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Randal J. Verbrugge and Saeed Zaman

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Improving Inflation Forecasts Using Robust Measures*

Randal Verbrugge
Federal Reserve Bank of Cleveland, US, and
NBER/CRIW

Saeed Zaman
Federal Reserve Bank of Cleveland, US

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Abstract

Both theory and extant empirical evidence suggest that the cross-sectional asymmetry across disaggregated price indexes might be useful in the forecasting of aggregate inflation. Trimmed-mean inflation estimators have been shown to be useful devices for forecasting headline PCE inflation. But does this stem from their ability to signal the underlying trend, or does it mainly come from their implicit signaling of asymmetry (when included alongside headline PCE)? We address this question by augmenting a "hard to beat" benchmark inflation forecasting model of headline PCE price inflation with robust measures of trimmed-mean estimators of inflation (median PCE and trimmed-mean PCE) and robust measures of the cross-sectional asymmetry (Bowley skewness; Kelly skewness) computed using the 180+ components of the PCE price index. We also construct new trimmed-mean measures of goods and services PCE inflation and their accompanying robust skewness. Our results indicate significant gains in the point and density accuracy of PCE inflation forecasts over medium- and longer-term horizons, up through and including the COVID-19 pandemic. We find that improvements in accuracy stem mainly from the trend information implicit in trimmed-mean estimators, but that skewness is also useful. Median PCE slightly outperforms trimmed-mean PCE; both outperform core PCE. For point forecasts, Kelly skewness is preferred; but for estimating stochastic volatility, Bowley skewness is preferred. An examination of goods and services PCE inflation provides similar inference.

Keywords: median PCE inflation, trimmed-mean PCE, disaggregate inflation, skewness, forecasting

JEL classifications: E31, E37, E52

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1. Introduction

Evolution in the value of money – i.e., inflation, or the percentage change in the price level – is a central concern of monetary policy. Accordingly, policymakers at most central banks monitor a range of inflation measures to come to an informed assessment about the underlying inflationary pressures. Over the past decade, increased attention has been paid to trimmed-mean inflation estimators,[1] as these provide signs of any broad-based inflationary pressures or the lack of them (see Mertens, 2016; Verbrugge, 2021). During the reopening of the economy in 2021 as the COVID-19 pandemic eased, when a handful of disaggregate components (e.g., used and new cars prices, airline fares, lodging) were experiencing strong inflationary pressures that were driving up aggregate inflation, the developments in trimmed-mean inflation measures provided particularly important information about the future trajectory of inflation.

Inflation in many countries has become notoriously difficult to forecast, possibly owing to the success of monetary policy in anchoring inflation expectations. But forecasters have had some success in approximating the inflation process as a univariate process; indeed, the simple univariate forecasting model of Faust and Wright (2013) is difficult to beat. Alternatively, inflation is often modeled as a multivariate process. The most popular multivariate specification is the Phillips curve, in which inflation is specified as a function of its own lags, an estimated unemployment (or output) gap, and possibly other covariates such as survey expectations. Indeed, the Phillips curve occupies a central place in the inflation forecasting literature;[2] it has

[1] In this paper, we refer to both median inflation measures (such as the median PCE) and trimmed-mean inflation measures (such as the trimmed-mean PCE) as trimmed-mean measures.
[2] See Gordon (2011) for its interesting history. The literature on forecasting inflation is vast. In addition to univariate models and Phillips curve models, VAR forecasting models are common. Occasionally, forecasters eschew the aggregate price index and instead forecast components of the price index (see, e.g., Tallman and Zaman, 2017) or use methods that estimate the common factor from a large number of disaggregated price indexes (see, e.g., Stock and Watson, 2016).

long been the bedrock of inflation forecasting, and its operation is often thought to be central to how monetary policy affects the economy.

Recent research has documented the usefulness of trimmed-mean estimators in improving inflation forecasts from a variety of time-series models (e.g., Dolmas, 2005; Detmeister, 2011; Meyer, Venkatu, and Zaman, 2013; Mertens, 2016; Dolmas and Koenig, 2019; and Meyer and Zaman, 2019). Carroll and Verbrugge (2019), who introduced the Federal Reserve Bank of Cleveland's median PCE inflation measure, highlight the usefulness of this inflation measure as an inflation trend estimator. Through a simple forecasting exercise, they highlight median PCE's forecasting ability (in forecasting future PCE inflation) compared to the trimmed-mean PCE and its superior forecasting ability compared to core PCE.

The consensus in the literature is that the superior performance of the trimmed-mean estimators in forecasting future inflation results from their ability to signal the trend in inflation. The main rationale behind this consensus is the following: when the underlying distribution is leptokurtic (fat-tailed) and the sample (i.e., the number of components or disaggregates used to compute the aggregate) is not large, as is the case for US inflation,[3] then trimmed-mean estimators are likely to be more accurate estimates of central tendency, compared to the sample mean.

