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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. consumer price index (CPI) and price index for personal consumption expenditures (PCE) that relies on relatively few variables. The model's nowcasting accuracy improves as information accumulates over a month or quarter, outperforming statistical benchmarks. In real-time comparisons, the model's headline inflation nowcasts substantially outperform those from the Blue Chip consensus and the Survey of Professional Forecasters. Across all four inflation measures, the model's nowcasting accuracy is comparable to the Federal Reserve Board's Greenbook.

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

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, firms, and central banks. Unfortunately, a long literature has documented that inflation is difficult to forecast accurately. These difficulties extend to contemporaneous forecasting, or nowcasting, of the inflation rate in the current month or quarter. 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 inflation nowcasting accuracy.

Our model nowcasts U.S. headline and core consumer inflation as measured by the consumer price index (CPI) and the price index for personal consumption expenditures (PCE) 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 quarterly nowcasts. To take advantage of the sequencing of incoming data over 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 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 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 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, but monthly and quarterly CPI inflation readings using seasonally adjusted data are also subject to substantive revisions: 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, we show that the model's nowcasts outperform a variety of statistical benchmarks, including other models that are used for nowcasting. 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 those from the Federal Reserve Board of Governors staff in the Greenbook. Despite the fact that 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 real-time out-of-sample comparisons, the model's nowcasts of headline CPI inflation outperform those from the Blue Chip consensus, with especially large outperformance as the quarter goes on. The model's nowcasts for headline CPI and PCE inflation also 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. Faust and Wright (2013) and Del Negro and Schorfheide (2013) show that inflation forecasts at longer horizons benefit by employing more accurate conditioning via nowcasts. In another context, Branch (2014) utilizes inflation nowcasts to estimate Taylor rules. Thus, this paper's compact model has broad applications to 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 the published version of Giannone et al. (2008). In one exception, Modugno (2013) applies a dynamic factor model—with a larger number of monthly, weekly, and daily data series compared with the limited set of variables we work with—to nowcast year-over-year U.S. CPI inflation. Monteforte and Moretti (2013) use a combination of a dynamic factor model to construct a measure of core inflation and mixed frequency data in the context of a mixed data sampling (MIDAS) regression model based on Ghysels et al. (2004, 2005) to nowcast year-over-year euro area inflation. We present results for nowcasting U.S. monthly, year-over-year, and quarterly inflation, especially because the latter is the usual jumping-off point for economists doing quarterly forecasting exercises. 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 inflation nowcasting model. Section III discusses the real-time data. Section IV assesses the model's performance for monthly, year-over-year, 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 conclues.

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 simple univariate and multivariate regression techniques. Third, we impose time-varying weights on disaggregate and aggregate variables in nowcasting the aggregate which deterministically depend on the available information set at a point in time, thereby taking advantage 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).

Our modeling approach focuses on nowcasting or near-term forecasting monthly inflation rates. In the United States, monthly inflation is usually reported in non-annualized terms as $\pi_t = 100(P_t / P_{t-1} - 1)$, where P_t is the price level in month t. Based on monthly price levels, we follow the usual conventions of statistical agencies to compute year-over-year inflation rates as $\pi_{t,t-12} = 100(P_t / P_{t-12} - 1)$ or quarterly inflation rates π_T measured at seasonally adjusted annualized rates as $\pi_T = 100[(P_T / P_{T-1})^4 - 1]$, where P_T denotes the price level in quarter T, which is the average of the three monthly price levels in that quarter: $P_T = (1/3)(P_{T,t=1} + P_{T,t=2} + P_{T,t=3})$.[1] We maintain 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 nowcasting model takes the general form

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

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 model structure allows us to incorporate information from diverse sources. First, given energy prices' role in headline price index volatility, high-frequency energy prices are a useful disaggregate to have in nowcasting headline inflation.[2] By contrast, when energy price volatility is tame, having core inflation as a disaggregate can be helpful given its large weight in headline inflation. Second, the timing of data releases affects nowcasts. The U.S. Bureau of Labor Statistics (BLS) releases the CPI around the middle of the following month; e.g., the May CPI is released around mid-June. An open question is the availability of higher frequency data with predictive content that would be available prior to the release of the CPI. The Bureau of Economic Analysis (BEA) typically releases the other major measure of consumer prices, the

[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.

[2] Modugno (2013) also discusses the importance of high-frequency energy prices in nowcasting inflation. Stock and Watson (2003) suggest 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.

PCE price index, around the end of the following month; e.g., the May PCE price index is released around the end of June, after the CPI for May is released. While the contents and coverage of the two price indexes differ, the CPI has 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 monthly core CPI inflation rate and core PCE inflation rate in month *t*, respectively—then $\mathbf{X}_t = \mathbf{0}$ in equation (1).

Because CPI releases precede PCE releases, we take advantage of this timing mismatch. If we have monthly core CPI inflation through month *t*, $\pi_t^{\text{Core CPI}}$, but we only have core PCE inflation through month *t*−1, $\pi_{t-1}^{\text{Core PCE}}$, we bridge core CPI to core PCE to nowcast the as-yet-unreleased monthly core PCE inflation rate in month *t*. Conditional on being in this state, the time-varying weights in equation (1) become

[3] We do not explore The Billion Prices Project at MIT as a potential disaggregate, but our framework could incorporate it in $\mathbf{X}_t$. 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 place a large weight on services, and internet purchases and prices comprise a small share of spending on goods. The exchange rate could affect core inflation through its effects on import prices, a point we return to below in the context of a competing model.

[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. Unfortunately, sources such as ALFRED do not have a long time series of real-time monthly core goods inflation and monthly core services inflation, which prevents a similar disaggregation in this paper.

$$\mathbf{A}_{s(t)} = \begin{bmatrix} 0 & 0 \\ a_{21} & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} 0 \\ b_2 \end{bmatrix},\ \mathbf{D}_{j,s(t)} = \mathbf{0}\ \forall\, j\,. \tag{2}$$

The coefficients in equation (2) are estimated over a window of length τ to nowcast $\hat{\pi}_t^{\text{Core PCE}}$.

In all other cases, we rely on the spirit of Atkeson and Ohanian (2001), who find that inflation over the previous four quarters is a difficult forecasting benchmark to beat, and we forecast monthly core inflation $\hat{\mathbf{Z}}_t$ using recursive 12-month moving averages, by fixing

$$\mathbf{A}_{s(t)} = \mathbf{I}_2,\ \mathbf{B}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = (1/12)\mathbf{I}_2,\ J = 12\,. \tag{3}$$

Thus, if we have data through time t−1 on $\mathbf{Z}_{t-1} = [\pi_{t-1}^{\text{Core CPI}}, \pi_{t-1}^{\text{Core PCE}}]'$, we use equation (3) to recursively generate forecasts for time t, t+1, …. If we have data through time t on $\pi_t^{\text{Core CPI}}$ but only through time t−1 on $\pi_{t-1}^{\text{Core PCE}}$, we first use equation (2) to nowcast $\hat{\pi}_t^{\text{Core PCE}}$ and then use equation (3) to recursively generate forecasts for time t+1, t+2, …, where $\hat{\pi}_t^{\text{Core PCE}}$ is included as an observation in taking the moving average. In this way, the arrival of a new core CPI reading affects its own forecast; because PCE release dates lag behind CPI, the arrival of core PCE inflation has no impact on core CPI. The arrival of a new core CPI reading also affects the nowcast for core PCE inflation for that month, and this nowcast in turn affects the core PCE inflation forecast for future months through the recursion. Once core PCE inflation data come out for that month, the forecast for core PCE inflation is potentially affected again, and the process resets.

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, denoted 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 retail food prices, and it is unclear which futures and spot market prices or price indexes would be most powerful in predicting food inflation. While we explore this possibility in the robustness section below, our baseline model follows the principle of parsimony and we 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 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. 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, denoted $\hat{\pi}_t^{\text{Gasoline}}$, which can also be used as one of the disaggregate variables in nowcasting headline inflation.

Underlying our nowcasts of gasoline price inflation is the fact that gasoline prices tend to revert toward the level predicted by the most recently observed oil price. We implement this

[5] The CPI and PCE price index treat food differently, suggesting there could potentially be two separate disaggregate series. In the CPI, the food index encompasses both food at home and food away from home, and the core CPI excludes all food. 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. Food services and accommodations 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.

relationship as follows. Suppose that gasoline price data are not available within month t but are at least partially available in month $t-1$. Let $P_{t-1}^{\text{Gasoline (NSA)}}$ be the average of those available non-seasonally adjusted prices, and let $\pi_{t-1}^{\text{Gasoline (NSA)}}$ denote the associated gasoline price inflation in month $t-1$. 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 $\hat{P}_t^{\text{Oil}}$.[6] Because movements in oil prices pass through to gasoline prices, the length of the gasoline inflation series can be extended to month t to match the length of the oil price series following a two-stage regression. First, we posit a longer-run relationship between oil and gasoline prices:

$$P_t^{\text{Gasoline (NSA)}} = \alpha + \beta P_t^{\text{Oil}} + error_{1,t}; \tag{4}$$

we let $\tilde{P}_t^{\text{Gasoline (NSA)}}$ denote the predicted gasoline price based on equation (4). Second, we posit an error correction model that incorporates the lagged discrepancy between gasoline prices and their predicted value:

$$\Delta P_t^{\text{Gasoline (NSA)}} = b\Delta P_t^{\text{Oil}} + c\left(P_{t-1}^{\text{Gasoline (NSA)}} - \tilde{P}_{t-1}^{\text{Gasoline (NSA)}}\right) + error_{2,t}. \tag{5}$$

Equations (4) and (5) can be estimated over a window τ_L of available data to capture these longer-run relationships.[7] The estimated coefficients are combined with the oil price forecast $\hat{P}_t^{\text{Oil}}$ to produce forecasts $\hat{P}_t^{\text{Gasoline (NSA)}}$ and $\hat{\pi}_t^{\text{Gasoline (NSA)}}$. Finally, because there is a seasonal pattern in gasoline prices that is removed from monthly (seasonally adjusted) inflation figures,

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[6] Omitting oil futures prices further limits the number of variables needed 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. When nowcasting quarterly inflation rates and hence multiple monthly inflation nowcasts are required, we still extend oil prices by one monthly observation; if we have P_t^{Oil}, we use the last daily oil price observation to produce $\hat{P}_{t+1}^{\text{Oil}}$.

[7] Imposing $b = \hat{\beta}$, equation (5) takes the form $\left(P_t^{\text{Gasoline (NSA)}} - \tilde{P}_t^{\text{Gasoline (NSA)}}\right) = a\left(P_{t-1}^{\text{Gasoline (NSA)}} - \tilde{P}_{t-1}^{\text{Gasoline (NSA)}}\right) + error_{2,t}$.

we seasonally adjust the gasoline price inflation forecast for month *t*, $\hat{\pi}_t^{\text{Gasoline (NSA)}}$, to produce $\hat{\pi}_t^{\text{Gasoline}}$.[8] Given 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.

