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Nowcasting U.S. Headline and Core Inflation

Edward S. Knotek II* and Saeed Zaman

Forecasting future inflation and nowcasting contemporaneous inflation are difficult. We propose a new and parsimonious model for nowcasting headline and core inflation in the U.S. price index for personal consumption expenditures (PCE) and the consumer price index (CPI). The model relies on relatively few variables and is tested using real-time data. The model's nowcasting accuracy improves as information accumulates over the course of a month or quarter, and it easily outperforms a variety of statistical benchmarks. In head-to-head comparisons, the model's nowcasts of CPI inflation outperform those from the Blue Chip consensus, with especially significant outperformance as the quarter goes on. The model's nowcasts for CPI and PCE inflation also significantly outperform those from the Survey of Professional Forecasters, with similar nowcasting accuracy for core inflation measures. Across all four inflation measures, the model's nowcasting accuracy is generally comparable to that of the Federal Reserve's Greenbook.

Keywords: inflation, nowcasting, forecasting, real-time data, professional forecasters, Greenbook.

JEL classifications: E3, E37, C53.

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I. Introduction

Inflation developments are important to a wide swath of economic actors, and projections of future inflation influence the present behavior of financial market participants, consumers and firms, and central banks. Unfortunately, a long literature has documented that inflation is extremely difficult to forecast accurately. These difficulties extend to contemporaneous forecasting of the inflation rate in the current month or current quarter, or nowcasting. As a result, the best available benchmarks for current quarter inflation nowcasting come from surveys of professional forecasters who employ a range of objective and subjective information. We present a relatively parsimonious statistical model that in many cases outperforms these benchmarks in terms of inflation nowcasting accuracy.

Our model nowcasts U.S. headline and core consumer inflation as measured by the price index for personal consumption expenditures (PCE) and the consumer price index (CPI) using a judiciously chosen small number of data series at different frequencies. Within our model, high-frequency data affect monthly nowcasts, and monthly nowcasts aggregate to form quarterly nowcasts. To take advantage of the sequencing of incoming data over the course of a month or quarter, the model features time-varying weights on disaggregate and aggregate variables in forecasting the aggregate coupled with deterministic model switching that depends on the available information set; disaggregates are only used when sufficient data are available to make them informative. Beyond these time-varying weights, we follow the recent literature that has emphasized the benefits of simplicity in inflation forecasting—as notably embodied in Atkeson and Ohanian (2001), among others—and rely on univariate and simple multivariate techniques estimated over relatively short rolling windows. These short rolling windows, along with high-frequency energy price data, play a key role in improving nowcasting accuracy. We view the relative parsimony of the model as a virtue, given the difficulties in forecasting inflation and the risks of overfitting forecasting exercises to historical patterns that may not persist into the future.

Taking the model to the data requires real-time data. This is especially true for PCE inflation, which is heavily revised with new data sources and benchmark revisions. But monthly and quarterly CPI inflation readings using seasonally adjusted data are also subject to substantive revisions: we document that revisions to headline CPI inflation are as large as revisions to headline PCE in absolute terms, though core CPI inflation revisions are slightly smaller than those for core PCE. Unfortunately, the availability of real-time data limits tests of the model to a relatively short time span, with the earliest readings available for 1999.

Over this time period, we show that the model's nowcasts easily outperform a variety of statistical benchmarks, especially over the course of a month or quarter. We then compare the model's performance with arguably the best available benchmarks (see, e.g., Faust and Wright 2013): subjective nowcasts from professional forecasters, both aggregates from private forecasters—as captured by the Blue Chip Economic Indicators consensus and the median forecast from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters (SPF)—and the forecasts from the Federal Reserve Board of Governors staff in the Greenbook. Notably, the comparison period includes volatile times that might be expected to favor subjective forecasts, including large swings in world oil prices, a financial crisis, and a deep recession.

The model's nowcasts in many cases outperform those from professional forecasters in terms of accuracy. In real-time out-of-sample comparisons, the model's nowcasts of headline CPI inflation outperform those from the Blue Chip consensus, with especially significant outperformance as the quarter goes on. The model's nowcasts for headline CPI and PCE inflation also significantly outperform those from the SPF, with similar nowcasting accuracy for core inflation measures. Across all four inflation measures, the model's nowcasting accuracy is comparable to that of the Greenbook.

Improving upon inflation nowcasting is not only of interest for its own sake. Recent work (e.g., Faust and Wright 2013, and Del Negro and Schorfheide 2013) shows that inflation forecasts at longer horizons benefit by employing more accurate conditioning via nowcasts. Thus, the compact model we present in this paper has broad applications to both academic economists and professional forecasters.

Our paper marks a departure from much of the nowcasting literature. In contrast to research that extracts common factors from a large number of data series, we judiciously choose a small number of data series at different frequencies to inform our nowcasts and do not use factor models. While the seminal nowcasting working paper of Giannone et al. (2006) originally considered both GDP and inflation, much of the nowcasting literature has proceeded to focus on GDP, following in the footsteps of the published version of Giannone et al. (2008). In one exception, Modugno (2013) applies a factor model—with a larger number of factors compared with the limited set of variables we work with—to nowcast year-over-year U.S. CPI inflation from one month to the next. We focus instead on nowcasting quarterly inflation, as this is the usual jumping-off point for economists doing quarterly forecasting exercises. Additionally, Monteforte and Moretti (2013) employ factor models to nowcast Euro area inflation. Nevertheless, despite its different structure, our inflation nowcasting model shares the finding in the nowcasting literature that as time passes and additional information arrives, nowcasts of the current period become more accurate on average (e.g., Bańbura et al. 2013).

This paper proceeds as follows. Section II presents the model we use for inflation nowcasting. Section III discusses the real-time data available for use in our study. Section IV assesses the model's performance for monthly and quarterly nowcasting, and Section V compares the model's inflation nowcasting accuracy with other forecasters. Section VI analyzes the sensitivity of our model to alternative specifications, and Section VII concludes.

II. An Inflation Nowcasting Model

At its core, our model follows a parsimonious approach to nowcasting inflation. First, we rely on a judiciously chosen set of data series to inform our estimates. Second, we combine relatively simple univariate and multivariate regression techniques. Third, we impose time-varying weights on disaggregate and aggregate variables in nowcasting the aggregate. These time-varying weights deterministically depend on the information set available at a given point in time, thereby taking advantage of the nature of the information flow to improve nowcasting accuracy. Disaggregate information is used for nowcasting the aggregate, in the spirit of Hendry and Hubrich (2011)—but only when this information is available and informative, resulting in time-varying weights, as discussed in Lütkepohl (2010).

Quarterly inflation π_T is usually measured at seasonally adjusted annualized rates as[1]

(1) $$\pi_T = 100\left[\left(\frac{P_T}{P_{T-1}}\right)^4 - 1\right],$$

where P_T denotes the price level in quarter T, which is the average of the three monthly price levels in that quarter:

[1] Notably, this formula is consistent with the way that the U.S. Bureau of Economic Analysis and the Blue Chip Economic Indicators survey report quarterly inflation rates, and we follow their convention.

(2) $$P_T = \frac{1}{3}\left(P_{T,t=1} + P_{T,t=2} + P_{T,t=3}\right).$$

Our nowcasting approach maintains consistency with this method of computing inflation: we keep track of available monthly price levels and then nowcast or forecast the missing monthly readings of a given quarter to construct quarterly inflation rates.

Our model takes the form

(3) $$\mathbf{A}_{s(t)}\mathbf{Z}_t = \mathbf{B}_{s(t)} + \mathbf{C}_{s(t)}\mathbf{X}_t + \sum_{j=1}^{J}\mathbf{D}_{j,s(t)}\mathbf{Z}_{t-j} + \boldsymbol{\varepsilon}_{s(t)},$$

where $\mathbf{Z}_t$ is an $n \times 1$ vector of aggregates, $\mathbf{X}_t$ is an $m \times 1$ vector of disaggregates that are informative over $\mathbf{Z}_t$, and $\boldsymbol{\varepsilon}_{s(t)} \sim N(\mathbf{0}, \boldsymbol{\Sigma})$. The coefficient matrices **A**, **B**, **C**, and $\mathbf{D}_j$ are $n \times n$, $n \times 1$, $n \times m$, and $n \times n$, respectively, and are allowed to vary over time depending on the available information set, denoted $s(t)$; in particular, **C** and $\mathbf{D}_j$ measure the weights put on the disaggregates and lagged aggregates, respectively.

This general model structure allows us to incorporate information coming from diverse sources. First and foremost, given the strong correlation between energy price volatility and headline price index volatility, high-frequency information on energy prices is an especially useful disaggregate component to have in nowcasting headline inflation.[2] By contrast, when energy price volatility is tame, focusing on core inflation as another disaggregate can be helpful given that core prices have a much larger weighting in headline inflation. Second, the timing of data releases influences inflation nowcasting. In the United States, the Bureau of Labor Statistics (BLS) typically releases the consumer price index for a given month around the middle of the following month; e.g., the December CPI is released around mid-January. Thus, an open

[2] The results in Stock and Watson (2003) suggest some predictive content from oil prices for U.S. inflation, but these can differ from the gasoline prices we use. In addition, Stock and Watson (2003) consider inflation forecasts over longer time horizons. Modugno (2013) also discusses the importance of high-frequency energy prices in nowcasting inflation.

question is the availability of higher frequency data that would be available prior to the release of the CPI and would have predictive content. The Bureau of Economic Analysis (BEA) typically releases the other major measure of consumer prices, the price index for personal consumption expenditures, around the end of the following month; e.g., the December PCE price index is released around the end of January, after the CPI for December is released. While the contents, coverage, and construction of the two price indexes differ, the CPI may have predictive content over the PCE price index during the interim period before the latter is released.

Nowcasting Core Inflation

High-frequency disaggregate data that have predictive content over core inflation are limited.[3] There are similar limitations on the availability of real-time disaggregated core inflation series at the monthly frequency, such as core goods and core services series.[4] Thus, if $\mathbf{Z}_t = [\pi_t^{\text{Core CPI}}, \pi_t^{\text{Core PCE}}]'$ is the aggregate of interest—where $\pi_t^{\text{Core CPI}}$ and $\pi_t^{\text{Core PCE}}$ are the month-over-month core CPI inflation rate and core PCE inflation rate in month t, respectively—then $\mathbf{X}_t = \mathbf{0}$ in equation (3). In the absence of disaggregate information, we rely on the spirit of Atkeson and Ohanian (2001), who find that inflation over the previous four quarters is a difficult forecasting benchmark model to beat: assuming data through month $t-1$ are available, we forecast monthly core inflation $\hat{\mathbf{Z}}_t$ using recursive 12-month moving averages, by fixing

[3] We do not explore The Billion Prices Project at MIT as a potential disaggregate for this paper, but our framework would be able to incorporate it in the vector $\mathbf{X}_t$. While that data series may have predictive content for core inflation, it only began in 2008 and is based predominantly on goods prices from online retailers. By contrast, core price indexes typically place a large weight on services, and internet purchases (and thus internet prices) comprise a small portion of consumer spending on goods.

[4] Peach et al. (2013) find it useful for forecasting purposes to separate core CPI goods inflation and core CPI services inflation and model the series separately, but their forecasting horizon is four quarters. Limited real-time monthly core goods and services data prevent a similar disaggregation in this paper.

(4) $$\mathbf{A}_{s(t)} = \mathbf{I}_2,\ \mathbf{B}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = (1/12)\mathbf{I}_2,\ J = 12\,.$$

As mentioned above, we also need to account for the timing of information flows when making nowcasts. Given that CPI releases typically precede PCE releases by two weeks, we can take advantage of this timing mismatch in this state to enhance nowcasting accuracy: the additional monthly core CPI inflation rate $\pi_t^{\text{Core CPI}}$ for month t is informative in nowcasting as-yet-unreleased monthly core PCE inflation in that month. Conditional on this state, the time-varying weights in equation (3) become

(5) $$\mathbf{A}_{s(t)} = \begin{bmatrix} 0 & 0 \\ a_{21} & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} 0 \\ b_2 \end{bmatrix},\ \mathbf{D}_{j,s(t)} = \mathbf{0}\ \forall\, j\,,$$

in what is essentially a bridge equation from core CPI to core PCE inflation. The coefficients in (5) can be estimated over some window of length τ to forecast $\hat{\pi}_t^{\text{Core PCE}}$. Beyond month t, however, neither disaggregate nor further core CPI data are available, and future monthly core inflation forecasts $\hat{\mathbf{Z}}_{t+k} = [\hat{\pi}_{t+k}^{\text{Core CPI}}, \hat{\pi}_{t+k}^{\text{Core PCE}}]'$, k=1,2,…, revert to recursively using equation (4).

Nowcasting Headline Inflation

In addition to core prices, food prices and energy prices are other key disaggregates for headline inflation.