But there is an alternative or complementary explanation for the trimmed-mean estimators' superior predictive performance that has received little attention. In addition to being fat-tailed, as discussed in Section 2, the underlying distribution of inflation components (disaggregates) is also asymmetric, with the degree of asymmetry evolving slowly over time. Consequently, in forecasting models, when trimmed-mean estimators are added alongside

[3]Technically, what matters is not the nominal number of components but rather, given the wide distribution of aggregation weights associated with the components, some notion of an *effective* number.

headline inflation measures, as they typically are in practice, the differential between the two provides an implicit signal about the current degree of asymmetry in the underlying distribution of the components. Both theory and extant evidence, reviewed below, suggest that this signal may have notable predictive content. In this paper, we explore this hypothesis and determine the extent to which the superior forecasting performance of trimmed-mean estimators is driven by their implicit signal of asymmetry. We also explore, following a conjecture in Carroll and Verbrugge (2019) regarding serially correlated forecast errors in the mid-2010s, whether direct inclusion of skewness measures alongside trimmed-mean estimators in forecasting models may further help improve the accuracy of their headline PCE inflation forecasts.[4]

Accordingly, this paper examines both the independent and the joint predictive performance of trimmed-mean estimators and robust asymmetry (skewness) measures to forecast aggregate PCE inflation.[5] Specifically, we make pairwise comparisons of forecast accuracy between univariate, bi-variate, and tri-variate vector autoregressive (VAR) model specifications. In constructing our VAR model specifications, we build upon the "hard-to-beat" Faust and Wright (2013) model, which is a simple univariate AR model in gaps, where the gap is defined as the difference between the inflation measure and long-run inflation expectations of PCE inflation. Our VAR models include additional covariates, a robust skewness statistic, and/or a trimmed-mean inflation measure.

The pairwise comparisons between model specifications allow us to examine both the marginal contribution of skewness measures and trimmed-mean estimators and their joint

[4] The findings of Rich, Verbrugge, and Zaman (2022) also support this conjecture.
[5] An active literature investigates characteristics of the price change distribution (such as asymmetry) *within narrowly defined commodity groups* in order to obtain clues about price adjustment mechanisms (e.g., Midrigan, 2011; Berger and Vavra, 2018; and Luo and Villar, 2020). In contrast, we study the asymmetry of the distribution of price changes *across* commodity groups, in order to obtain clues about the evolution of prices over time.

contribution to potential improvements in the accuracy of PCE inflation forecasts (point and density) above and beyond the univariate AR model of Faust and Wright (2013).[6] For example, to assess the conjecture of Carrol and Verbrugge (2019), we compare the accuracy of PCE inflation forecasts from a tri-variate VAR specification, which jointly models the dynamics of aggregate PCE inflation, a trimmed-mean inflation estimator (median PCE or trimmed-mean PCE), and a robust skewness measure (Bowley skewness or Kelly skewness), to that from a bi-variate VAR model specification, which, along with PCE inflation, includes just the trimmed-mean estimator.

To complete our analysis and provide a broader perspective on forecasting performance, we also compare the accuracy of the aggregate PCE inflation forecast from our VAR model specifications with robust inflation measures: (1) to the bi-variate VAR model embedding a Phillips curve specification, (2) a bi-variate VAR model specification consisting of the exclusionary estimator (core PCE inflation) alongside aggregate PCE inflation, and (3) a tri-variate VAR model specification consisting of PCE and core PCE inflation and a skewness measure (Bowley or Kelly). Finally, motivated by a growing literature exploring the predictive content of goods and services, we investigate the predictive content of robust goods and services measures.

Our key findings are as follows: 1) We find that including our robust measures in the Faust and Wright (2013) benchmark forecasting model improves its ability to forecast aggregate PCE inflation. The statistically significant gains in the accuracy of both the point and the density forecasts are achieved for forecast horizons 1.5 years ahead and greater, which are the forecast horizons most relevant to monetary policymakers. Most of the improvements in accuracy are due

[6] Our approach should not be confused with more common approaches that posit an asymmetric or nonlinear relationship between slack and inflation (e.g., Ashley and Verbrugge, 2020).

to the ability of the trimmed-mean estimators to signal a trend, with only marginal improvements in their ability to send an implicit signal about the skewness. Consistent with the conjecture of Carroll and Verbrugge (2019), the statistically significant gains in accuracy are predominantly observed over the financial crisis and onward sample, including the COVID-19 pandemic period. 2) We find slightly stronger support for median PCE over trimmed-mean PCE in forecasting aggregate PCE inflation, and both outperform the exclusion estimator, core PCE. 3) The model specification embedding the Phillips curve is significantly inferior to specifications without the Phillips curve. 4) For point forecasting, we generally find support for the Kelly skewness statistic over the Bowley skewness measure and from using skewness measures based on month-to-month rather than 12-month trailing inflation rates. However, the Bowley skewness measure is found to be more useful for estimating stochastic volatility. 5) Re-running our analysis separately on goods and services PCE inflation (the two main categories of headline PCE inflation) gives results consistent with the findings for headline PCE inflation.