If gasoline price data are available for all or part of month *t*, then we let $P_t^{\text{Gasoline (NSA)}}$ be the average of the available non-seasonally adjusted prices, we use them to compute monthly gasoline inflation, $\pi_t^{\text{Gasoline (NSA)}}$, and we seasonally adjust the data to nowcast $\hat{\pi}_t^{\text{Gasoline}}$, which is a nowcast because we may not have all of the gasoline price data for the month and because we do not have the exact seasonal factor. As additional high-frequency gasoline price data arrive during month *t*, the values of $\pi_t^{\text{Gasoline (NSA)}}$ and $\hat{\pi}_t^{\text{Gasoline}}$ are updated.

Finally, we can construct nowcasts and forecasts of headline inflation rates using the model in equation (1) and weights that vary deterministically with the available state of information. 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 monthly CPI inflation rate and PCE inflation rate in month *t*, respectively. The vector of relevant disaggregates for headline inflation is

$$\mathbf{X}_t = \left[\pi_t^{\text{Core CPI}}, \pi_t^{\text{Core PCE}}, \pi_t^{\text{Food}}, \pi_t^{\text{Gasoline}}\right]'. \tag{6}$$

For states in which we have π_t^{CPI} but not π_t^{PCE}, we again bridge the headline CPI reading to headline PCE; the time-varying weights

[8] We seasonally adjust our measure of gasoline price inflation as follows. Let $\pi_{t,Y}^{\text{CPI, Gasoline}}$ denote monthly inflation in the seasonally adjusted CPI for gasoline in month *t* of year *Y*, and let $\pi_{t,Y}^{\text{Gasoline (NSA)}}$ denote our measure of monthly gasoline price inflation based on high-frequency data in month *t* of year *Y*. We construct a seasonal factor for month *t* in year *Y* by taking the average difference between the non-seasonally adjusted and seasonally adjusted measures for the same month in the preceding three years: $sf_{t,Y} = (1/3)\sum_{j=1\text{ year}}^{3\text{ years}} (\pi_{t,Y-j}^{\text{Gasoline (NSA)}} - \pi_{t,Y-j}^{\text{CPI, Gasoline}})$. Because it is based on information from previous years, we can apply this seasonal factor to derive a seasonally adjusted nowcast of gasoline price inflation in month *t* of year *Y*: $\hat{\pi}_{t,Y}^{\text{Gasoline}} = \hat{\pi}_{t,Y}^{\text{Gasoline (NSA)}} - sf_{t,Y}$. Note that gasoline CPI readings only enter into seasonal adjustment; $\hat{\pi}_t^{\text{Gasoline}}$, where we suppress the year subscript, is our disaggregate of interest.

$$\mathbf{A}_{s(t)} = \begin{bmatrix} 0 & 0 \\ a_{21} & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} 0 \\ b_2 \end{bmatrix},\ \mathbf{C}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = \mathbf{0} \text{ for all } j \tag{7}$$

can be estimated over a window of data of length τ to produce a nowcast $\hat{\pi}_t^{\text{PCE}}$. For states in which we have $\hat{\pi}_t^{\text{Gasoline}}$, we pair that nowcast with the forecasts of $\hat{\pi}_t^{\text{Food}}$, $\hat{\pi}_t^{\text{Core CPI}}$, and $\hat{\pi}_t^{\text{Core PCE}}$ generated earlier to complete the vector $\hat{\mathbf{X}}_t$. The time-varying weights

$$\mathbf{A}_{s(t)} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\ \mathbf{B}_{s(t)} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix},\ \mathbf{C}_{s(t)} = \begin{bmatrix} c_{11} & 0 & c_{13} & c_{14} \\ 0 & c_{22} & c_{23} & c_{24} \end{bmatrix},\ \mathbf{D}_{j,s(t)} = \mathbf{0} \text{ for all } j \tag{8}$$

are estimated over a window of data of length τ and we can then forecast $\hat{\mathbf{Z}}_t = [\hat{\pi}_t^{\text{CPI}}, \hat{\pi}_t^{\text{PCE}}]'$ using $\hat{\mathbf{X}}_t$. Incoming high-frequency data on gasoline prices that affect $\hat{\pi}_t^{\text{Gasoline}}$ will affect $\hat{\mathbf{X}}_t$ and headline inflation nowcasts through equation (8), as will incoming data that affect the forecasts for food and core inflation. 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

$$\mathbf{A}_{s(t)} = \mathbf{I}_2,\ \mathbf{B}_{s(t)} = \mathbf{0},\ \mathbf{C}_{s(t)} = \mathbf{0},\ \mathbf{D}_{j,s(t)} = (1/12)\mathbf{I}_2,\ J = 12\,. \tag{9}$$

The use of past headline inflation (rather than core inflation) to predict future headline inflation is consistent with the results in Crone et al. (2013).

As with the procedure for core inflation set out earlier, nowcasts or forecasts of headline inflation can enter the recursion in equation (9) if they are part of the 12-month window. Also as with core inflation, because PCE inflation is released after CPI inflation, we only bridge from CPI to PCE if there is an additional CPI reading. Hence, nowcasts or forecasts for headline CPI inflation are determined by equations (8) or (9), whereas nowcasts or forecasts of headline PCE inflation are determined by equations (7), (8), or (9) depending on the available information set.

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. While long historical series are readily available from the BLS, the BEA, and data collection sites, 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.[9] Thus, the currently available historical time series may differ substantially from what would have been available to forecasters at some point in the past.

To assess the need for real-time data—which are generally more difficult to come by at the model's monthly frequency—we document 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.[10] 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.[11] In the quarterly data, Figure 1(a) plots differences between initial

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[9] 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.

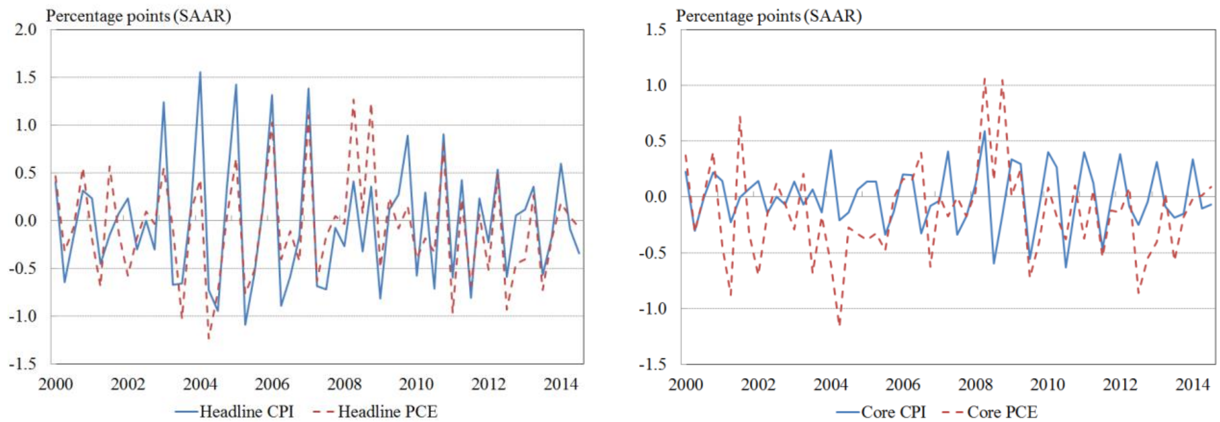
[10] Monthly real-time data come from the St. Louis Fed's Archival Federal Reserve Economic Data (ALFRED). The "final" vintage data were downloaded on August 19, 2015. Because the CPI went through July 2015 while the PCE price index went through June 2015, we treated the June 2015 CPI and PCE inflation readings as the last available observations. 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. We stop the comparison at the end of 2014 because the 2015 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.

[11] 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

and final vintage headline inflation, while Figure 1(b) plots the differences in core inflation. The revisions are large and 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. While the average revision is near zero, the average absolute revision was not negligible. Headline CPI revisions were larger in absolute terms and more volatile than headline PCE revisions during this time, while core CPI revisions were smaller than core PCE revisions.

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 were downloaded on August 19, 2015. To treat our inflation measures similarly, we consider the June 2015 CPI and PCE inflation observations to be the last available readings. The initial quarterly inflation reading is computed as soon as all of the monthly price index readings for the quarter are available.

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	0.08	0.00	0.03	-0.01	0.07	-0.02	0.05
Standard deviation	0.10	0.06	0.04	0.03	0.09	0.06	0.07	0.05
Quarterly Data								
Average	-0.03	0.51	0.00	0.21	-0.07	0.43	-0.14	0.33
Standard deviation	0.64	0.37	0.27	0.16	0.55	0.35	0.42	0.29

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 were downloaded on August 19, 2015. To treat our inflation measures similarly, we consider the June 2015 CPI and PCE inflation observations to be the last available readings. The comparisons begin in June 2000 (2000Q2) and end in December 2014 (2014Q4).

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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.

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

The St. Louis Fed's 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.[12]

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 prices, we use Brent crude spot prices from the Financial Times, which are available starting in 1987. We consider the robustness of our results to using West Texas Intermediate crude spot prices below. The final needed series is the seasonally adjusted CPI for gasoline, which is used to seasonally adjust retail gasoline prices from EIA. Combining data from ALFRED and Haver Analytics, we have real-time coverage of the gasoline CPI back to January 1999.

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

[12] In the PCE price index, food services are part of core inflation, while food and beverages purchased for off-premises consumption are not. Having a measure of inflation in the latter could benefit headline PCE inflation nowcasts (as would the CPI equivalent, which is the food at home series), but these series are not available with long real-time histories. Thus, we rely on the CPI for food.

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 in key unmodeled inflation components that are subsumed in the constant terms and may vary over time. 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 assess the nowcasting accuracy of our model along several dimensions. As one standard metric for point forecast evaluation, we examine root mean squared errors (RMSEs). The combination of real-time data, differing estimation schemes, and generated regressors in our model imposes challenges in evaluating the statistical significance in reductions in RMSEs from our model with plausible alternatives; while we report results from tests of conditional predictive ability based on Giacomini and White (2006), we view these as approximations.[13] As a second metric, we assess nowcasting accuracy via the directional forecast approach of Pesaran and Timmermann (2009), as in Baumeister et al. (2015). Directional accuracy is measured by success ratios, defined as the percentage of times that the nowcasting model correctly predicted the change in the rate of inflation from the previous period; success ratios greater than 0.5 indicate improvement over a no-change forecast.