In theory, high-frequency futures and spot market prices for raw food items could have predictive content over monthly consumer food inflation π_t^{Food} and serve as useful disaggregate indicators $\mathbf{X}_t$ for food inflation and thus headline inflation. However, raw food prices are a small determinant of consumer food prices, especially as food goes through processing, and it is unclear which futures and spot market prices or price indexes would be most powerful in predicting food inflation. As such, we follow the principle of parsimony and forecast monthly food inflation as we did for monthly core inflation in the absence of disaggregate information: assuming we have data through month $t-1$, we forecast $\hat{\pi}_t^{\text{Food}} = (1/12)\sum_{j=1}^{12} \pi_{t-j}^{\text{Food}}$ and can then recursively forecast $\hat{\pi}_{t+k}^{\text{Food}}$, k=1,2,….[5]

Energy prices offer a contrast to food prices, because gasoline prices dominate fluctuations in consumer energy prices, and gasoline prices are heavily influenced by oil prices.[6] Gasoline prices and oil prices are available at a higher frequency than monthly and can be used to nowcast gasoline price inflation after seasonal adjustment, $\hat{\pi}_t^{\text{Gasoline}}$, which can also be used as one of the disaggregate variables in nowcasting headline inflation.

If gasoline price data are available within month t, let $P_t^{\text{Gasoline (NSA)}}$ be the average of those non-seasonally adjusted prices and use them to compute monthly gasoline inflation, $\pi_t^{\text{Gasoline (NSA)}}$. We nowcast $\hat{\pi}_t^{\text{Gasoline}}$ by using the recent past to seasonally adjust $\pi_t^{\text{Gasoline (NSA)}}$.[7]

If gasoline price data are not available within month t, we exploit the fact that gasoline prices over the next month tend to return toward the level predicted by the most recently

[5] There are separate series for food in the CPI and the PCE price index, and the appropriate disaggregate series therefore could differ as well. In the CPI, the food index encompasses both food at home and food away from home, and the core CPI by extension excludes food at home and food away from home. In the PCE price index, food and beverages purchased for off-premises consumption are classified as nondurable goods and are excluded from the core PCE price index. However, food services and accommodations—a category that includes purchased meals and beverages—are classified as services and are included in the core PCE price index. This change took effect with the BEA's 2009 comprehensive revisions. Given real-time data limitations discussed in more detail below, we consider a single CPI food series that is used as a disaggregate measure for both CPI and PCE inflation.

[6] Since 1997, the monthly correlation between energy inflation and gasoline inflation in the CPI is 0.97 and gasoline prices explain about 79% of the variance of energy prices, despite the fact that gasoline is only about half of the energy basket.

[7] We construct historical seasonal factors by subtracting monthly inflation in the seasonally adjusted CPI for gasoline $\pi_{t-j}^{\text{CPI, Gasoline}}$ from our measure of monthly gasoline price inflation based on high-frequency data $\pi_{t-j}^{\text{Gasoline (NSA)}}$ and then apply the average seasonal factor over the last three years to the current month's $\pi_t^{\text{Gasoline (NSA)}}$ to nowcast $\hat{\pi}_t^{\text{Gasoline}}$; i.e., letting $sf_t = (1/3)\sum_{j=1\text{ year}}^{3\text{ years}} (\pi_{t-j}^{\text{Gasoline (NSA)}} - \pi_{t-j}^{\text{CPI, Gasoline}})$, $\hat{\pi}_t^{\text{Gasoline}} = \pi_t^{\text{Gasoline (NSA)}} - sf_t$. Note that gasoline CPI readings only enter into seasonal adjustment; in what follows, $\hat{\pi}_t^{\text{Gasoline}}$ is our disaggregate of interest.

observed oil price.[8] We implement this relationship as follows. Letting P_{t-1}^{Oil} denote the average of available oil price readings within month $t-1$, assume that oil prices follow a random walk at a daily frequency to extend the monthly oil price series by one additional monthly observation to $\hat{P}_t^{\text{Oil}}$.[9] Because movements in oil prices pass through to gasoline prices, the length of the gasoline inflation series can be extended to month t following a two-stage regression. First, we posit a longer-run relationship between oil and gasoline prices:

$$P_t^{\text{Gasoline (NSA)}} = \alpha + \beta P_t^{\text{Oil}} + error_{1,t}; \tag{6}$$

we let $\tilde{P}_t^{\text{Gasoline (NSA)}}$ denote the predicted gasoline price based on equation (6). Second, we posit an error correction model that incorporates the lagged discrepancy between gasoline prices and their predicted value:

$$\Delta P_t^{\text{Gasoline (NSA)}} = b\Delta P_t^{\text{Oil}} + c\left(P_{t-1}^{\text{Gasoline (NSA)}} - \tilde{P}_{t-1}^{\text{Gasoline (NSA)}}\right) + error_{2,t}. \tag{7}$$

Equations (6) and (7) can be estimated over some window τ_L of available data to capture these longer-run relationships.[10] The estimated coefficients are combined with oil price forecasts $\hat{P}_t^{\text{Oil}}$ to produce forecasts of $\hat{P}_t^{\text{Gasoline (NSA)}}$ and $\hat{\pi}_t^{\text{Gasoline (NSA)}}$, which in turn can be seasonally adjusted as above to produce $\hat{\pi}_t^{\text{Gasoline}}$. Given the CPI and PCE price index release lags, we typically have one or two more months of gasoline inflation nowcasts or forecasts, $\hat{\pi}_{t+k}^{\text{Gasoline}}$, $k \geq 0$, than we have inflation data on the other series.

[8] When nowcasting quarterly inflation rates (and hence multiple monthly inflation nowcasts are required), if we already have some oil price data in month t then we also use this procedure to forecast $\hat{\pi}_{t+1}^{\text{Gasoline}}$.

[9] By omitting oil future prices, this assumption further limits the number of variables needed for the exercise without sacrificing forecasting accuracy; see Alquist and Kilian (2010) for evidence that a no-change (random walk) forecast can beat futures prices as a near-term predictor of oil prices.

[10] By imposing the constraint $b = \hat{\beta}$, equation (7) admits the gap form $\left(P_t^{\text{Gasoline (NSA)}} - \tilde{P}_t^{\text{Gasoline (NSA)}}\right) = a\left(P_{t-1}^{\text{Gasoline (NSA)}} - \tilde{P}_{t-1}^{\text{Gasoline (NSA)}}\right) + error_{2,t}$.

Finally, we can construct nowcasts and forecasts of headline inflation rates using the model in equation (3) and weights that vary deterministically with the available state of information. We let $\mathbf{Z}_t = [\pi_t^{\text{CPI}}, \pi_t^{\text{PCE}}]'$ be the aggregate of interest, where π_t^{CPI} and π_t^{PCE} are the month-over-month CPI inflation rate and PCE inflation rate in month *t*, respectively. The vector of relevant disaggregates for headline inflation is

(8) $$\mathbf{X}_t = \left[\pi_t^{\text{Core CPI}}, \pi_t^{\text{Core PCE}}, \pi_t^{\text{Food}}, \pi_t^{\text{Gasoline}}\right]'.$$

For states in which we have π_t^{CPI} but not π_t^{PCE}, the time-varying weights

(9) $$\mathbf{A}_{s(t)} = \begin{bmatrix} 0 & 0 \\ a_{21} & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} 0 \\ b_2 \end{bmatrix},\ \mathbf{C}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = \mathbf{0} \text{ for all } j$$

can be estimated over a window of data of length τ to forecast $\hat{\pi}_t^{\text{PCE}}$. For states in which we have $\hat{\pi}_t^{\text{Gasoline}}$ and thus the complete vector $\hat{\mathbf{X}}_t$, the time-varying weights

(10) $$\mathbf{A}_{s(t)} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix},\ \mathbf{C}_{s(t)} = \begin{bmatrix} c_{11} & 0 & c_{13} & c_{14} \\ 0 & c_{22} & c_{23} & c_{24} \end{bmatrix},\ \mathbf{D}_{j,s(t)} = \mathbf{0} \text{ for all } j$$

are estimated over a window of data of length τ and we can forecast $\hat{\mathbf{Z}}_t = [\hat{\pi}_t^{\text{CPI}}, \hat{\pi}_t^{\text{PCE}}]'$. And in states for which we lack $\hat{\pi}_t^{\text{Gasoline}}$ and thus do not have the complete disaggregate vector $\hat{\mathbf{X}}_t$, we use recursive 12-month moving averages by fixing

(11) $$\mathbf{A}_{s(t)} = \mathbf{I}_2,\ \mathbf{B}_{s(t)} = \mathbf{0},\ \mathbf{C}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = (1/12)\mathbf{I}_2,\ J = 12.$$

III. Data Sources and the Need for Real-Time Data

Implementing the model requires a number of monthly inflation series from the CPI and the PCE price index, along with higher frequency data on gasoline and oil prices. These series are readily available from the BLS, the BEA, and data collection sites, with time series extending decades into the past. However, both the CPI and the PCE price index are subject to data revisions—from new estimates of seasonal patterns in the case of the CPI to regular comprehensive revisions in the case of the PCE price index.[11] Thus, the currently available historical time series may differ substantially from what would have been available to forecasters at some point in the past. In that case, real-time data—which are generally more difficult to come by at the model's monthly frequency, especially beyond the headline price indexes, and have a relatively small number of vintages—may be requisite.

As a first step, we investigate the extent to which the most recent ("final") vintage data differ from real-time data using headline and core inflation in the CPI and PCE price index. Monthly real-time data come from the Federal Reserve Bank of St. Louis' Archival Federal Reserve Economic Data (ALFRED). The "final" vintage data are those available as of March 28, 2014, thus the last available monthly observations for both CPI and PCE are those for February 2014. By contrast, the initial inflation readings are the first available ones at the monthly or quarterly frequency. The comparisons begin in the middle of 2000, which correspond to the earliest availability of monthly real-time PCE inflation measures.[12]

Despite the fact that CPI measures are only subject to seasonal revisions and not the comprehensive revisions of the PCE measures, data revisions appear substantial when looking at either CPI or PCE inflation.[13] In terms of quarterly data, Figure 1(a) plots differences between

[11] The non-seasonally adjusted CPI is not subject to revisions and is final when published, making year-over-year inflation rates computed from that index invariant to the passage of time. For monthly and quarterly inflation readings, however, the NSA CPI data are of little use because of predictable seasonal fluctuations.

[12] We stop the comparison at the end of 2013 because the 2014 CPI readings have not been subject to revision yet. The CPI's seasonal factors for the previous five years are subject to revision once each year is complete: for example, after the December 2013 CPI was released, the BLS revised the seasonal factors for 2009 through 2013.

[13] Faust and Wright (2013) find that "revisions to CPI and core CPI inflation are trivial; but revisions to the other inflation measures are large" (p. 9). This may reflect the manner in which they compute revisions. Instead of using the final (most recent) vintage of data, they examine inflation as of the real-time rate recorded two quarters after the

initial and final vintage headline inflation, while Figure 1(b) plots the differences in core inflation. The characteristics of revisions do not appear markedly different for the headline inflation measures. Table 1 presents statistics on the differences for both quarterly inflation rates and monthly inflation rates. Across all measures, the average revision is essentially zero during this time. Core CPI revisions are smaller than core PCE revisions. However, headline CPI revisions are larger in absolute terms and more volatile than headline PCE revisions.

Because of the magnitudes of these revisions, using final vintage data and conducting pseudo real-time analysis would be problematic for our nowcasting exercise. This is especially true when comparing nowcasts to those from other forecasters, as different information sets would contaminate the comparisons. As such, the model only utilizes series for which real-time historical data are available.

The ALFRED database contains real-time vintages for the monthly PCE price index and core PCE price index starting with the June 2000 readings. Real-time monthly headline CPI coverage begins with June 1972, and monthly core CPI coverage begins with November 1996. The model also requires a measure of food inflation, and ALFRED has the real-time food CPI starting with November 1996.[14]

Higher frequency data are available for energy prices. Every Monday, the Energy Information Administration (EIA) publishes average retail gasoline prices for all grades based on a survey of approximately 800 retail gasoline outlets, with the series beginning in 1993. For oil

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quarter in question. Because the BLS revises the CPI only once per year, this methodology reduces the number of possible CPI revisions. In comparing data revisions across countries, Giannone et al. (2012) report that U.S. CPI is not revised, which is only the case for year-over-year inflation computed from the NSA CPI.

[14] Separate food indexes should be used because of coverage differences between the CPI and the PCE price index; e.g., nowcasting headline PCE inflation would benefit from having a measure of inflation in food and beverages purchased for off-premises consumption, because conceptually these data feed into headline PCE inflation. In turn, if an additional CPI release were available, then the CPI for food at home could be used as a proxy for that month's PCE food and beverages purchased for off-premises consumption. Unfortunately, neither the CPI for food at home nor the PCE price index for food and beverages purchased for off-premises consumption are available with long real-time histories, so the CPI for food is used as the single measure of food inflation.

prices, we use Brent crude spot prices from the Financial Times, which are available starting in 1987. Implicitly, we assume that both series are unrevised and the currently available readings correspond to their real-time equivalents.