The paper is organized as follows. Section 2 describes the trimmed-mean inflation estimators and skewness statistics. Section 3 describes the data. Section 4 details the model specifications and the design of the forecasting exercise. Section 5 discusses results. Section 6 explores the efficacy of skewness measures for estimating stochastic volatility. Section 7 concludes.

2. Trimmed-Mean Estimators and Skewness Measures

A price index is a stochastic process that is a complicated convolution of thousands of stochastic processes. The price movements of very particular goods, such as “premium gasoline at the BP Station on 4th and Elm in Lorain, Ohio” and “regular gasoline at the Shell station at 300 Main Street in Cleveland, Ohio,” are aggregated into (changes in) a regional gasoline index, and national gasoline indexes are constructed as weighted averages of regional gasoline indexes. (Some indexes, such as television, auto, and rent indexes, incorporate various adjustments that reflect changes in the quality of the goods and services over time.) Finally, changes in the personal consumption expenditure price Index (PCE price index) are a weighted average of the changes in the indexes of over 180 commodities and services. The weights change over time, reflecting substitution patterns, entry and exit of goods and outlets, and so on.

The evolutions of the underlying stochastic processes are not independent. They reflect a variety of forces such as monetary impulses, changes in transportation costs, transaction technologies and tastes, and productivity growth. They reflect price pressures on *groups* of goods and services. And they reflect idiosyncratic movements as well, themselves driven by changes in information, tastes, technologies, market disruptions, the birth and death of particular outlets, and so on. Any of these influences could be transient or persistent.

One manifestation of the complexity of the evolution of the underlying price process is the cross-sectional distribution of disaggregated component price indexes. Figure 1 depicts a histogram of the monthly inflation rates across 180+ components of the PCE price index for May 2018.

[Figure 1 here]

It is clear that these components experienced significantly different inflation rates in May 2018 and that there are some extreme outliers. The presence of such outliers and the sensitivity of the sample mean to outliers motivate a prominent approach to the estimation of trend inflation: the use of limited-influence inflation estimators, such as a median CPI or trimmed-mean CPI (see Bryan and Cecchetti, 1994) or a median PCE (see Carroll and Verbrugge, 2019) and trimmed-mean PCE (see Dolmas, 2005). Such measures appear to capture trend inflation inasmuch as they remove noise from inflation, track ex-post measures of its trend,[7] and have been shown to improve inflation forecasting (see, e.g., Smith, 2004; Meyer and Pasaogullari, 2010; Ball and Mazumder, 2011; Norman and Richards, 2012; Meyer, Venkatu, and Zaman, 2013; Meyer and Venkatu, 2014; and Meyer and Zaman, 2019).

Figure 1 also illustrates that not only is the cross-sectional distribution highly kurtotic, but it is also asymmetric – and typically left-skewed. Indeed, for this reason, the trimmed-mean PCE uses asymmetric trimming. In particular, to ensure that the trimmed-mean PCE price index is unbiased on average over long periods, 24 percent is trimmed from the lower tail, while 31 percent is trimmed from the upper tail (see Dolmas 2005, 2009).

However, the degree of asymmetry is not stable, but changes over time. We illustrate this using two robust asymmetry estimators, Bowley skewness and Kelly skewness statistics, which we define below. As Dolmas (2005) points out, robust asymmetry estimators are to be preferred, since moment estimators (such as the third centered moment) are all strongly influenced by outliers.

[7] Dolmas (2005) finds that the trimmed-mean PCE inflation measure tracked an ex-post trend inflation measure much more closely than the ex-food and energy ("core") PCE price index. Detmeister (2011) finds that trimmed-mean measures outperform exclusionary indexes (like core PCE) in tracking the ex-post inflation trend and forecasting future inflation. Mertens (2016) finds that the trimmed-mean PCE provides the best signal of trend inflation. Verbrugge (2021) summarizes and extends a wide variety of evidence comparing trimmed-mean measures to core measures and concludes that trimmed-mean measures will better serve monetary policy deliberations and communication. In their current practice, both the Bank of Canada and the Reserve Bank of New Zealand eschew the use of traditional core inflation measures.

