures of underlying inflation, including their strengths and weaknesses. Section 3 motivates our specification of the dynamic factor model, and also describes the data set and estimation procedure used to construct the real-time UIG. In Section 4, we compare the UIG with traditional underlying inflation measures using descriptive statistics as well as forecast performance. Section 5 presents our conclusions.

2. Underlying Inflation: A Review of Approaches and Measures

This section examines various approaches to estimating underlying inflation, and highlights measures included in our analysis. The discussion helps to motivate the modeling strategy adopted for the UIG.

For any observed headline inflation rate π_t, the rate can always be decomposed as:

$$\pi_t = \pi_t^* + c_t , \tag{1}$$

where π_t^* denotes the underlying rate of inflation and c_t denotes deviations of inflation from the underlying inflation rate. While the concept of underlying inflation is generally agreed upon, the best method for estimating the underlying inflation rate is not—a wide range of proposed measures of π_t^* exist. One dimension along which the measures differ is the choice of methodology. Another area of difference is the nature of the data set, with some measures only using price data and others including additional variables. We now examine and comment in more detail on some of the more popular approaches and corresponding measures used to estimate underlying inflation.[7]

The term "core inflation" is widely used by practitioners and academics to represent a measure of underlying inflation that is less volatile than headline inflation. Measures of core inflation gained attention in the 1970s when large price movements in food and oil complicated the task of estimating the trend in inflation. This experience highlighted the importance of developing methods that could filter out

[7] There are measures of underlying inflation that are derived from financial markets (for example, breakeven inflation using Treasury Inflation-Protected Securities) or consumer surveys (for example, the University of Michigan Inflation Expectations data). However, these measures provide a forecast of future underlying inflation rather than an estimate of current underlying inflation. Consequently, we exclude them from our analysis.

transitory price movements in order to identify the persistent part of inflation. One strategy suggested by Gordon (1975) and Eckstein (1981) associates the transitory elements with food and energy prices and argues for excluding these items from the price index every month. Another strategy, suggested by Bryan and Cecchetti (1994), associates the transitory elements with those items displaying the largest price movements—both increases and decreases—in a particular month and argues for computing trimmed mean and median measures in which the excluded items are allowed to change each month.[8] In the United States, statistical agencies publish monthly measures of the CPI and the PCE deflator that exclude the food and energy subcomponents, while various Federal Reserve Banks calculate trimmed mean and median measures for the CPI and the PCE deflator.[9]

An attractive feature of core inflation measures is that they are easy to construct and to understand. Further, their forecast performance, as shown by Atkeson and Ohanion (2001), can be very similar to, or even better than, measures of underlying inflation based on more complicated approaches.[10]

There are, however, limitations to core inflation measures and the practice of excluding volatile components. In the case of the ex-food and energy measure, the specific subcomponents to be removed are determined in a strictly backward-looking manner based on the historical behavior of the noise in the inflation release. For example, although in the 1970s it may have been reasonable to exclude temporary oil price increases from core inflation measures, it makes less sense to do so now because oil price changes appear to be more persistent.[11] This discussion illustrates an inherent difficulty in the construction of core inflation measures: What is temporary only becomes apparent in retrospect and not in advance.[12]

[8] See Bryan and Cecchetti (1994, 1999), Bryan, Cecchetti, and Wiggins (1997), Dolmas (2005), and Meyer, Venkatu, and Zaman (2013) for a discussion of methodologies.

[9] The Federal Reserve Bank of Cleveland reports trimmed mean and median measures for the CPI (suggested by Bryan and Pike [1991]), while the Federal Reserve Banks of Dallas and San Francisco report, respectively, trimmed mean and median measures for the PCE deflator.

[10] Although some studies report evidence favorable to the forecast performance of core inflation measures, Crone et al. (2013) have reported that the relative forecast performance of core inflation measures can be sensitive to the choice of the inflation measure and time horizon of the forecast.

[11] James Hamilton and Menzie Chinn have written several blog posts on oil prices that illustrate this point. Furthermore, Cecchetti and Moesnner (2008) points out that the exclusion of energy from this measurement has imparted a bias to medium-term measures of inflation.

[12] In their comprehensive comparison of core inflation measures, Rich and Steindel (2007) conclude that no single core measure outperforms the others over different sample periods owing to the fact that there is considerable variability in the nature and sources of transitory price movements.

In the case of the trimmed mean and median measures, another concern is that excluding components that display large price changes (in either direction) may remove early signals of a change in trend inflation that tend to show up in the tails of the price change distribution. Therefore, even though the trimmed mean or median measures may display a low average forecast error over long-dated episodes, they may be a lagging indicator at important times such as turning points in trend inflation. More generally, the practice of excluding large price changes narrows the range of possible reported outcomes during a given time period. Consequently, core inflation measures can suffer both from being late to recognize changes in underlying inflation and from understating the extent of such changes.[13]

Because of the limitations of core inflation measures, model-based techniques have been used to develop measures of underlying inflation for the United States. Within this approach, one strategy has focused on the application of time-series smoothing methods. Examples include the integrated moving average (IMA) model of Nelson and Schwert (1977), the four-quarter moving average model of Atkeson and Ohanian (2001), the exponential smoothing model of Cogley (2002), and the stochastic volatility model of Stock and Watson (2007). However, these applications involve univariate time-series methods and only examine aggregate inflation for their analyses. More recently, Stock and Watson (2016) have proposed a measure of underlying inflation that is based on the estimation of a multivariate unobserved components-stochastic volatility model using price data for the subcomponents of the PCE deflator. Although Stock and Watson (2016) also associate underlying inflation with the estimated common component of multiple inflation series, they do not include nonprice data.

Another strategy within this approach involves model estimation using additional nonprice data. One prominent example includes Gordon (1982) "triangle"-type models.[14] Gordon estimates a backward-looking Phillips curve model and combines price data along with labor market information and additional covariates to capture exogenous pricing pressures, such as those from energy. Underlying inflation measures can then be derived as the endpoint of the within-sample prediction values from the model, with the estimation period varied either in a recursive manner or through a rolling window. One criticism of the estimated measure of underlying inflation is that there are limitations on the number of variables that can be added to the model as

[13] Footnote 3 in the Introduction touched upon these points.

[14] The triangle model is a common approach to modeling inflation in the Federal Reserve System (Rudd and Whelan 2007).

a result of degrees of freedom issues. Another criticism is that it is very sensitive to the particular model specification (Stock and Watson 2008).

Quah and Vahey (1995) provide another example, in which they propose a slightly different definition of underlying inflation based on the long-run neutrality of inflation. Specifically, they define underlying inflation as the "component of measured inflation" that has no medium- to long-run impact on real output. However, their approach requires the estimation of a SVAR model that has been criticized on the grounds that it is difficult to formulate and imposes tenuous identifying restrictions.

Taken together, the issues we have outlined speak to the limitations associated with various measures of underlying inflation. Given these limitations, we view dynamic factor models as providing an attractive framework in which to develop an improved measure. Among the reasons motivating our choice is the fact that dynamic factor models have received increased attention and gained greater popularity because their specification allows for the use of a broad data set without requiring adherence to strong theoretical guidelines for estimation purposes. The UIG is related to this modeling strategy and is formalized in greater detail in the next section.

3. New York Fed Staff Underlying Inflation Gauge (UIG)

The New York Fed Staff UIG is based on the estimation of a dynamic factor model using price data as well as economic and financial variables. This section motivates our modeling strategy and highlights its important features, including a broad data approach and flexibility to extract information from many indicators. We then describe the specification of the dynamic factor model and illustrate its role in the construction of the UIG. With regard to the dynamic factor model, we also provide a general discussion of issues related to model parameterization and estimation procedure. After describing the data set used for the analysis, we examine the estimated UIG series and their behavior.

The research that corresponds most closely to our work on the UIG is by Amstad and Fischer (2009a, 2009b), who developed a gauge for Switzerland, and by Amstad, Huan, and Ma (2014),[15] who developed one for China—both relying on the methodology of Cristadoro et al. (2005) in a real-time framework. Giannone and Matheson (2007) and Khan, Morel, and Sabourin (2013) adopt a similar approach to construct an inflation gauge for New Zealand and Canada, respectively, but their analyses only use disaggregated price data.[16] Further, related work has employed dynamic factor models of the type used in this study to explore several issues related to inflation dynamics. For example, Altissimo, Mojon, and Zaffaroni (2009) investigate persistence in aggregate inflation in the euro area, while Amstad and Fischer (2009b) explore the impact of macroeconomic announcements on weekly updates of forecasts for Swiss core inflation, and Amstad and Fischer (2010) construct monthly pass-through estimates from import prices to consumer prices in Switzerland.

3.1 Methodology

From a policy perspective as well as a forecasting perspective, there are several reasons why it is beneficial to add rather than exclude information to measure underlying inflation. As argued in Bernanke and Boivin (2003), monetary policymaking operates in a "data-rich environment." Furthermore, Stock and Watson (1999, 2002, 2010) show that broader information sets can improve forecast accuracy in certain time periods. Therefore, several authors (including Galí [2002]) argue that policymakers would benefit from a more comprehensive measure that can cull and encapsulate the relevant information for inflation from a large data set.

By their design, factor models can be applied to a broad data set and therefore offer a particularly attractive framework to summarize price pressures in a formal and systematic way as well as to gauge sustained movements in inflation. The key feature of this class of models is that although the data set contains a large number of variables, a significant amount of their co-movement can be explained using a low number of series—referred to as factors. In addition to the work cited in this article that has used large data factor models to derive measures of underlying inflation, this modeling strategy has been used to construct measures of economic activity.[17]

[15] For an update see People's Bank of China (2016).

[16] The inflation gauge developed by Giannone and Matheson (2007) and Khan, Morel, and Sabourin (2013) is similar to the prices-only version of the UIG discussed later in this article.

[17] With regard to the latter application, Altissimo et al. (2001) use a dynamic factor model to produce EuroCoin, which provides a monthly reading of euro area GDP, while the Chicago Fed National Activity Index offers a monthly gauge of U.S. GDP.

For this study, we follow Cristadoro et al. (2005) and use the generalized dynamic factor model developed by Forni et al. (2000, 2001, 2005) that draws upon the work of Brillinger (1981) and allows for the application to large data sets. The following discussion is intended to provide the reader with a general understanding of the theoretical framework and estimation procedure used to construct the UIG, as well as to preview issues that will receive subsequent attention.

Let X_t represent the time t values of the N series that make up our large data set such that $X_t = [x_{1,t}, x_{2,t}, \ldots, x_{N,t}]$. For convenience, let $x_{1,t}$ denote the monthly inflation rate. We assume that the behavior of $x_{1,t}$ can be described as the sum of two unobserved components using a formulation similar to equation (1):

$$x_{1,t} = x^*_{1,t} + e_{1,t}\,, \tag{2}$$

where $x^*_{1,t}$ denotes our variable of interest, the underlying rate of inflation, and $e_{1,t}$ is a component reflecting movements in inflation related to other factors such as short-run dynamics, seasonality, measurement error, and idiosyncratic shocks. A central element of our analysis is to use the dynamic factor model methodology to estimate $x^*_{1,t}$ using information from present and past values of X.

The dynamic factor model assumes that the variables in X_t can be represented as the sum of two mutually uncorrelated, unobserved components without trend: the common component $\chi_{i,t}$—which is assumed to capture a high degree of co-movement between the variables in X_t—and the idiosyncratic component $\xi_{i,t}$. The premise of a dynamic factor model is that the common component reflects the influence of a few factors that act as a proxy for the fundamental shocks that drive behavior in an economy, while the idiosyncratic component reflects the influence of variable specific shocks. More formally, we can summarize the time-series process for each variable in X_t as

$$x_{i,t} = \chi_{i,t} + \xi_{i,t} = \sum_{h=1}^{q}\sum_{k=0}^{s} \alpha_{i,h,k}\,\mu_{h,t-k} + \xi_{i,t}\,, \tag{3}$$

where the common component $\chi_{i,t}$ is defined by the same q common factors, $\mu_{h,t}$, but which may be associated with different coefficients and lag structures, with maximum lag s. The appeal of the dynamic factor model is that it provides a convenient dimension reduction technique. That is, it enables us to use a small number of factors to summarize the information from a large data set.