[13] Clark and McCracken (2009) discuss issues with real-time data and tests of equal forecast accuracy. We report the Giacomini-White test based on our use of rolling windows in our baseline model, but several of the alternative statistical specifications we present use expanding windows. In our cases, the Giacomini-White test results are very similar to those from Diebold and Mariano (1995) tests for equal forecast accuracy, with the adjustment for small samples of Harvey et al. (1997) as applied to nowcasting in Carriero et al. (2015).

IV. Model Performance for Monthly, Year-Over-Year, and Quarterly Inflation

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 property, whether examining the ability of the model to nowcast monthly inflation, year-over-year inflation, 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 forecast accuracy is the choice of what constitutes the "actual" data realizations (or "truth"). Ex post revisions 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 is one 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 third monthly estimate of PCE prices as "truth," similar to Tulip (2009) and a number of other researchers; we treat CPI symmetrically.[14,15]

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

[15] In computing all nowcasting accuracy statistics, 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 large one-time drop in the PCE price index for insurance. The decline in this component was so large that monthly core PCE inflation for September 2001 fell to its lowest recorded reading. The decline was unwound in October 2001. CPI was not affected by these insurance payments.

Nowcasting Monthly Inflation

Monthly inflation readings come out around the middle (CPI) or end (PCE price index) of the following month. Over the course of a given month *t*, the arrival of the month *t*−1 inflation estimate contains relevant information and influences the nowcast for the current month *t*. 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.

We illustrate the model's monthly nowcasting performance for CPI and PCE inflation at six representative dates listed in Table 2. Assuming that month *t* is the target month being nowcasted, Case 1 is the final day of month *t*−1, and case 5 is the last day of the target month *t*. Case 6 is the middle of month *t*+1, when the CPI is released for month *t* and only the PCE price index is left to be nowcasted (in this case, backcasted) for month *t*.

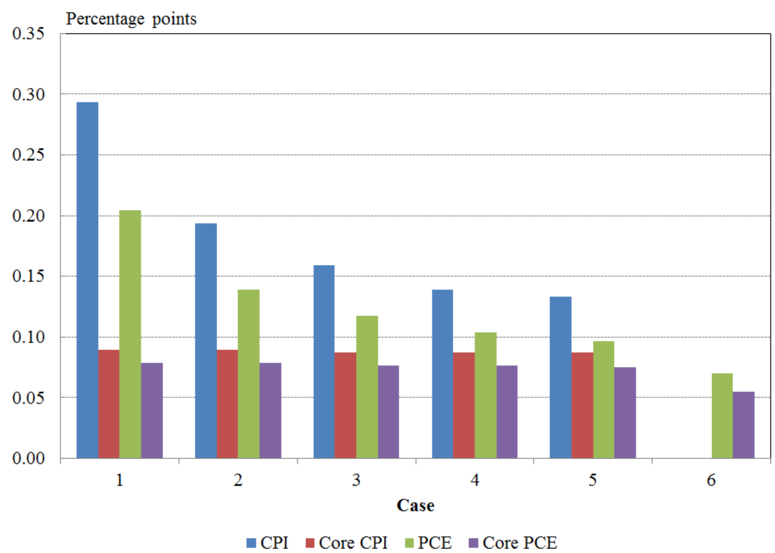
Table 2: Monthly Nowcasting Performance Cases

	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.

We use the real-time data that would have been available in each assumed case to nowcast monthly inflation rates, running from September 2000 to June 2015. Figure 2 plots the monthly RMSEs from our baseline model; we also show the RMSEs in the table below.

The monthly core inflation RMSEs change little over time, consistent with using recursive 12-month moving averages to forecast missing monthly data in our baseline model, but they do drift progressively lower. Assuming month t is the target month to nowcast, the arrival of the core CPI reading for month $t-1$ (case 3) reduces the RMSE for core CPI by 0.002 percentage point. This also generates a reduction in RMSE for core PCE: the month $t-1$ core CPI inflation is bridged to nowcast month $t-1$ core PCE inflation, which is now one of the 12 observations used to nowcast the core PCE inflation rate in month t. There is a small reduction in RMSE upon the arrival of the month $t-1$ core PCE release (case 5), because this data point—instead of a nowcast—is now one of the 12 observations used to nowcast the core PCE inflation rate in month t. Once core CPI for the target month t is released (case 6), bridging that reading to core PCE reduces RMSE by 0.021 percentage point. In a sense, this is the first available data release for the month t being nowcasted in terms of core inflation.

Figure 2: Baseline Model, Root Mean Squared Nowcast Errors, Monthly Inflation



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 errors 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 June 2015.

The pattern is different for headline inflation because of the availability of higher-frequency energy prices within month t. Headline inflation RMSEs decline steadily and significantly over the course of time. By day 8 of month t (case 2), when at least one weekly reading on retail gasoline prices is available for the month, RMSEs fall sharply from where they were immediately prior to the start of the month, and they move lower as additional gasoline price data accumulate. The accuracy of nowcasting headline PCE inflation benefits from the arrival of the monthly CPI readings, both in case 3 when the time $t-1$ CPI reading becomes available and in case 6 when the time t CPI reading becomes available. Immediately prior to the inflation releases for the targeted month t, nowcasting RMSEs for headline CPI and PCE are less than half of their values compared with where they stood on the final day of month $t-1$.[16]

We compare the model's monthly nowcasting performance with three competing models. The first alternative uses a random walk in monthly inflation, $\hat{\pi}_t = \pi_{t-k}$, where the nowcast for the target month t is based on the most recent available real-time monthly inflation rate from k months ago.

The second alternative is a mixed data sampling (MIDAS) model based on Ghysels et al. (2004, 2005). Monteforte and Moretti (2013) apply a MIDAS model to nowcast euro area inflation.[17] For nowcasting or forecasting monthly inflation at horizon h, π_{t+h}, we consider a MIDAS with leads specification of the form:

$$\pi_{t+h} = \alpha_{(h)} + \sum_{j=0}^{P(M)-1} \chi_{j+1,(h)} \pi_{t-j} + \sum_{j=0}^{P(M)-1} \gamma_{j+1,(h)} Z_{t-j} + \beta_{(h)} \sum_{j=0}^{P(HF)-1} \omega_{P(HF)-j}(\theta_{(h)}^{HF}) X_{P(HF)-j,t+1}^{HF} + e_{t+h} \,. \quad (10)$$

For exposition, we assume that lagged dependent monthly variables are available through month t; other monthly variable(s) Z are also available through month t; $P(M)$ is the number of lags of

[16] 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.

[17] Monteforte and Moretti (2013) also use a factor model to generate a measure for core inflation, but we omit this step as we use core inflation measures from U.S. statistical agencies instead.

the monthly variables, which we set to one; at any given point in time, we have $P(HF)$ high-frequency observations, $X^{HF}_{1,t+1},\ldots,X^{HF}_{P(HF),t+1}$, in month t+1, and we use all $P(HF)$ of them as high-frequency leads. Our coefficients can vary with the forecast horizon, as captured by the (h) subscripts. As discussed in Ghysels (2015), we identify $\beta_{(h)}$ by assuming $\sum_{j=0}^{P(HF)-1}\omega_{P(HF)-j}(\theta^{HF}_{(h)})=1$. We estimate the model via nonlinear least squares and parameterize the MIDAS polynomial with the Beta density. While Monteforte and Moretti (2013) construct three MIDAS models each with three daily data series geared toward nowcasting euro area inflation, we focus on parsimonious specifications using only the data series in our baseline model. Preliminary analysis favored this parsimonious approach over MIDAS regression models featuring a larger number of high-frequency indicators along the lines of Monteforte and Moretti (2013).[18] To take advantage of potential gains coming from model averaging, some of which are documented in Andreou et al. (2013), we run two separate MIDAS regressions using our two high-frequency data series—the first with daily oil prices and a second with weekly gasoline prices, both of which enter the model in natural log first differences—and then construct an average nowcast or forecast for the monthly inflation series at horizon h.

The third alternative is a dynamic factor model (DFM) based on Modugno (2013) for nowcasting the U.S. CPI, and which built on earlier work by Giannone et al. (2006, 2008). Following Modugno (2013), the model combines data at the monthly, weekly, and daily

[18] We tailor each set of explanatory variables Z to the inflation measure being nowcasted or forecasted and the variables available when making that nowcast or forecast. Doing so gives the MIDAS models the benefit of the deterministic model switching we propose in the baseline model. The dependent variable's own lag is always included. For core CPI inflation, Z only contains lagged CPI inflation. For CPI inflation, Z contains lagged core CPI inflation, lagged gasoline inflation, and lagged food inflation. For core PCE inflation, if there is one more core CPI reading than core PCE, then Z only contains contemporaneous core CPI inflation, similar to our baseline approach; otherwise, Z contains lagged core CPI inflation. For PCE inflation, we use the same convention: if there is one more CPI reading than PCE, then Z only contains contemporaneous CPI inflation; otherwise, Z contains lagged core PCE inflation, lagged gasoline inflation, and lagged food inflation.

frequencies into a business day frequency factor model with missing observations that are cast in a state space representation. The dynamic factor model takes the general form:

$$y_t = Cf_t + \varepsilon_t,\ \ \varepsilon_t \sim N(0,\Sigma) \tag{11}$$

with y_t a vector of observations, C a matrix of loadings, ε_t a vector of idiosyncratic components, and f_t a vector of unobserved common components following a VAR given by

$$Bf_t = A(L)\, f_{t-1} + u_t,\ \ u_t \sim N(0,Q)\,, \tag{12}$$

where B and $A(L)$ are matrices governing factor dynamics, some of which may be time-varying. Modugno (2013) shows how monthly, weekly, and daily variables and factors can be stacked appropriately in equations (11) and (12) and how the unobserved daily factors aggregate to weekly and monthly factors, which in turn inform nowcasts and forecasts of the monthly variables. As in Modugno (2013), we estimate relevant parameters via the approach of Bańbura and Modugno (2012). Our dynamic factor model dataset is slightly smaller than in Modugno (2013), but our nowcasting results are highly comparable.[19] We report results for a model specification with 1 factor and 6 lags, which we found generated the most accurate out-of-sample nowcasts in the specifications we considered.