The final needed series is the seasonally adjusted CPI for gasoline, which is used to seasonally adjust retail gasoline prices from EIA. ALFRED has real-time data on the CPI for gasoline starting in April 2011, but we were able to extend the real-time coverage of the gasoline CPI back to January 1999 based on data from Haver Analytics.

Thus, we can perform real-time out-of-sample nowcasting starting with February 1999 for the CPI and July 2000 for the PCE price index. In total, our nowcasting model uses only 8 data series—monthly CPI, core CPI, food CPI, gasoline CPI, PCE, and core PCE; weekly retail gasoline prices; and daily oil prices—though we have many data vintages to conduct the real-time analysis. Rather than incorporate components' weights explicitly, the model estimates the historical contributions of disaggregated series to the aggregate, including "other" effects that are subsumed in the constant terms and may vary over time in response to high-frequency fluctuations in key unmodeled inflation components. Coupling these considerations with the need to estimate few model parameters, we use short rolling windows (τ=24 monthly observations) to capture potential time-variation in the coefficients. In order to ensure that our two-stage regression captures the longer-term relationship between oil and gasoline prices, we estimate it using a longer rolling window (τ_L=60 monthly observations). We consider robustness to rolling window sizes in Section VI.

We focus primarily on root mean squared errors (RMSEs) as our measure of nowcasting accuracy, which give a sense of the absolute errors involved in nowcasting inflation. We use Diebold and Mariano (DM, 1995) tests for equal forecast accuracy between our model's nowcasts and those from other sources, with the adjustment for small samples of Harvey et al. (1997) as applied to nowcasting in Carriero et al. (2012); for simplicity, we report the *p*-values for rejection of the null hypothesis of equal predictive accuracy using MSE as the metric, based on two-sided *t*-statistic tests.

IV. Model Performance at Monthly and Quarterly Horizons

A common finding in the nowcasting literature is that as time passes and additional information arrives, nowcasts of the current period generally become more accurate on average (e.g., Bańbura et al. 2013). Our inflation nowcasting model shares this basic property, whether examining the ability of the model to nowcast monthly or quarterly inflation. While we focus attention on a limited number of cases in this section, the model can produce nowcasts at a daily frequency.

An open question when evaluating real-time nowcast and forecast accuracy is the choice of what constitutes the "actual" data realizations (or "truth"), because inflation data releases are subject to revisions ex post. Revisions can take a variety of forms, including new seasonal factors, the incorporation of more complete source data, and new methodologies. It is also difficult to know whether professional forecasters aim to forecast the initial data release, which may be seen as a measure of forecasting prowess, or whether their forecasts aim to capture subsequent revisions as well, which may or may not be mean zero in expectation. To incorporate more complete source data but not necessarily methodological revisions that may have been impossible to predict, we treat the BEA's third estimate of PCE prices as "truth," similar to Tulip

(2009) and a number of other researchers.[15] For compatibility, we use the same timing convention for both PCE and CPI inflation measures.[16]

Monthly Nowcasting Performance

Monthly inflation readings come out with a lag: for a given month under consideration, the BLS publishes the CPI around the middle of the following month, and the BEA publishes the PCE price index around the end of the following month. Over the course of a given month, the arrival of the previous month's inflation estimate contains relevant information and influences the current month's nowcast. Oil prices and retail gasoline prices arrive at the daily and weekly frequency, respectively, and the flow of these data sources also impacts the nowcast.

While precise release dates of these series vary from one month to the next, we illustrate the model's monthly nowcasting performance for CPI and PCE inflation at six representative dates listed in Table 2. Case 1 is the final day of the month preceding the target month being nowcasted, and case 5 is the last day of the target month. Case 6 is the middle of the month following the target month being nowcasted, when the CPI is released and only the PCE price index is left to be nowcasted (in this case, backcasted).

[15] The third estimate had previously been called the "first final" estimate; see Tulip (2009). At the very end of the sample, we treat the last available reading as the "truth." Note that Tulip (2009) uses quarterly data from the Federal Reserve Bank of Philadelphia's real-time database, so including the third estimate required using the real-time reading available two quarters later.

[16] In computing all statistics related to nowcast accuracy, we exclude nowcasts for PCE and core PCE inflation for the months of September 2001 and October 2001 in the monthly exercises, and 2001Q3 and 2001Q4 in the quarterly exercises, because these observations are extreme outliers in our short sample. The September 11, 2001, terrorist attacks triggered insurance payments that caused a very large, one-time drop in the price index for insurance in personal consumption expenditures. The decline in this component was so large that monthly core PCE inflation for September 2001 fell dramatically to its lowest recorded reading. The decline was subsequently unwound in October 2001, thereby boosting core PCE inflation as well. The CPI was not affected by these insurance payments.

We run the exercise using the real-time data that would have been available under each of our case assumptions, starting with nowcasts of September 2000 and concluding with nowcasts of December 2013 monthly inflation rates. Figure 2 plots the monthly RMSEs for the six cases. Table 3 displays the model's monthly RMSEs along with RMSEs from an alternative forecasting model using a random walk in monthly inflation, $\hat{\pi}_t = \pi_{t-1}$, where the availability of π_{t-1} varies depending on the case.

Turning first to core inflation, the monthly RMSEs generally change little over time, consistent with using recursive 12-month moving averages to forecast missing monthly data, but they do drift progressively lower. The arrival of the previous month's core CPI (case 3) produces a trivial reduction in RMSE for core CPI of 0.002 percentage point. This also generates a reduction in RMSE for core PCE—the previous month's core CPI inflation release is informative about the as-yet-unobserved rate of core PCE inflation for the preceding month, which in turn is used to nowcast the target month's core PCE inflation rate. We see an additional small reduction in RMSE upon the arrival of the previous month's core PCE (case 5) for the same reason. Once the core CPI for the target month being nowcasted is released (case 6), bridging that reading to core PCE reduces RMSE by 0.014 percentage point. In a sense, this is the first available data release for the month being nowcasted in terms of core inflation. DM tests reject the null of equal predictive accuracy in favor of our model over the alternative in which monthly inflation follows a random walk, strongly for core CPI inflation and moderately for core PCE inflation.

The pattern is different for headline inflation because of the availability of higher-frequency energy prices. Headline inflation RMSEs decline steadily and significantly over the course of time. By day 8 of the month (case 2), when at least one weekly reading on retail gasoline prices is available, RMSEs fall sharply from where they were immediately prior to the start of the month, and they drift lower as more gasoline price data accumulate. As with core PCE, the accuracy of nowcasting headline PCE inflation further benefits from the arrival of the monthly CPI readings, as these provide additional information on the previous month's PCE inflation (case 3). Immediately prior to the inflation releases, nowcasting RMSEs for headline CPI and PCE are about one-half their values compared with the day prior to the start of the month. DM tests of equal predictive accuracy decisively favor the model over the random walk alternatives for headline inflation.[17]

In related work, Modugno (2013) uses a factor model with a larger number of data series to nowcast year-over-year inflation in the non-seasonally adjusted headline CPI; e.g., nowcasts made during the month of July 2013 are for the CPI inflation rate between July 2012 and July 2013. Using data between January 2001 and December 2011, Modugno (2013) reports nowcast RMSEs of 0.23 percentage point on the day after the previous month's CPI is released, a 56.6 percent improvement over the 0.53 percentage point RMSEs from a random walk model in which year-over-year inflation is expected to remain unchanged from one month to the next. As an extension, we can adapt our model to follow Modugno (2013) in nowcasting year-over-year inflation.[18] Using the same sample period, our model produces RMSEs of 0.16 percentage point for year-over-year CPI inflation on the day after the previous month's CPI is released, for a further 30.4 percent gain in RMSE.

[17] Because of the very small number of data series in our model, we do not pursue a decomposition of nowcast revisions based on news shocks as in, e.g., Modugno (2013) or Bańbura et al. (2013), though such a decomposition could be presented in practice. On days in which neither the CPI nor the PCE price index is released (or revised), core inflation nowcasts are not revised and any revisions to headline inflation are due to energy (gasoline and oil) price movements. The deterministic model switching we implement would modestly complicate the interpretation of news shock; see Section VI for an alternative specification that omits model switching.

[18] To undo the seasonal adjustment in our month-over-month inflation rates to nowcast year-over-year inflation in the NSA CPI, we add the difference between the same month's NSA monthly inflation and SA monthly inflation for the previous 3 years to our nowcasted SA estimate.

Quarterly Nowcasting Performance

Because there are a larger number of data releases over the course of a quarter, we illustrate the model's quarterly nowcasting performance for CPI and PCE inflation at 14 representative dates, diagrammed in Figure 3. We again start with the first case on the day prior to the start of the quarter, and the thirteenth case is the final day of the quarter. The fourteenth case is when the CPI for the third month of the quarter is released, so at that point only the PCE measures are left to nowcast for the immediately concluded quarter.

We compare the model with a number of simple competing statistical forecasts that have been shown to have respectable inflation forecasting properties (see Faust and Wright 2013). All of the competing forecasts only use the real-time data that would have been available at a given point in time within quarter *T*; e.g., data release lags imply that the last available quarterly inflation reading at the very beginning of a quarter would actually be from two quarters earlier. Where necessary, the targeted quarter *T* is forecasted recursively. The competing models are:

1. A quarterly random walk, where today's expected inflation rate is equal to the last available quarterly reading, $E_T \pi_T = \pi_{T-1}$.
2. A four-quarter random walk, where today's expected annualized quarterly inflation rate equals the inflation rate over the last four available quarters, $E_T \pi_T = 100(P_{T-1} / P_{T-1-4} - 1)$, similar to Atkeson and Ohanian (2001).
3. An AR(1) model, $\pi_T = \alpha_0 + \alpha_1 \pi_{T-1} + e_T$, estimated using the entire real-time (expanding) sample.
4. An AR(1) model estimated using a real-time five-year rolling window.

5. An AR(4) model, $\pi_T = \alpha_0 + \sum_{i=1}^{4} \alpha_i \pi_{T-i} + e_T$, with coefficient estimates based on the entire expanding real-time sample.
6. An AR(1) model in inflation gaps, $x_T = \alpha_0 + \alpha_1 x_{T-1} + e_T$, with $x_T = \pi_T - \pi_T^{LR}$ (see Kozicki and Tinsley 2001, Cogley et al. 2010, Clark 2011, and Faust and Wright 2013). Long-run inflation expectations within a quarter, π_T^{LR}, are measured by the Blue Chip consensus inflation expectation five-to-ten years ahead that would have been available in that quarter in real time and are assumed to follow a random walk in the future. We estimate the inflation gap coefficients on real-time expanding samples with the first gap observation in the second quarter of 1984.[19]
7. The unobserved components model with stochastic volatility (UC-SV) from Stock and Watson (2007); see also Stock and Watson (2010). For each of our inflation series, we begin the UC-SV estimation in the first quarter of 1960 and use the real-time data that would have been available at the time.

Figure 4 shows the quarterly root mean square nowcast errors from the model and the competing statistical forecasts. The statistical forecasts show few changes in forecast accuracy across the cases as time goes by; these changes occur when new or revised CPI and PCE data are released.[20] Because the short sample makes the analysis sensitive to outliers, we exclude the fourth quarter of 2008 when computing the RMSEs.[21]

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[19] The Blue Chip consensus reports long-run forecasts of CPI inflation and GDP deflator inflation. As in Faust and Wright (2013), we assume that long-run forecasts of PCE inflation (and core PCE inflation) are equal to those for the GDP deflator, and that long-run forecasts for core CPI inflation are equal to those for headline CPI inflation. The long-run forecasts are typically released in March and October. Because March is late in the first quarter, we assume the March forecasts were only available in real-time as of the second quarter. Long-run CPI forecasts first appeared in March 1983, were not reported in October 1983, then reappeared on a continuous basis starting in March 1984.

[20] The largest revisions to the statistical forecasts' accuracy occur in case 3 for CPI and case 5 for PCE, when the third monthly reading for the previous quarter is released thus completing the quarter and the forecasts are conducted using an additional data point. In the case of the AR(1) model with a rolling window, these cases also

Figures 4(a) and 4(c) show that the model's nowcasts for headline inflation—whether measured by the CPI or the PCE price index—tend to broadly outperform the forecasts from a variety of statistical models. The outperformance is apparent even at the very beginning of the exercise (case 1, immediately prior to the start of the quarter). During the first month of the quarter, the arrival of high-frequency readings on gasoline and oil prices help to reduce the model's nowcast errors by about one-third. As a result, by the end of the first month of the quarter being nowcasted (case 5), the model's RMSEs are about one-half those from the best competing statistical models.[22] Nowcasting errors decrease as the quarter goes along and more information is accumulated, with a considerable improvement in CPI nowcasting accuracy once the first monthly CPI report of the quarter is released (case 7). Immediately prior to the release of the quarterly inflation rate, the typical error for headline CPI and PCE inflation is approximately ¼ percentage point at an annual rate.