Looking at the first time-series variable, $x_{1,t}$, as well as equations (2) and (3) yields

$$x_{1,t} = x^*_{1,t} + e_{1,t} = \chi_{1,t} + \xi_{1,t}\,. \tag{4}$$

Because our notion of the underlying rate of inflation relates to the long-run, or persistent, component of aggregate inflation, we would like this property to carry over to the common component in equation (4). It is important to note that, as proposed by Cristadoro et al. (2005), $\chi_{1,t}$ can be separated into a long-run (persistent) component, $\chi^{LR}_{1,t}$, and a short-run component, $\chi^{SR}_{1,t}$, based on a specified cut-off frequency for the data. Accordingly, we can rewrite equation (4) as

$$x_{1,t} = x^*_{1,t} + e_{1,t} = \chi^{LR}_{1,t} + \chi^{SR}_{1,t} + \xi_{1,t}\,. \tag{5}$$

From equation (5), we can then think of the underlying rate of inflation in terms of the following association:

$$x^*_{1,t} = \chi^{LR}_{1,t}\,. \tag{6}$$

That is, the UIG is defined as the long-run common component of monthly inflation. As previously described, one difference between our approach and that of Stock and Watson (1999, 2016) concerns our additional filtering of the common component to isolate its persistent element. This difference is illustrated and may be best understood by comparing equation (4) with equation (6).

Although our interest focuses on $\chi^{LR}_{1,t}$, neither the common component $\chi_{1,t}$ nor the factors underlying its behavior are observable and therefore they must be estimated. Because some aspects of the estimation and the construction of the UIG are quite technical, we refer readers to Cristadoro et al. (2005) and Forni et al. (2000, 2001, 2005) for more information, rather than explore these issues in further detail here.[18] Instead, we turn our attention to the specification of three key parameters of the model. In particular, we need to select a cut-off horizon to filter out short-run fluctuations in the data as incorporated in equation (5), and select the number of factors q and the number of maximum lags s as described in equation (3).[19]

We select a cut-off frequency of twelve months to extract $\chi^{LR}_{1,t}$ from $\chi_{1,t}$. Lags in the monetary transmission mechanism suggest that inflation at a horizon of one year or less is relatively insensitive to changes in current monetary policy. Therefore there is little that policymakers can do to affect

[18] For example, estimation of the dynamic factor model and smoothing of the UIG are undertaken in the frequency domain.

[19] For New York Fed internal analysis, these settings are evaluated on a regular basis.

these fluctuations in inflation. Consequently, if monetary policy has been achieving its objective of price stability with well-anchored inflation expectations, then the effects of changes in current monetary policy on expected inflation will be at horizons of greater than twelve months. In addition, this choice enables us to remove seasonal effects.

With respect to the number of common factors, our analysis will involve settings of $q = 1$ and $q = 2$. To preview the results discussed in Section 3.3, the difference in the number of specified dynamic factors reflects variations in the nature of the data set. In particular, we find that only one factor is relevant when the price data are considered alone but that two factors provide a proper representation when we include the nonprice variables in the data environment. The q factors are allowed to influence UIG not only contemporaneously but also with a maximum number of lags s. Our choice of $s = 12$ is motivated by several considerations that include consistency with the one-year cut-off band for the common component and the monthly frequency of the data.[20]

Thus, the UIG at time t is then defined as the predicted long-run common component of the monthly inflation rate from estimation of equation (3) with settings of $q = 1$ or $q = 2$, $s = 12$, and a cut-off frequency of twelve months. That is,

$$x^{*}_{1,t} = \hat{\chi}^{LR}_{1,t} \,. \tag{7}$$

The previous discussion and formulation in equations (1) through (7) highlight several key properties of the UIG. The definition of the UIG is consistent with the idea that a measure of underlying inflation should reflect a common as well as a persistent element in the component parts of aggregate price indexes. In addition, the presence of multiple factors does not restrict movements in underlying inflation to those driven by a single type of shock. The estimated factors take into account the co-movement of variables in both the cross-sectional and the time-series dimensions, without imposing any restrictions on the sign or magnitude of the correlations.

Moreover, the analysis does not require that the factors either be extracted from a pre-selected partition of the data set or pre-identified as a specific type of shock. Lastly, the UIG is well suited to evaluate whether a large price change is likely to persist over a specified period of time as the UIG's movement is not restricted in either speed or magnitude.[21] Specifically, our inferences about movements in underlying inflation are informed by an empirical framework that allows for a broad representation of economic and financial developments at the same time that it allows information from this large data set to be extracted in a flexible manner and to be summarized in a very parsimonious way.

3.2 Data

There is no objective criterion to judge which data should or should not be included in the large information set. Consequently, we rely on the experience of the New York Fed staff and include the series considered to be the most relevant determinants of inflation. The data set has remained the same since 2005 when we began construction of the UIG.

We use data from the following two broad categories: (1) consumer, producer, and import prices for goods and services and (2) nonprice variables such as labor market measures, money aggregates, producer surveys, and financial variables (short- and long-term government interest rates, corporate and high-yield bonds, consumer credit volumes and real estate loans, stocks, and commodity prices). We refrain from including every available indicator that could have an impact on inflation because research on factor models (Boivin and Ng 2006) shows that doing so does not come without risks.[22] Our approach is to include the variables that were regularly followed by the New York Fed staff in their assessment over several economic cycles. This procedure not only offers the benefit of drawing upon the staff's long-term experience, but also maintains some continuity in the set of variables used to construct the UIG. Such continuity is important because it helps ensure that a change in the UIG is not caused by changes in the data composition through the addition or removal of a data series. The weighting of each series in the UIG changes over time and is determined by the factor model as new observations become available and existing data are revised. Chart 1 provides more information on the current data set used, while the Data Appendix provides a detailed listing of the variables.

[20] Further analysis indicated that the results were not sensitive to variation in the number of these lags.

[21] An additional advantage of our UIG concept compared with traditional underlying inflation measures is that it enables us to focus on a particular horizon of interest that will, in this case, align with that of policymakers. As previously discussed, the horizon of interest for this study is twelve months and longer.

[22] Their results suggest that factors estimated using more data do not necessarily lead to better forecasting results. The quality of the data must be taken into account, with the use of more data increasing the risk of "leakage of noise" into the estimated factors.

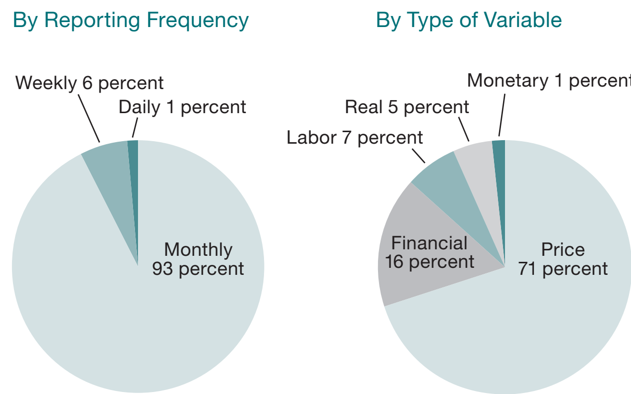
Sample Range

Based on substantial evidence of structural breaks in the U.S. inflation process (see Clark [2004] and Stock and Watson [2008] for a comprehensive evaluation), we limit our analysis of the data to the period starting in January 1993. For similar reasons, the OECD (2005) divides the sample for a multicountry study of inflation into the subperiods 1984-95 and 1996-2004. In addition, a tension exists between our large data set and the dynamic factor model—which relies on a balanced data set to start the estimation—requiring us to strike a balance between the length of the time period and the range of indicators for the study. These considerations reinforced the choice of January 1993 as the start date because an earlier time period would have limited significantly the number of time series that could be included in the analysis.

3.3 Estimation Results

In this section, we discuss some additional details of the estimation procedure, the number of factors used to summarize the information content of our data set, and the behavior of the resulting UIG series. Following conventional practice in the factor model literature, prior to estimation we transformed the data to induce stationarity and standardized each series so that it has zero mean and unit variance.[23] Because of the standardization process, the initially estimated UIG series is driftless and must be re-normalized by assigning an average growth rate to it. We use 2.25 percent for the CPI and 1.75 percent for the PCE. When we began the project at the end of 2004, these numbers were very close to the respective average inflation rates starting from 1993.[24]

Chart 1
Breakdown of UIG Series



Source: Authors' calculations.

With regard to the number of factors, different articles find that much of the variance in U.S. macroeconomic variables is explained by two factors. Giannone, Reichlin, and Sala (2005) show this result using hundreds of variables for the period 1970-2003, while Sargent and Sims (1977) examine a relatively small set of variables and use frequency domain factor analysis for the period 1950-70. Watson (2004) notes that the two-factor model provides a good fit for U.S. data during the postwar period, and that this finding is quite robust. Hence, in most large data-factor-model applications the number of factors is set to two. Often one factor is associated with real variables (such as GDP or aggregate demand), while the second factor is associated with nominal prices (such as the CPI).

Our choice of the number of factors is not based on the considerations described above. Rather we draw upon the previously cited literature and include the lowest number of factors needed to represent our data environment properly—without labeling the factors (as either real or nominal) or interpreting them. We start our examination of the UIG measure by presenting estimates based only on price data from the CPI and PCE.[25] One

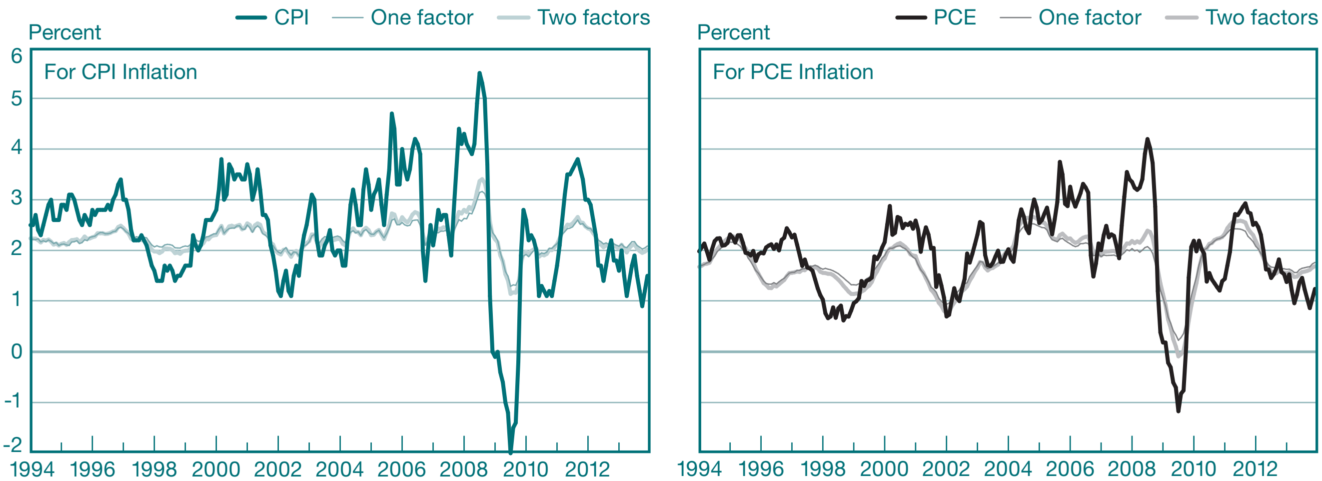
[23] Almost all variables were transformed to growth rates to induce stationarity, except for a small number for which no transformation was required. Using the variables listed in the Data Appendix, no transformation was applied to the eighteen variables in the Real Variables group, the first seventeen variables in the Labor group, and the Standard and Poor's 500 Price Earnings Ratio Index in the Financials group.