Table 3 shows that our nowcasting model has historically generated lower RMSEs than the three competing model nowcasts. The MIDAS models and the dynamic factor model generated lower RMSEs in only one case each. In many cases for headline CPI and PCE inflation, the reductions in RMSEs coming from the baseline model compared with the

[19] Modugno (2013) used 8 monthly, 4 weekly, and 15 daily series. Due to data availability and real-time data limitations, along with our interest in nowcasting headline and core inflation for the CPI and PCE price index, we use 6 monthly variables (CPI inflation, core CPI inflation, PCE inflation, core PCE inflation, food inflation, gasoline inflation), 4 weekly variables (diesel fuel price, regular grade retail gasoline price, midgrade retail gasoline price, and premium retail gasoline price), and 14 daily series (Brent crude oil, foodstuffs price index, grains price index, fats and oils price index, raw sugar price, raw industrials price index, agricultural commodities price index, textiles and fibers price index, industrial metals price index, steel scrap prices, the 10-year Treasury note constant maturity yield, the 3-month Treasury bill rate, the S&P 500 stock price index, and the nominal trade-weighted exchange value of the dollar against major currencies).

alternative models are substantial. In the case of core inflation, our baseline model is highly competitive with the alternative approaches in spite of its extreme parsimony; there is little benefit from the more sophisticated and computationally intensive MIDAS models and dynamic factor model, even though the latter includes some high-frequency information that could have a bearing on core inflation (e.g., the exchange rate).

Table 3: Root Mean Squared Nowcast Errors, Monthly Inflation

		Case					
Measure	Model	1	2	3	4	5	6
CPI	Baseline	0.294	0.194	0.159	0.139	0.133	--
	Random walk	**0.480*** **	**0.480*** **	**0.366*** **	**0.366*** **	**0.366*** **	--
	MIDAS	**0.303**	**0.296*** **	**0.258*** **	**0.261*** **	**0.250*** **	--
	DFM	**0.305**	**0.265*** **	**0.264*** **	**0.268*** **	**0.273*** **	--
Core CPI	Baseline	0.089	0.089	0.087	0.087	0.087	--
	Random walk	**0.112*** **	**0.112*** **	**0.106*** **	**0.106*** **	**0.106*** **	--
	MIDAS	**0.091**	**0.090**	**0.090**	**0.090**	**0.091**	--
	DFM	**0.090**	**0.091**	**0.091**	**0.091**	**0.091**	--
PCE	Baseline	0.205	0.139	0.117	0.104	0.097	0.070
	Random walk	**0.344* **	**0.344*** **	**0.344*** **	**0.344*** **	**0.263*** **	**0.263*** **
	MIDAS	**0.244* **	**0.250*** **	**0.240*** **	**0.240*** **	**0.171*** **	0.056**
	DFM	**0.212**	**0.186*** **	**0.187*** **	**0.188*** **	**0.189*** **	**0.186*** **
Core PCE	Baseline	0.078	0.078	0.077	0.077	0.075	0.055
	Random walk	**0.159* **	**0.159* **	**0.159* **	**0.159* **	**0.120**	**0.120* **
	MIDAS	**0.104**	**0.104**	**0.082**	**0.081**	**0.096**	**0.059* **
	DFM	0.078	**0.080**	**0.082**	**0.084** **	**0.082** **	**0.081*** **

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. *, **, and *** denote rejection of the null of equal conditional predictive ability for the baseline model compared with each alternative model at the 10%, 5%, and 1% level, respectively, based on the Giacomini-White test. **Bold** entries denote that the baseline model produces smaller RMSEs than the alternative model. Inflation rates are month-over-month percent changes in seasonally adjusted data, so errors 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 June 2015.

The top panel of Table 4 shows the success ratios for our baseline model and the two competing nowcasting models, computed as the percentage of nowcasts that correctly predicted whether inflation increased or decreased compared with the preceding monthly reading. The bottom panel shows the *p*-values from the Pesaran-Timmermann test for directional forecast accuracy. For headline inflation, our baseline model generates considerably higher success ratios and lower *p*-values almost across-the-board. For core inflation, meanwhile, the results are mixed, suggesting that our parsimonious baseline model is highly competitive with MIDAS models and dynamic factor models.[20]

Table 4: Directional Forecast Accuracy Statistics, Monthly Inflation

Measure	Model	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6
		Success ratios					
CPI	Baseline	**0.753**	**0.815**	**0.876**	**0.921**	**0.916**	--
	MIDAS	0.719	0.663	0.798	0.803	0.826	--
	DFM	0.449	0.539	0.815	0.798	0.815	--
Core CPI	Baseline	0.528	0.528	0.652	0.652	0.652	--
	MIDAS	**0.584**	**0.579**	0.652	0.657	0.652	--
	DFM	0.562	0.517	**0.702**	**0.697**	**0.708**	--
PCE	Baseline	**0.697**	**0.781**	**0.876**	**0.899**	**0.876**	0.916
	MIDAS	0.618	0.562	0.472	0.478	0.758	**0.927**
	DFM	0.472	0.506	0.556	0.590	0.764	0.775
Core PCE	Baseline	0.500	0.500	**0.624**	**0.624**	**0.719**	**0.798**
	MIDAS	**0.539**	0.494	0.539	0.506	0.713	0.792
	DFM	**0.539**	**0.506**	0.489	0.522	0.713	0.713
		Pesaran-Timmermann p-values					
CPI	Baseline	2.4E-10	1.1E-16	0	0	0	--
	MIDAS	7.2E-9	4.4E-6	4.4E-13	1.4E-13	1.1E-16	--
	DFM	0.257	0.181	3.4E-15	8.3E-13	4.6E-14	--
Core CPI	Baseline	0.522	0.522	0.011	0.011	0.011	--
	MIDAS	0.046	0.059	1.7E-3	9.9E-4	1.8E-4	--
	DFM	0.149	0.431	5.4E-6	1.7E-5	1.6E-6	--
PCE	Baseline	4.6E-7	3.9E-14	0	0	0	0
	MIDAS	6.8E-4	0.014	0.215	0.326	7.1E-10	0
	DFM	0.807	0.422	0.017	1.8E-04	6.7E-9	4.2E-10
Core PCE	Baseline	0.954	0.954	0.025	0.025	4.4E-7	1.1E-14
	MIDAS	0.405	0.492	0.341	0.937	1.3E-5	5.3E-14
	DFM	0.156	0.360	0.947	0.573	5.7E-6	5.7E-6

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. Success ratios report the percentage of nowcasts that correctly predicted whether inflation increased or decreased compared with the preceding monthly reading, and *p*-values come from the Pesaran-Timmermann test of directional forecast accuracy. **Bold** entries denote the highest success ratio for each inflation measure in each case. PCE and core PCE statistics exclude September and October 2001. The exercise uses real-time data from September 2000 through June 2015.

[20] Our combination of monthly data and real-time data limit the number of alternative models we pursue. For example, another approach could be to extract principal components from a dataset of the subcomponents of headline or core inflation and generate forecasts as in Stock and Watson (2002a, 2002b). But real-time databases such as ALFRED have extremely limited histories of monthly subcomponents of the PCE price index; the same is true for the seasonally adjusted subcomponents of the CPI.

While the results above use the entire sample of real-time data from September 2000 to June 2015, we ran a split-sample exercise as well, with the early sample running from September 2000 to December 2007 and the late sample running from January 2008 to June 2015. We find that the patterns of RMSEs were not markedly different between the early and the late sample, and our basic results still hold: our nowcasting model consistently outperforms the MIDAS and dynamic factor models for headline inflation and is comparable for core inflation.

Nowcasting Year-Over-Year Inflation

Modugno (2013) and Monteforte and Moretti (2013) both nowcast year-over-year inflation rates rather than monthly inflation rates. Using the same underlying monthly models and the same cases described above, Table 5 assesses the ability of the models to nowcast year-over-year inflation.[21] Our same basic results hold, so we omit results on directional forecast accuracy: there continue to be only two cases in which the MIDAS models and the dynamic factor model produce smaller RMSEs than our baseline model, and the outperformance of our baseline model is notable for headline CPI and PCE inflation and smaller for core inflation measures.

In the closest related work to this paper, Modugno (2013) uses a dynamic factor model to nowcast year-over-year inflation in the headline CPI between January 2001 and December 2011, a slightly shorter sample than ours. During that sample, Modugno (2013) reports a nowcast RMSE 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

[21] Our random walk model now assumes a random walk in year-over-year inflation rather than in monthly inflation. Our baseline model, the MIDAS models, and the dynamic factor model continue to use monthly inflation rates, and then we compute the implied year-over-year inflation rates.

which year-over-year inflation is expected to remain unchanged from its previous reading. Using the same sample period and focusing on the day after the previous month's CPI is released, our model produces RMSEs of 0.16 percentage point for year-over-year CPI inflation, for a further 30.4 percent reduction in RMSE.

Table 5: Root Mean Squared Nowcast Errors, Year-Over-Year Inflation

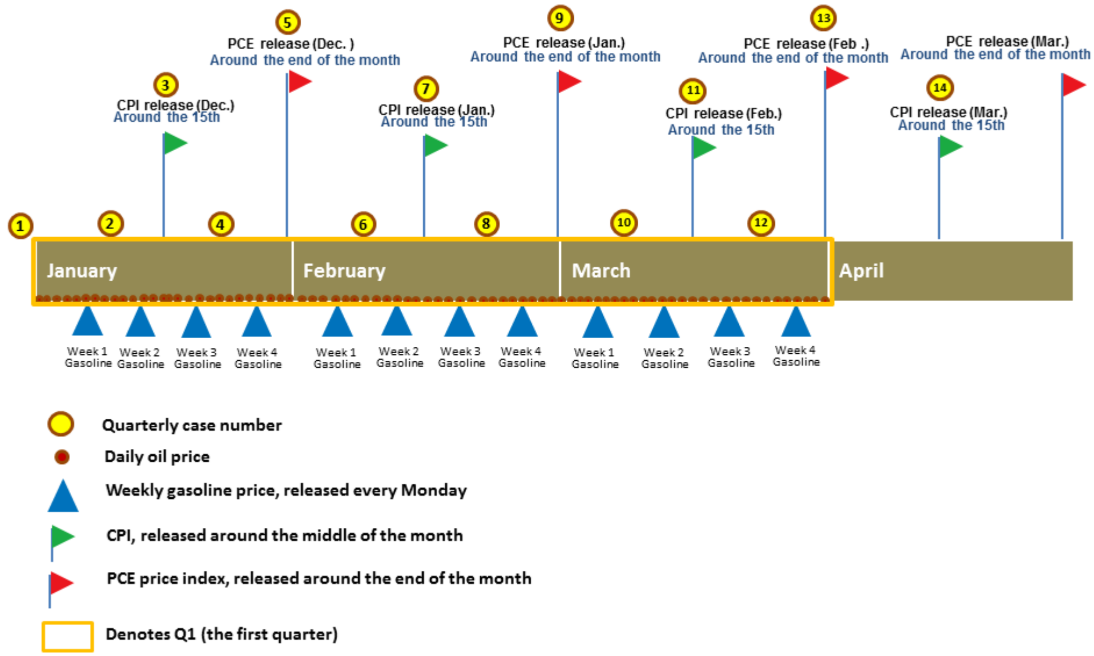
		Case					
Measure	Model	1	2	3	4	5	6
CPI	Baseline	0.361	0.280	0.175	0.157	0.154	--
	Random walk	**0.830*** **	**0.830*** **	**0.497*** **	**0.497*** **	**0.497*** **	--
	MIDAS	**0.466*** **	**0.476*** **	**0.278*** **	**0.279*** **	**0.267*** **	--
	DFM	**0.460*** **	**0.427*** **	**0.277*** **	**0.279*** **	**0.287*** **	--
Core CPI	Baseline	0.153	0.153	0.100	0.100	0.100	--
	Random walk	**0.193*** **	**0.193*** **	**0.124*** **	**0.124*** **	**0.124*** **	--
	MIDAS	**0.157**	**0.156**	**0.102**	**0.102**	**0.102**	--
	DFM	**0.156**	**0.157**	**0.101**	**0.102**	**0.102**	--
PCE	Baseline	0.303	0.260	0.219	0.209	0.157	0.137
	Random walk	**0.595*** **	**0.595*** **	**0.595*** **	**0.595*** **	**0.364*** **	**0.364*** **
	MIDAS	**0.383*** **	**0.396*** **	**0.300*** **	**0.299*** **	**0.214*** **	0.128*
	DFM	**0.357*** **	**0.335*** **	**0.336*** **	**0.337*** **	**0.226*** **	**0.221*** **
Core PCE	Baseline	0.215	0.215	0.196	0.196	0.144	0.129
	Random walk	**0.266** **	**0.266** **	**0.266*** **	**0.266*** **	**0.191** **	**0.191** **
	MIDAS	**0.233**	**0.237**	**0.197**	**0.194**	**0.147**	**0.129**
	DFM	0.206	**0.209**	**0.210* **	**0.211* **	**0.144**	**0.144*** **

