Inflation, Trends, and Long-Run Expectations: Perspectives from Forecasting Research

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For some time now, the Federal Open Market Committee (FOMC) has wrestled with questions surrounding a shortfall of inflation from the objective of 2 percent. A key question is whether a shortfall will persist and – in the broader context of soft inflation for the better part of the past 10 years – mean that standard frameworks for forecasting inflation are much less useful than they once were. More specific questions surround the stability and general efficacy of the conventional Phillips curve; the level of the underlying long-run trend of inflation and its value for forecasting inflation; and the measurement of long-run inflation expectations and their role in the inflation process. For example, does the weakness of inflation in the face of a strong economy necessarily mean the slope of the Phillips curve has fallen? As additional examples, to what extent are survey-based measures of long-run inflation expectations reliable indicators of the long-run trend in inflation, and are econometric trend measures or survey-based expectations more useful for forecasting inflation?

To provide perspective on some of these questions, this memo draws on the large body of academic and central bank research on inflation forecasting. The first section presents a simple, general forecasting model and summarizes the established research findings on the key components of the model. The second section uses a specific model, developed in Chan, Clark, and Koop (2018), to shed some light on recent inflation behavior, inflation's long-run trend, and long-run inflation expectations. The third section summarizes the analysis and briefly discusses implications.

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As the memo will describe, as frustrating as recent inflation challenges have been, in historical context they are not necessarily unusual by the standards of the research literature on inflation forecasting. With any given model or approach, forecast uncertainty is sizable, and through the lens of some simple benchmarks, recent uncertainty appears consistent with historical norms. Considerable uncertainty also surrounds the choice of components in a forecasting model. For example, in historical comparisons, several models incorporating different measures of trend inflation have performed about equally well in forecasting inflation. Yet, at a given moment in time, these same specifications can yield very different forecasts. In addition, the historical evidence indicates forecasting performance is subject to considerable instabilities over time. For example, an indicator that improves forecast accuracy over one period rarely does so over most other periods. Regarding current levels of inflation, its long-run trend, and long-run inflation expectations, the flexible model of Chan, Clark, and Koop (2018) yields stable trend estimates, but those trends are slightly to modestly below levels consistent with PCE inflation of 2 percent; forecasts from the model gradually return to these below-target trends. However, forecasts from the model advocated in Faust and Wright (2013), which has fared well in historical comparisons, put PCE inflation back at 2 percent by the end of next year.

On the basis of these findings, the memo concludes that, although it is premature to infer that something has recently gone wrong with our forecasting models, there remains considerable scope for developing better ones, and it continues to be important to consider a range of indicators and forecasts, as well as the considerable uncertainty around the inflation outlook.

Lessons from the Research Literature on Forecasting

The inflation models commonly considered in the forecasting literature share the basic structure of models commonly used at central banks. In general, these models relate inflation to:

economic drivers that may include measures of economic activity and import price inflation; a measure of trend inflation or long-run inflation expectations; and past inflation. The basic model takes the following form:

$$\pi_t - \pi_t^* = \alpha' X_{t-1} + \beta(\pi_{t-1} - \pi_{t-1}^*) + e_t, \tag{1}$$

in which π_t denotes inflation at an annualized quarterly rate; π_t^* measures trend inflation (as detailed below, captured with either an econometric trend or a long-run inflation expectation); X_{t-1} contains the set of economic drivers; and e_t denotes the prediction error. (As described in Detmeister, Laforte, and Rudd (2014), the Board staff's forecasting framework shares this basic structure.) The model is written in a one-step ahead predictive form with inflation in period *t* on the left-hand side and period *t-1* information on the right-hand side; multi-step forecasts can be obtained by iterating forward and combining one-step ahead forecasts.

Many studies in the literature generalize this model along various dimensions, such as by including longer lags or allowing the coefficients of the model to vary over time. Some studies have considered non-linear versions, in which the sensitivity of inflation to economic activity varies with the strength of the economy.[1] However, the simple formulation of equation (1) suffices to capture the essential elements and to provide a basis for organizing implications from the literature on forecasting of inflation. Although such forecasting specifications are not structural economic models, as described below they reflect some of the key drivers of inflation in new Keynesian dynamic stochastic general equilibrium (DSGE) models.

Historically, the errors of inflation forecasts obtained with such models of the general form of equation (1) have been sizable, with some variation in magnitudes over time. Figure 1 reports absolute values of year-ahead forecast errors (headline inflation in the top panel and core inflation in the bottom panel) obtained from a simple – but historically effective – version of the

[1] See, for example, Kumar and Orrenius (2014), Nalewaik (2016), and Doser, et al. (2017).

model due to Faust and Wright (2013).[2] (As detailed below, their specification restricts the general model by omitting economic drivers and fixing the coefficient β.) Forecasts have been more accurate in the period since 1990 than for most of the 1980s, with the exception of large headline inflation forecast errors (associated with commodity price swings) around the period of the Great Recession.[3] Since 1990, the absolute error has averaged about ¾ percentage point for headline PCE inflation and ½ percentage point for core inflation.[4] Forecast accuracy over the past several years has been broadly comparable to these historical norms. Although recent forecast errors appear modestly larger than those observed for much of the 2001-2007 economic expansion, they are comparable in size to the errors of the 1990s.

That said, estimates not shown in the interest of brevity indicate that, for forecasting inflation one year ahead, the variation of inflation "explained" by this version of the basic model – that is, the predictive content of the forecasts for inflation outcomes (both headline and core), as captured by a simple correlation of the forecasts with actual inflation – appears to have been relatively small in recent years.[5] As this relates to some of the recent frustrations with inflation forecasts, one might view the glass as half-full or half-empty: forecast accuracy is in line with historical norms, but the forecasts haven't had strong predictive content for inflation outcomes, (with exceptions in selected years). Put another way, although the size of the unpredictable

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[2] For simplicity, these results are based on the currently available measures of inflation and abstract from data revisions. Although data revisions sometimes can be sizable, evidence from various studies indicate that the basic findings described in this paragraph also apply in real-time forecasts. In the reported results, the forecasts are constructed with the model given in equation (2), using the FRB/US measure of inflation expectations (PTR). Year-ahead forecasts are obtained by iterating forward one-step ahead forecasts and time-aggregating to obtain four-quarter rates. As in Faust and Wright (2013), the forecasts are constructed by assuming long-run inflation expectations remain constant at the most recently observed (at the time the forecast is formed) value.

[3] These findings obtain with not only this forecasting model but also other common one-year ahead forecasts, such as forecasts of inflation (four-quarter rates) in the GDP price index from the Survey of Professional Forecasters or simple forecasts of headline and core PCE inflation specified as the past year's (four-quarter) inflation rate.

[4] The corresponding root mean square errors are 1.2 for headline inflation and 1.0 for core inflation.