[24] As noted in the discussion, a value needs to be selected to allow for a nonzero mean of the underlying inflation measure. When we started this analysis, the Federal Reserve Board had not stated a numerical inflation goal. In January 2012, the Federal Open Market Committee agreed to a longer-run goal of a 2 percent PCE inflation rate.
A growing number of countries establish their monetary policy more or less explicitly according to an inflation target. In these countries, information on the inflation target (or the specific point target, if available) can be used to construct the average of the underlying inflation measure.

[25] We refer to these as the UIG estimates using prices-only data for the CPI and PCE. References to the "UIG for CPI inflation" and "UIG for PCE inflation" indicate measures derived using additional nonprice variables. The Data Appendix lists the series used in the analysis.
In particular, the prices-only model for the UIG for CPI inflation uses the first 222 listed variables in the Prices group, while the prices-only model for the UIG for PCE inflation uses all 254 variables. The former choice facilitates the comparison to a core CPI measure that only uses CPI subcomponents, while the latter choice reflects the earlier release date of the CPI data and their usefulness in predicting PCE inflation.
The model for the UIG for CPI inflation uses the first 242 listed variables in the Prices group and the variables from all the other groups (a total of 345), while the model for the UIG for PCE inflation uses all of the listed variables (a total of 357) in the Data Appendix.

Chart 2

UIG Estimates Using Only Price Data



Sources: Bloomberg L.P.; authors' calculations.

Notes: CPI is consumer price index; PCE is personal consumption expenditures deflator.

would expect these series to be driven by a single factor, since the data set comprises nominal variables only. The left and right panels of Chart 2 show the one- and two-factor estimates of the prices-only UIG for CPI inflation and PCE inflation, respectively, along with the twelve-month change in the relevant price index. As shown, there is little difference between the two estimates, offering support for the view that only one factor is relevant when the price data are considered alone.

Chart 3 shows the one- and two-factor estimated UIGs incorporating the nonprice variables in our data set through December 2013, along with the relevant twelve-month inflation rate. Three findings are noteworthy. First, the estimates now show larger cyclical fluctuations and appear to track inflation more closely. Second, starting in 2005 they correctly capture a broadly declining trend despite the temporary large increase in inflation in the first half of 2008. Moreover, when we turn to the period of the global financial crisis, we are immediately struck by how quickly the UIG begins to signal the deceleration in inflation starting in the second half of 2008 as a decline in trend inflation. In particular, a marked downturn in the UIG emerges as early as December 2008. Taken together, these findings suggest that the additional information contained in the nonprice variables is quite important both in terms of trend/cycle decomposition as well as in the timeliness of identifying shifts in underlying inflation. Third, the estimates based on two or more factors for the most part differ little from one another, a result that underlies our adoption of two factors for the dynamic factor model.[26]

Real-Time Updates and Data Revisions

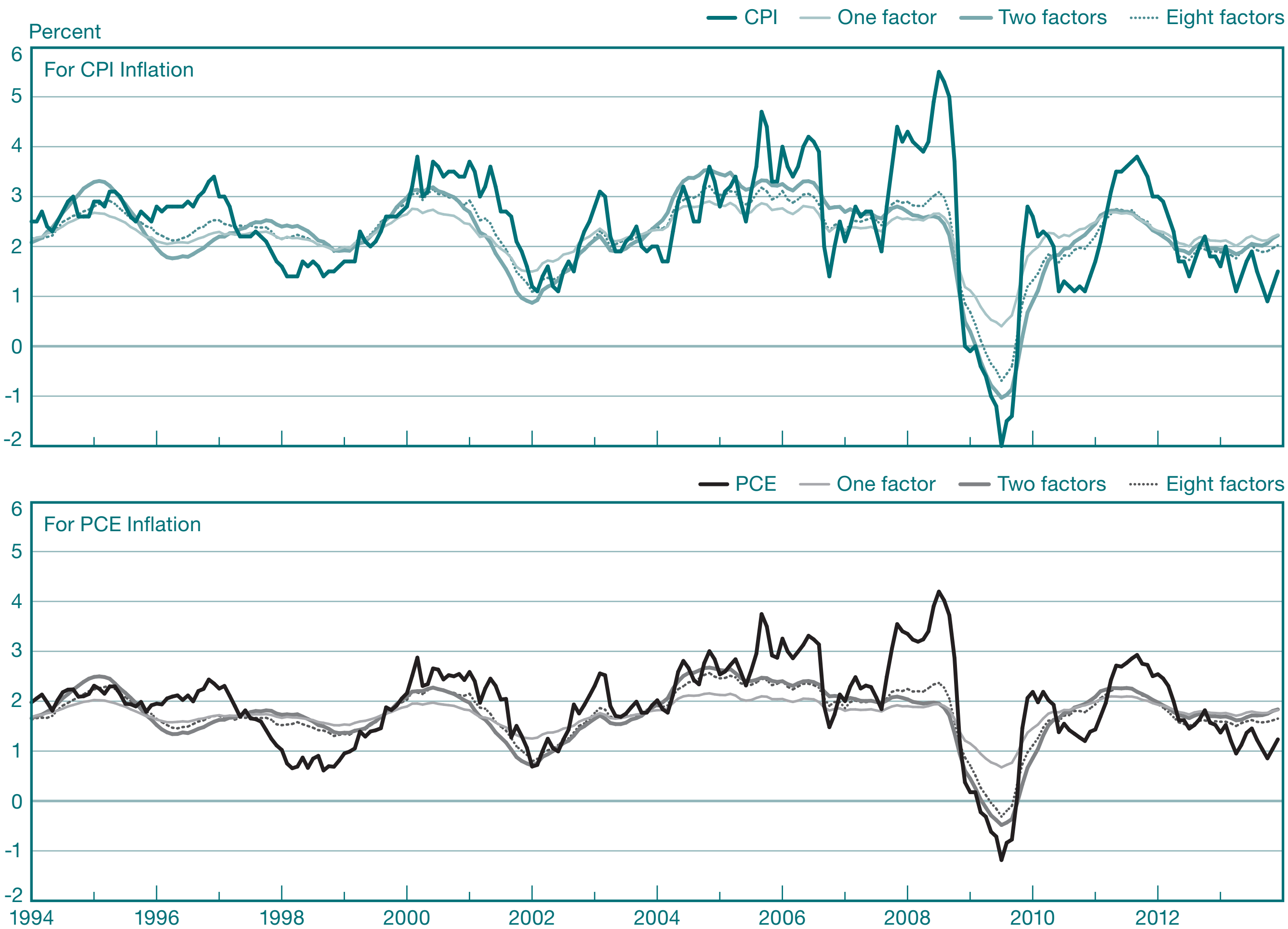
The UIG offers a monthly gauge of underlying inflation but is updated daily, following Amstad and Fischer (2009a, 2010) in their work using Swiss data. The monthly dating of the UIG is motivated by the monthly frequency of inflation reports in the United States. The daily updates allow for a close monitoring of the inflation process and also provide a basis to assess movements in underlying inflation that stem from daily changes in financial markets between monthly inflation reports.[27]

[26] Specifically, we considered estimates of the UIG that included as many as eight factors.

[27] Because our data set includes the most current daily information available, it results in an unbalanced panel structure. Therefore, some series end in month *T*, while others end in months *T*-1, *T*-2, . . . *T*-*j*. To address the unbalanced panel structure at the end of the sample, we use the methodology of Altissimo et al. (2001) and Cristadoro et al. (2005), which provides procedures to fill in the missing observations and create a balanced panel for estimation purposes.

Chart 3

UIG Estimates Using Different Numbers of Factors



Sources: Bloomberg L.P.; authors' calculations.

Notes: CPI is consumer price index; PCE is personal consumption expenditures deflator.

The daily UIG updates contrast with the monthly data releases of headline and core inflation measures. More generally, daily UIG updates can also be used to identify the sources of a change in inflation forecasts by determining the impact of a particular economic or financial news release—for example, the unemployment rate or an ISM (Institute for Supply Management) number—on underlying inflation.[28]

One aspect of the UIG updates is particularly important and merits special attention. Specifically, a UIG update not only generates a reassessment of the measure's behavior during the current month, but also for all previous months. This revisionist history occurs because each time the dynamic factor model is re-estimated, the addition of new data and revisions to existing data result in changed parameters as well as a more informed inference about the (estimated) factors throughout time.[29] As shown by equations (3), (5), and (7), changes in the time-series behavior of the factors will result in a different path for the predicted value of the persistent component of monthly inflation and hence the UIG. We explore and quantify the relevance of these revisions in the next section.

[28] Amstad and Fischer (2009b, 2010) provide an example of this type of analysis using an event study approach for Swiss inflation.

[29] Technically, this is referred to as smoothing the state vector in the dynamic factor estimation procedure.

Because of the revisionist nature of the UIG, it is important to limit other sources of variability as much as possible to derive a reliable signal of underlying inflation. Therefore, most of the selected data is either not revised or is subject to limited revisions. This implies that we must rely heavily on survey data for measures of real activity and not use more traditional measures based on National Income and Product Accounts (NIPA) data.[30] Another advantage of survey data is that it is usually released more quickly than expenditure and production data. Additionally, we use data that is not seasonally adjusted and, following Amstad and Fischer (2009a, 2009b), apply filters within the estimation procedure to generate a seasonally adjusted estimate of underlying inflation. We adopt this approach primarily because it prevents revisions in our measure of underlying inflation from being driven by concurrent seasonal adjustment procedures.

4. Comparing Measures of Underlying Inflation

This section compares core inflation measures and the UIG measures for CPI and PCE inflation. We begin by commenting on general features of the measures' behavior. Next we turn to statistical properties of the various underlying inflation measures and compare their ability to track and forecast inflation.

4.1 General Features and Statistical Properties

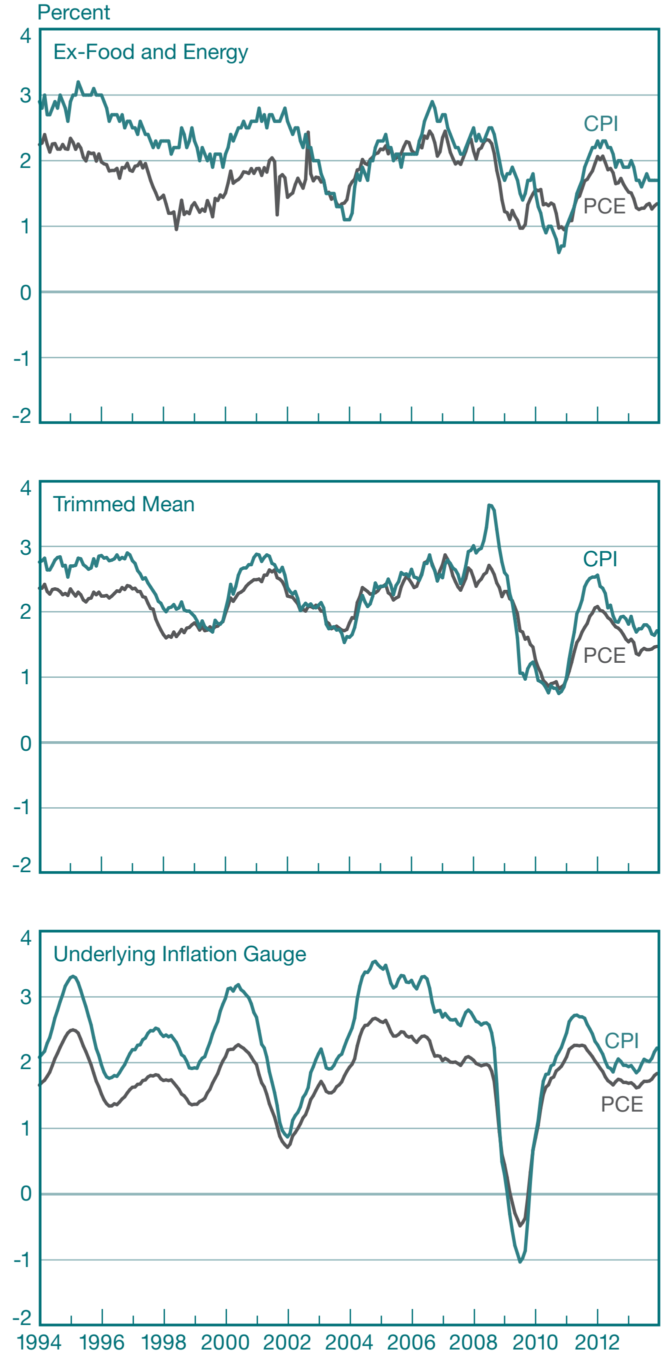
The underlying inflation measures in this study differ across two dimensions: methodology and price index. We begin the comparison by investigating the relative importance of each of these considerations. Chart 4 plots three underlying inflation measures—ex-food and energy, trimmed mean, and UIG—for the two price indexes, while Chart 5 plots underlying inflation measures for the same price indexes along with the twelve-month inflation rate.[31] As shown, we find that the general behavior of the different measures of underlying inflation is driven mainly by the choice of methodology and less by the choice of the price

[30] The NIPA data provides a detailed snapshot of the production of goods and services in the United States and the income that results. They are produced by the Bureau of Economic Analysis of the Department of Commerce and are an important source of data on U.S. economic activity.