The model uses a smaller number of variables for core inflation readings, and as a result changes in the core inflation nowcasts occur less frequently. Core CPI nowcasts depend only on the history of the series, so changes coincide with CPI releases (cases 3, 7, and 11). With each subsequent new CPI release, nowcasting accuracy improves, as shown in Figure 4(b). Meanwhile, core PCE inflation relies on a combination of past core PCE inflation and core CPI readings, if the latter have an additional month of data. Consequently, core PCE inflation

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entail dropping an earlier observation. Subsequent changes in forecast accuracy reflect revisions to previous months' releases.

[21] Quarterly CPI inflation went from about 6 percent at an annual rate in 2008Q3 to −9 percent in 2008Q4. The statistical models completely fail to predict this swing in inflation, with absolute errors in the vicinity of 15 percentage points. By contrast, this paper's nowcasting model quickly picks up the depths of the swing: by the middle of 2008Q4, the model was nowcasting headline CPI inflation of −7 percent, and the nowcast had fallen to −9 percent by the end of the quarter.

[22] For headline CPI, the DM test statistics reject the null of equal forecast accuracy at the 10 percent level in case 1, at the 5 percent level in case 2, and at the 1 percent level in case 3 and beyond. For headline PCE, the differences are statistically significant at the 10 percent level in case 2, at the 5 percent level in cases 3 and 4, and at the 1 percent level in case 5 and beyond.

nowcasting accuracy improves with each additional CPI or PCE release, as shown in Figure 4(d), with notable improvement occurring once the first monthly PCE reading of the quarter is released (case 9).[23] As with headline inflation, immediately prior to the release of the quarterly inflation rate the typical error for core inflation is 0.1 to 0.3 percentage point at an annual rate.

V. Nowcasting Horseraces with Professional Forecasters

Recent work by Faust and Wright (2009, 2013) shows that nowcasts of inflation by professional forecasters tend to outperform those from statistical models.[24] In fact, Faust and Wright (2013) go a step further and suggest that subjective forecasts may hold a distinct advantage because of their ability to "add expert judgment" to models (p. 20). Improving upon inflation nowcasting is not only of interest for its own sake: Faust and Wright (2013) and Del Negro and Schorfheide (2013) show that taking advantage of more accurate inflation nowcasts can also improve inflation forecasting accuracy at longer horizons.[25] Therefore, the true test of an inflation nowcasting model is through comparisons with other forecasters.

In this section, we compare the model's nowcasts with three benchmarks. The first two comparisons come from private forecasters that are available contemporaneously in real-time: the monthly Blue Chip Economic Indicators survey and the quarterly Survey of Professional Forecasters (SPF) compiled by the Federal Reserve Bank of Philadelphia. The final comparison

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[23] For core CPI, DM tests reject the null of equal forecast accuracy at the 5 percent level in cases 3 through 6 and at the 1 percent level in case 7 and beyond. For core PCE, the DM test statistics are statistically significant at the 1 percent level in case 7 and beyond.

[24] Ang et al. (2007) examine forecasts of four-quarter inflation—which are importantly influenced by the nowcast—and similarly find strong support for survey inflation forecasts over a number of model-based forecasts.

[25] These results are not quite as strong when using a mixed-frequency VAR in Schorfheide and Song (2013). Nevertheless, the best-fitting MF-VAR in Schorfheide and Song (2013) produces inflation nowcasts with RMSEs approximately double those in the Greenbook.

uses inflation nowcasts from the Federal Reserve Board's Greenbook, which are only released to the public with a 5-year delay.

Across all the comparisons, we ensure identical information sets: we match the dates when the surveys or Greenbook forecasts were conducted with the real-time data available for the model's nowcasts. We show both RMSEs for the model's nowcasts and nowcasts from other forecasters to give a sense of absolute errors, along with ratios of mean-squared errors expressed in terms of the professional forecasters' errors relative to those from the model.

The model's nowcasts in many cases outperform professional forecasters. Real-time data availability limits the comparisons to a relatively short time span, with the earliest comparisons in 1999. Nevertheless, the model's nowcasting accuracy for headline inflation tends to easily outperform the Blue Chip consensus and the SPF median, especially the former as the quarter goes on, and the model's headline inflation nowcasting accuracy is comparable to the accuracy of the Greenbook. Meanwhile, core inflation nowcasting accuracy from the model is not statistically distinguishable from nowcasts made by private forecasters or the Board staff.

Illustration: Nowcasting Headline CPI Inflation in 2013Q2

Before conducting formal nowcast comparisons, Figure 5 offers a real-time nowcasting illustration using headline CPI inflation in the second quarter of 2013. In the beginning of the quarter in April, the Blue Chip consensus nowcast was 1.8 percent at an annual rate. The average of the ten highest forecasts was above 2 percent, and the average of the ten lowest forecasts was below 1 percent. By mid-May, the Blue Chip consensus nowcast was 1.5 percent; around that same time, the median forecast from the Federal Reserve Bank of Philadelphia's

Survey of Professional Forecasters was 1.6 percent. The Blue Chip consensus nowcast fell to 0.5 percent by early June. In early July, after the end of the second quarter but before the quarterly inflation rate was available, the Blue Chip consensus had fallen further to 0 percent.

We also show the model's daily nowcasts of headline CPI inflation in the quarter. The model began the quarter nowcasting headline inflation of approximately 0 percent; it never thought that inflation would be close to 2 percent. After falling off in mid-April alongside falling oil prices, it began to move back toward 0 percent in the second half of the month. From late April through the end of the quarter, the model expected headline CPI inflation would be in the range of 0 to −0.5 percent at an annual rate.

When the BLS released the June CPI report on July 16, headline CPI inflation for 2013Q2 came in just below 0 percent. In terms of absolute errors, the model outperformed the SPF and the Blue Chip consensus in three of four cases during the quarter.

Comparison with the Blue Chip Economic Indicators Survey

The Blue Chip Economic Indicators survey of private professional forecasters provides forecasts of major U.S. economic indicators, including quarterly CPI inflation. Blue Chip forecasts start with the first quarter for which complete data are not yet available, which allows for nowcasting comparisons. Blue Chip consensus forecasts are averages across the forecasters in the survey.

The Blue Chip survey is typically released around the 10^{th} of each month. However, the survey is actually conducted over a two-day period before then, which is usually mentioned in the release. For the purposes of the comparisons, we fix the model's real-time dataset to match the survey period.[26]

Given the timing of the Blue Chip survey and the publication of CPI data, we compare Blue Chip nowcasting accuracy with the model at four different points in time for each quarter. For example, nowcasts of the first quarter are conducted at the January, February, March, and April Blue Chip survey dates; the April Blue Chip survey date is about one to two weeks before the BLS releases all the data needed to compute first quarter CPI inflation.[27] The nowcast evaluation spans the second quarter of 1999 through the fourth quarter of 2013.

As information over the quarter accumulates and we move from Month 1 (at the very beginning of the quarter) through Month 4 (the survey from the month immediately following the quarter, right before the quarterly CPI is available), nowcasting accuracy improves for both the Blue Chip consensus and the nowcasting model. Table 4 shows monotonic reductions in RMSEs from both nowcasts across the four cases. However, the model's nowcasts are more accurate on average than Blue Chip nowcasts at each point in time. The outperformance is modest in Month 1 and not statistically significant based on the DM test. By Month 2, the model's nowcasting outperformance is quantitatively larger based on RMSE and significant at the 5 percent level. In months 3 and 4, the model's nowcasts generate considerably smaller RMSEs, and DM tests decisively reject the null of equal forecast accuracy.

Figure 6 plots the competing nowcasts from the model and Blue Chip along with the actual quarterly CPI inflation rate for each case. As is evident in the figures, overall the model's nowcasts are quite effective in tracking the actual CPI inflation in all four cases, with the cases

[26] When the Blue Chip survey dates are not listed, we assume the survey date was the first Thursday of the month. If the first Thursday is the first day of the month, we assume the survey date was the first Tuesday of the month.
[27] Compared with the quarterly exercise in the previous section and in Figure 3, the Blue Chip survey dates roughly correspond to cases 2, 6, 10, and 13.

later in the quarter doing an excellent job in accurately nowcasting inflation given their expanded information sets. However, the outperformance of the model is not universal, as Blue Chip nowcasts were sometimes more accurate than those from the model.

The time period under consideration contains a wide range of events, including the mild 2001 recession, a long period of rising oil prices, the financial crisis and subsequent plunge in oil prices during a deep recession, and the moderate recovery since then. In the face of these events, judgmental nowcasts from professional forecasters may have had a large inherent advantage over model-based nowcasts, because the former could look outside the model and incorporate other information during rapidly changing circumstances. Given that a small number of variables—six—determine the model's CPI nowcasts, this outperformance vis-à-vis Blue Chip is particularly noteworthy.

Comparison with the Survey of Professional Forecasters

The SPF is published quarterly and is released around the middle of the second month of the quarter. The Federal Reserve Bank of Philadelphia publishes the historical dates on which the survey has been conducted; these are typically about one week prior to the release date, which means that SPF nowcasts of current quarter inflation are made before the first monthly CPI reading for the quarter is released.[28] As before, we match information sets that would have been available to the professional forecasters with the information set when making the model's nowcasts. The SPF has a long history of reporting CPI forecasts, and we perform CPI nowcast comparisons beginning in the second quarter of 1999. The SPF also began to report core CPI inflation, headline PCE inflation, and core PCE inflation in the first quarter of 2007, and we

[28] This roughly corresponds to Case 6 from the quarterly exercise in the previous section.

conduct comparisons with these three series starting at that point. In all cases, we end the comparisons in the fourth quarter of 2013. We use the SPF median nowcasts to eliminate outliers and as a check on the Blue Chip consensus exercise, which uses averages.

Table 5 reports results. The model's nowcasts for headline CPI and PCE inflation outperform the SPF nowcasts by 0.39 and 0.25 percentage point on average, respectively, and DM tests reject the null of equal forecast accuracy at the 5 percent level despite the small samples. Meanwhile, the nowcasting horseraces between the model and the professional forecasters for core inflation are a draw: RMSEs are basically equal, the ratio of MSEs is close to 1, and the DM tests cannot reject equality of forecast accuracy.

Figure 7 plots the competing nowcasts from the model and the SPF along with the data for each series. As with the Blue Chip comparison, the model does not uniformly beat the SPF nowcasts for headline inflation. Rather, the model's outperformance relates to its ability to capture the volatility in inflation; this is especially apparent in the shorter sample in Figure 7(c), where the SPF nowcasts tend to be too stable compared with realized inflation.

We view the results for headline and core inflation as perhaps somewhat surprising. The model's core inflation nowcasts reflect extreme parsimony. Nevertheless, the core inflation nowcasts coming from the SPF are quite similar to those from the model, whether looking at the statistics in Table 5 or the actual nowcasts in Figure 7(b) and Figure 7(d). This finding raises the possibility that professional forecasters are using a roughly similar method for nowcasting core inflation, suggesting that our model is essentially capturing professional forecasters' near-term inflation expectations; or, alternative, that a minor variant of Atkeson and Ohanian (2001) is still a key inflation forecasting benchmark. The model's outperformance for headline PCE inflation confirms the earlier findings from the Blue Chip exercise for a second inflation measure and offers further evidence that judgmental nowcasts may face limits during extraordinary times.

Comparisons with the Federal Reserve Board's Greenbook

We also compare our model's nowcasts with those made by the staff economists at the Federal Reserve Board of Governors in the so-called Greenbook. A commonly held view is that Greenbook nowcasts and short-term forecasts for inflation and real GDP are the gold standard. For example, Romer and Romer (2000) show that Greenbook forecasts prior to 1991 for inflation and output were superior to those of private forecasters. Subsequent studies by Sims (2002) and Faust and Wright (2007) documented that current-quarter Greenbook inflation forecasts are on average superior to a variety of forecasting approaches. Bernanke (2007) briefly describes the range of models, indicators, expertise, and extensive judgment used to inform near-term inflation forecasts by Board staff.