[5] Reduced predictability is likely associated with a falloff in inflation persistence: estimates of models with time-varying parameters indicate the persistence of inflation has been lower in the period since the early 1990s than before.

component of inflation (the forecast error, represented by the error term of equation (1)) hasn't changed much, the magnitude of the predictable component (captured by the lags of inflation and other indicators on the right-hand side of equation (1)) has been smaller in recent years than in the past.

In addition, some participants might be more concerned about patterns in the direction of forecast errors than the magnitude of the errors. For example, the Faust and Wright (2013) model has consistently over-predicted inflation for much of the past 10 years. However, in the aggregate, the Committee's year-ahead forecasts have not displayed a clear bias. For 2008 through 2016, the mid-point of SEP submissions made at the beginning of each year or the end of the previous year has had an average error of less than +/- 10 basis points for both headline and core PCE inflation, with over-predictions about as common as under-predictions.[6]

Role of economic drivers

As described in the companion memo Fuhrer (2018), in canonical DSGE models, the real marginal cost of production of output is a key driver of inflation. Under some assumptions, real marginal cost can be represented by an output gap. Many studies of inflation forecasting have considered the efficacy of output gap estimates, as well as unemployment gap estimates and other indicators of marginal cost, for forecasting inflation. Still others have examined the predictive content of a broader array of measures of economic activity, such as growth rates of output rather than gaps, and productivity growth. The forecasting literature has also considered a wide range of other indicators that might be thought to have predictive content for inflation,

[6] Using the publicly available projection summaries, the mid-point of SEP forecasts is measured as the mid-point of central tendencies for 2008 through 2015 and the median for 2016. For 2008 through 2012, the forecasts are taken from the January SEP of each year. For 2013 through 2016, the forecasts are taken from December SEP of the previous year. Actual inflation is measured with the currently available headline and core PCE price indexes.

including various asset prices, import prices, exchange rates, and measures of supply shocks related to food or energy.

Despite the theoretical role of economic drivers in structural models and their relationship to inflation based on conventional wisdom, the evidence from the forecasting literature indicates that the variables considered generally do not improve forecast accuracy on a consistent basis. In fact, including such variables typically harms forecast accuracy; inflation models that exclude indicators of economic activity, import prices, or other indicators yield more accurate forecasts.[7] That said, the literature provides ample evidence of indicators that are sometimes – but not consistently over long time periods – helpful for forecasting inflation. Put another way, instabilities in the performance of inflation forecasting models that include economic indicators are the norm and not the exception.[8] One notable example is that, conditional on knowing that the state of the economy is weak, a Phillips curve can be successful in forecasting inflation (Dotsey, Fujita, and Stark (2017)).[9]

These forecasting challenges raise an obvious question: why do economic drivers fail to consistently improve forecasts of inflation? The literature has not yet produced a definitive answer.[10] One econometric explanation is that, although it is truly the case that inflation is related to economic drivers (e.g., the "true" model is a Phillips curve), the relationship is

[7] See, for example, Stock and Watson (1999, 2003, 2007), Faust and Wright (2013), and Dotsey, Fujita, and Stark (2017).
[8] See, for example, Stock and Watson (2003) and Giacomini and Rossi (2009).
[9] The conditional predictive ability found by Dotsey, Fujita, and Stark (2017) may be seen as consistent with the evidence in Stock and Watson (2010) that inflation consistently falls around recessions. However, Dotsey, Fujita, and Stark find that such conditional predictive ability existed in the period before the mid-1980s and not after.
[10] Data revisions may contribute to some of the difficulties detailed in this paragraph. For example, additional noise in preliminary estimates of inflation and indicators such as output gaps and output growth may weaken estimated relationships. In addition, in real time, one-sided filtering at the end of a sample may make it more difficult to estimate output or unemployment gaps precisely enough to be useful for forecasting inflation. For example, Orphanides and Van Norden (2005) find conventional econometric estimates of output gaps to be sufficiently imprecise in real time that output growth is more useful for forecasting inflation. However, Edge and Rudd (2016) find that the real-time accuracy of the Board staff's output gap estimates has improved in recent years, such that, for forecasting inflation, real-time output gap estimates are no less effective than revised estimates. Nonetheless, the Phillips curve still fails to beat the accuracy of benchmark univariate models of inflation.

somewhat weak, with the result that it is often difficult to see accuracy gains with using the drivers to forecast inflation.[11] With econometric models, forecast accuracy hinges on precisely estimated coefficients, and with limited samples of data available in real time, it is difficult to estimate coefficients precisely enough.[12] Yet another explanation is that model instabilities are simply common in inflation forecasting models.[13] Such instabilities might reflect data mining and model overfitting by researchers: statistically speaking, searching for predictive content across variables and models (sometimes known as data snooping) increases the chances of finding a spurious – and therefore not robust across samples – result of predictive content. Alternatively, in forecasting models that are reduced forms of stable structural models, instabilities might arise due to the Lucas critique.

The at-best mixed track record of inflation forecasting models that include economic drivers such as output gaps also points to considerable uncertainty surrounding the appropriate model. Any number of specifications might be seen as viable models of inflation. Such model uncertainty is distinct from uncertainty stemming from parameter estimation and from the error term indicated in the model of equation (1). Conceptually, model averaging can help mitigate or manage model uncertainty. In the forecasting research literature, many studies have found model and forecast averaging (across many models and forecasts) to be effective for improving

[11] For example, Clark and McCracken (2006) attribute a significant portion of the weakness of the out-of-sample forecasting performance of the Phillips curve to the limited power of out-of-sample comparisons to detect true predictive content.

[12] More specifically, observed forecast errors reflect not only the "true" errors of a model but also sampling imprecision associated with estimating coefficients. With the limited data samples available in model-based macroeconomic forecasting, sampling imprecision plays a significant role. As a result, "shrinkage" techniques such as Bayesian estimation are commonly used, especially with larger models, and known to be generally effective in reducing the influence of sampling imprecision and improving forecast accuracy.

[13] As one piece of evidence of instabilities that can be modeled successfully, D'Agostino, Gambetti, and Giannone (2013) find that allowing time variation in the parameters and error variances improves forecasts of inflation. Faust and Wright (2013) also find that such models fare relatively well in inflation forecasting.

forecast accuracy.[14] However, in a broad assessment, Faust and Wright (2013) note that other evidence in the literature indicates that forecast combination does not constitute a "magic bullet" for improving the performance of forecasting models.

Role of long-run trend or inflation expectations

Some familiar DSGE or related structural models incorporate a time-varying trend of inflation, typically driven by time variation in the central bank's inflation target.[15] Examples include the FRB/US model and the DSGE models of the Federal Reserve Banks of Chicago and New York. Depending on other aspects of model specification, the time-varying trend of inflation may or may not complicate the DSGE model's Phillips curve (by adding variables and making some coefficients depend on trend inflation). Some of the academic work with the time-varying trend extension of DSGE models appears to have been motivated in part by evidence from the forecasting literature that, for out-of-sample forecasting of inflation, the best-performing models take a general form in which inflation fluctuates around a smoothly time-varying trend.[16] Cecchetti, et al. (2017) characterize such a model as one in which inflation varies around a time-varying local mean.