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. *, **, and *** denote rejection of the null of equal conditional predictive ability for the baseline model compared with each alternative model at the 10%, 5%, and 1% level, respectively, based on the Giacomini-White test. **Bold** entries denote that the baseline model produces smaller RMSEs than the alternative model. Inflation rates are year-over-year percent changes, so errors are expressed in percentage points. PCE and core PCE statistics exclude September and October 2001. The exercise uses real-time data from September 2000 through June 2015.

Nowcasting Quarterly Inflation

Because there are a larger number of data releases over the course of a quarter, we illustrate the baseline model's nowcasting performance for quarterly inflation at 14 representative dates, diagrammed in Figure 3.

Figure 3: Data Flow Timing



We compare the model with a number of alternatives. The three quarterly statistical models we consider have respectable inflation forecasting properties (see Faust and Wright 2013).[22] All forecasts are made using the data that would have been available in real time; 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.

1. A four-quarter random walk, where today's expected annualized quarterly inflation rate is the inflation rate over the last four available quarters; e.g., if the most recent available observation was in quarter $T-1$, $E_T \pi_T = 100(P_{T-1} / P_{T-1-4} - 1)$, similar to Atkeson and Ohanian (2001).

[22] We also considered a variety of other quarterly models which we do not show, including: a quarterly random walk model; AR(1) and AR(4) models estimated using real-time five-year rolling windows; AR(1) and AR(4) models estimated on the entire expanding real-time sample; direct rather than recursive AR(1) and AR(4) models; and AR(p) models estimated using five-year rolling windows, the entire expanding real-time sample, or inflation in "gap" form estimated using the entire expanding real-time sample, where the choice of p was based on the AIC in real time. These models were generally outperformed by the models shown.

2. 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 real time and are assumed to follow a random walk in the future. We estimate the coefficients on real-time expanding samples with the first gap observation in the second quarter of 1984.[23]
3. The unobserved components model with stochastic volatility (UC-SV) from Stock and Watson (2007). For each inflation series, we begin the estimation in the first quarter of 1960 and use the real-time data that would have been available at the time.

We also consider the two competing mixed frequency nowcasting models set out above that can take advantage of high-frequency weekly and daily data, again using the real-time data that would have been available at the time.

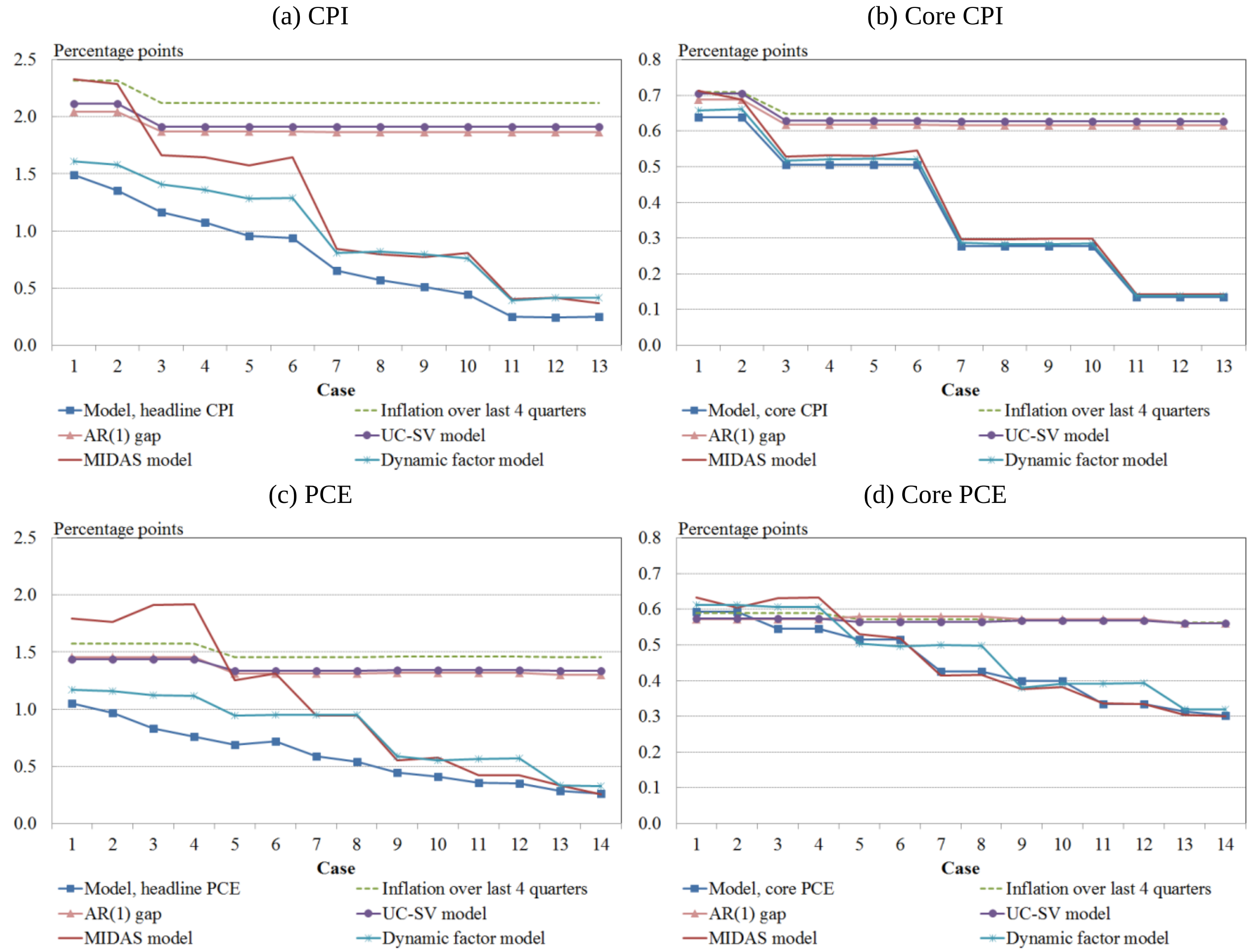
4. MIDAS models, similar in spirit to Monteforte and Moretti (2013).
5. A dynamic factor model, based on Modugno (2013).

Figure 4 shows the quarterly nowcast RMSEs from the model and the competing quarterly forecasting models and nowcasting models. The quarterly forecasting models show few changes in forecast accuracy across the cases as time goes by; these changes occur when

[23] The Blue Chip consensus reports long-run forecasts of CPI inflation and GDP deflator inflation. As in Faust and Wright (2013), we assume long-run forecasts of PCE inflation (and core PCE inflation) are equal to those for the GDP deflator, and 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.

new or revised CPI and PCE data are released.[24] Because the short sample makes the analysis sensitive to outliers, we exclude the fourth quarter of 2008 when computing the RMSEs.[25]

Figure 4: Root Mean Squared Nowcast Errors, Quarterly Inflation



Notes: 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.

Figures 4(a) and 4(c) show that the baseline model's nowcasts for headline inflation—whether measured by the CPI or the PCE price index—tend to broadly outperform the forecasts

[24] The largest revisions to the quarterly 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. Other changes in forecast accuracy reflect data revisions.

[25] Quarterly CPI inflation went from 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 near 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.

and nowcasts from a variety of models, both quarterly forecasting models and alternative mixed-frequency nowcasting models. The outperformance is apparent even immediately prior to the start of the quarter (case 1). During the first month of the quarter, the arrival of high-frequency readings on gasoline and oil prices helps to reduce the model's nowcast errors by about one-third. 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 quickly shows large improvements compared with the best competing quarterly forecasting models; 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 AR(1) gap model and the UC-SV model. Meanwhile, the model's improvements over the best alternative mixed-frequency nowcasting model are smaller, but the improvements are nevertheless persistent throughout the quarter.

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 nowcasting accuracy improves with each additional CPI or PCE release, as shown in Figure 4(d). 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. The model's nowcasts for core inflation rates are considerably more accurate than those coming from quarterly forecasting models and are highly competitive with those from the MIDAS model and the dynamic factor model.[26]

V. Nowcasting Horseraces with Professional Forecasters

Faust and Wright (2009, 2013) show that professional forecasters' inflation nowcasts tend to outperform those from statistical models.[27] In fact, Faust and Wright (2013) suggest that subjective nowcasts may hold a distinct advantage through their ability to "add expert judgment" to models (p. 20). Improved nowcasts are not only of interest for their own sake: Faust and Wright (2013) and Del Negro and Schorfheide (2013) show that taking advantage of more accurate inflation nowcasts improves inflation forecasting accuracy at longer horizons. Thus, we test our inflation nowcasting model by competing with other forecasters.

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

[26] In the interest of space, we omit formal statistical results for all measures and all quarterly cases. For headline inflation, Giacomini-White tests reject the null of equal conditional predictive ability between the model and the alternative models at conventional significance levels in the vast majority of cases for both CPI and PCE inflation, and the model generates considerably higher success ratios and lower *p*-values based on the Pesaran-Timmermann directional forecast accuracy test. For core inflation measures, the model exhibits similar improvements over the quarterly forecasting alternatives, while Giacomini-White and Pesaran-Timmermann results are less conclusive compared with the alternative mixed-frequency models.