Bowley Skewness Statistic

Following Kim and White (2004) and Dolmas (2005), we here compute the (weighted) Bowley (1920) coefficient of skewness,[8] given by

$$Bowley = \frac{Q_3 + Q_1 - 2Q_2}{Q_3 - Q_1} \qquad (1)$$

where Q_i is the i^{th} quartile of the distribution of component price changes (in a given month), and we have suppressed time subscripts for clarity. As implied by the formula, in its construction, the Bowley statistic uses observations in the middle 50 percent of the distribution; that is, it excludes 25 percent of the observations from each tail. For each month, we compute *Bowley skewness* over the number of components available. [9] We calculate two measures of Bowley skewness: one based on disaggregate components' month-to-month (m-o-m) inflation rates and the other one based on those components' 12-month trailing inflation rates (y-o-y).

Kelly Skewness Statistic

The (weighted) Kelly skewness statistic is defined as

$$Kelly = \frac{P_{90} + P_{10} - 2P_{50}}{P_{90} - P_{10}} \qquad (2)$$

where P_i is the i^{th} percentile of the distribution of component price changes (in a given month), and we have suppressed time subscripts for clarity. As is evident from the formula, in constructing its skewness estimate, the Kelly statistic excludes 10 percent of the observations

[8] Typically, the Bowley measure is computed using unweighted data, as the statistic implicitly assumes that data are drawn independently from a particular distribution. However, limited-influence inflation estimators are invariably computed as weighted versions of their respective estimators, to ensure that the resulting location estimates reliably track inflation, which (in official statistics) is computed as a weighted average of the underlying components. In like manner, we compute a weighted version of the Kelly measure. Owing to the necessity of using weights, the use of the (otherwise excellent) standard triple skewness statistic (see Randles et al., 1980; Verbrugge, 1997) is contraindicated.

[9] Coverage of the PCE has increased over time, particularly in services. For example, in 1960, the Bureau of Economic Analysis (BEA) did not estimate home healthcare consumption, and services such as internet services did not exist. We compute Bowley and Kelly skew statistics using 182 categories of goods and services, which are listed in Appendix A1.

from each tail, i.e., 20 percent of the observations. For each month, we compute *Kelly skewness* over the number of components available. As in the case of Bowley skewness, we compute two measures of Kelly skewness: one based on disaggregate components' m-o-m inflation rates and the other based on those components' y-o-y inflation rates.

Figure 2 plots Bowley and Kelly skewness measures from 1978 through June 2021 based on disaggregates' m-o-m inflation rates.[10] Figure 3 plots the corresponding skewness measures based on disaggregates' y-o-y rates. Depicted are the three-month moving average of these monthly skewness measures. Three observations stand out. First, asymmetry (skewness) displays significant medium-frequency variation. Second, most of the time, the skew is negative. Third, at times, the two measures of skewness (i.e., Bowley and Kelly) disagree with one another, especially when skewness measures are constructed using disaggregates' 12-month trailing rates. For example, in Figure 3, between 2014 and 2018, the Kelly statistics indicate a strongly negative skew, whereas the Bowley statistics indicate periods in which the skew was positive.

[Figure 2 here]

[Figure 3 here]

Why might robust skewness measures have predictive content? There are four reasons. First, leading theories of price-setting behavior (e.g., Ball and Mankiw, 1994) indicate that inflation is linked to asymmetric price adjustment. Second, there is compelling statistical evidence that asymmetry correlates with inflation (e.g., Verbrugge, 1999). Third, as discussed

[10] Please see Appendix Figure A1 for the profile of monthly, 3-month moving average, and 12-month moving average of the Bowley skewness measure, and Figure A2 for the corresponding figures for the Kelly measure.

below, a leading approach to estimation of trend inflation involves trimming outliers. To deliver unbiased trend estimates, such trimming must be asymmetric, since asymmetry in the cross-sectional price index distribution would otherwise induce bias (for the same reason that a sample mean departs from a sample median in a skewed sample). However, the degree of this asymmetry is time varying, implying that optimal trimming should similarly be time-varying and tied to the current degree of asymmetry. Statistical theory indicates that *optimal* trimming can depend on the degree and nature of the asymmetry (see, e.g., Jureckova, Koenker, and Welsh, 1994; Olive, 2008). Naturally, this suggests that a next-generation trimmed-mean PCE price index might incorporate a more flexible trimming procedure that, over time, adapts the degree of trimming to the degree of asymmetry. But since trimmed means have proven to be reliable signals of trend inflation, the time variation in skewness suggests that incorporating information about the degree of asymmetry in empirical models alongside the trimmed-mean estimators (including trimmed-mean PCE) may be helpful for forecasting.