With respect to the specification of trend in the forecasting literature, the best-performing versions of the model (1) make use of two different types of measures. In broad terms, these trend measures, embedded in selected models described in this section, perform comparably in

[14] See, for example, Wright (2009), Bjornland, et al. (2012), and Hubrich and Skudelny (2017).
[15] Seminal studies with time-varying inflation trends in structural models include Ireland (2007) and Cogley and Sbordone (2008). Some current DSGE models use survey-based long-run forecasts of inflation as measures of expectations that are included to inform the model's estimates of inflation dynamics and the trend. As Del Negro, Giannone, and Schorfheide (2015) note, such an approach can be viewed as a shortcut to a more structural approach of incorporating learning mechanisms, such as the central bank learning about the output-inflation tradeoff and seeking to set inflation in an optimal way.
[16] For example, Del Negro and Schorfheide (2013) motivate their DSGE model specification with some discussion of the forecasting literature. Key econometric references include, among others, Kozicki and Tinsley (2001), Stock and Watson (2007), Faust and Wright (2013), and Clark and Doh (2014).

forecasting inflation.[17] One approach is to simply define the trend as a long-run forecast from a survey such as the Survey of Professional Forecasters (SPF) or Blue Chip Economic Indicators.[18] Conceptually, measuring trend with a long-horizon expectation is consistent with a common econometric definition of trend as a very long-horizon forecast.[19] It is also consistent with some evidence that private sector forecasters anchor their longer-horizon forecasts around the values of central bank inflation targets.[20] In a comprehensive assessment of inflation forecasting, Faust and Wright (2013) find that the following simple specification, with trend inflation measured as the 7-to-11-year ahead forecast from the Blue Chip survey, performs robustly in historical inflation forecasting:[21]

$$\pi_t - \pi_t^* = 0.46(\pi_{t-1} - \pi_{t-1}^*) + e_t. \tag{2}$$

A second commonly used approach involves specifying a simple process for the trend and estimating it with inflation and, in some studies, additional inflation indicators. In this approach, the trend is commonly treated as unobserved and assumed to be a random walk process, with the combined model for actual and trend inflation taking the form:

$$\pi_t - \pi_t^* = \beta(\pi_{t-1} - \pi_{t-1}^*) + e_t \tag{3}$$

$$\pi_t^* = \pi_{t-1}^* + n_t. \tag{4}$$

[17] See, for example, the comparisons in Clark and Doh (2014) and Chan, Clark, and Koop (2018).
[18] Yet another option could be to measure trend inflation with long-horizon inflation compensation reflected in nominal Treasury and TIPS yields or inflation swaps. However, the short sample of available data precludes historical evaluation of predictive content over a long sample. Moreover, Faust and Wright (2013) argue inflation compensation is too distorted by liquidity and inflation risk premia to be useful for forecasting inflation.
[19] Specifically, it is consistent with the Beveridge-Nelson decomposition.
[20] See, for example, Mehrotra and Yetman (2014).
[21] Faust and Wright (2013) fixed the coefficient at the value of 0.46 obtained by estimating an AR process for inflation in the GNP deflator with data for 1947 through 1959. In their forecasting models for GDP and PCE measures of inflation, Faust and Wright used Blue Chip expectations of inflation in the GDP price index; in models of CPI and core CPI inflation, they used Blue Chip expectations of CPI inflation.

In this approach, inflation can be viewed as reflecting trend and cycle components, with the cycle captured by a mean-reverting process for inflation less trend.[22] Standard econometric methods yield the trend estimate as a projection of the unobserved trend conditional on the observed inflation time series and the model of equations (3) and (4). As noted above, some analyses extend the model by allowing longer lags or time variation in the coefficient β.[23] A number of studies, including Stock and Watson (2007), Clark and Doh (2014), and Chan, Clark, and Koop (2018), have found specific versions of the model with an econometric trend as in equations (3) and (4) to perform well in historical inflation forecasting.

Some other studies have further extended the econometric trend approach by adding other indicators to the model. For example, one approach adds to the model survey-based measures of inflation expectations or bond yields, making them functions of the unobserved trend in inflation.[24] In this case, the resulting estimate of trend is informed by not only inflation but also inflation expectations or bond yields, and trend inflation is restricted in that the model treats it as closely related to these other indicators. The next section of the memo will use a more flexible version of such a model to provide some perspective on recent inflation, its trend, and long-run inflation expectations.

Although allowing a time-varying inflation trend captured by an econometric process has been established as helpful for forecasting inflation in historical analyses, the economic foundations of these representations of trend have some important limitations. Perhaps most

[22] See, for example, Stock and Watson (2007). Many such studies commonly specify the model to include stochastic volatility in the error terms of equations (3) and (4). Stochastic volatility improves model fit and forecast accuracy.
[23] Some other studies work with related, alternative model representations that yield a conceptually and empirically similar econometric trend. These models are simple autoregressions or vector autoregressions with time-varying parameters. See, for example, Cogley, Primiceri, and Sargent (2010) and Peneva and Rudd (2017).
[24] See, for example, Mertens (2016). Still other work, such as Kozicki and Tinsley (2012), takes a somewhat different econometric approach, assuming a process for inflation and survey expectations to be consistent with model-implied forecasts, and estimating the model with data on both inflation and survey expectations.

importantly, these approaches abstract from modeling the fundamental drivers of changes in trend inflation. In typical applications, the estimated trend is informed by the low frequency component of inflation but not much more. Although it is possible to use other, forward-looking indicators, such as bond yields, to inform and in some ways improve trend inflation estimates, there isn't much evidence that doing so helps forecast accuracy.[25] In addition, the efficacy of including time-varying trends in inflation models may be driven by the unique circumstances of the upward trend in inflation from the mid-1960s through the early 1980s and the subsequent disinflation. As these events fade further into the past, if inflation remains relatively stable, the importance of modeling a time-varying trend in inflation – either with a survey-based expectation or econometrically – could decline.

Although some studies have concluded that one measure of trend inflation is better for forecasting than another, in broad comparisons there is little to distinguish the performance of different econometric trend specifications that fit within the class described above or to distinguish the purely survey-based approach from econometric trend approaches. One possible explanation relates to inflation persistence. Historically, inflation has been persistent, partly due to a time-varying trend and partly due to persistence in inflation less trend (the cyclical component of inflation). Limited samples of data make it difficult to precisely separate persistence due to trend from that due to inflation less trend, which in turn leads to challenges in establishing meaningful differences in forecasting performance for broadly similar measures of trend inflation.

[25] See, for example, Clark and Doh (2014).