[31] The upper panel of Chart 5 also includes the CPI Median, which is used for the forecast performance evaluation in Section 4.2. There is, however, no measure of the PCE Median that is readily available. The core inflation measures plotted in each panel are constructed as twelve-month changes.

Chart 4

Underlying Inflation Gauges for CPI and PCE Inflation

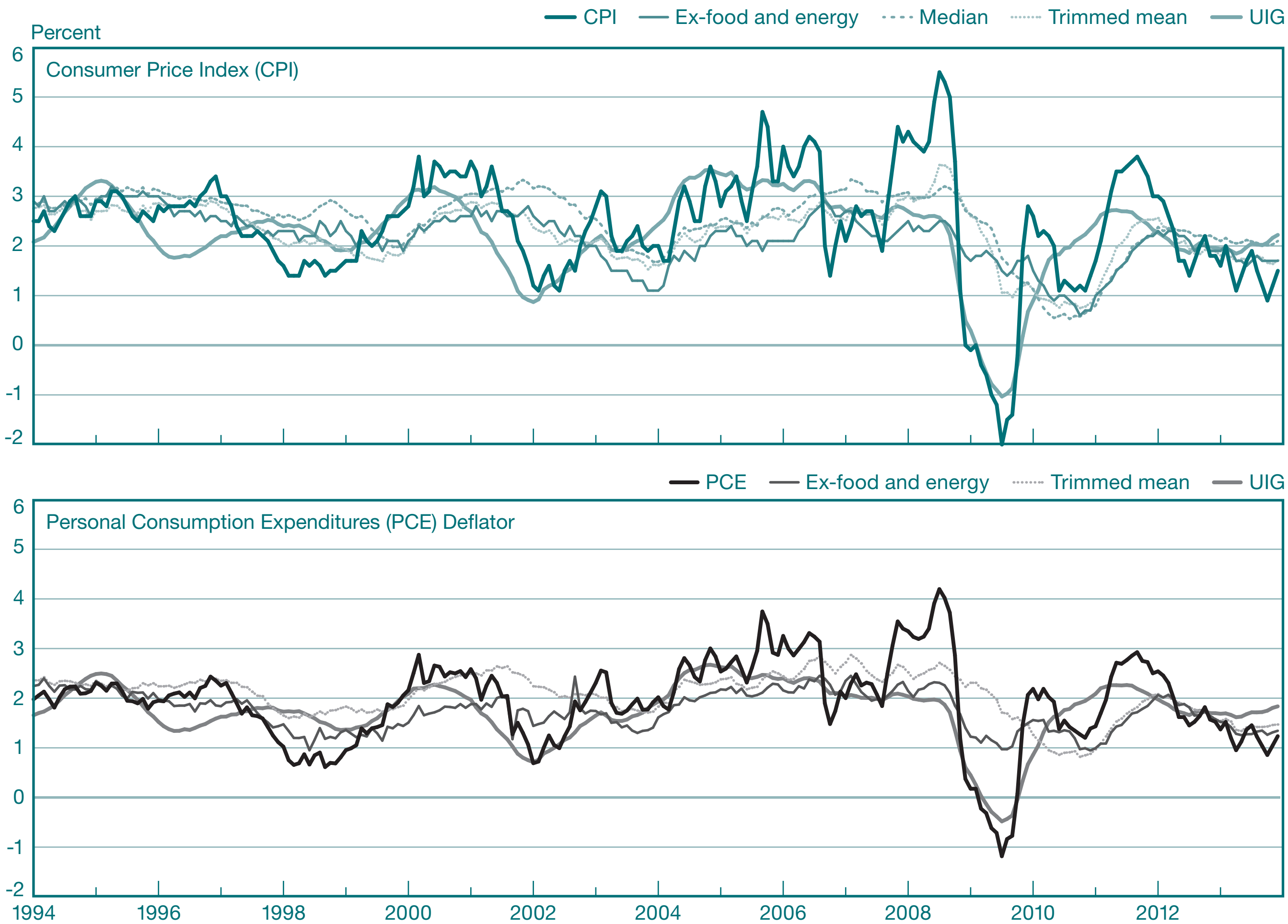


Sources: Bloomberg L.P.; authors' calculations.

Notes: CPI is consumer price index; PCE is personal consumption expenditures deflator.

Chart 5

A Comparison of Underlying Inflation Gauges



Sources: Bloomberg L.P.; authors' calculations.

index. While Chart 4 displays a level shift across the price indexes, there is a strong correlation between the underlying inflation measures within each panel. In Chart 5, however, there is a lower correlation between the underlying inflation measures, which is particularly evident when we look at the core inflation measures relative to the UIG.

We now examine three statistical features of the various underlying inflation measures: smoothness, the correlation with headline CPI inflation and headline PCE inflation, and the correlation between the UIG for CPI inflation and the UIG for PCE inflation.

First, smoothness is typically associated with the volatility of a series—measured using a metric such as a standard deviation—with lower volatility viewed as a favorable criterion in the evaluation of underlying measures of inflation. Our view, however, is that using a conventional measure of volatility for such an evaluation is problematic because it does not distinguish between volatility at high and low frequencies. In particular, the relevant property for a measure of underlying inflation is not its overall volatility, but rather its ability to match the lower-frequency trend of inflation and to produce little high-frequency noise. Consequently, overall volatility is uninformative as a criterion because the same value can be generated from alternative configurations of volatility at high and low frequencies.

With the previous discussion serving as background, we can address the issue of smoothness of the underlying inflation measures by analyzing the nature of their volatility. As shown

Table 1
CPI and PCE Standard Deviation, Sample Period Jan 1994–Dec 2013

	CPI	CPI UIG	CPI UIG Prices Only	CPI Ex-Food and Energy	CPI Trimmed Mean	CPI Median
Standard deviation	1.12	0.85	0.31	0.53	0.57	0.64

	PCE	PCE UIG	PCE UIG Prices Only	PCE Ex-Food and Energy	PCE Trimmed Mean
Standard deviation	0.86	0.59	0.53	0.39	0.44

Sources: Bloomberg L.P.; authors' calculations.

Notes: CPI is consumer price index; PCE is personal consumption expenditures deflator.

in Table 1, the UIG (augmented by the nonprice variables) has a lower standard deviation than CPI/PCE inflation, but a higher standard deviation than the various core measures of inflation. At the same time, Chart 4 shows that the UIG is smoother—that is, has less high-frequency noise—than the various core inflation measures.[32] Thus, the ex-food and energy measure and, to a lesser extent, the trimmed mean retain more high-frequency noise, which makes it more difficult for a policymaker to determine if changes in a core inflation measure merit a policy action. Moreover, it is now evident that the higher standard deviation of the UIG reported in Table 1 is largely driven by its variability around the time of the Great Recession, which likely relates to a shift in trend inflation. Thus, this discussion should make clear the importance of judging the volatility of a measure of underlying inflation in relation to the low-frequency movements in inflation.

Second, the UIG closely tracks headline CPI/PCE inflation and is also able to provide additional information that is not incorporated in core inflation measures. Compared with the core inflation measures, the UIG displays the highest correlation with CPI inflation and PCE inflation, respectively (see Table 2, panels A and B). At the same time, the UIG is less correlated with the core inflation measures, although this finding holds more for the CPI than the PCE deflator. In both cases, however, it is evident that the UIG is providing a different signal than the traditional underlying inflation measures. This conclusion is confirmed by a simple principal components analysis (PCA) on the CPI and underlying inflation measures that include the UIG.[33] As shown by the factor loadings given in Table 3, the traditional underlying inflation measures are grouped in the first principal component, while the UIG and CPI inflation are grouped in the second principal component.

Third, although there are clear differences between the UIG for CPI inflation and the UIG for PCE inflation, the two are highly correlated with one another, as shown in Table 2, panel C. This is also true if we restrict the data set for extracting factors to prices only. Going forward, we will focus more on the CPI-based UIG to streamline the discussion and because the measure has the advantage that the CPI is subject only to very minor and infrequent revisions, whereas the PCE is subject to major revisions, especially in the non-market-based prices.[34]

4.2 Forecast Performance

One rationale for developing underlying measures of inflation is to produce more accurate forecasts of inflation than those generated using only the headline measure. For any evaluation, it is particularly important that the forecast exercise reflects a realistic setting. Following Cogley (2002) and others,

[32] This should not be surprising because we exclude short-run fluctuations in inflation from the construction of the UIG.

[33] Principal component analysis arranges variables in groups (referred to as principal components) based on their statistical behavior. This is done in a way that ensures by construction that variables with similar behavior are grouped in the same principal component, with each of the principal components uncorrelated with the others.

[34] However, both underlying inflation gauges for the CPI and for the PCE are calculated daily by the New York Fed internally.

Table 2

CPI and PCE Correlations

Panel A: CPI Correlations					
	CPI UIG	CPI	CPI Ex-Food and Energy	CPI Trimmed Mean	CPI Median
CPI UIG	1.00				
CPI	0.74	1.00			
CPI Ex-food and energy	0.24	0.38	1.00		
CPI Trimmed mean	0.35	0.61	0.83	1.00	
CPI Median	0.20	0.34	0.89	0.89	1.00

Panel B: PCE Correlations				
	PCE UIG	PCE	PCE Ex-Food and Energy	PCE Trimmed Mean
PCE UIG	1.00			
PCE	0.74	1.00		
PCE Ex-food and energy	0.53	0.73	1.00	
PCE Trimmed mean	0.21	0.48	0.79	1.00

Panel C: UIG Correlations, Sample Period Jan 1994–Dec 2013				
	CPI UIG	CPI UIG Prices Only	PCE UIG	PCE UIG Prices Only
CPI UIG	1.00			
CPI UIG prices only	0.61	1.00		
PCE UIG	0.98	0.59	1.00	
PCE UIG prices only	0.88	0.66	0.93	1.00

Sources: Bloomberg L.P.; authors' calculations.

Notes: CPI is consumer price index; PCE is personal consumption expenditures deflator.

we initially evaluate the within-sample performance of the various measures of underlying inflation by estimating the following regression equation for monthly horizon h:

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h (\pi_t - \pi_t^m) + \varepsilon_{t+h}, \tag{8}$$

where π_t^m denotes the relevant measure of underlying inflation. Because underlying inflation is intended to measure trend inflation, the term $(\pi_t - \pi_t^m)$ can be interpreted as the transitory component of monthly inflation at time t that is expected to dissipate over time. That is, the term provides a measure of the expected reversal in current inflation.