Last, the time variation in asymmetry is informative about time variation in the properties of the convolution. Verbrugge (1999) indicates that asymmetry in the cross-sectional distribution is associated with the underlying conditional variance-covariance structure, which is time varying. We are intrigued by the possibility that a direct estimate of the asymmetry – an estimate that is a nonlinear function of the cross-sectional association or relationship of the underlying stochastic processes –may have beneficial information for inflation forecasting and separately for informing estimates of stochastic volatility in equations defining inflation dynamics.

Median and Skew by Goods and Services

A growing literature has documented the importance of forecasting inflation by separately modeling and forecasting the goods and services sub-categories of aggregate inflation (see Tallman and Zaman, 2017). Motivated by this line of research, we are curious to see if gains in the accuracy of goods and services inflation forecasts are possible, by computing robust measures (separately) for goods and for services. Furthermore, this decomposition could provide a better understanding of the movements of the aggregate robust measures (e.g., median PCE and the overall skewness). Accordingly, we next construct the robust measures (median and skewness) for goods and services PCE. Figure 4 plots median goods PCE inflation and median services PCE inflation alongside median PCE inflation. A quick visual inspection indicates a striking similarity between the median PCE inflation and median services PCE inflation. This suggests that both indexes categorize the median components with similar price changes.[11]

[Figure 4 here]

Figure 5 plots the (Kelly) skewness measures computed separately by services and goods categories. Also plotted is the aggregate skewness, which is computed using all the PCE components.[12] The skewness measures plotted correspond to the 12-month moving average of the monthly skewness estimates. A few observations immediately stand out. First, it is common to observe positive skewness in services inflation, whereas it is rare in goods inflation. Second, overall negative skewness is driven both by the negative skewness in the goods inflation over most of the sample and by the fact that goods inflation has been negative. Negative goods

[11] Interestingly, in computing the median PCE, over our sample period, about 82 percent of the time (i.e., for 435 out of 533 months), the identified median component belonged to the services category.

[12] Because aggregate, goods, and services skewness measures are constructed separately, the aggregate skewness is not the sum of the skewness in goods PCE and the skewness in services PCE.

inflation influences overall skewness because, given typically positive overall inflation, components within the goods category have generally fallen in the left tail of the price change distribution and thus contribute to the negative skew in aggregate PCE inflation. Third, in recent months, both goods and services inflation have been experiencing positive skewness, contributing to the positive skewness in aggregate PCE inflation. Interestingly, this positive skewness in the goods inflation coincides with sharp increases in goods inflation, driven by the dramatic shift in consumption away from services and toward goods in conjunction with supply-chain pressures. This represents a notable shift from the negative goods inflation observed over the past three decades.

[Figure 5 here]

3. Data

All of the empirical analysis uses data at monthly frequency spanning January 1978 through June 2021. We use data on the personal consumption expenditures price index (PCE), PCE excluding food and energy components (core PCE), and data on both price indices and nominal expenditure shares of 182 components of PCE.[13] All of the PCE data are available from the Bureau of Economic Analysis (and retrieved from Haver Analytics). The monthly series of the unemployment rate (16 years plus) is available from the Bureau of Labor Statistics (BLS). Trimmed-mean PCE inflation is obtained from the website of the Federal Reserve Bank of Dallas. Median PCE inflation is obtained from the website of the Federal Reserve Bank of Cleveland. The measure of long-run inflation (denoted PTR) is obtained from the FRB/US model of the Federal

[13] The supporting appendix (Table A1) lists all of the 182 disaggregated components used to construct the robust asymmetry measure. It is worth mentioning that if we instead use the 154 components that go into constructing core PCE, the resulting estimates of the asymmetry measure are similar to the one obtained with all 182 components.

Reserve Board. The measure of the natural rate of unemployment is obtained from the Congressional Budget Office (CBO). We compute skewness measures based on both month-to-month inflation rates and on 12-month inflation rates. For inflation itself, we work with 12-month inflation rates, since our target variable of interest is the 12-month PCE inflation rate.[14]

4. Models and Forecasting Setup

In the inflation forecasting literature, modeling inflation in "gap" form, where the gap is defined as the deviation of inflation from its underlying trend (i.e., long-run inflation), has been shown to be quite helpful in improving the accuracy of inflation forecasts (e.g., Faust and Wright, 2013; Zaman, 2013; Clark and Doh, 2014; and Tallman and Zaman, 2017). In fact, a simple univariate autoregressive (AR) model of inflation in the gap is widely recognized as an "amazingly hard to beat" benchmark (e.g., Faust and Wright, 2013). Accordingly, our design of the forecasting exercise is inspired by modeling inflation in gap form. Specifically, to assess the marginal contribution of trimmed-mean estimators and skewness measures to improving the accuracy of inflation forecasts, we extend the univariate inflation in the gap model to a multivariate setup.[15] First, we build a bi-variate Bayesian VAR[16] of headline PCE inflation and median PCE inflation, where both inflation measures are specified as deviation from the PTR.[17] We denote this specification *"BVAR: PCE + Median."* We compare this bi-variate BVAR's accuracy in