Despite the similarity in forecast accuracy over periods of 20-30 years, at any given point in time, models with different trends can yield disparate forecasts of future inflation.[26] Consider, for example, current – using data through 2017:Q3 – forecasts of headline PCE inflation obtained from: (1) a version of the model of Faust and Wright (2013), as in equation (2), that measures trend inflation with the SPF expectation of PCE inflation and assumes the trend to remain at its 2017:Q3 value over the forecast horizon; and (2) the Stock and Watson (2007) formulation of the model with an econometric trend, corresponding to equations (3) and (4) with the coefficient β set to 0. The Faust-Wright forecast has inflation rising to reach 2 percent in late 2018.[27] The Stock-Watson forecast puts inflation at about 1.3 percent for the foreseeable future. (Forecasts of core PCE inflation are qualitatively similar, although the Stock-Watson forecast is a little higher, at 1.5 percent.) The difference in the forecasts reflects a sizable gap between the current trends assumed or estimated by each model. Taken in isolation, these forecasts of course would have quite different implications for policy. However, historical evidence that shows these models to have comparable forecast accuracy suggests that both projections should get some weight in assessing the inflation outlook.

As this current forecast comparison suggests, the choice of trend measure represents another important source of forecast model uncertainty. Survey-based measures and selected econometric measures all can perform well and in that respect be seen as viable. Given other work in the forecasting literature on model combination, it would be natural to consider an

[26] The evidence in studies such as Faust and Wright (2013), Clark and Doh (2014), and Chan, Clark, and Koop (2018) indicates that this statement about similarity in forecast accuracy generally applies across horizons ranging from short (1-2 quarters ahead) to medium (1-2 years ahead) to long (6-10 years ahead). However, in part reflecting some of the instabilities in performance described above, the literature includes exceptions.

[27] As noted in the previous subsection, in recent years forecasts from the preferred model of Faust and Wright (2013) have exceeded inflation outcomes. Although the model has historically performed well, this recent bias might be seen as raising questions about the model – in keeping with the questions surrounding inflation described in the introduction.

average of forecasts from models with alternative measures of trend. However, the available evidence on historical forecasting has failed to find any gain in forecast accuracy to doing so.[28]

One Model-Based Perspective on Inflation, Inflation Trends, and Survey Expectations

To provide perspective on the recent behavior of inflation, its trend, and survey measures of long-run inflation expectations, this section uses an econometric model that fits within the class described above. The model is designed to not only forecast inflation but also permit an assessment of the relationships among inflation, its trend, and inflation expectations, allowing considerable flexibility in the relationships. In particular, the model permits an assessment of the information content of measured long-run inflation expectations for trend inflation.[29]

The model includes as observed variables both inflation and a survey-based, long-run inflation expectation, denoted s_t, and trend inflation as an unobserved variable:

$$\pi_t - \pi_t^* = \beta_t(\pi_{t-1} - \pi_{t-1}^*) + e_t \tag{5}$$

$$s_t = d_{0,t} + d_{1,t}\pi_t^* + v_t \tag{6}$$

$$\pi_t^* = \pi_{t-1}^* + n_t. \tag{7}$$

The coefficients β_t, $d_{0,t}$, and $d_{1,t}$ follow simple statistical processes that permit smooth time variation.[30] This model relates both inflation and the survey expectation to trend inflation. Accordingly, both inflation and the survey expectation inform the estimate of the trend, with

[28] Clark and Doh (2014) find no gain to averaging forecasts across models featuring different treatments of trend inflation. As noted above, although many studies have found model and forecast averaging to be effective for improving forecast accuracy, Faust and Wright (2013) observe that forecast combination does not constitute a magic bullet.
[29] The model can be extended to also include information on short-horizon survey forecasts or economic activity. In Chan, Clark, and Koop (2018), adding a short-horizon forecast from Blue Chip yielded results very similar to those for the baseline model with just a long-run expectation. Adding an unemployment gap to the inflation equation (5) had little effect on estimated trend inflation but caused model fit and forecast performance to deteriorate.
[30] More specifically, β_t follows a random walk process bounded to impose stationarity on inflation less its trend, and $d_{0,t}$ and $d_{1,t}$ follow AR(1) processes. In the interest of brevity, the section omits a description of some complications included in the specification actually used: stochastic volatility in the innovations of equations (5) and (7) and a moving order process of order one in the error term of equation (6). See Chan, Clark, and Koop (2018) for further details on the model, referred to as specification M1.

implicit weights reflecting their signal for the trend implied by the model of equations (5) through (7) and the processes of the coefficients.[31]

By design, the model admits the possibility that the survey expectation may not be closely tied to trend inflation. The survey expectation may move more or less than one-for-one with trend inflation (with an equation (6) slope coefficient $d_{1,t}$ that differs from 1) or differ from trend by a constant wedge (with a non-zero intercept $d_{0,t}$). The model also allows for time variation in the sluggishness of the cyclical component of inflation (through the coefficient β_t of equation (5)) and in the links between the survey expectation and the trend (through the coefficients $d_{0,t}$ and $d_{1,t}$ of equation (6)). Although this flexible formulation can be used to provide a useful empirical assessment, it – like other models featuring econometric trends of inflation – cannot answer some of the economic questions surrounding inflation's behavior. For example, it does not explain why long-run inflation expectations exceed an econometric estimate of inflation's long-run trend, nor does it link expectations or trend inflation to monetary policy.

From estimates obtained with various measures of inflation and inflation expectations for the United States, Chan, Clark, and Koop (2018) conclude that long-run survey expectations provide additional information that both improves the model's ability to fit actual inflation and improves estimates of trend inflation by reducing real-time imprecision.[32] However, the estimates also indicate that the survey forecasts cannot simply be equated with trend inflation: although the surveys move with the trend to a large extent, persistent differentials exist.[33] Applying the model to data for a few other countries yields similar results. Finally, for

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[31] That is, the estimation method yields a trend estimate that is a projection of the unobserved trend conditional on the observed inflation and expectations time series and the model of equations (5) through (7).

[32] The general results described here have some robustness across measures of inflation and survey expectations. Chan, Clark, and Koop (2018) focus on results for CPI inflation and long-run inflation expectations from Blue Chip. They report qualitatively similar results with (1) core CPI inflation and the same Blue Chip expectations and (2) PCE inflation and the PTR expectations of the FRB/US model.

[33] The differentials reflect both estimates of the intercept $d_{0,t}$ that exceed 0 and estimates of the slope coefficient $d_{1,t}$ that sometimes differ from 1.

forecasting U.S. inflation, this generalized model is as accurate as the best-performing benchmarks described above (particularly, models attributed to Stock and Watson (2007) and Faust and Wright (2013)).

Figures 2 and 3 provide estimates of trend inflation obtained with the model of equations (5) through (7), using quarterly data through 2017:Q3. One set of estimates is based on PCE inflation – either headline (top panel) or core (bottom panel) – and long-run inflation expectations measured with the PTR series of the FRB/US model, with data starting in 1960 (to make recent changes easier to discern, the charts report trend estimates starting in 1990).[34] Motivated by ongoing discussion of the information content of the University of Michigan's Survey of Consumers, a second set of estimates is based on CPI inflation – again, either headline or core –and the 5-to-10-year ahead median Michigan inflation expectation, with data starting in 1990.[35] The Michigan survey is paired with CPI inflation in light of the broader public's likely greater familiarity with CPI compared to PCE inflation.