[27] 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.

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 highly comparable to nowcasts made by private forecasters or the Board staff.

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. The Blue Chip survey is typically released around the 10th of each month, but the survey is conducted over an earlier two-day period that is usually mentioned in the release; we match this timing in our model.[28]

[28] 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.

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 collected in the January, February, March, and April Blue Chip surveys; 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.[29] The nowcast evaluation spans the second quarter of 1999 through the second quarter of 2015.

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 6 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, with somewhat lower RMSEs in months 1 and 4 and substantially lower RMSEs in months 2 and 3. In terms of directional forecast accuracy, the model produces higher success ratios and lower *p*-values from the Pesaran-Timmermann test for months 1, 2, and 3; by the fourth month of the quarter, both nowcasts always predict the sign of the change in inflation.

The time period under consideration contains a range of events, including the mild 2001 recession, a period of rising oil prices, the financial crisis and plunge in oil prices during a deep recession, and a moderate subsequent economic recovery. Faced with such 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—

[29] 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.

six—determine the model's CPI nowcasts, this outperformance vis-à-vis Blue Chip is particularly noteworthy.

Table 6: Blue Chip CPI Nowcasting Comparisons

	Blue Chip survey conducted in:			
	Month 1	Month 2	Month 3	Month 4
Model RMSE	1.812	1.053	0.482	0.270
Blue Chip RMSE	1.878	1.416	0.829	0.399
Ratio, average Blue Chip MSE to model MSE	1.075	1.808	2.965	2.190
GW *p*-values for test of conditional predictive ability	0.512	0.036	0.001	0.003
Model success ratio	0.862	0.846	0.938	1
Blue Chip success ratio	0.754	0.815	0.908	1
Model Pesaran-Timmermann *p*-values	4.9E-9	2.6E-8	3.2E-12	NA
Blue Chip Pesaran-Timmermann *p*-values	3.8E-5	3.0E-7	1.1E-10	NA

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 errors are expressed in annualized percentage points. GW denotes Giacomini-White. Success ratios report the percentage of nowcasts that correctly predicted whether inflation increased or decreased compared with the preceding quarterly reading, and *p*-values come from the Pesaran-Timmermann test of directional forecast accuracy. The exercise uses real-time data from 1999Q2 through 2015Q2.

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 survey dates; these dates are 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.[30] We match information sets that would have been available to the professional forecasters with the model's information set. 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 started reporting core CPI inflation, headline PCE inflation, and core PCE inflation in the first quarter of 2007, and we conduct comparisons with these three series starting at that point. In all cases, we end the

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

comparisons in the second quarter of 2015. We use the SPF median nowcasts to eliminate outliers and as a check on the Blue Chip consensus exercise, which uses averages.

Table 7 reports results. The model's nowcasts for headline CPI and PCE inflation outperform the SPF nowcasts by 0.40 percentage point and 0.28 percentage point on average, respectively, and the model is more successful along directional forecast accuracy metrics for headline inflation as well. Meanwhile, similar to some of the results presented above when comparing the model's core inflation nowcasts to those from MIDAS models and dynamic factor models, the nowcasting horseraces between the model and the professional forecasters for core inflation are essentially a draw, with similar RMSEs and directional forecast accuracy.

Table 7: Survey of Professional Forecasters Nowcasting Comparisons

	CPI	Core CPI	PCE	Core PCE
Model RMSE	0.981	0.565	0.806	0.518
SPF RMSE	1.381	0.577	1.089	0.504
Ratio, average SPF MSE to model MSE	1.980	1.043	1.823	0.948
GW *p*-values for test of conditional predictive ability	0.009	0.758	0.007	0.747
Model success ratio	0.877	0.824	0.941	0.706
SPF success ratio	0.831	0.824	0.794	0.676
Model Pesaran-Timmermann *p*-values	1.8E-09	4.2E-03	4.6E-07	0.027
SPF Pesaran-Timmermann *p*-values	9.2E-08	3.8E-04	3.2E-04	0.219

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 errors are expressed in annualized percentage points. GW denotes Giacomini-White. Success ratios report the percentage of nowcasts that correctly predicted whether inflation increased or decreased compared with the preceding quarterly reading, and *p*-values come from the Pesaran-Timmermann test of directional forecast accuracy. The CPI exercise uses real-time data from 1999Q2 through 2015Q2. The core CPI, PCE, and core PCE exercises use real-time data from 2007Q1 (the first available SPF estimates) through 2015Q2.

We view the results for headline and core inflation as perhaps somewhat surprising. 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 can be improved upon. 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 we are looking at the statistics in Table 7 or the actual nowcasts themselves, which we show in the Appendix. This finding raises the possibility that professional forecasters are using a similar method for nowcasting core inflation, suggesting that our model is essentially capturing professional forecasters' near-term inflation expectations; or, alternatively, that a variant of Atkeson and Ohanian (2001) is still a difficult inflation forecasting benchmark to beat.

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 are the gold standard. For example, Romer and Romer (2000) show that Greenbook inflation forecasts prior to 1991 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.[31] Bernanke (2007) describes the range of models, indicators, expertise, and extensive judgment used to inform Board staff's near-term inflation forecasts.

Greenbook forecasts are produced in the week prior to each of the Federal Open Market Committee's (FOMC) regularly scheduled meetings. We match the model's real-time information set to the Greenbook date. The eight FOMC meetings each year have historically been spaced irregularly, with essentially two meetings per quarter. For the sake of our 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 early or late in the

[31] This contrasts with Branch (2014), wherein SPF inflation nowcasts are a proxy for monetary policymakers' nowcasts. In that context, improved nowcasts could affect Taylor rule estimates.

quarter make these effectively two different exercises.[32] 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 2009, which is the last publicly available Greenbook.

Table 8 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, and the success ratios are slightly lower. However, the differences in nowcasting accuracy are not large quantitatively with the exception of headline CPI inflation in H1. Additionally, conventional test statistics would fail to reject equal predictive ability in any of the cases considered. We interpret the statistical evidence—and the nowcasts themselves, which we show in the Appendix—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.

Table 8: Greenbook Nowcasting Comparisons

	CPI		Core CPI		PCE		Core PCE	
	H1	H2	H1	H2	H1	H2	H1	H2
Model RMSE	1.321	0.364	0.503	0.268	1.004	0.398	0.590	0.422
Greenbook RMSE	1.090	0.322	0.528	0.257	0.859	0.349	0.554	0.400
Ratio, average Greenbook MSE to model MSE	0.680	0.782	1.102	0.918	0.732	0.768	0.881	0.902
GW *p*-values for test of conditional predictive ability	0.176	0.364	0.509	0.615	0.255	0.241	0.378	0.485
Model success ratio	0.814	1	0.767	0.837	0.816	0.921	0.737	0.868
Greenbook success ratio	0.907	1	0.721	0.884	0.895	0.921	0.763	0.947
Model Pesaran-Timmermann *p*-values	3.9E-5	NA	1.7E-3	9.2E-5	2.1E-4	5.5E-7	1.6E-2	1.6E-5
Greenbook Pesaran-Timmermann *p*-values	7.6E-8	NA	7.5E-2	4.3E-6	2.8E-6	8.8E-7	7.9E-3	8.1E-8

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 errors are expressed in annualized percentage points. GW denotes Giacomini-White. Success ratios report the percentage of nowcasts that correctly predicted whether inflation increased or decreased compared with the preceding quarterly reading, and *p*-values come from the Pesaran-Timmermann test of directional forecast accuracy. The CPI and core CPI exercises use real-time data from 1999Q2 through 2009Q4. The PCE and core PCE exercises use real-time data from 2000Q3 through 2009Q4. PCE and core PCE statistics exclude 2001Q3 and 2001Q4.

[32] 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.

VI. Assessing Nowcasting Accuracy and Sensitivity

To illustrate key drivers of the model's nowcasting accuracy, we consider robustness 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 9. The model's nowcasting performance is highly robust to minor 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 vary 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 (2), (7), and (8). Our 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 15 to 38 percent on average, and Greenbook headline inflation nowcasts notably outperform our model. 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.

Table 9: Relative Quarterly RMSEs from Alternative Assumptions

	CPI		Core CPI		PCE		Core PCE	
Alternative model assumptions	H1	H2	H1	H2	H1	H2	H1	H2
1. τ=12 months	1.02	1.01	1	1	1.05	1.04	1.01	1.03
2. τ=36 months	0.99	1.00	1	1	1.01	0.99	1.00	1.00
3. τ=120 months	1.25	1.38	1	1	1.19	1.15	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	1.00	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	1.05	1.01	1.11	1.01	1.07	1.04	1.14	1.06
8. J=24 months	1.00	1.03	1.03	1.04	0.97	1.00	0.95	0.98
9. J=36 months	1.00	1.03	1.05	1.05	0.98	1.01	0.96	0.99
10. Use CRB foodstuffs to nowcast π_t^{Food}	1.00	1.02	1	1	0.99	1.01	1	1
11. Drop π_t^{Food}	1.01	1.02	1	1	1.01	1.01	1	1
12. Use WTI instead of Brent crude oil prices	1.03	1.01	1	1	1.02	1.00	1	1
13. Drop oil prices as a predictor of π_t^{Gasoline}	1.11	1.02	1	1	1.09	1.01	1	1
14. Drop π_t^{Gasoline}	1.67	1.95	1	1	1.54	1.48	1	1
15. Extend oil prices as a predictor of π_t^{Gasoline}	1.05	1.01	1	1	1.04	1.00	1	1
16. Drop bridging equations	1.03	1.01	1	1	1.05	1.06	1.05	1.09
17. Single models, no model switching	1.05	1.01	1	1	1.08	1.06	1.05	1.09
18. Use AR(1) instead of J=12 month moving avg.	1.02	1.01	1.01	1.03	0.98	0.98	0.95	0.98

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.