14 Furthermore, the Federal Reserve's inflation goal is framed in terms of the 12-month inflation rate in PCE inflation.

15 Faust and Wright (2013) estimate a quarterly AR(1) gap model. Since we work with models estimated with data at a monthly frequency, we use a monthly AR(3) gap model.

16 Bayesian VARs are widely used to forecast macroeconomic variables. We use BVAR models similar to those used in Banbura, Giannone, and Reichlin (2010) and Knotek and Zaman (2019). We set lag length=3 to be consistent with the AR(3) benchmark model. We relegate the BVAR model details to Appendix A.2.

17 PTR is the survey-based long-run (5- to 10-years-ahead) PCE inflation expectations series from the Federal Reserve Board of Governor's FRB/US econometric model.

forecasting headline PCE inflation to that of the univariate inflation in the gap model. This comparison would give us a sense of the marginal contribution of median PCE inflation above and beyond headline PCE inflation's own history in improving the forecast accuracy of headline PCE inflation. This marginal contribution of median PCE would reflect both the superior measure of the central tendency (signal about the underlying trend) and the implicit signal about the current degree of asymmetry (skewness).

Second, to get a rough approximation of the extent to which skewness contributes to the median PCE's marginal contribution, we construct another bi-variate BVAR of headline PCE and a skewness measure (either Bowley or Kelly). We denote this specification as *"BVAR: PCE + Skew (B),"* when the skewness measure is Bowley, and *"BVAR: PCE + Skew (K),"* when the skewness measure is Kelly. A comparison between this bi-variate BVAR's accuracy in forecasting headline PCE inflation and the one estimated in the previous step, along with the comparison of this bi-variate BVAR with the univariate headline PCE inflation model, would give us a sense of the extent to which skewness is contributing to the marginal contribution of median PCE relative to the signal about the trend to improve the forecast accuracy of headline PCE inflation.

Third, we construct a tri-variate BVAR by adding the skewness measure (Bowley or Kelly) to the bi-variate BVAR of headline PCE and median PCE. We denote this specification as *"BVAR: PCE + Median + Skew (B),"* when the skewness measure is Bowley, and *"BVAR: PCE + Median + Skew (K),"* when the skewness measure is Kelly. We then compare the forecasting accuracy of the tri-variate BVAR to that of the bi-variate BVAR (constructed in the first step) and to the univariate model. The comparison of the tri-variate BVAR to the bi-variate BVAR would give us a sense of the marginal contribution of the "direct" measure of skewness above and beyond that of median PCE and headline PCE, noting that median PCE already embeds an *implicit* signal about the skewness (when added alongside the headline PCE). Similarly, comparing the tri-variate BVAR with the univariate model would give us a sense of the combined usefulness of median PCE and the "direct" measure of skewness in improving the forecast accuracy of headline PCE inflation.

We repeat this exercise by replacing median PCE with the trimmed-mean PCE, which gives us a bi-variate BVAR, *"BVAR: PCE + Trim,"* and tri-variate BVARs *"BVAR: PCE + Trim + Skew (B)"* and *"BVAR: PCE + Trim + Skew (K)."* Then we repeat replacing the trimmed-mean PCE with core PCE, which gives us bi-variate BVAR, *"BVAR: PCE + Core,"* and tri-variate BVARs *"BVAR: PCE + Core + Skew (B)"* and *"BVAR: PCE + Core + Skew (K)."*

Fourth, we assess the value added of our robust measures in improving the accuracy of the inflation forecasts from the Phillips curve specifications. A long list of papers has documented the inferior accuracy of forecasts from the Phillips curve models compared to forecasts from models with univariate specifications (e.g., Faust and Wright, 2013). More recently, Ball and Mazumder (2020) and Ashley and Verbrugge (2022) show the competitive accuracy of the inflation forecasts from Phillips curve models based on trimmed-mean inflation measures. Accordingly, we examine whether the inclusion of median PCE (or trimmed-mean PCE) and skewness in the Phillips curve specification helps improve accuracy. If it does, are the gains large enough to make the accuracy of the forecast competitive with the univariate benchmark? To preview the result, we find that inclusion of the robust measures helps to improve the forecast accuracy of the Phillips curve model, but the gains are small: the accuracy of the forecasts remains significantly inferior compared to the univariate benchmark. Because of the small gains in accuracy, in the interest of brevity, and to facilitate comparison, we simply report the forecast accuracy from the Phillips curve specification without the robust measures, which we denote as *"BVAR: PCE + UR,"* where UR refers to the unemployment rate gap constructed as the difference between the unemployment rate and the CBO's estimate of the natural rate of unemployment.