Two desirable properties of an underlying measure of inflation are unbiasedness ($\alpha_h = 0$ and $\beta_h = -1$) and the capability to explain a substantial amount of the future variation in inflation. If β_h were negative but less than (greater than) one in absolute value, then the deviation between headline inflation and the underlying inflation measure $(\pi_t - \pi_t^m)$ would overstate (understate) the magnitude of subsequent changes in inflation, and thus would also overstate (understate) the magnitude of the current transitory deviation in inflation. This specification also nests the random walk model of Atkeson and Ohanion (2001) when $\alpha_h = \beta_h = 0$.

When equation (8) is estimated within sample, our main interest is testing for unbiasedness and whether the transitory deviation in inflation displays the correct size ($\beta_h = -1$). Using the sample period January 1993 through December 2013, we are unable to reject either hypothesis.[35] However, note that

[35] Using quarterly data from the period 1978-2004 and examining traditional underlying inflation measures, Rich and Steindel (2007) find that the property of unbiasedness can be rejected, but there is less evidence against the hypothesis that the coefficient on the deviation equals –1.

Table 3
Principal Components Analysis (PCA) on Core Inflation Measures and the UIG

	PCA1	PCA2	PCA3	PCA4	PCA5
CPI	0.40	0.53	–0.60	0.28	0.33
UIG	0.31	0.67	0.64	–0.19	–0.12
CPI Ex-food and energy	0.49	–0.32	0.30	0.74	–0.14
CPI Trimmed mean	0.52	–0.15	–0.34	–0.40	–0.65
CPI Median	0.49	–0.37	0.16	–0.42	0.65
Variance Proportion	0.65	0.26	0.06	0.03	0.01
Cumulative Proportion	0.65	0.91	0.96	0.99	1.00

Sources: Bloomberg L.P.; authors' calculations.

Note: CPI is consumer price index.

the test for unbiasedness of the UIG suffers from pre-test bias because the UIG must be centered separately from the estimation of the factors.[36]

Note of Caution for the Forecasting Exercises

We now investigate the relative forecast performance of the underlying inflation measures. It is often argued that such an exercise allows for the identification of a preferred underlying inflation measure. However, this type of comparison raises a number of issues that require careful consideration.

The most difficult issue in the interpretation of forecasting results concerns the appropriate loss function to evaluate forecast accuracy. The standard approach is to use a quadratic loss function for the forecast errors. Consider the following examples:

- Case 1: For total inflation between 1 and 3 percent, the root mean square error (RMSE) at a twelve-month horizon for underlying measure A is 1 percentage point, while for measure B it is 1.1 percentage points.

- Case 2: For total inflation outside the range of 1 to 3 percent, the RMSE at a twelve-month horizon for underlying measure A is 2 percentage points, while for measure B it is 1.2 percentage points.

If policymakers use measure A, they will be slower to recognize a change in underlying inflation than they would be if they used measure B. Suppose the policymaker successfully uses measure B to conduct monetary policy so that total inflation is rarely outside a range of 1 to 3 percent; a forecast evaluation would favor measure A if actual inflation was outside the 1 to 3 percent range less than 10 percent of the time. Therefore, forecast accuracy may not be informative about the usefulness of an underlying inflation measure for stabilization purposes.

Another important issue raised by the forecast exercise concerns the choice of the sample period. Long time periods can be problematic because they may cover different inflation regimes. Furthermore, because most industrialized countries successfully stabilized their inflation rates before the global financial crisis, static inflation forecasts (that is, a constant) might be more accurate than model-based forecasts generated from earlier periods when there was greater variability in inflation. The opposite result might hold for measures with greater variability during the global financial crisis. Therefore it is important to conduct our forecasting exercise over a sample displaying significant variation in inflation as well as over different subsample periods. The behavior of inflation in the United States since 2000 displays these features because it is relatively tranquil during the pre-2008 period but extremely volatile during the post-2008 period.

Finally, forecasting exercises are often undertaken in a pseudo-real-time manner in which estimation is conducted using a single vintage data set. In practice, the actual data used might have been revised subsequently. In our case,

[36] As mentioned in Section 3.3 and in footnote 24, the standardization of the variables requires us to assign an average value for the underlying inflation gauges for CPI inflation and PCE inflation.

the UIG (for CPI inflation) is constructed from data that is either not revised or only revised slightly (some PPI [producer price index] prices) but whose future values may lead to reassessments of the UIG's previous values—a feature not found in more traditional underlying inflation measures.[37]

A "Horse Race": UIG versus Core Inflation Measures

We first consider the results of a forecasting exercise based on equation (8).[38] Using data through period t, we can estimate the following regression equation:

$$\pi_t = \pi_{t-h} + \alpha_h + \beta_h (\pi_{t-h} - \pi^m_{t-h}) + \varepsilon_t \,. \tag{9}$$

The estimated equation can then be iterated forward by h periods to generate a forecast:

$$\hat{\pi}_{t+h} = \pi_t + \hat{\alpha}_{h|t} + \hat{\beta}_{h|t} (\pi_t - \pi^m_t), \tag{10}$$

where $\hat{\alpha}_{h|t}$ and $\hat{\beta}_{h|t}$ are the estimated regression coefficients using data through time t.

Estimation starts in 1994, while the forecasting range spans the period from 2000 through the end of 2013. To account for possible sensitivity of the forecast comparisons to this sample period, we also consider three different subsample periods: first, a pre-crisis subsample from 2000-07, a time range that could be considered a representative inflation cycle because it encompasses moderate cyclical phases in CPI inflation; second, a crisis subsample that captures the period from 2008 until the end of 2013; and third, for comparison purposes, a sample from 2001-07 that is also considered in Stock and Watson (2008). We compare the forecast performance of the UIG with the ex-food and energy, trimmed mean, and median measures. We also include a prices-only version of the UIG as well as the prior twelve-month change in the CPI in the forecast exercise.

The results in Table 4 show that the UIG clearly outperforms the traditional underlying inflation measures in forecasting headline CPI inflation before the crisis,

[37] This feature of the UIG was discussed in Section 3.3 and footnote 29.

[38] To ensure comparability we use the same setting as in 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).

Table 4

Out-of-Sample Performance in Root Mean Square Error for CPI

Whole Inflation Cycle: Sample Period, Jan 2000–Dec 2013

	$h = 12$
UIG	**1.35**
UIG prices only	1.54*
CPI Ex-food and energy	1.73**
CPI Trimmed mean	1.80**
CPI Median	1.81**
CPI ($t-h$)	*1.94****

Pre-Crisis: Sample Period, Jan 2000–Dec 2007

	$h = 12$
UIG	**0.93**
UIG prices only	**0.93**
CPI Ex-food and energy	*1.32***
CPI Trimmed mean	1.28**
CPI Median	1.26**
CPI ($t-h$)	1.25***

During the Crisis: Sample Period, Jan 2008–Dec 2012

	$h = 12$
UIG	**1.85**
UIG prices only	2.25**
CPI Ex-food and energy	2.32*
CPI Trimmed mean	2.56**
CPI Median	2.62**
CPI ($t-h$)	*2.88****

Stock and Watson (2008): Sample Period, Jan 2001–Dec 2007

	$h = 12$
UIG	**0.96**
UIG prices only	**0.96**
CPI Ex-food and energy	1.27*
CPI Trimmed mean	1.22**
CPI Median	1.24**
CPI ($t-h$)	*1.28****

Source: Authors' calculations.

Notes: Estimation starts in January 1994. Out-of-sample forecast exercise runs through December 2013. Text in **boldface** signifies the lowest root mean square error (RMSE). Text in *italics* signifies the highest RMSE. Diebold-Mariano test of the null hypothesis of equal RMSE against the alternative hypothesis that the RMSE of UIG is lower. Test statistics use the Newey-West covariance matrix estimator. CPI is consumer price index.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

during the crisis, and over the whole sample range. This is evident from the lowest reported RMSE over all samples. To analyze the UIG forecast performance further, we apply the Diebold-Mariano (1995) testing procedure.[39] The results show that the forecast errors from the UIG are lower than those from the traditional underlying inflation measures, at a 5 percent statistical significance level during the crisis and mostly at a 1 percent statistical significance level before the crisis and over the whole sample.

When we focus solely on the traditional underlying inflation measures, they do not differ much in their forecasting performance, confirming the previous findings in Rich and Steindel (2007). However, there are three notable observations for the traditional underlying inflation measures. First, all underlying inflation measures outperform the use of the prior twelve-month change in total CPI—the random walk forecast—which, not surprisingly, displays the highest forecast errors among the reported measures and samples during the crisis.[40] Second, the forecasting performance of the CPI trimmed mean and CPI median are remarkably similar over all samples. Third, the forecasting performance of the popular CPI ex-food and energy measure relative to the other measures is better during the crisis than before the crisis.

What makes the forecast accuracy of the UIG superior to that of core inflation measures and the popular random walk model? One consideration is that our methodology combines cross-sectional and time-series smoothing methods to derive a measure of underlying inflation. As noted by Cristadoro et al. (2005), the application of filtering techniques within the dynamic-factor-model structure enables us to move from isolating the $\chi_{1,t}^{LR} + \chi_{1,t}^{SR}$ component in equation (5) to extracting only the $\chi_{1,t}^{LR}$ component in equation (6). Gains to forecast accuracy also seem to arise from including nonprice data in the sample. While the UIG and the prices-only version display equal forecast accuracy in two of the cases in Table 4, the UIG always achieves the lowest RMSE across each time period. Consequently, the results suggest that the combination of the large data panel and filtering techniques has the benefit of offering forecast accuracy that is either comparable to or better than forecasts based solely on prices.

[39] Diebold and Mariano (1995) propose and evaluate explicit tests of the null hypothesis of no difference in the forecast accuracy of two competing models.

[40] The random walk forecast is the current value of the variable, which would be expected to perform poorly during episodes when inflation is particularly volatile.

UIG Revisions Historically and during the Crisis Period

An important consideration in judging the results in Table 4 is that the UIG is derived using the full sample data set that incorporates the latest revised values of the nonprice components. That is, all previous monthly readings of the UIG are informed by future information. Even though equations (9) and (10) are estimated in a recursive manner, this feature of the UIG might be viewed as an advantage in the conduct of the forecast exercises. However, there would appear to be a more general question about the nature of the UIG revisions that extends beyond the significance of using the currently updated values for forecasting purposes.

There are several ways that we can try to qualify and quantify the importance of this issue. One option is that we can examine the magnitude of revisions to past UIG estimates for CPI inflation and determine if they were small. In doing so, we will consider a twenty-six-month period before the crisis from November 2005 to December 2007 and a forty-four-month period during the crisis from January 2008 to August 2011. This first phase covers a time period with economic changes that were very typical when judged on a historical basis, while the second phase covers a time period of historically large economic changes. Given the events in the most recent crisis, we think of the second subsample as a real-world stress test that provides an assessment of the maximal revision that can occur to the UIG.

We examine the daily revisions to each of the monthly UIG estimates over 240 workdays (approximately one year).[41] The results of this exercise are presented in Chart 6 for the absolute size of the change, where we plot the mean and median of the change of the UIG estimate from the x^{th} workday compared with the final estimate. We examine absolute values to ensure that large changes in one direction are not canceled out by large changes in the opposite direction. Although the CPI release for a particular month is not made available until the middle of the following month, estimation of the UIG for that month can proceed without delay.