As indicated in Figures 2 (PCE) and 3 (CPI), recent estimates of trend inflation appear to be slightly to modestly below levels consistent with PCE inflation of 2 percent – in keeping with the baseline assessment of Board staff (which in turn informs the judgmental inflation projection

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[34] Board staff have constructed the PTR series to capture the trend in PCE inflation. The PTR series splices (1) SPF expectations to (2) earlier expectations from a survey by Richard Hoey to (3) an econometric estimate obtained with the approach of Kozicki and Tinsley (2001). Until 2007, when SPF expectations of PCE inflation became available, the PTR series adjusts the reported Hoey and SPF expectations of CPI inflation for the average differential between CPI and PCE inflation. In estimates of the model described in this section, similar results obtain with an alternative measure of survey expectations from Peneva and Rudd (2017) that adjusts the series to account for methodology changes reflected in PCE prices but not real-time SPF expectations of CPI inflation. Using this alternative expectations measure lowers the differential between the expectation and the trend estimate up until about 1999, after which estimates are little affected.

[35] To assess dependence on particular measures of expectations, a third set of estimates (not shown) is based on CPI inflation paired with a long-run inflation expectation measured with a CPI-based PTR series (constructed as PTR omitting the CPI-PCE adjustment and using SPF expectations of CPI rather than PCE inflation since 2007). These estimates are qualitatively similar to those described above. For core CPI inflation, measuring expectations with PTR-CPI yields results essentially the same as those described for Michigan expectations. For headline CPI inflation, the trend obtained with the PTR-CPI expectation is a little lower and slightly less variable in recent years than the estimate obtained with the Michigan expectation.

in the Tealbook). In general, both the PTR and Michigan expectations measures exceed the estimated long-run trends in headline and core inflation, both at present and historically. However, the estimated trends have remained broadly stable over the past couple of years.

More specifically, after peaking in 1981 at 1.3 percentage points, the differential between the PTR measure of expectations and the estimated trend in headline PCE inflation narrowed through the mid-1990s and then stabilized (Figure 2). As of 2017:Q3, the model-estimated trend PCE inflation rate is 1.7 percent, compared to a long-run PTR (and SPF) expectation of 2 percent. The trend estimate has been within 5 basis points of 1.7 percent since early 2013. This trend rate is only very slightly lower than the estimate of 1.8 percent for 2007:Q4, when the recession started. The current trend estimate for core PCE inflation stands at 1.6 percent. Although there is uncertainty around the trend estimates, the upper bound of the 68 percent confidence interval is 1.9 percent for headline inflation and 1.7 percent for core, in both cases slightly to modestly short of the Committee's 2 percent objective.

The difference between the Michigan expectation and the estimated CPI inflation trend also narrowed for much of the 1990s; then, after stabilizing, this difference began to drift up in advance of the Great Recession before narrowing again more recently, to the levels that prevailed in the early 2000s (Figure 3). As of 2017:Q3, the model-estimated trend in headline CPI inflation is 2.1 percent, compared to the Michigan expectation of 2.5 percent. Under an assumption that the normal differential between CPI and PCE inflation remains at its 2000-2017 historical average of 30 basis points, the model's current estimate of the trend in headline CPI inflation is slightly below levels consistent with PCE inflation of 2 percent. If instead the normal differential is taken to be the 20 basis point difference in the current (2017:Q4) long-run expectations of CPI and PCE inflation from the SPF, the estimated trend from the headline CPI inflation model is only a little below a level consistent with the FOMC's 2 percent PCE inflation objective. That said, the current 1.9 percent estimate of the trend from the core CPI inflation model is more unambiguously below a level that would be consistent with PCE inflation of 2 percent.

The estimated trends in headline and core CPI inflation have been stable for the past two years, but at levels slightly (10-20 basis points with headline inflation and a little less with core inflation) below the estimates for 2012-2013. Since the Great Recession began, the Michigan survey has posted a sharper falloff than the estimated trends for headline and CPI inflation; the model estimates attribute most of the change in the Michigan survey expectation to a decline in the intercept of equation (6).

The inflation forecasts from the model reported (on a Q4/Q4 basis) in Figures 4 and 5 directly reflect the trend estimates; the forecasts are slightly to modestly below levels consistent with 2 percent PCE inflation.[36] As indicated in Figure 4, the model projects a small rise of PCE inflation to its 1.7 percent trend, achieved in 2019:Q4. The model makes a similar projection for core PCE inflation. As shown in Figure 5, headline CPI and core CPI inflation are forecast to rise to their estimated trends of 2.1 percent and 1.9 percent, respectively. Of course, uncertainty surrounding these forecasts is considerable, and inflation rates consistent with PCE inflation of 2 percent are within or not much outside 68 percent confidence bands. For example, in the estimates based on PCE inflation and the PTR measure of expectations, the 68 percent band around the forecast of PCE inflation in 2019:Q4 ranges from 0.9 percent to 2.4 percent; the 68 percent band around the projection of core PCE inflation in 2019:Q4 ranges from 1.3 percent to 1.9 percent.

[36] With this model, the forecasts do not involve any assumption about the levels of inflation expectations over the forecast horizon. The forecasts are constructed conditional on the model and observed data on inflation and expectations through 2017:Q3.

Summary and Implications

While historical precedent may be cold comfort, in the context of the evidence from the research literature on inflation forecasting, the recent challenges in forecasting inflation are not all that unusual. With any given model or approach, forecast uncertainty is sizable, and recent uncertainty appears consistent with historical norms. Considerable uncertainty also surrounds the choice of the components of a forecasting model. For example, in the past, several models of inflation incorporating different measures of trend inflation have performed about equally well in forecasting inflation. Yet, at a given moment in time, historically successful specifications can yield very different forecasts. Moreover, although conventional structural models imply economic drivers such as the output gap and import prices should be useful predictors of inflation, in practice including such drivers in models typically reduces forecast accuracy. Finally, the historical evidence indicates forecasting performance is subject to considerable instabilities over time.

Regarding current levels of inflation, its trend, and long-run inflation expectations, a flexible model developed in Chan, Clark, and Koop (2018) yields stable trend estimates in recent years, below the corresponding levels of the survey-based inflation expectations included in the model to inform the trend estimate. The estimated trends are slightly to modestly below levels consistent with PCE inflation of 2 percent, and forecasts from the model gradually return to these trends. Among forecasts from other models successful in the literature, some are broadly consistent with this picture and others more optimistic. In particular, projections from the Stock and Watson (2007) model are modestly below those from the Chan, Clark, and Koop (2018) model. But an alternative forecast from the preferred model of Faust and Wright (2013) – one plausible in light of its historical success in the broader forecasting literature – has PCE inflation rising back to 2 percent by the end of next year, reflecting its assumed anchoring at survey-based long-run expectations.