Greenbook forecasts are produced in the week prior to each of the Federal Open Market Committee's (FOMC) regularly scheduled meetings. As with the other comparisons, we fix the model's real-time information set based on the Greenbook release date. The eight regular FOMC meetings each year have historically been spaced somewhat irregularly, but there are essentially two meetings per quarter, one in the first half of the quarter and one in the second half. For the sake of our nowcast evaluation exercise, we classify Greenbook nowcasts based on whether they were made in the first or second half of the quarter as H1 and H2, respectively; the different information sets available either early or late in the quarter make these effectively two different exercises.[29] All four inflation measures in the paper are available in Greenbook, and our nowcasting exercise starts in the second quarter of 1999 for headline and core CPI inflation and the third quarter of 2000 for headline and core PCE inflation. The exercise ends in the fourth quarter of 2008, which is the last publicly available Greenbook.

Table 6 presents the comparisons. Nowcast errors across all inflation metrics decline dramatically from the first half of the quarter to the second half as additional information accumulates. With the exception of core CPI inflation in the first half of the quarter, the model's nowcast RMSEs are slightly larger than Greenbook's. However, the differences in forecasting accuracy are not large quantitatively nor are they statistically significant.

Figure 8 plots the inflation nowcasts made in the first and second half of each quarter. By the second half of the quarter, the model's nowcasts are typically very close to the Greenbook across all inflation measures and across the entire sample. We interpret the graphical results and statistical analyses as suggesting that our model's nowcasting accuracy is basically comparable to the combined judgment, modeling expertise, and resources devoted to inflation nowcasting in Greenbook for the time period under consideration.

VI. Assessing Nowcasting Accuracy and Sensitivity

To illustrate key drivers of the model's nowcasting accuracy, we consider a large number of robustness checks to the model and its assumptions—some small (e.g., changing rolling window lengths used in estimation) and others large (e.g., dropping disaggregates)—and show their effect on quarterly RMSEs in Table 7. The model's nowcasting performance is highly robust to minor

[29] Because of the irregular timing of Greenbook, we place the cutoff for H1 as on or before the 20th day of the middle month of the quarter.

variations, but nowcasting performance deteriorates when gasoline inflation is excluded from the set of relevant disaggregates and when very long windows are used to estimate parameters.

We first consider robustness to the length of estimation windows. To capture potential time-variation—in relationships between CPI and PCE inflation measures, between disaggregate and aggregate measures, as well as in unmodeled inflation components that are subsumed in constant terms—we use rolling windows of τ=24 monthly observations to estimate equations (5), (9), and (10). Nowcasts benefit from short windows: modestly expanding or contracting the window length has a trivial impact on nowcasting accuracy, but accuracy deteriorates as the window grows; e.g., with τ=120 months (line 3), quarterly RMSEs for headline inflation increase 16 to 47 percent on average, and Greenbook headline inflation nowcast outperformance is statistically significant. We use a longer window (τ_L=60 monthly observations) to estimate the two-stage regression giving the long-run relationship between oil and gasoline prices. Nowcasts are trivially affected as this window expands or contracts modestly, but using very long windows or expanding windows on all observations (line 6) causes headline inflation nowcasting RMSEs to deteriorate by 15 to 16 percent early in the quarter. We also consider variations in J, which governs the number of terms used in forecasting via recursive moving averages. Increasing J from the baseline of 12 months causes a bifurcation: RMSEs for core CPI inflation tend to rise, while RMSEs for core PCE inflation are slightly lower.

We also consider changes to the set of disaggregates. Dropping π_t^{Food} as a disaggregate in nowcasting headline inflation has a minor impact on RMSE (line 10). By contrast, excluding energy price measures has a large effect. If daily oil prices are excluded from the model (line 11), RMSEs increase 9 to 11 percent in the first half of the quarter, suggesting that current oil prices are a good predictor of future gasoline prices and, by extension, their influence on inflation.[30] Dropping π_t^{Gasoline} as a disaggregate (line 12) causes a large deterioration in nowcast accuracy, as RMSEs for headline inflation increase 40 to 104 percent and subjective nowcasts easily outperform the model.

Finally, we consider changes to the model's structure. Assuming that the last observed oil prices are useful predictors of gasoline prices far into the future—compared with our baseline assumption that they are only useful for one month—allows for computing arbitrary $\hat{\pi}_{t+k}^{\text{Gasoline}}$ for $k \geq 0$ and eliminates equation (11); doing so causes a minor increase in RMSE (line 13). A second potential change to the model structure is to drop the bridging of core CPI to core PCE and headline CPI to headline PCE during the interim when the previous month's CPI is available but before PCE readings are released, thereby eliminating equations (5) and (9). Nowcasts of CPI and core CPI are unaffected, but RMSEs for PCE and core PCE rise modestly (line 14), suggesting that such a bridging approach assists with nowcasting.[31] The third structural change combines the previous two by extending the use of oil prices and dropping the bridging equations, so that equation (4) is the single model for core inflation nowcasts and equation (10) is the single model for headline inflation nowcasts (line 15). RMSEs are modestly higher than the baseline, consistent with gains for the types of deterministic model switching we propose.[32]

[30] In this case, the two-stage regression relating oil and gasoline prices is omitted and $\hat{\pi}_t^{\text{Gasoline}}$ only enters the model if there are weekly data on gasoline prices within month t.
[31] Providing further evidence that this bridging approach is helpful, Greenbook's core PCE nowcasts in the first half of the quarter are now more accurate than those from this alternative model at the 10 percent level.
[32] While not reported, we separately consider alternatives in which we replace the default for making forecasts of monthly variables as a moving average with J terms (and hence coefficients $1/J$) with an AR(p) model estimated over a rolling window of length τ=24 months. Employing an AR(1) model produces results that are generally similar to the baseline. But nowcasting performance tends to worsen as p becomes larger.

VII. Conclusion

This paper develops a new model for nowcasting U.S. headline and core inflation. The model is relatively parsimonious, relying on a small number of data series and simple univariate and multivariate regressions alongside time-varying weights on disaggregate and aggregate variables that take advantage of the state of the information flow over the course of a month or quarter. These features contrast with other nowcasting approaches that often utilize large datasets to extract common factors. Similar to these other approaches, however, we show that nowcasts of both monthly and quarterly inflation improve as time passes and additional information arrives.

In head-to-head comparisons using real-time data, the model's nowcasts often outperform the best available alternatives: nowcasts from professional forecasters. In particular, the model's nowcasts of headline CPI and PCE inflation generally are more accurate than those from either the Blue Chip consensus or the Survey of Professional Forecasters, and they rival the nowcasting accuracy of the Greenbook. Nowcasts of core CPI and PCE inflation, which are made using very simple univariate techniques in the spirit of Atkeson and Ohanian (2001), are essentially on a par with those from the SPF and the Greenbook.

Given the well-documented difficulties in forecasting inflation, the model developed in this paper has the potential to reduce both nowcasting errors and longer-horizon forecasting errors for academic economists and professional forecasters. An open question for further investigation is whether a similar model with time-varying weights on disaggregate and aggregate components could be useful for nowcasting other series, such as GDP. The approach that we follow has also stressed the principle of parsimony in nowcasting inflation, relying on very few data series. Bringing additional data to bear—for example, by relying on disaggregate information from core goods and core services in nowcasting core inflation, or drilling down to a fine level of disaggregation to assist in bridging from core CPI inflation to core PCE inflation prior to the release of the latter—has the potential to improve nowcasting accuracy even further as real-time data availability increases.

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Table 1: Differences between Initial and Final Vintage Inflation Rates

	CPI		Core CPI		PCE		Core PCE	
	Difference	Absolute difference	Difference	Absolute difference	Difference	Absolute difference	Difference	Absolute difference
Monthly Data								
Average	0.00	0.09	0.00	0.03	-0.01	0.07	-0.01	0.05
Standard deviation	0.11	0.07	0.04	0.03	0.09	0.06	0.07	0.05
Quarterly Data								
Average	-0.02	0.54	0.00	0.18	-0.04	0.41	-0.11	0.32
Standard deviation	0.66	0.37	0.24	0.15	0.53	0.35	0.42	0.28

Notes: Monthly inflation rates are non-annualized percent changes, while quarterly inflation rates are annualized percent changes. Difference measures are initial readings less final readings. Final vintage inflation data are those available as of March 28, 2014. The last available monthly observations for both CPI and PCE inflation are those for February 2014. The comparisons begin in June 2000 (2000Q2) and end in December 2013 (2013Q4).

Table 2: Monthly Nowcasting Performance Cases

	Date	Example: Nowcasting target month is January
Case 1	Last day of the previous month	Last day of December, assume have CPI and PCE through November.
Case 2	Day 8 of the target month	Have at least one weekly retail gasoline reading, have CPI and PCE through November.
Case 3	Day 15 of the target month	Have at least two weekly retail gasoline readings, assume receive CPI for December, have PCE through November.
Case 4	Day 22 of the target month	Have at least three weekly retail gasoline readings, CPI through December, PCE through November.
Case 5	Last day of the target month	Have all weekly retail gasoline readings, CPI through December, assume receive PCE for December.
Case 6	Day 15 of the following month	Have all weekly retail gasoline readings, assume receive CPI for January, have PCE through December.

Table 3: Monthly Root Mean Square Nowcast Errors

	Case					
	1	2	3	4	5	6
Model						
CPI	0.301	0.196	0.161	0.142	0.136	--
Core CPI	0.091	0.091	0.089	0.089	0.089	--
PCE	0.210	0.141	0.119	0.106	0.100	0.073
Core PCE	0.081	0.081	0.079	0.079	0.078	0.057
Alternative model: Random walk in monthly inflation						
CPI	0.493***	0.493***	0.374***	0.374***	0.374***	--
Core CPI	0.113***	0.113***	0.109***	0.109***	0.109***	--
PCE	0.354***	0.354***	0.354***	0.354***	0.270***	0.270***
Core PCE	0.166*	0.166*	0.166*	0.166*	0.125	0.125*

Notes: Case 1 is right before the start of the month. Case 2 is day 8 of the month. Case 3 is day 15 of the month, at which point the previous month's CPI is assumed to be available. Case 4 is day 22 of the month. Case 5 is the last day of the month, at which point the previous month's PCE price index is assumed to be available. Case 6 is day 15 of the following month, at which point the CPI for the month being nowcasted is assumed to be available. The alternative model assumes monthly inflation follows a random walk, $\hat{\pi}_t = \pi_{t-1}$. * and *** denote rejection of the null hypothesis of equal predictive accuracy of the model and the alternative at the 10% and 1% level, respectively. Inflation rates are month-over-month percent changes in seasonally adjusted data, so numbers are expressed in non-annualized percentage points. PCE and core PCE statistics exclude September and October 2001. The exercise uses real-time data from September 2000 through December 2013.

Table 4: Blue Chip CPI Nowcasting Comparisons

	Blue Chip survey conducted in:			
	Month 1	Month 2	Month 3	Month 4
Model RMSE	1.83	1.07	0.48	0.27
Blue Chip RMSE	1.90	1.45	0.84	0.41
Ratio, average Blue Chip MSE to model MSE	1.07	1.85	2.99	2.21
Diebold-Mariano *p*-values for test of equal MSE	0.559	0.043	0.001	0.003

Notes: Comparisons are matched based on Blue Chip survey dates; e.g., when nowcasting the first quarter, month 1 would refer to the Blue Chip survey date in January, month 2 would be February's date, and month 3 would be March's date. The Blue Chip survey in month 4 (e.g., April) is conducted prior to the availability of CPI inflation data for the previous quarter and is the final nowcast. Quarterly inflation rates are seasonally adjusted annualized percent changes, so numbers are expressed in annualized percentage points. The exercise uses real-time data from 1999Q2 through 2013Q4.

Table 5: Survey of Professional Forecasters Nowcasting Comparisons

	CPI	Core CPI	PCE	Core PCE
Model RMSE	1.00	0.58	0.85	0.55
Survey of Professional Forecasters RMSE	1.39	0.58	1.11	0.52
Ratio, average SPF MSE to model MSE	1.95	1.01	1.68	0.91
Diebold-Mariano *p*-values for test of equal MSE	0.019	0.944	0.027	0.611

Notes: Real-time comparisons are based on the SPF survey dates. SPF expectations for each quarter are the median value. Quarterly inflation rates are seasonally adjusted annualized percent changes, so numbers are expressed in annualized percentage points. The CPI exercise uses real-time data from 1999Q2 through 2013Q4. The core CPI, PCE, and core PCE exercises use real-time data from 2007Q1 (the first available SPF estimates) through 2013Q4.

Table 6: Greenbook Nowcasting Comparisons

	CPI		Core CPI		PCE		Core PCE	
	H1	H2	H1	H2	H1	H2	H1	H2
Model RMSE	1.34	0.36	0.51	0.27	1.05	0.41	0.62	0.42
Greenbook RMSE	1.11	0.32	0.53	0.27	0.87	0.35	0.56	0.40
Ratio, average Greenbook MSE to model MSE	0.68	0.80	1.05	0.93	0.69	0.74	0.82	0.87
Diebold-Mariano *p*-values for test of equal MSE	0.225	0.474	0.775	0.694	0.215	0.207	0.180	0.446

Notes: Real-time comparisons are based on the Greenbook forecast dates. Forecasts made on or before the 20th day of the middle month of the quarter are in H1, and forecasts made after the 20th day of the middle month of the quarter are in H2. Quarterly inflation rates are seasonally adjusted annualized percent changes, so numbers are expressed in annualized percentage points. The CPI and core CPI exercises use real-time data from 1999Q2 through 2008Q4. The PCE and core PCE exercises use real-time data from 2000Q3 through 2008Q4. PCE and core PCE statistics exclude 2001Q3 and 2001Q4.