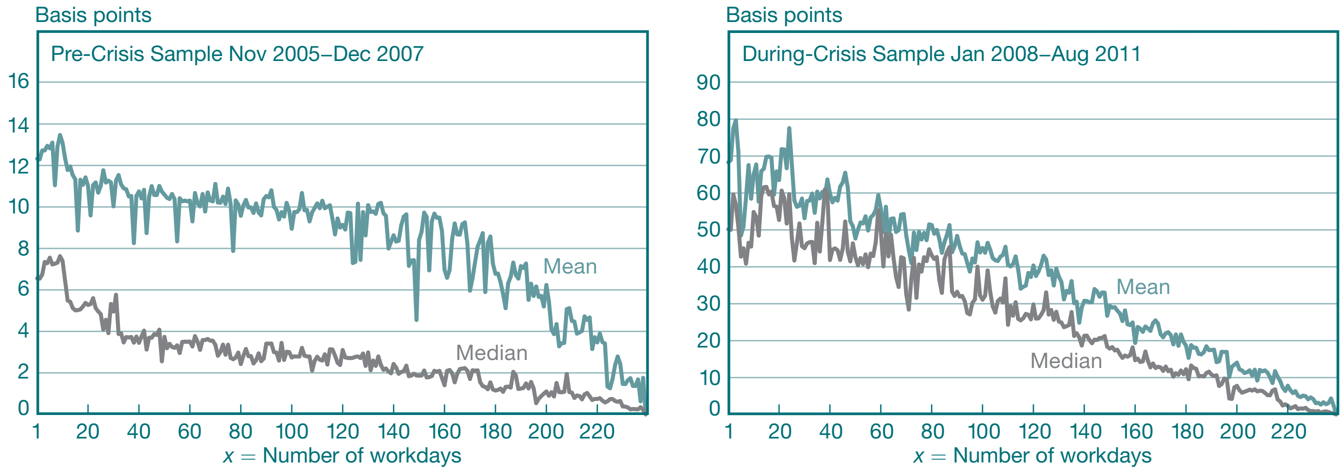
As shown, the largest changes in the estimate of the UIG for a month usually occur within the first one and a half months (thirty workdays). During a normal business cycle (November 2005 to December 2007), the maximal

[41] For the November 2005 to December 2007 sample period, we look at the revisions for each of these months for up to a year. This results in an equal number of observations for each month.

Chart 6

Absolute Change of UIG Estimates

From the x^{th} Workday Compared with the Final Estimate One Year Later



Source: Authors' calculations.

Note: One year equals 240 workdays.

median revision in the UIG peaks at about 7 basis points (0.07 percentage point) before and 4 basis points after the monthly CPI publication (Chart 6, left panel).[42] Given an average CPI inflation rate of around 2.25 percent (twelve-month change) between 1994 and 2014, these maximum changes in the UIG seem relatively minor. After the first thirty days, the median and mean revisions converge to zero.[43] Since 2008, with the large decline in CPI inflation and the deep recession in the United States, revisions in the input variables and consequently the UIG have been considerably larger. During this period of extremely volatile news flows, the maximal median revision in the UIG was around 60 basis points before and 40 basis points after the CPI publication (Chart 6, right panel).

We can also explore the issue of UIG revisions by examining the behavior of the UIG estimated in real-time using different data vintages. The upper and lower panels of Chart 7 depict the estimated UIG series on a quarterly basis from December 2005 to December 2007 and from March 2008 to December 2011, respectively. In each case, the series is estimated through the relevant end-of-month period and provides a value through the previous month.[44] The first set of data vintages again relates to the pre-crisis period, while the second set includes the crisis period. The plots also depict the realized twelve-month change in the CPI.

Several interesting findings emerge from the charts. As shown in Chart 7, upper panel, while the CPI inflation rate displays considerable variability, the UIG is more stable. This stability suggests that the UIG viewed the fluctuation in inflation as largely transitory. In addition, the subsequent updates do not yield significant revisions to the historical behavior of the UIG. It is also interesting to note from the lower panel that subsequent updates during the crisis period generated meaningful revisions to the UIG around turning points in inflation. However, the revisions largely exclude the Great Recession episode and focus on the level rather than the timing associated with the other turning points. This latter finding is particularly

[42] For convenience, Chart 6 is plotted in basis points—100 basis points is equivalent to 1 percentage point.

[43] Because the mean is more sensitive to outliers than the median, the slower convergence of the mean to zero likely reflects the sustained period of CPI inflation greater than 3 percent in the evaluation period—an ex ante unlikely event given our re-normalization process that centers the UIG at 2.25 percent and the volatility of the CPI from 1993 to 2005.

[44] This is because of the one-month publication lag of the CPI price series. For example, the UIG estimated using the December 30, 2005, data vintage covers the period January 1995–November 2005.

Chart 7

UIG Revisions during Pre-Crisis and Crisis Periods

Sources: Bloomberg, L.P.; authors' calculations.

Notes: Gray lines depict the estimated UIG series as measured on the following dates: Upper panel: Dec 2005, Jun 2006, Dec 2006, Jun 2007, and Dec 2007. Lower panel: Mar 2008, Jun 2008, Dec 2008, Dec 2009, Dec 2010, and Dec 2011. The UIG series is estimated through the relevant end-of-month period and provides a value through the previous month. CPI is consumer price index.

noteworthy because of the importance and difficulty of identifying turning points in the inflation process.

The preceding evidence suggests several important findings about revisions to the UIG. The revisions converge to zero fairly quickly, particularly after the first month. In addition, while revisions to the UIG have been more notable during the post-2007 period, they have not affected the dating of the turning point during the Great Recession. Rather, revisions have largely changed the level of the UIG associated with earlier turning points, not the timing of these points. Consequently, we view the UIG as providing a strong and reliable signal for an approaching change in trend inflation. Taking all of this evidence together, we consider the impact of revisions on the UIG as limited.

CPI and the Labor Market as Drivers of UIG

As a final step, we examine in more detail the changes in the estimated path of the UIG since 1995 using data through the last

Chart 8

Change in the UIG Following the Release of Various Economic Indicators

Source: Authors' calculations.

Notes: CPI is consumer price index. The shaded areas indicate periods designated recessions by the National Bureau of Economic Research.

two months of 2008 and the first month of 2009—three months during which economic activity was contracting sharply. For each month we show the path of the UIG after the release of the CPI in the two prior months and the release of the U.S. Employment Situation report for the prior month that falls between the two CPI releases. The results are presented in Chart 8. The results for November indicate little response to the CPI releases or the employment report for October 2008. In December 2008, it can be seen that the November CPI had a large effect on the current value of the UIG and the estimates for the previous twenty-four months. Lastly, the December 2008 employment report produced a large change in the UIG estimated during January 2009 and significantly altered its whole history.

5. Conclusions

This article explains the construction of the New York Fed Staff Underlying Inflation Gauge (UIG), highlights several of its attractive features and properties, compares its performance to existing measures of underlying inflation and reviews the experience of the New York Fed with real-time updates of the UIG, made internally since 2005. The article serves as useful background for the publication of monthly updates of the UIG for CPI inflation later in 2017.

Of particular note, the UIG summarizes the information content in a broad data set including asset prices and real variables such as the unemployment rate. Unlike traditional core inflation measures, the UIG does not restrict its scope to price data. Therefore it can incorporate the idea that many economic variables may affect the inflation process. The carefully chosen data set reflects the information that New York Fed staff economists consider to be the most relevant determinants of inflation.

In addition, unlike traditional underlying inflation gauges, the UIG can be updated daily. As shown in the analysis, this property is of particular importance during a crisis period, such as 2007-09. Further, the UIG adds to the literature in that it focuses on the persistent part of the common component in the broad data set. The resulting smooth movements of the UIG provide policymakers with a strong and reliable signal for an approaching turning point in trend inflation—that is, a change in underlying inflation that is likely to persist and therefore warrant a possible policy response.

The UIG is also strongly correlated with headline inflation and contains additional useful information beyond that found in traditional core measures. As a result, the

UIG can be used as a complement to, rather than as a substitute for, other core inflation measures.

Last, the UIG significantly outperforms traditional core measures when forecasting headline inflation. These findings hold for a sample from 2000 through 2013, as well as for a sample focusing on an average economic regime before the crisis and an extremely volatile sample during the crisis.

Data Appendix: UIG Variables

Prices

1. CPI-U: All items (NSA, 1982–84 = 100)
2. CPI-U: All items less energy (NSA, 1982–84 = 100)
3. CPI-U: All items less food (NSA, 1982–84 = 100)
4. CPI-U: All items less food and energy (NSA, 1982–84 = 100)
5. CPI-U: All items less medical care (NSA, 1982–84 = 100)
6. CPI-U: All items less shelter (NSA, 1982–84 = 100)
7. CPI-U: All items less food and shelter (NSA, 1982–84 = 100)
8. CPI-U: All items less food, shelter, and energy (NSA, 1982–84 = 100)
9. CPI-U: All items less food, shelter, energy, used cars and trucks (NSA, 1982–84 = 100)
10. CPI-U: Commodities (NSA, 1982–84 = 100)
11. CPI-U: Durable commodities (NSA, 1982–84 = 100)
12. CPI-U: Nondurable commodities (NSA, 1982–84 = 100)
13. CPI-U: Services (NSA, 1982–84 = 100)
14. CPI-U: Services less rent of shelter (NSA, Dec 82 = 100)
15. CPI-U: Transportation services (NSA, 1982–84 = 100)
16. CPI-U: Other services (NSA, 1982–84 = 100)
17. CPI-U: Services less medical care services (NSA, 1982–84 = 100)
18. CPI-U: Energy (NSA, 1982–84 = 100)
19. CPI-U: Apparel less footwear (NSA, 1982–84 = 100)
20. CPI-U: Energy commodities (NSA, 1982–84 = 100)
21. CPI-U: Utilities and public transportation (NSA, 1982–84 = 100)
22. CPI-U: Food and beverages (NSA, 1982–84 = 100)
23. CPI-U: Food (NSA, 1982–84 = 100)
24. CPI-U: Food at home (NSA, 1982–84 = 100)
25. CPI-U: Domestically produced farm food (NSA, 1982–84 = 100)
26. CPI-U: Cereals and bakery products (NSA, 1982–84 = 100)
27. CPI-U: Cereals and cereal products (NSA, 1982–84 = 100)
28. CPI-U: Flour and prepared flour mixes (NSA, 1982–84 = 100)
29. CPI-U: Breakfast cereal (NSA, 1982–84 = 100)
30. CPI-U: Rice, pasta, and cornmeal (NSA, 1982–84 = 100)
31. CPI-U: Bakery products (NSA, 1982–84 = 100)
32. CPI-U: White bread (NSA, 1982–84 = 100)
33. CPI-U: Bread other than white (NSA, 1982–84 = 100)
34. CPI-U: Cakes, cupcakes, and cookies (NSA, 1982–84 = 100)
35. CPI-U: Fresh cakes and cupcakes (NSA, 1982–84 = 100)
36. CPI-U: Cookies (NSA, 1982–84 = 100)
37. CPI-U: Other bakery products (NSA, 1982–84 = 100)
38. CPI-U: Fresh sweetrolls, coffeecakes, and doughnuts (NSA, 1982–84 = 100)
39. CPI-U: Crackers, bread, and cracker products (NSA, 1982–84 = 100)
40. CPI-U: Frozen and refrigerated bakery products, pies, tarts, etc. (NSA, 1982–84 = 100)
41. CPI-U: Meats, poultry, fish, and eggs (NSA, 1982–84 = 100)
42. CPI-U: Meats, poultry, and fish (NSA, 1982–84 = 100)
43. CPI-U: Meats (NSA, 1982–84 = 100)
44. CPI-U: Beef and veal (NSA, 1982–84 = 100)
45. CPI-U: Uncooked ground beef (NSA, 1982–84 = 100)
46. CPI-U: Pork (NSA, 1982–84 = 100)

Prices (*continued*)