Fifth, to assess the usefulness of robust measures of goods and services inflation in improving the accuracy of goods and services inflation forecasts, we perform two sets of forecasting exercises similar to those described previously. Specifically, in the first exercise, we assess the predictive ability of the robust measures (median and skewness) for goods inflation by estimating three separate BVAR models: "BVAR: G. PCE + Skew (K)," which is a bi-variate VAR of goods PCE inflation and Kelly skewness based on goods inflation; "BVAR: G. PCE + Median," which is a bi-variate VAR of goods PCE inflation and median goods PCE inflation; and "BVAR: G. PCE + Median + Skew (K)," which is a tri-variate VAR of goods PCE inflation, median goods PCE inflation, and Kelly skewness based on goods inflation. In the second exercise, we assess the predictive ability of the robust measures for services inflation by estimating three separate BVAR models: "BVAR: S. PCE + Skew (K)," which is a bi-variate VAR of services PCE inflation and Kelly skewness based on services inflation; "BVAR: S. PCE + Median," which is a bi-variate VAR of services PCE inflation and median services PCE inflation; and "BVAR: S. PCE + Median + Skew (K)," which is a tri-variate VAR of services PCE inflation, median services PCE inflation, and Kelly skewness based on services inflation. For goods and services inflation, we focus on the Kelly skewness measure because, as discussed in the results section, Kelly skewness outperformed Bowley skewness in all the exercises involving aggregate PCE inflation.

Pseudo-Out-of-Sample Forecasting

Even though we have real-time data available for aggregate PCE inflation and the unemployment rate, the availability of real-time data at the disaggregate component level (required to compute the median PCE and skewness) is limited; therefore, we resort to pseudo-out-of-sample forecast evaluation. We perform forecasting evaluation using a recursively expanding window of estimation. All the models are estimated using data starting in January 1978 and forecast evaluation is performed over the sample from January 1994 through June 2021. At each recursive run, forecasts are produced up to three years out (i.e., the forecast horizon, h ranges from h=1 to h=36 months ahead). The point forecasts, which are the posterior mean of the density forecasts, are evaluated using the metric of the mean squared forecast error (MSE). To assess the statistical significance of gains in the accuracy of point forecasts between the two models, we use the Diebold and Mariano test (with the Newey-West correction) using the two-sided tests of the standard normal. The density forecasts are evaluated using the widely used metric of the logarithmic predictive score (parametric normal approximation), and the statistical significance is assessed using the likelihood-ratio test of Amisano and Giacomini (2007), where the test statistics use a two-sided t-test.

A Bias-Adjusted Alternative (Two-Step Algorithm)

An alternative approach to examining the efficacy of skewness in improving the accuracy of inflation forecasts is to create a bias-adjusted trimmed-mean measure – where the bias adjustment is informed using the skewness – and then evaluate this measure's predictive ability versus its non-bias-adjusted counterpart. In principle, this bias-adjusted measure will embed both direct and implicit information about the skewness. We perform this analysis as a robustness check.

This approach is implemented using a two-step algorithm. In the first step, an estimate for the bias, defined as the moving average of the gap between the trimmed-mean inflation measure and the headline inflation measure, is computed.

$$Gap_t^{TMeasurePCE} = \pi_t^{TMeasurePCE} - \pi_t^{HeadlinePCE} \qquad (3)$$

To compute the moving average of the gap, a 36-month window is adopted, which is commonly used in the literature for trend estimation (see Rich, Verbrugge, and Zaman, 2022, and Verbrugge, 2021, among others):

$$Bias_t^{TMeasurePCE} = \frac{1}{36}\sum_{s=t}^{t-36} Gap_s^{TMeasurePCE} \qquad (4)$$

In the second step, the bias computed in the previous step is then regressed on the skewness to compute the bias, which is then applied to the trimmed-mean measure to construct the (bias) adjusted trimmed-mean inflation measure.

$$Bias_t^{TMeasurePCE} = \theta + \lambda(skew_t) + \varepsilon_t \qquad (5)$$

where $skew$ refers to a 12-month moving average of skewness.

$$\pi_t^{TMeasurePCE,Bias-adjusted} = \pi_t^{TMeasurePCE} - \theta - \lambda(skew_t) \qquad (6)$$

The bias-adjusted trimmed-mean measure is added alongside the headline inflation measure to construct a bi-variate model, whose accuracy is then compared to that of the bi-variate model of headline inflation and the (unadjusted) trimmed-mean inflation measure. The comparison of the forecast accuracy of headline inflation between these two bi-variate models indicates the marginal value of skewness.