We also consider changes to the disaggregates. We first examine the role of food inflation in the model. The Commodity Research Bureau (CRB) produces a daily spot commodity price index for foodstuffs, which is potentially a source of high-frequency data that could be used to help nowcast π_t^{Food}. Line 10 shows that using CRB foodstuffs spot prices to help nowcast monthly CPI food inflation—instead of the moving average approach used to forecast CPI food inflation in the baseline model—has little effect on the accuracy of our headline inflation nowcasts.[33] Dropping π_t^{Food} as a disaggregate in nowcasting headline inflation

[33] In keeping with the parsimonious nature of our model, we considered various simple models relating CRB foodstuffs to CPI food inflation. Preliminary analysis showed a lag between seasonally adjusted foodstuffs spot prices and CPI food inflation. To exploit this lag, we bridge from monthly CRB foodstuffs spot price inflation in month $t-j$ to CPI food inflation in month t, where we choose j to maximize R^2 at each point in time. We include CPI food inflation in month $t-1$ as an additional regressor. Alternative model specifications—including directly

also has a minor impact on RMSEs (line 11). We next examine the role of gasoline and oil prices in the model. Using WTI spot oil prices instead of Brent as our measure of crude oil prices has essentially no impact on our results (line 12), despite the fact that a wedge between the two measures opened up during our sample period. Excluding energy price measures has a large effect on the accuracy of our model. If daily oil prices are excluded from the model (line 13), RMSEs increase 9 to 11 percent in the first half of the quarter, suggesting that current oil prices help predict future gasoline prices and, by extension, their influence on inflation.[34] Dropping π_t^{Gasoline} as a disaggregate (line 14) causes a large deterioration in nowcast accuracy, as RMSEs for headline inflation increase 48 to 95 percent.

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 (9); doing so causes a minor increase in RMSE (line 15). 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 (2) and (7). Nowcasts of CPI and core CPI are unaffected, but RMSEs for PCE and core PCE rise modestly (line 16), suggesting that such a bridging approach assists with nowcasting. The third structural change combines the previous two by extending the use of oil prices and dropping the bridging equations, so that equation (3) is the single model for core inflation nowcasts and equation (8) is

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using foodstuffs inflation as the measure of food inflation in our model, error correction models relating foodstuffs to the CPI for food, and different assumptions for how we bridged foodstuffs to CPI food inflation—had little effect on the results.

[34] 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 at least some weekly data on gasoline prices within month *t*.

the single model for headline inflation nowcasts (line 17). RMSEs are modestly higher than the baseline, consistent with gains for the types of deterministic model switching we propose. Finally, we consider an alternative in which we replace the default for making forecasts of monthly variables as recursive 12-month moving averages (and hence coefficients 1/12) in equations (3) and (9) with an AR(1) model estimated over a rolling window of length τ=24 months. Doing so has a very modest impact, slightly worsening our nowcasts of core and headline CPI but improving our nowcasts of core and headline PCE.[35]

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 some other nowcasting approaches that utilize larger 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 various statistical models and arguably 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 as well as competing MIDAS and dynamic factor models used for

[35] While not reported, using additional AR terms to forecast the disaggregates tends to worsen our quarterly nowcasts, especially for CPI inflation measures. Estimating an AR(1) model using a rolling window of length τ produces smaller nowcast RMSEs than if we instead used an AR(p) model, where p was chosen based on the AIC.

nowcasting, and they rival the nowcasting accuracy of the Greenbook. The accuracy of the model's nowcasts for core CPI and PCE inflation, which are made using very simple univariate and multivariate techniques, are essentially on a par with those from more sophisticated and computationally intensive MIDAS models and dynamic factor models and the expert judgment used in 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. In addition, it is worth noting that our nowcasting exercise takes place in an era of anchored long-run inflation expectations, which played a role in dampening the volatility of core inflation readings. Additional empirical work would be needed to examine the extent to which a framework similar to ours would generate good nowcasts during a period of unanchored long-run inflation expectations.

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IX. Appendix: Model and Professional Forecasters' Nowcasts

This appendix shows the actual nowcasts coming from the model with those from professional forecasters, using matched information sets as in Section V.

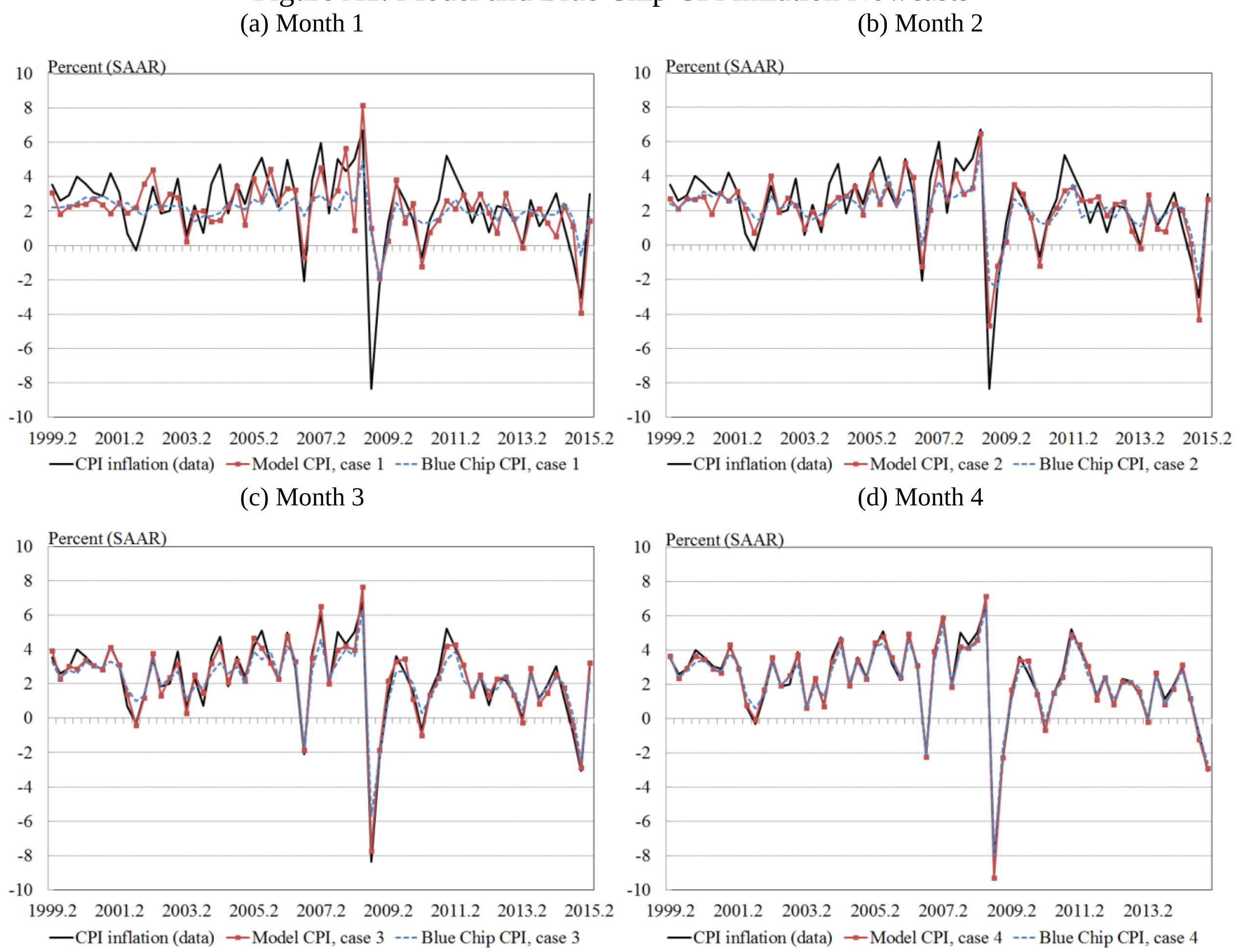
Figure A1 plots the competing nowcasts from the model and Blue Chip for each of the four cases set out above along with the actual quarterly CPI inflation rate. The model's nowcasts are very effective in tracking actual CPI inflation in all four cases, especially as time goes on and more information is available. However, the outperformance of the model is not universal, as Blue Chip nowcasts were sometimes more accurate than those from the model.

Figure A2 plots the nowcasts from the model and the SPF along with the inflation 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.

Figure A3 plots the nowcasts from the model and the Greenbook, separating nowcasts based on whether they were made in H1 or H2 of each quarter. By H2, the model's nowcasts are typically very close to the Greenbook across all inflation measures and across the entire sample.

Figure A4 provides 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 SPF was 1.6 percent. The Blue Chip consensus nowcast fell to 0.5 percent by early June and to 0 percent in early July. We trace out the daily headline CPI nowcasts from our model and show that after starting the quarter near zero then falling off in mid-April, 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.

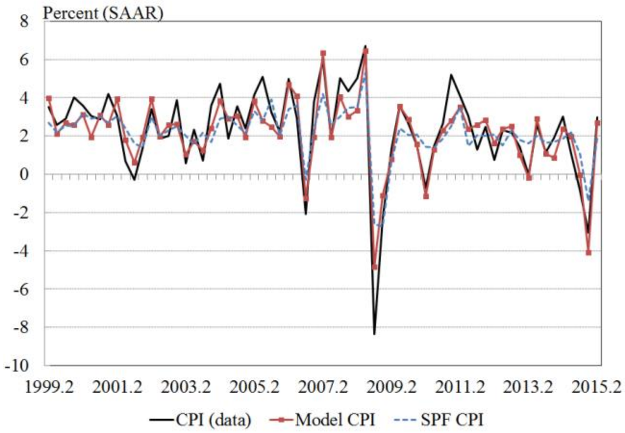
Figure A1: Model and Blue Chip CPI Inflation Nowcasts



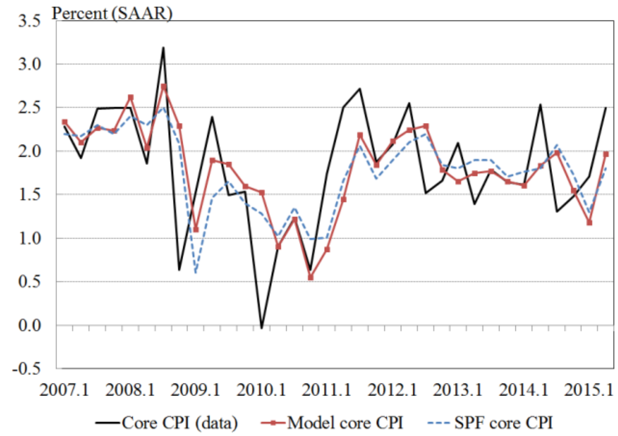
Notes: Cases are defined by the Blue Chip survey dates. Month 1 is the Blue Chip survey date for the first month of the quarter being nowcasted (e.g., January when nowcasting Q1). Month 2 is the Blue Chip survey date for the second month of the quarter being nowcasted. Month 3 is the Blue Chip survey 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 2015Q2.