47. CPI-U: Bacon and related products (NSA, 1982–84 = 100)
48. CPI-U: Ham (NSA, 1982–84 = 100)
49. CPI-U: Ham excluding canned (NSA, 1982–84 = 100)
50. CPI-U: Pork chops (NSA, 1982–84 = 100)
51. CPI-U: Other meats (NSA, 1982–84 = 100)
52. CPI-U: Frankfurters (NSA, 1982–84 = 100)
53. CPI-U: Lamb and organ meats (NSA, 1982–84 = 100)
54. CPI-U: Poultry (NSA, 1982–84 = 100)
55. CPI-U: Fresh whole chicken (NSA, 1982–84 = 100)
56. CPI-U: Fresh and frozen chicken parts (NSA, 1982–84 = 100)
57. CPI-U: Fish and seafood (NSA, 1982–84 = 100)
58. CPI-U: Canned fish and seafood (NSA, 1982–84 = 100)
59. CPI-U: Frozen fish and seafood (NSA, 1982–84 = 100)
60. CPI-U: Eggs (NSA, 1982–84 = 100)
61. CPI-U: Dairy and related products (NSA, 1982–84 = 100)
62. CPI-U: Fresh whole milk (NSA, 1982–84 = 100)
63. CPI-U: Cheese and related products (NSA, 1982–84 = 100)
64. CPI-U: Ice cream and related products (NSA, 1982–84 = 100)
65. CPI-U: Fruits and vegetables (NSA, 1982–84 = 100)
66. CPI-U: Fresh fruits and vegetables (NSA, 1982–84 = 100)
67. CPI-U: Fresh fruits (NSA, 1982–84 = 100)
68. CPI-U: Apples (NSA, 1982–84 = 100)
69. CPI-U: Bananas (NSA, 1982–84 = 100)
70. CPI-U: Oranges, including tangerines (NSA, 1982–84 = 100)
71. CPI-U: Fresh vegetables (NSA, 1982–84 = 100)
72. CPI-U: Potatoes (NSA, 1982–84 = 100)
73. CPI-U: Lettuce (NSA, 1982–84 = 100)
74. CPI-U: Tomatoes (NSA, 1982–84 = 100)
75. CPI-U: Other fresh vegetables (NSA, 1982–84 = 100)
76. CPI-U: Frozen vegetables (NSA, 1982–84 = 100)
77. CPI-U: Nonalcoholic beverages and beverage materials (NSA, 1982–84 = 100)
78. CPI-U: Carbonated drinks (NSA, 1982–84 = 100)
79. CPI-U: Coffee (NSA, 1982–84 = 100)
80. CPI-U: Roasted coffee (NSA, 1982–84 = 100)
81. CPI-U: Instant freeze-dried coffee (NSA, 1982–84 = 100)
82. CPI-U: Other food at home (NSA, 1982–84 = 100)
83. CPI-U: Sugar and sweets (NSA, 1982–84 = 100)
84. CPI-U: Sugar and artificial sweeteners (NSA, 1982–84 = 100)
85. CPI-U: Fats and oils (NSA, 1982–84 = 100)
86. CPI-U: Butter (NSA, 1982–84 = 100)
87. CPI-U: Margarine (NSA, 1982–84 = 100)
88. CPI-U: Other foods at home (NSA, 1982–84 = 100)
89. CPI-U: Soups (NSA, 1982–84 = 100)
90. CPI-U: Frozen and freeze dried prepared food (NSA, 1982–84 = 100)
91. CPI-U: Snacks (NSA, 1982–84 = 100)
92. CPI-U: Seasonings, condiments, sauces, spices (NSA, 1982–84 = 100)

Prices (*continued*)

93. CPI-U: Other condiments (NSA, 1982–84 = 100)
94. CPI-U: Food away from home (NSA, 1982–84 = 100)
95. CPI-U: Alcoholic beverages (NSA, 1982–84 = 100)
96. CPI-U: Alcoholic beverages at home (NSA, 1982–84 = 100)
97. CPI-U: Beer, ale and malt beverages at home (NSA, 1982–84 = 100)
98. CPI-U: Distilled spirits at home (NSA, 1982–84 = 100)
99. CPI-U: Whiskey at home (NSA, 1982–84 = 100)
100. CPI-U: Distilled spirits excluding whiskey at home (NSA, 1982–84 = 100)
101. CPI-U: Wine at home (NSA, 1982–84 = 100)
102. CPI-U: Alcoholic beverages away from home (NSA, 1982–84 = 100)
103. CPI-U: Housing (NSA, 1982–84 = 100)
104. CPI-U: Shelter (NSA, 1982–84 = 100)
105. CPI-U: Rent of primary residence (NSA, 1982–84 = 100)
106. CPI-U: Rent of shelter (NSA, 1982–84 = 100)
107. CPI-U: Housing at school excluding board (NSA, Dec 82 = 100)
108. CPI-U: Other lodging away from home including hotels/motels (NSA, 1982–84 = 100)
109. CPI-U: Owners' equivalent rent of primary residence (NSA, Dec 82 = 100)
110. CPI-U: Fuels and utilities (NSA, 1982–84 = 100)
111. CPI-U: Fuels (NSA, 1982–84 = 100)
112. CPI-U: Fuel oil and other fuels (NSA, 1982–84 = 100)
113. CPI-U: Fuel oil (NSA, 1982–84 = 100)
114. CPI-U: Other [than fuel oil] household fuels (NSA, Dec 86 = 100)
115. CPI-U: Household piped gas and electricity (NSA, 1982–84 = 100)
116. CPI-U: Household electricity (NSA, 1982–84 = 100)
117. CPI-U: Utility [piped] gas service (NSA, 1982–84 = 100)
118. CPI-U: Water and sewerage maintenance (NSA, 1982–84 = 100)
119. CPI-U: Garbage and trash collection (NSA, Dec 83 = 100)
120. CPI-U: Household furnishings and operation (NSA, 1982–84 = 100)
121. CPI-U: Household furniture and bedding (NSA, 1982–84 = 100)
122. CPI-U: Bedroom furniture (NSA, 1982–84 = 100)
123. CPI-U: Household laundry equipment (NSA, 1982–84 = 100)
124. CPI-U: Clocks, lamps, and decorator items (NSA, 1982–84 = 100)
125. CPI-U: Indoor plants and flowers (NSA, Dec 90 = 100)
126. CPI-U: Housekeeping supplies (NSA, 1982–84 = 100)
127. CPI-U: Apparel (NSA, 1982–84 = 100)
128. CPI-U: Men's and boys' apparel (NSA, 1982–84 = 100)
129. CPI-U: Men's apparel (NSA, 1982–84 = 100)
130. CPI-U: Men's suits, sport coats, and outerwear (NSA, 1982–84 = 100)
131. CPI-U: Men's furnishings (NSA, 1982–84 = 100)
132. CPI-U: Men's pants and shorts (NSA, 1982–84 = 100)
133. CPI-U: Boys' apparel (NSA, 1982–84 = 100)
134. CPI-U: Women's and girls' apparel (NSA, 1982–84 = 100)
135. CPI-U: Women's apparel (NSA, 1982–84 = 100)
136. CPI-U: Women's outerwear (NSA, 1982–84 = 100)
137. CPI-U: Women's dresses (NSA, 1982–84 = 100)
138. CPI-U: Girls' apparel (NSA, 1982–84 = 100)

Prices (*continued*)

139. CPI-U: Footwear (NSA, 1982–84 = 100)
140. CPI-U: Men's footwear (NSA, 1982–84 = 100)
141. CPI-U: Boys' and girls' footwear (NSA, 1982–84 = 100)
142. CPI-U: Women's footwear (NSA, 1982–84 = 100)
143. CPI-U: Infants' and toddlers' apparel (NSA, 1982–84 = 100)
144. CPI-U: Watches and jewelry (NSA, Dec 86 = 100)
145. CPI-U: Watches (NSA, Dec 86 = 100)
146. CPI-U: Jewelry (NSA, Dec 86 = 100)
147. CPI-U: Transportation (NSA, 1982–84 = 100)
148. CPI-U: Private transportation (NSA, 1982–84 = 100)
149. CPI-U: New and used vehicles (NSA, Dec 97 = 100)
150. CPI-U: New vehicles (NSA, 1982–84 = 100)
151. CPI-U: New cars (NSA, 1982–84 = 100)
152. CPI-U: New trucks (NSA, Dec 83 = 100)
153. CPI-U: Used cars and trucks (NSA, 1982–84 = 100)
154. CPI-U: Motor fuel (NSA, 1982–84 = 100)
155. CPI-U: Gasoline (NSA, 1982–84 = 100)
156. CPI-U: Unleaded regular gasoline (NSA, 1982–84 = 100)
157. CPI-U: Unleaded premium gasoline (NSA, 1982–84 = 100)
158. CPI-U: Motor vehicle parts and equipment (NSA, 1982–84 = 100)
159. CPI-U: Tires (NSA, 1982–84 = 100)
160. CPI-U: Vehicle parts and equipment excluding tires (NSA, 1982–84 = 100)
161. CPI-U: Motor oil, coolants, and fluids (NSA, 1982–84 = 100)
162. CPI-U: Motor vehicle maintenance and repair (NSA, 1982–84 = 100)
163. CPI-U: Motor vehicle body work (NSA, 1982–84 = 100)
164. CPI-U: Motor vehicle maintenance and servicing (NSA, 1982–84 = 100)
165. CPI-U: Motor vehicle insurance (NSA, 1982–84 = 100)
166. CPI-U: Public transportation (NSA, 1982–84 = 100)
167. CPI-U: Airline fare (NSA, 1982–84 = 100)
168. CPI-U: Other intercity transportation (NSA, 1982–84 = 100)
169. CPI-U: Intracity public transportation (NSA, 1982–84 = 100)
170. CPI-U: Medical care (NSA, 1982–84 = 100)
171. CPI-U: Medical care commodities (NSA, 1982–84 = 100)
172. CPI-U: Prescription drugs and medical supplies (NSA, 1982–84 = 100)
173. CPI-U: Nonprescription drugs and medical supplies (NSA, 1982–84 = 100)
174. CPI-U: Internal/respiratory over-the-counter drugs (NSA, 1982–84 = 100)
175. CPI-U: Nonprescription medical equipment and supplies (NSA, 1982–84 = 100)
176. CPI-U: Medical care services (NSA, 1982–84 = 100)
177. CPI-U: Professional medical care services (NSA, 1982–84 = 100)
178. CPI-U: Physicians' services (NSA, 1982–84 = 100)
179. CPI-U: Dental services (NSA, 1982–84 = 100)
180. CPI-U: Eyeglasses and eye care (NSA, Dec 86 = 100)
181. CPI-U: Services by other medical professionals (NSA, Dec 86 = 100)
182. CPI-U: Hospital and related services (NSA, 1982–84 = 100)
183. CPI-U: Outpatient hospital services (NSA, Dec 86 = 100)
184. CPI-U: Recreation (NSA, Dec 97 = 100)

Prices (*continued*)