Based on the inflation forecasting literature, it is premature to conclude from recent experience that something has gone wrong with all of our models. In broad terms, the models are no more limited now than in earlier periods. Research to improve inflation forecasting models and techniques remains important. In setting the course of monetary policy, it continues to be important to consider a range of indicators, a range of forecasts drawn from approaches that have been shown to be effective historically, and the considerable uncertainty that surrounds the inflation outlook.

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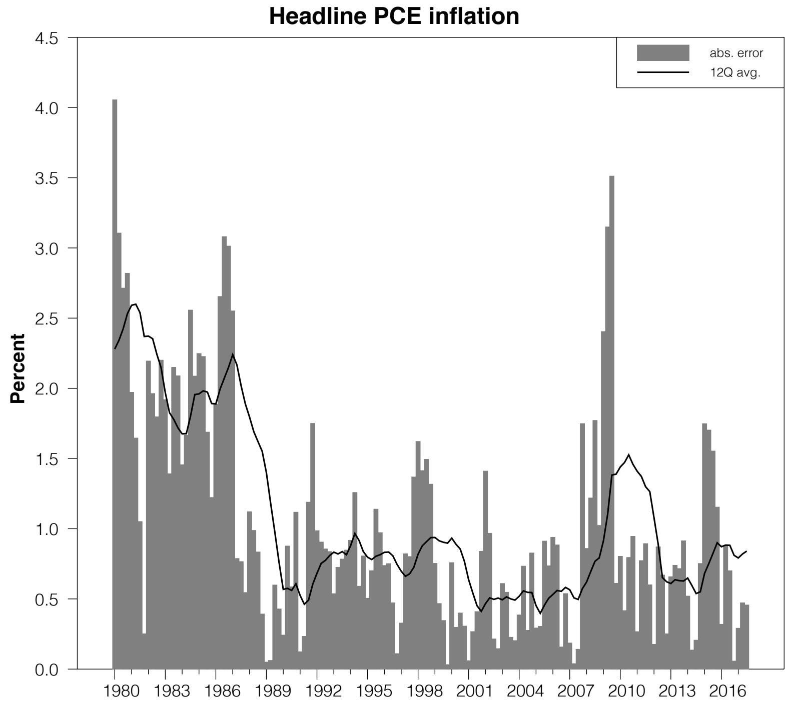
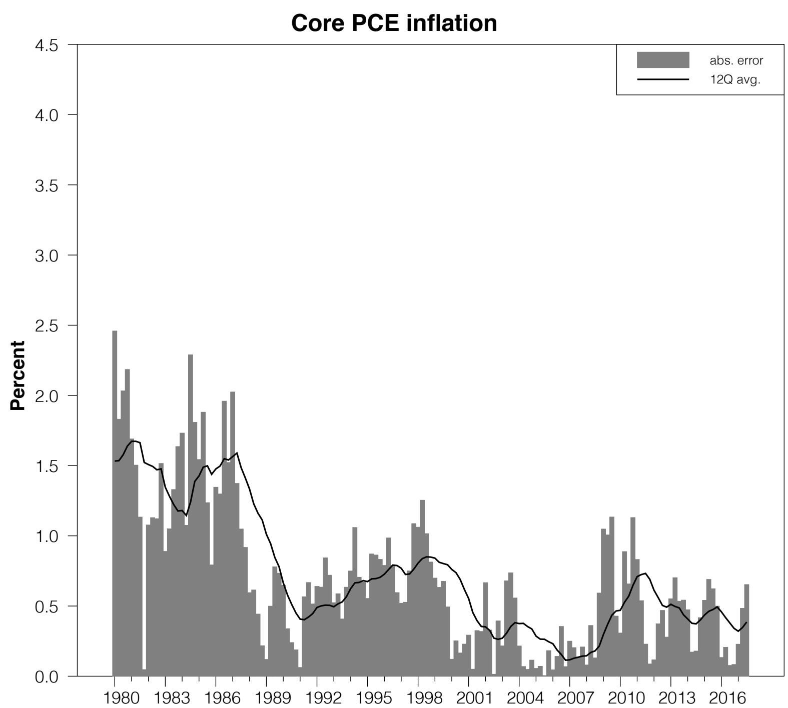
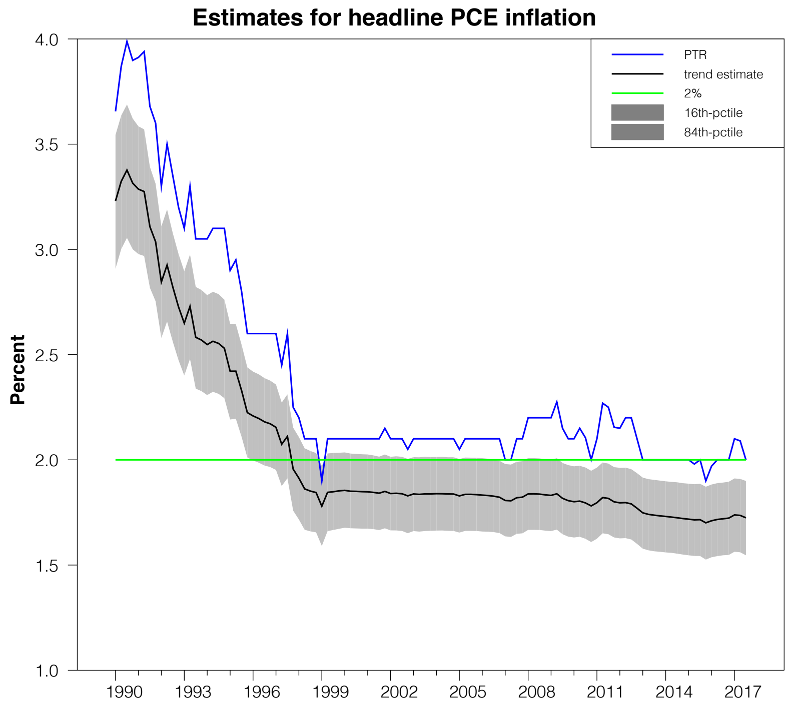
Figure 1: Absolute Values of Year-Ahead Forecast Errors