Figure A2: Model and SPF Inflation Nowcasts

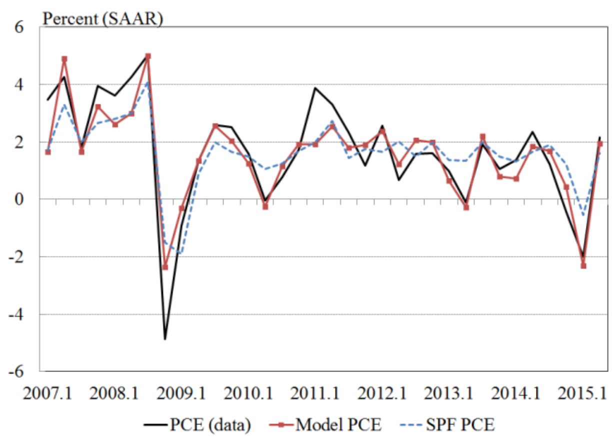
(a) Headline CPI



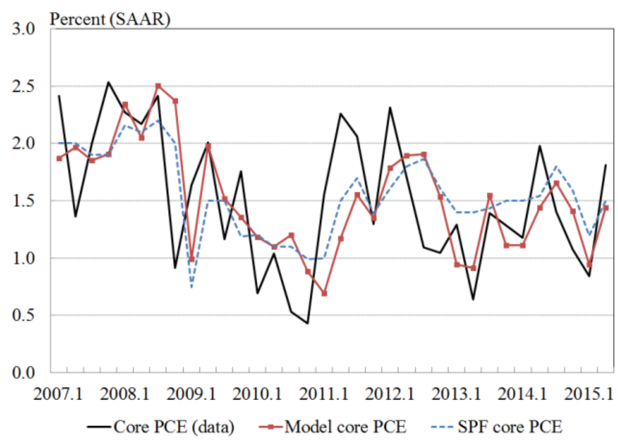
(b) Core CPI



(c) Headline PCE



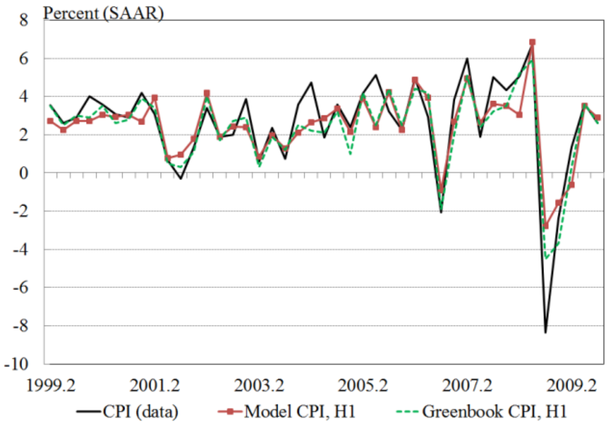
(d) Core PCE



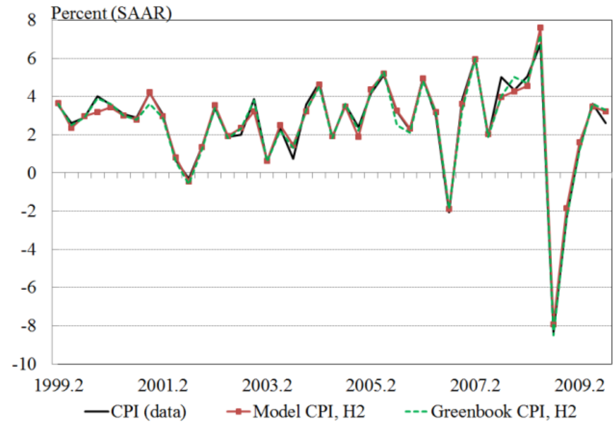
Notes: Real-time comparisons are based on the SPF survey dates. SPF expectations for each quarter are the median value. Quarterly inflation rates are seasonally adjusted annualized percent changes. The CPI exercise uses real-time data from 1999Q2 through 2015Q2. The core CPI, PCE, and core PCE exercises use real-time data from 2007Q1 (the first available SPF estimates) through 2015Q2.

Figure A3: Model and Greenbook Inflation Nowcasts

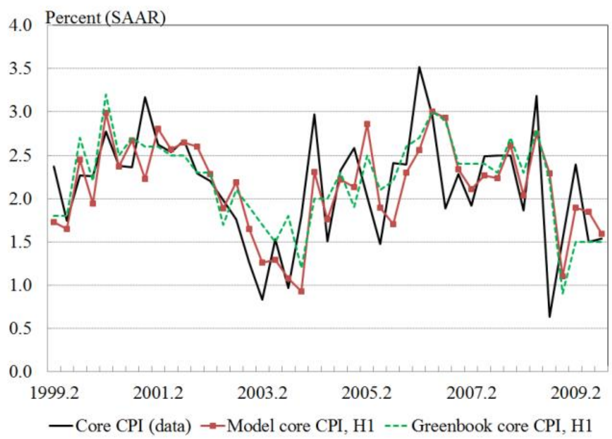
(a) CPI, first half of quarter



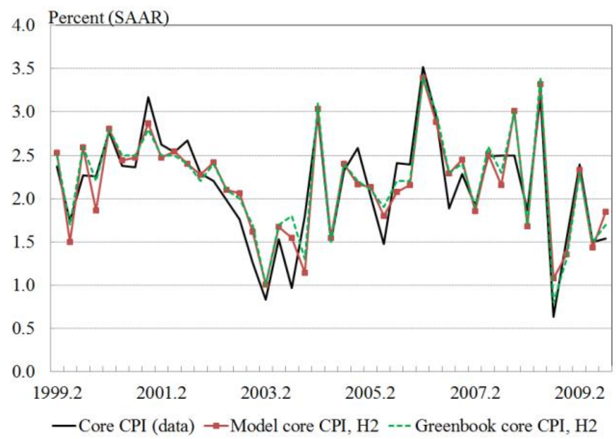
(b) CPI, second half of quarter



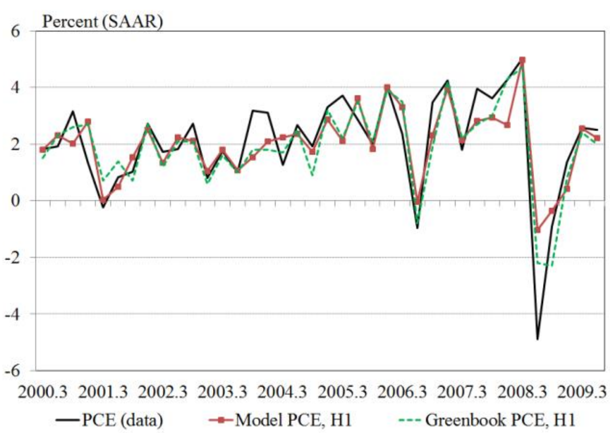
(c) Core CPI, first half of quarter



(d) Core CPI, second half of quarter



(e) PCE, first half of quarter



(f) PCE, second half of quarter

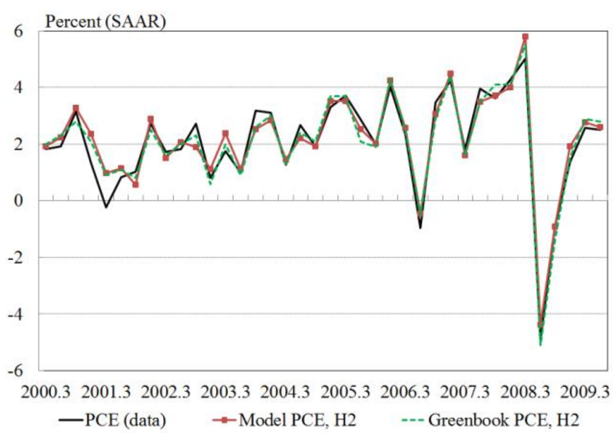
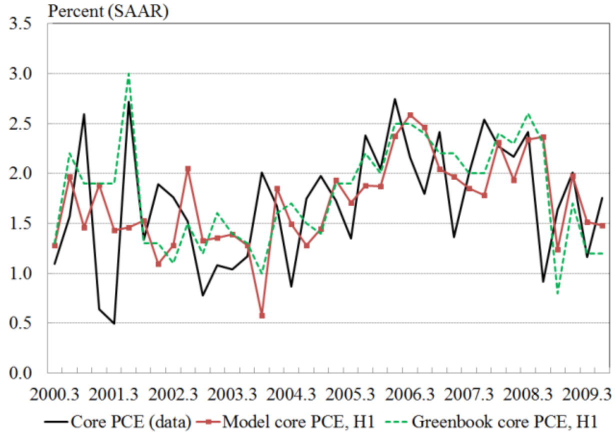
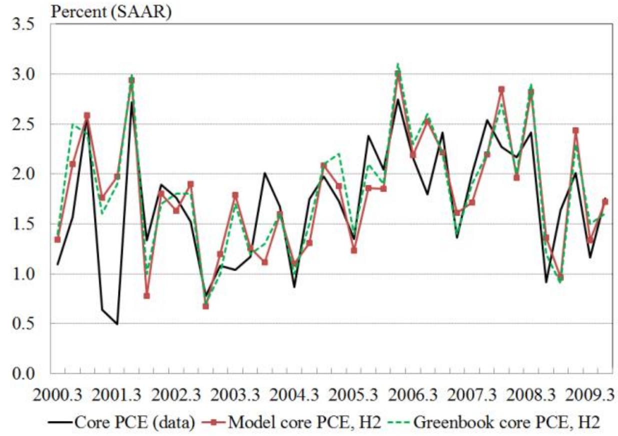


Figure A3 (continued): Model and Greenbook Inflation Nowcasts

(g) Core PCE, first half of quarter

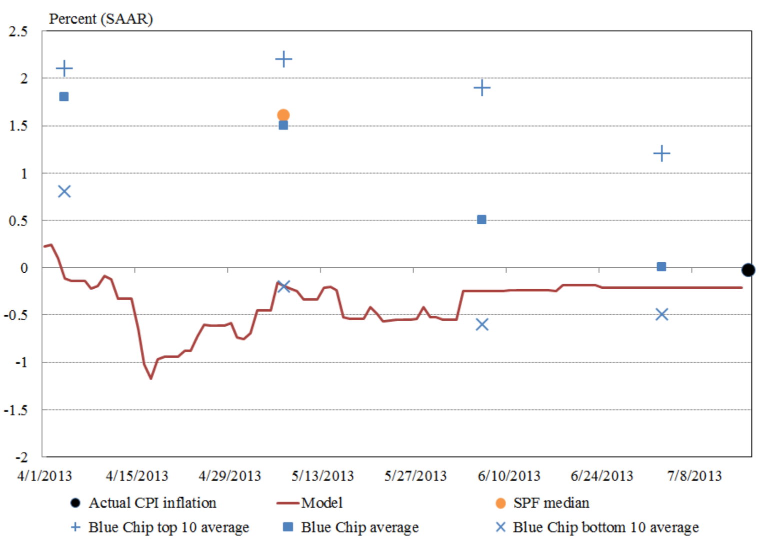


(h) Core PCE, second half of quarter



Notes: 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 2009Q4. The PCE and core PCE exercises use real-time data from 2000Q3 through 2009Q4.

Figure A4: 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 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 reported by the BLS for 2013Q2.