185. CPI-U: Video and audio (NSA, Dec 97 = 100)
186. CPI-U: TV sets (NSA, 1982–84 = 100)
187. CPI-U: Cable and satellite TV and radio service (NSA, Dec 83 = 100)
188. CPI-U: Audio equipment (NSA, 1982–84 = 100)
189. CPI-U: Pets and pet products (NSA, 1982–84 = 100)
190. CPI-U: Sporting goods (NSA, 1982–84 = 100)
191. CPI-U: Sport vehicles including bicycles (NSA, 1982–84 = 100)
192. CPI-U: Sports equipment (NSA, 1982–84 = 100)
193. CPI-U: Photographic equipment and supplies (NSA, 1982–84 = 100)
194. CPI-U: Toys (NSA, 1982–84 = 100)
195. CPI-U: Admissions (NSA, 1982–84 = 100)
196. CPI-U: Fees for recreational lessons/instructions (NSA, Dec 86 = 100)
197. CPI-U: Recreational reading materials (NSA, 1982–84 = 100)
198. CPI-U: Education and communication (NSA, Dec 97 = 100)
199. CPI-U: Education (NSA, Dec 97 = 100)
200. CPI-U: Educational books and supplies (NSA, 1982–84 = 100)
201. CPI-U: Tuition, other school fees, and child care (NSA, 1982–84 = 100)
202. CPI-U: College tuition and fees (NSA, 1982–84 = 100)
203. CPI-U: Elementary and high school tuition and fees (NSA, 1982–84 = 100)
204. CPI-U: Child care and nursery school (NSA, Dec 90 = 100)
205. CPI-U: Communication (NSA, Dec 97 = 100)
206. CPI-U: Postage services (NSA, 1982–84 = 100)
207. CPI-U: Information and information processing (NSA, Dec 97 = 100)
208. CPI-U: Land-line telephone services, local charges (NSA,1982–84 = 100)
209. CPI-U: Land-line interstate toll calls (NSA, 1982–84 = 100)
210. CPI-U: Land-line intrastate toll calls (NSA, 1982–84 = 100)
211. CPI-U: Information technology, hardware, and services (NSA, Dec 1988 = 100)
212. CPI-U: Other goods and services (NSA, 1982–84 = 100)
213. CPI-U: Tobacco and smoking products (NSA, 1982–84 = 100)
214. CPI-U: Personal care (NSA, 1982–84 = 100)
215. CPI-U: Personal care products (NSA, 1982–84 = 100)
216. CPI-U: Cosmetics, perfumes, bath, nail preparations and implements (NSA, 1982–84 = 100)
217. CPI-U: Personal care services (NSA, 1982–84 = 100)
218. CPI-U: Miscellaneous personal services (NSA, 1982–84 = 100)
219. CPI-U: Legal services (NSA, Dec 86 = 100)
220. CPI-U: Funeral expenses (NSA, Dec 86 = 100)
221. CPI-U: Financial services (NSA, Dec 86 = 100)
222. CPI-U: Stationery, stationery supplies, gift wrap (NSA, 1982–84 = 100)
223. PPI: Finished consumer goods (NSA, 1982 = 100)
224. PPI: Finished consumer foods (NSA, 1982 = 100)
225. PPI: Finished consumer foods: Unprocessed (NSA, 1982 = 100)
226. PPI: Finished consumer foods: Processed (NSA, 1982 = 100)
227. PPI: Finished consumer goods excluding foods (NSA, 1982 = 100)
228. PPI: Consumer nondurable goods less food (NSA,1982 = 100)
229. PPI: Consumer durable goods (NSA, 1982 = 100)
230. PPI: Finished capital equipment (NSA, 1982 = 100)

Prices (*continued*)

231. PPI: Capital equipment: Manufacturing industries (NSA, 1982 = 100)
232. PPI: Capital equipment: Nonmanufacturing industries (NSA, 1982 = 100)
233. PPI: Finished goods [including foods and fuel] (NSA, 1982 = 100)
234. PPI: Intermediate materials, supplies, and components (NSA, 1982 = 100)
235. PPI: Crude materials for further processing (NSA, 1982 = 100)
236. PPI: Finished goods excluding foods (NSA, 1982 = 100)
237. PPI: Offices of physicians (Dec 96 = 100)
238. PPI: Home health care services (Dec 96 = 100)
239. PPI: Commercial natural gas (NSA, Dec 90 = 100)
240. Import Price Index: All imports (NSA, 2000 = 100)
241. Export Price Index: All exports (NSA, 2000 = 100)
242. FRB Dallas: Trimmed-mean 12-month PCE inflation rate (%)
243. PCE: Chain Price Index (SA, 2000 = 100)
244. PCE less food and energy: Chain Price Index (SA, 2000 = 100)
245. PCE: Durable goods: Chain Price Index (SA, 2000 = 100)
246. PCE: Nondurable goods: Chain Price Index (SA, 2000 = 100)
247. PCE: Services: Chain Price Index (SA, 2000 = 100)
248. Real PCE: Durable goods: Motor vehicles and parts (SAAR, Mil.Chn.2000$)
249. Import Price Index: Foods, feeds and beverages (NSA, 2000 = 100)
250. Import Price Index: Industrial supplies and materials (NSA, 2000 = 100)
251. Import Price Index: Capital goods (NSA, 2000 = 100)
252. Export Price Index: Foods, feeds, and beverages (NSA, 2000 = 100)
253. Export Price Index: Industrial supplies and materials (NSA, 2000 = 100)
254. Export Price Index: Capital goods (NSA, 2000 = 100)

Real Variables

1. ISM: Mfg: New Orders Index (NSA, 50+ = Econ Expand)
2. ISM: Mfg: Production Index (NSA, 50+ = Econ Expand)
3. ISM: Mfg: Employment Index (NSA, 50+ = Econ Expand)
4. ISM: Mfg: Vendor Deliveries Index (NSA, 50+ = Econ Expand)
5. ISM: Mfg: Inventories Index (NSA, 50+ = Econ Expand)
6. ISM: Mfg: Prices Index (NSA, 50+ = Econ Expand)
7. ISM: Mfg: Backlog of Orders Index (NSA, 50+ = Econ Expand)
8. ISM: Mfg: New Export Orders Index(NSA, 50+ = Econ Expand)
9. ISM: Mfg: Imports Index (NSA, 50+ = Econ Expand)
10. ISM: Nonmfg: New Orders Index (NSA, 50+ = Econ Expand)
11. ISM: Nonmfg: Business Activity Index (NSA, 50+ = Econ Expand)
12. ISM: Nonmfg: Employment Index (NSA, 50+ = Econ Expand)
13. ISM: Nonmfg: Supplier Deliveries Index (NSA, 50+ = Econ Expand)
14. ISM: Nonmfg: Inventory Change Index (NSA, 50+ = Econ Expand)
15. ISM: Nonmfg: Prices Index (NSA, 50+ = Econ Expand)
16. ISM: Nonmfg: Orders Backlog Index (NSA, 50+ = Econ Expand)
17. ISM: Nonmfg: New Export Orders Index (NSA, 50+ = Econ Expand)
18. ISM: Nonmfg: Imports Index (NSA, 50+ = Econ Expand)

Data Appendix: UIG Variables (Continued)

Labor

1. Unemployment rate: 16–24 years (NSA, %)
2. Unemployment rate: 25–34 years (NSA, %)
3. Unemployment rate: 35–44 years (NSA, %)
4. Unemployment rate: 45–54 years (NSA, %)
5. Unemployment rate: 55 years and over (NSA, %)
6. Civilian employment-population ratio: 16–24 years (NSA, ratio)
7. Civilian employment-population ratio: 25–34 years (NSA, ratio)
8. Civilian employment-population ratio: 35–44 years (NSA, ratio)
9. Civilian employment-population ratio: 45–54 years (NSA, ratio)
10. Civilian employment-population ratio: 55 years and over (NSA, ratio)
11. Average weeks unemployed: 16–19 years (NSA)
12. Average weeks unemployed: 20–24 years (NSA)
13. Average weeks unemployed: 25–34 years (NSA)
14. Average weeks unemployed: 35–44 years (NSA)
15. Average weeks unemployed: 45–54 years (NSA)
16. Average weeks unemployed: 55–64 years (NSA)
17. Average weeks unemployed: 65 years and over (NSA)
18. Unemployment (NSA, thousands)
19. Number unemployed for less than 5 weeks (NSA, thousands)
20. Number unemployed for 5–14 weeks (NSA, thousands)
21. Number unemployed for 15–26 weeks (NSA, thousands)
22. Number unemployed for 15 weeks and over (NSA, thousands)
23. Unemployment insurance: Initial claims (Number, NSA)

Money

1. Money stock: M1 (NSA, billions $)
2. Money stock: M2 (NSA, billions $)
3. Adjusted monetary base (NSA, millions $)
4. Adjusted reserves of depository institutions (NSA, millions $)
5. Adjusted nonborrowed reserves of depository institutions (NSA, millions $)

Financials

1. Cash price: gold bullion, London commodity price, PM Fix (US$/troy oz)
2. Gold: London PM Fix (US$/troy oz)
3. Gold spot ($/oz) NSA
4. Spot commodity price—West Texas Intermediate crude oil, Cushing OK
5. Federal funds effective rate
6. 3-month Treasury bill rate coupon equivalent
7. 6-month Treasury bill rate coupon equivalent
8. 1-year Treasury bill yield at constant maturity (% p.a.)
9. 5-year Treasury note yield at constant maturity (% p.a.)
10. 7-year Treasury note yield at constant maturity (% p.a.)
11. 10-year Treasury note yield at constant maturity (% p.a.)
12. LIBOR Eurodollar 11 A.M. Fixing 1 month
13. LIBOR Eurodollar 11 A.M. Fixing 3 month
14. LIBOR Eurodollar 11 A.M. Fixing 6 month

Data Appendix: UIG Variables (Continued)

Financials (*continued*)

15. LIBOR Eurodollar 11 A.M. Fixing 9 month
16. LIBOR Eurodollar 11 A.M. Fixing 1 year
17. Spot price (euro/$) (Revised backwards)
18. Spot price (GBP/$)
19. Spot price (yen/$)
20. Spot Price (Swiss franc/$)
21. Board Narrow Nominal Effective Exchange Rate Index: United States (2000 = 100)
22. Board Broad Nominal Effective Exchange Rate: United States (2000 = 100)
23. Bank credit: all commercial banks (NSA, billions $)
24. Total revolving U.S. consumer credit outstanding
25. Total non-revolving U.S. consumer credit outstanding
26. Securities in bank credit: all commercial banks (NSA, billions $)
27. U.S. government securities in bank credit: all commercial banks (NSA, billions $)
28. Real estate loans in bank credit: all commercial banks (NSA, billions $)
29. Commercial and Industrial loans in bank credit: All commercial banks (NSA, billions $)
30. Consumer loans in bank credit: All commercial banks (NSA, billions $)
31. Moody's seasoned Aaa corporate bond yield (% p.a.)
32. Moody's seasoned Baa corporate bond yield (% p.a.)
33. Merrill Lynch High Yield Master II yield
34. New York Stock Exchange Composite Index
35. New York Stock Exchange total volume
36. Standard and Poor's 500 Price Earnings Ratio Index
37. Dow Jones Industrial Average
38. Dow Jones Wilshire 5000 Composite Index Full Cap
39. Light Sweet Crude Oil Futures Price: 1st exp contract nearby settlement (EOP, $/bbl)
40. Light Sweet Crude Oil Futures Price: 3 month contract settlement (EOP, $/bbl)
41. Light Sweet Crude Oil Futures Price: 6 month contract settlement (EOP, $/bbl)
42. No 2 Heating Oil Futures Price: 1st exp contract nearby settlement (EOP, $/gal)
43. No 2 Heating Oil Futures Price: 3 month contract settlement (EOP, $/gal)
44. No 2 Heating Oil Futures Price: 6 month contract settlement (EOP, $/gal)
45. Unleaded gasoline futures price: 1st exp contract nearby settlement (EOP, $/gal)
46. Unleaded Gasoline Futures Price: 3 month contract settlement (EOP, $/gal)
47. New York Harbor Conventional Gasoline Regular Spot Price FOB (EOP cents/gal)
48. Gas Oil Futures Price: 1st exp contract nearby settlement (EOP, $/metric ton)
49. Unleaded Premium Gasoline Price, NY gal (EOP, $/gal)
50. Unleaded Gas, Regular, Non-Oxygenated: NY (EOP, $/gal)
51. Natural Gas Price, Henry Hub, LA ($/mmbtu)
52. Dow Jones AIG Futures Price Index (Jan 2, 1991 = 100)
53. Dow Jones AIG Spot Price Index (Jan 7, 1991 = 100)
54. FIBER Industrial Materials Index: All Items (1990 = 100)
55. Goldman Sachs Commodity Nearby Index (EOP, Dec 31, 1969 = 100)
56. S&P 500 Futures Price: 1st exp contract nearby settlement (EOP, Index)
57. S&P 400 Midcap Futures Price: 1st exp contract nearby settlement (EOP, Index)

Editor's note:
This data appendix has been updated to reflect the removal of a duplicate price series (CPI-U: Other fresh vegetables). The article's conclusions remain the same.

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