Table 7: Relative Quarterly RMSEs from Alternative Assumptions

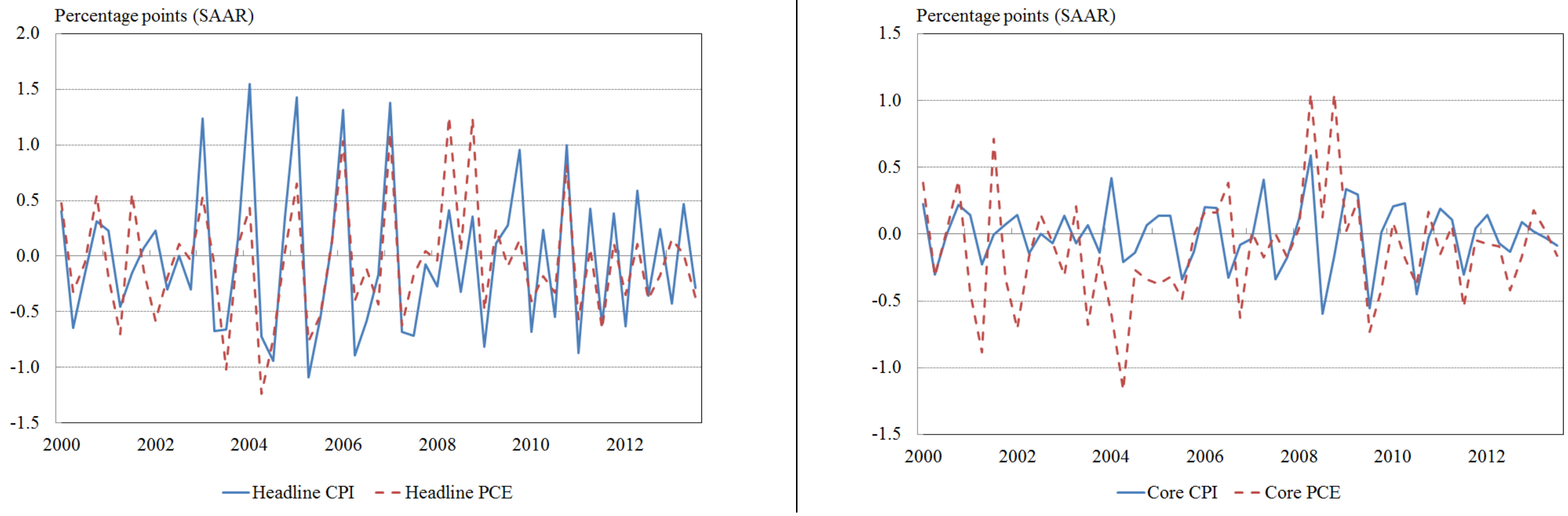
Alternative model assumptions	CPI H1	CPI H2	Core CPI H1	Core CPI H2	PCE H1	PCE H2	Core PCE H1	Core PCE H2
1. τ=12 months	1.02	1.01	1	1	1.06	1.04	1.01	1.03
2. τ=36 months	1.00	0.99	1	1	1.01	0.98	1.00	1.00
3. τ=120 months	1.27	1.47	1	1	1.20	1.16	1.00	1.01
4. τ_L=48 months	1.00	1.00	1	1	1.00	1.00	1	1
5. τ_L=72 months	0.99	1.00	1	1	0.99	1.00	1	1
6. τ_L=entire expanding real-time sample	1.16	1.05	1	1	1.15	1.03	1	1
7. J=6 months	1.04	1.00	1.10	1.01	1.06	1.04	1.14	1.06
8. J=24 months	1.01	1.04	1.04	1.05	0.98	1.00	0.95	0.98
9. J=36 months	1.01	1.05	1.06	1.07	0.99	1.01	0.96	0.99
10. Drop π_t^{Food}	1.01	1.03	1	1	1.01	1.01	1	1
11. Drop oil prices as a predictor of $\pi_t^{Gasoline}$	1.11	1.03	1	1	1.09	1.01	1	1
12. Drop $\pi_t^{Gasoline}$	1.65	2.04	1	1	1.48	1.40	1	1
13. Extend oil prices as a predictor of $\pi_t^{Gasoline}$	1.02	1	1	1	1.02	1	1	1
14. Drop bridging equations	1	1	1	1	1.03	1.05	1.05	1.09
15. Single models, no model switching	1.02	1	1	1	1.06	1.05	1.05	1.09

Notes: Relative quarterly RMSEs are defined as the alternative model RMSE divided by the baseline model RMSE, so numbers greater than 1 imply higher RMSEs from the alternative model assumption(s). H1 (H2) reports the average relative quarterly RMSEs for the first (second) half of the quarter, which includes cases 1 through 7 (cases 8 through 14) as defined in Figure 3. The baseline model features τ=24 months, τ_L=60 months, and J=12 months.

Figure 1: Differences between Initial and Final Vintage Inflation, Quarterly Data

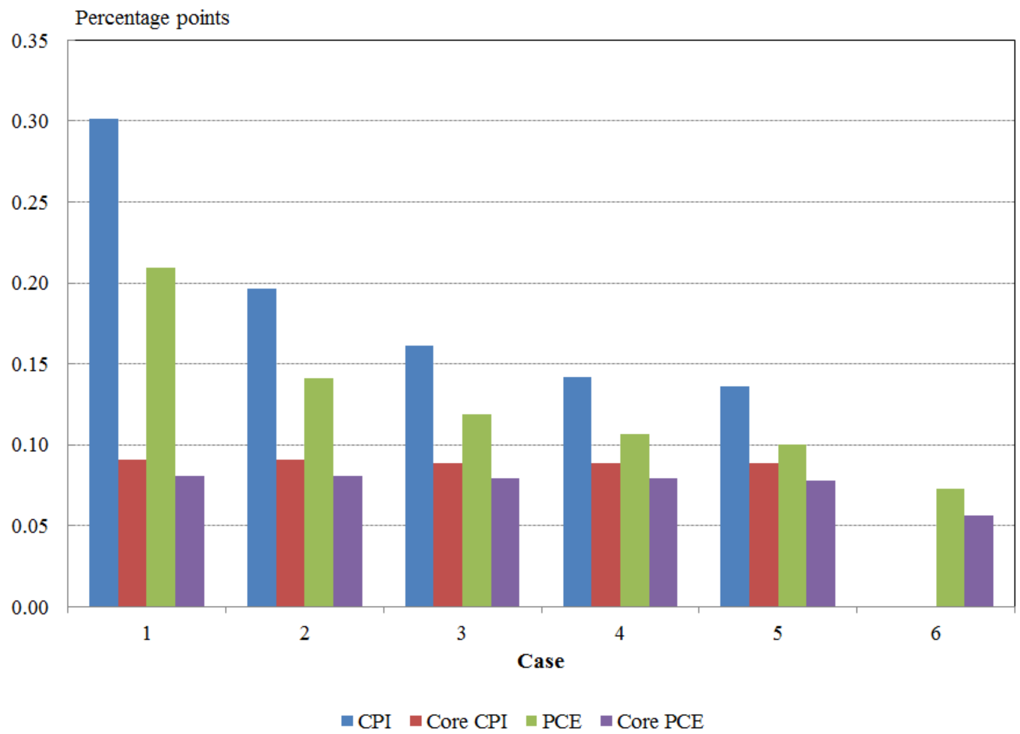
(a) Headline Inflation

(b) Core Inflation



Notes: Measures are initial readings less final readings. Final vintage inflation data are those available as of March 28, 2014. The last available observations for both CPI and PCE inflation are those for February 2014. The initial quarterly inflation reading is computed as soon as all of the monthly price index readings for the quarter are available.

Figure 2: Monthly Root Mean Square Nowcast Errors



Notes: Case 1 is right before the start of the month. Case 2 is day 8 of the month. Case 3 is day 15 of the month, at which point the previous month's CPI is assumed to be available. Case 4 is day 22 of the month. Case 5 is the last day of the month, at which point the previous month's PCE price index is assumed to be available. Case 6 is day 15 of the following month, at which point the CPI for the month being forecasted is assumed to be available. Inflation rates are month-over-month percent changes, so numbers are expressed in non-annualized percentage points. PCE and core PCE statistics exclude September and October 2001. The exercise uses real-time data from September 2000 through December 2013.

Figure 3: Data Flow Timing

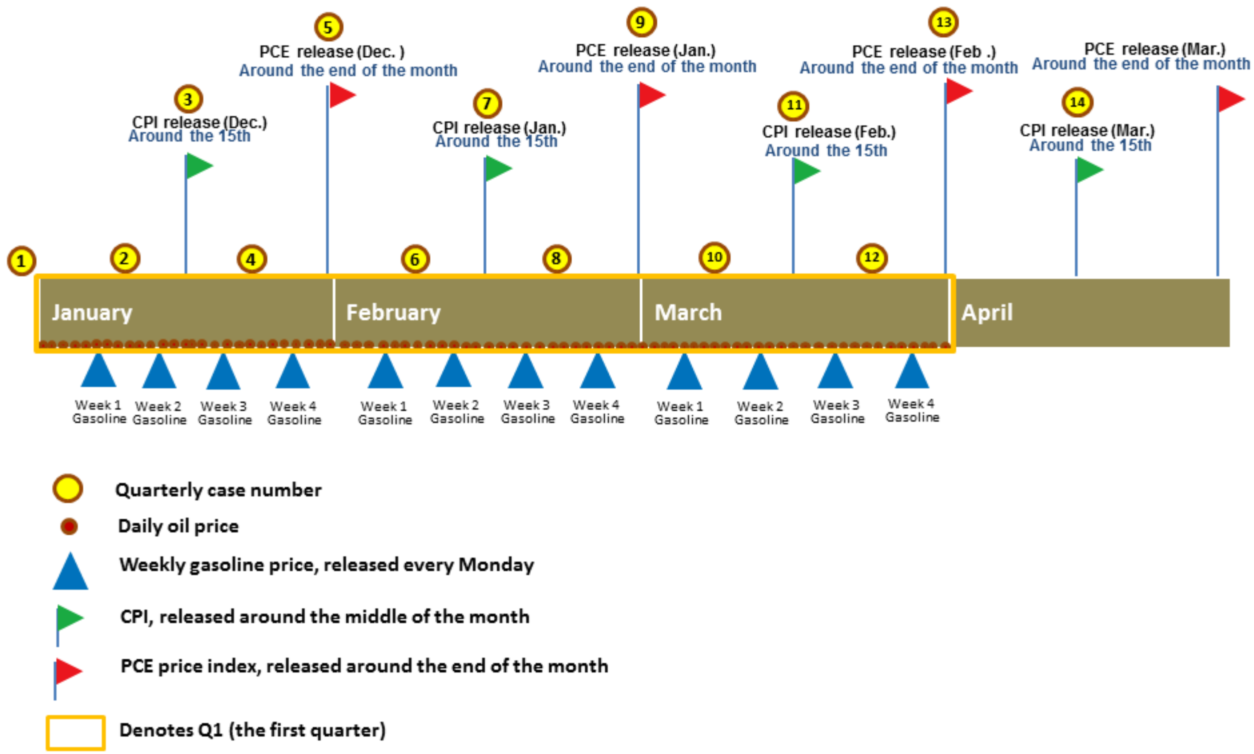
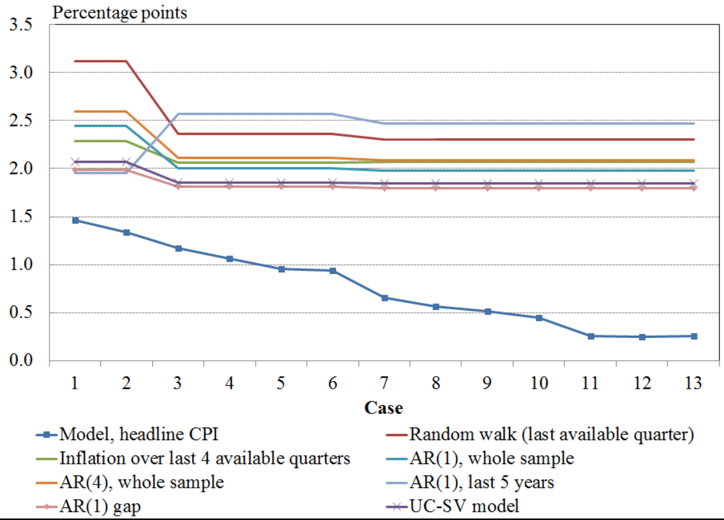
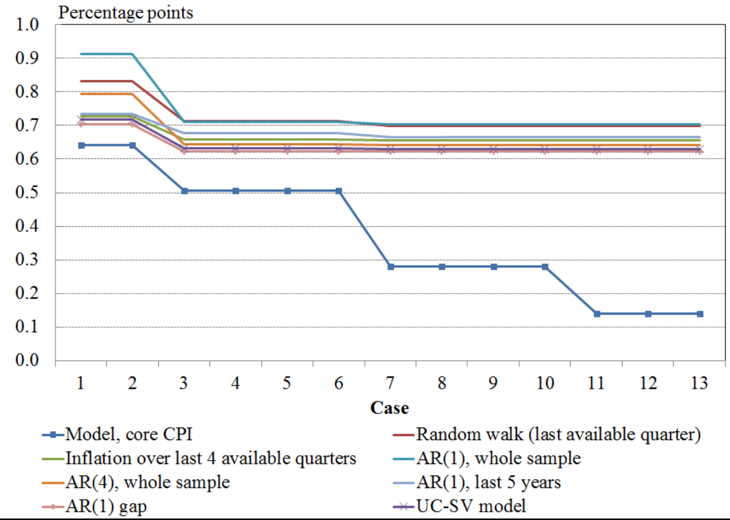