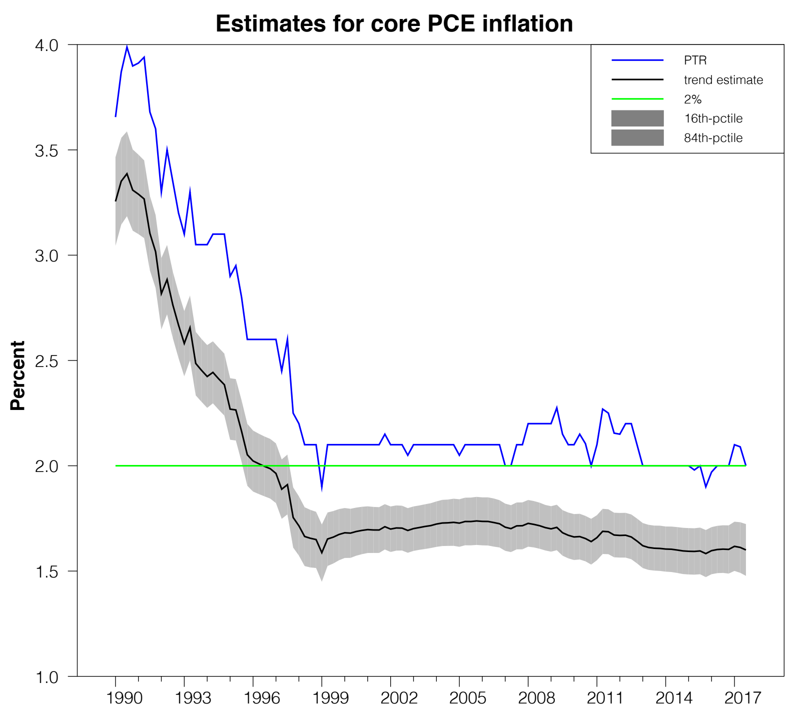




Note: The figure reports absolute forecast errors obtained from the Faust and Wright (2013) model with a fixed AR(1) coefficient of 0.46 and trend inflation measured by the PTR trend of the FRB/US model. Sources: Bureau of Economic Analysis, Federal Reserve Board of Governors, and author's calculations.

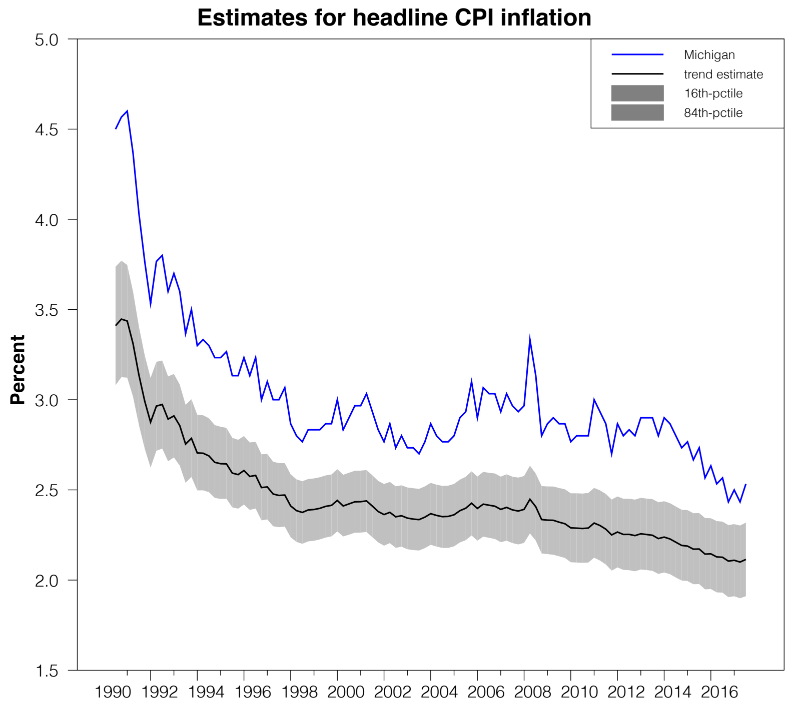
Figure 2: Trend Estimates for PCE Inflation Measures

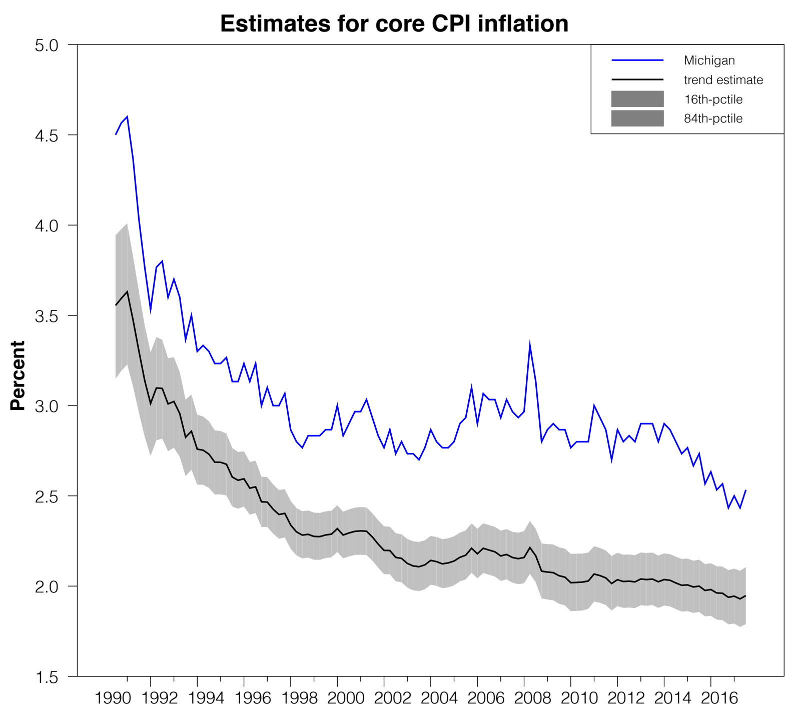




Note: The figure reports estimates obtained from the model of Chan, Clark, and Koop (2018) with data on headline or core PCE inflation and the PTR measure of long-run inflation expectations. Sources: Bureau of Economic Analysis, Federal Reserve Board of Governors, and author's calculations.

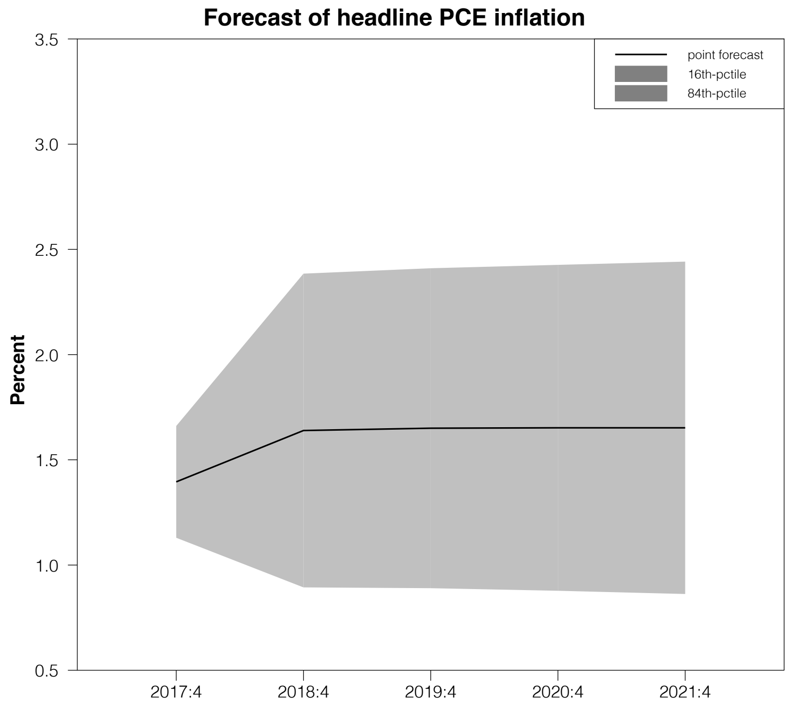
Figure 3: Trend Estimates for CPI Inflation Measures