Figure 4: Quarterly Root Mean Square Nowcast Errors

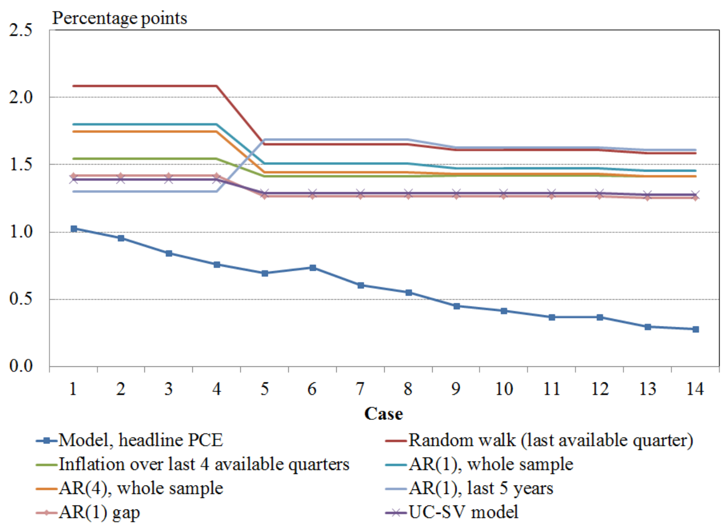
(a) CPI



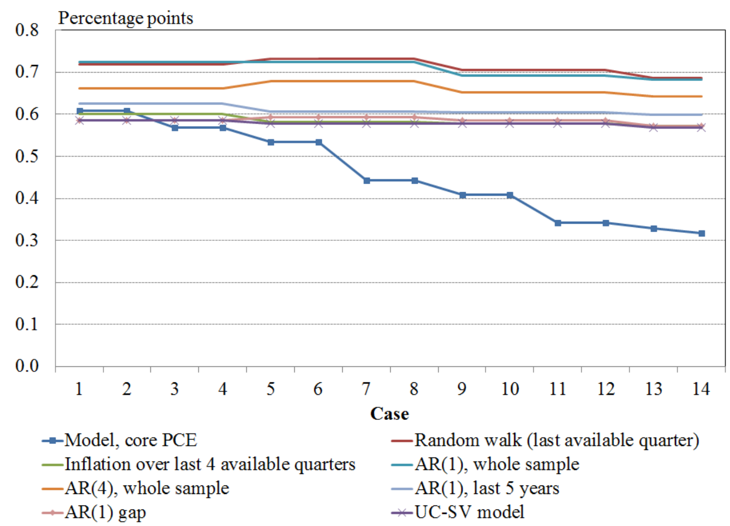
(b) Core CPI



(c) PCE

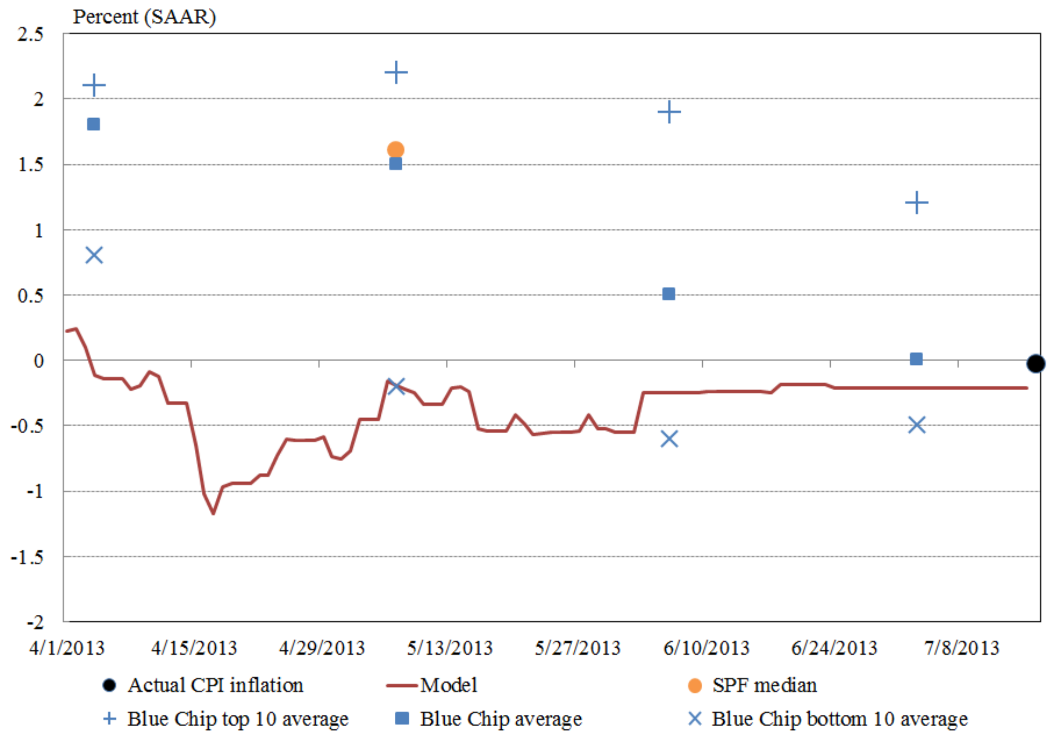


(d) Core PCE



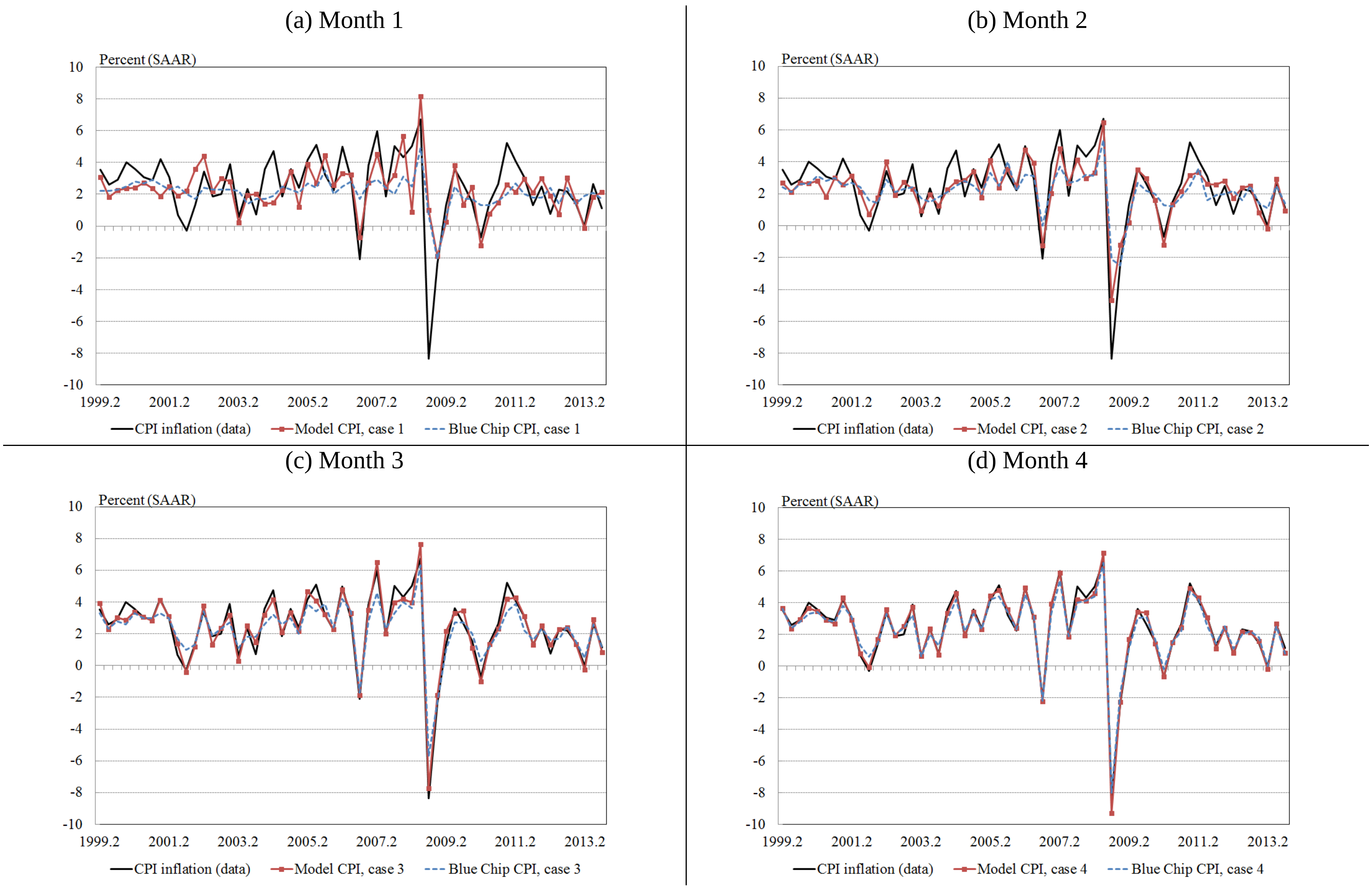
Notes to Figure 4: See Figure 3 for the timing of the 14 cases. Quarterly inflation rates are seasonally adjusted annualized rates, so numbers are expressed in annualized percentage points. All RMSE statistics exclude 2008Q4. PCE and core PCE statistics also exclude 2001Q3 and 2001Q4. The exercise uses real-time data from 2000Q4 through 2013Q4.