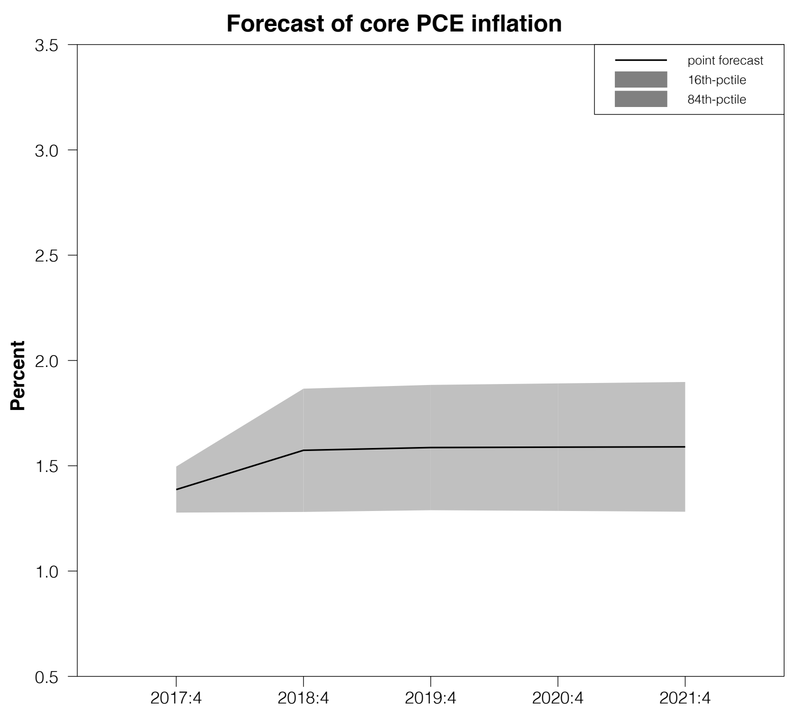




Note: The figure reports estimates obtained from the model of Chan, Clark, and Koop (2018) with data on headline or core CPI inflation and the Michigan measure of long-run inflation expectations. Sources: Bureau of Labor Statistics, University of Michigan Survey of Consumers, and author's calculations.

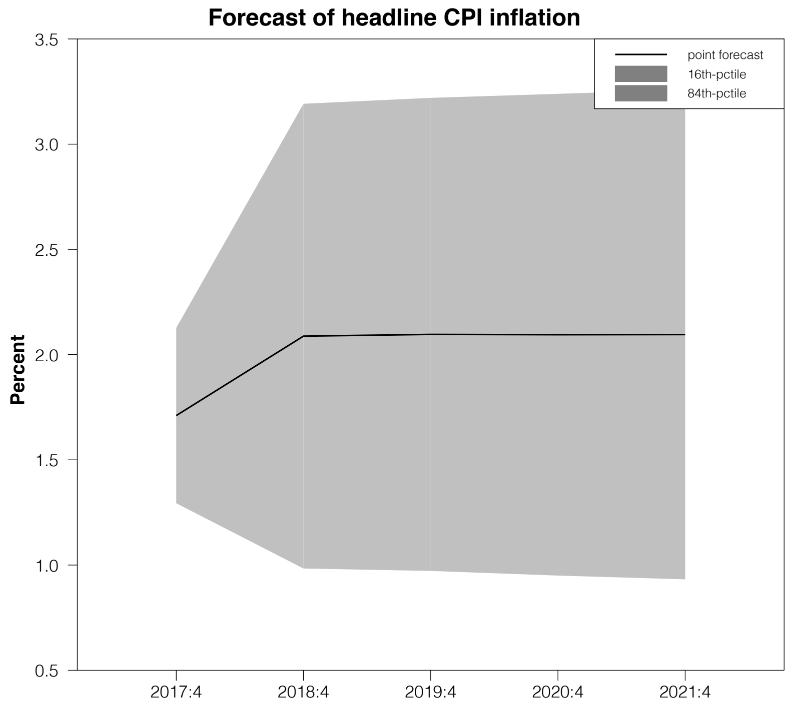
Figure 4: Forecasts of PCE Inflation Measures

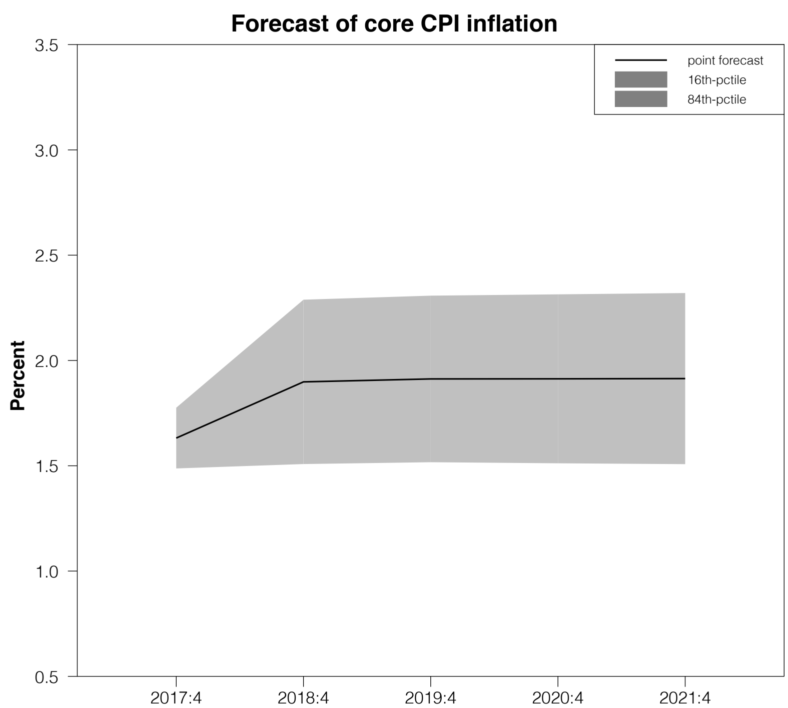




Note: The figure reports forecasts obtained from the model of Chan, Clark, and Koop (2018) with data on headline or core PCE inflation and the PTR measure of long-run inflation expectations. Sources: Bureau of Economic Analysis, Federal Reserve Board of Governors, and author's calculations.

Figure 5: Forecasts of CPI Inflation Measures





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