Figure 5: Real-Time Nowcasts of Headline CPI Inflation in 2013Q2



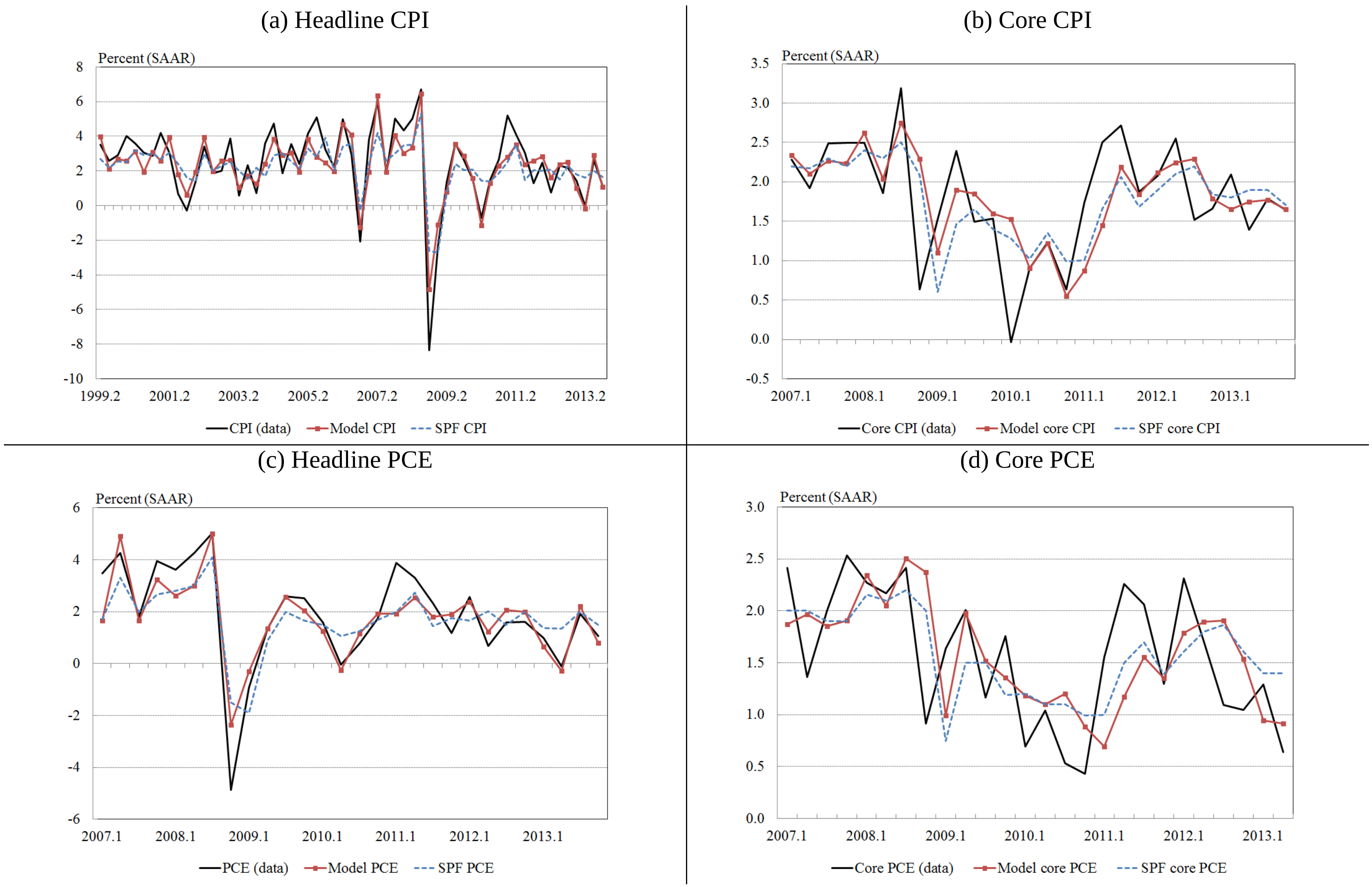
Notes: The Blue Chip marks show 2013Q2 nowcasts of headline inflation from the Blue Chip Economic Indicators surveys that were released in April, May, June, and July of 2013. The SPF median is from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters for 2013Q2. The red line shows daily nowcasts of headline CPI inflation from the model. The solid black circle is the actual annualized CPI inflation rate in 2013Q2.

Figure 6: Model and Blue Chip CPI Inflation Nowcasts



Notes to Figure 6: Cases are defined by the Blue Chip survey dates. Month 1 is the Blue Chip survey date for the first month of the quarter being nowcasted (e.g., January when nowcasting Q1). Month 2 is the Blue Chip survey date for the second month of the quarter being nowcasted. Month 3 is the Blue Chip survey date for the third month of the quarter being nowcasted. Month 4 is the Blue Chip survey date for the first month of the quarter following the quarter being nowcasted (e.g., April when nowcasting Q1). Quarterly inflation rates are seasonally adjusted annualized percent changes. The exercise uses real-time data from 1999Q2 through 2013Q4.

Figure 7: Model and SPF Inflation Nowcasts



Notes to Figure 7: Real-time comparisons are based on the SPF survey dates. SPF expectations for each quarter are the median value. Quarterly inflation rates are seasonally adjusted annualized percent changes. The CPI exercise uses real-time data from 1999Q2 through 2013Q4. The core CPI, PCE, and core PCE exercises use real-time data from 2007Q1 (the first available SPF estimates) through 2013Q4.

Figure 8: Model and Greenbook Inflation Nowcasts

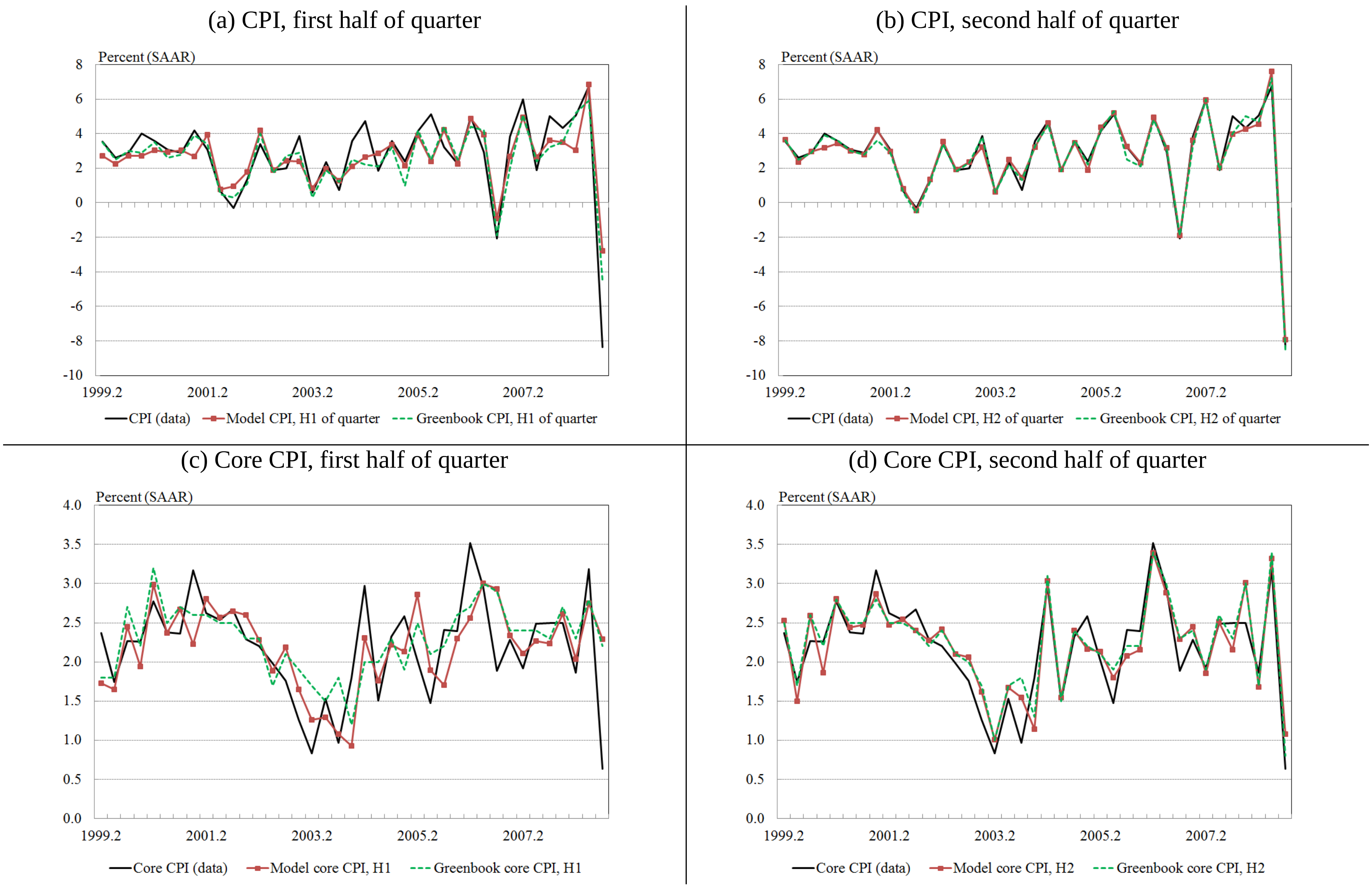
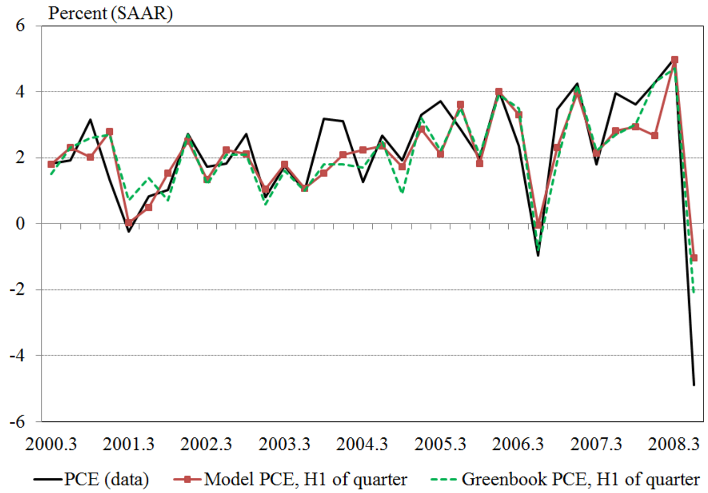
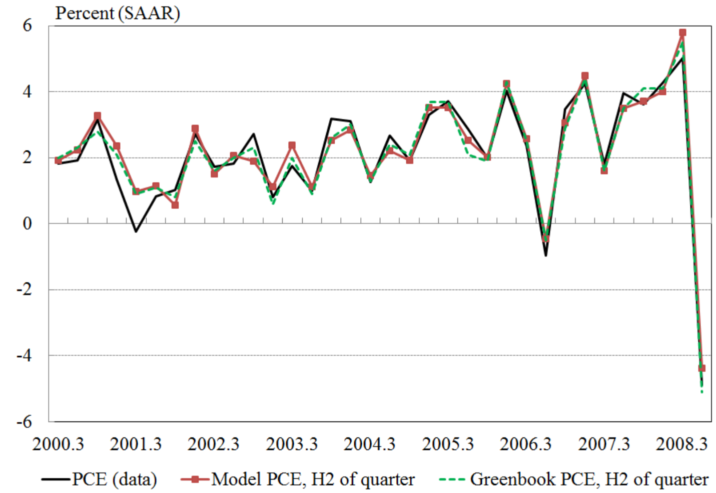


Figure 8 (continued): Model and Greenbook Inflation Nowcasts

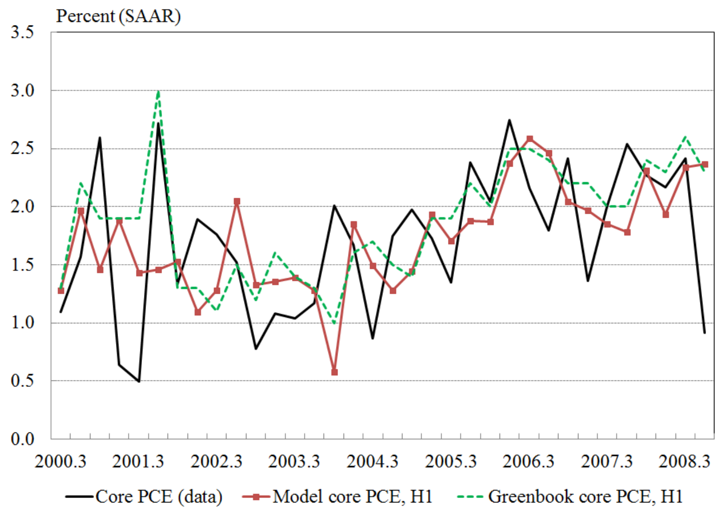
(e) PCE, first half of quarter



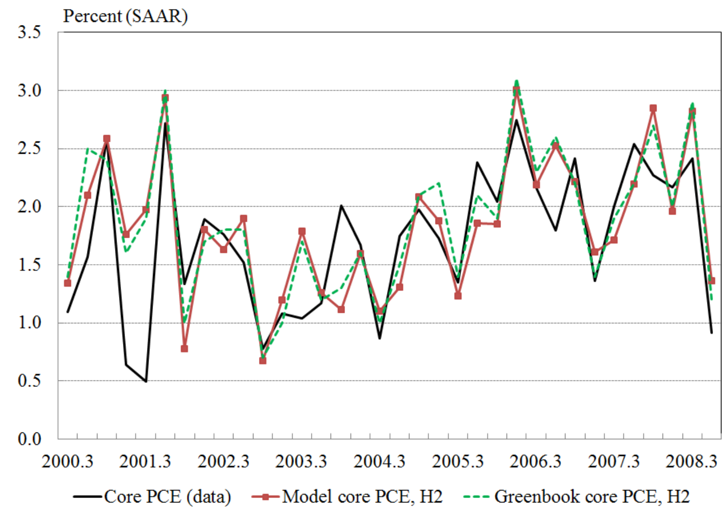
(f) PCE, second half of quarter



(g) Core PCE, first half of quarter



(h) Core PCE, second half of quarter



Notes to Figure 8: Real-time comparisons are based on Greenbook forecast dates. Forecasts made on or before the 20th day of the middle month of the quarter are in H1, and forecasts made after the 20th day of the middle month of the quarter are in H2. Quarterly inflation rates are seasonally adjusted annualized percent changes, so numbers are expressed in annualized percentage points. The CPI and core CPI exercises use real-time data from 1999Q2 through 2008Q4. The PCE and core PCE exercises use real-time data from 2000Q3 through 2008Q4.