The two-step approach yields very similar inferences. To conserve space, we report the results from this approach in the appendix Table A4.

5. Forecasting Results

Table 1 reports the results of the point forecast evaluation comparing inflation forecast accuracy across several model specifications. The results correspond to model specifications that use Kelly skewness measures constructed based on disaggregates' month-to-month inflation rates;[18] we compute the three-month moving averages as our estimates of the skewness measures that enter the models.[19]

We find that Kelly skewness contains more predictive content for inflation than does Bowley skewness (see appendix Tables A2 and A3). The findings that Kelly is preferred to Bowley, that the skewness constructed from the components' month-to-month inflation rates is preferred to the corresponding 12-month trailing rates, and that the three-month window for the moving average of monthly skewness is preferred to other window lengths suggest that for skewness to be useful in forecasting PCE inflation, it matters how the skewness measure is constructed.

To conserve space, the forecast accuracy is reported for select forecast horizons. The top panel of the table reports results corresponding to the full sample (1994-2021), the middle panel corresponds to the pre-Great Recession sample (1994-2007), and the bottom panel corresponds to the financial crisis and onward sample (2008-2021). In each panel, the numbers reported in the first row are the root mean squared error (RMSE) from the benchmark univariate inflation in the gap model, denoted "*AR(3)-PCE.*" And the rows below it are ratios that report relative MSEs (relative to MSEs from the AR(3) PCE). Thus, a ratio of more than 1 indicates that the univariate

[18] The results based on model specifications in which skewness measures are constructed based on disaggregates' 12-month trailing inflation rates are found to be inferior compared to those obtained using skewness measures constructed from month-to-month inflation rates. Owing to space constraints, we do not report these results in the paper, but they are available upon request from the authors.
[19] The three-month moving average was preferred to other window lengths (e.g., 1, 2, 4, 6, 8, 10, 12).

inflation in the gap model is more accurate on average than the model being compared.

The results reported in Table 1 suggest four observations. First, adding trimmed-mean estimators to the model improves the forecast accuracy of the aggregate PCE inflation forecasts for most forecast horizons but worsens forecast accuracy in the near term. The gains in forecast accuracy are greater from including the median PCE than trimmed-mean PCE and core PCE. In addition, a larger number of gains in accuracy are classified as statistically significant in the case of median PCE compared to the other two, especially for forecast horizons 18 months ahead and greater.[20] Second, the inclusion of the Kelly skewness measure with or without the inclusion of trimmed-mean estimators marginally improves the forecast accuracy of the aggregate PCE inflation for most forecast horizons. But for the near-term forecast horizon, Kelly skewness plays a non-trivial role, since its inclusion improves forecast accuracy, primarily by converting statistically significant losses to insignificant losses of smaller magnitude. However, in the sample before the Great Recession, skewness measures did not help improve accuracy. Third, consistent with the findings in the literature, the bi-variate Phillips curve specification significantly underperforms.

[Table 1 here]

Table 2 reports the density forecast evaluation results. The first row in each panel reports the log-score of the density forecasts from the AR(3) inflation gap model. The higher the log-score, the more accurate the density forecast. All other rows report relative log-scores (i.e., log-score of the model being compared minus the log-score of the AR(3) inflation gap model).

[20] Our finding that the inclusion of median PCE improves the forecast accuracy of aggregate PCE inflation over the medium- to longer-term horizons is consistent with the findings of Crone et al. (2013), who find similar support for median CPI inflation in forecasting aggregate CPI inflation.

Negative entries indicate that the univariate inflation in the gap model is more accurate on average than the model being compared. Because most entries in the table are positive (except for one-month ahead) and those for horizons 18 months ahead and beyond are statistically significant, it indicates that the addition of the trimmed-mean measures contributes to the increased accuracy of the headline PCE inflation density forecasts. In contrast, adding the skewness measures helps slightly at select forecast horizons. These results are consistent with the point forecast evaluation results.

[Table 2 here]

Forecasting Performance during the Great Recession and the COVID Pandemic

We next illustrate the marginal efficacy of our robust inflation measures in forecasting aggregate PCE inflation during crisis periods, which are periods normally associated with heightened uncertainty. We focus on two crisis periods: the great financial crisis (also known as the Great Recession) [GFC] and the great pandemic crisis [GPC], which is still ongoing at the time of writing. Specifically, we examine the forecasting performance of our BVAR models for 12-months-ahead forecasts generated during the GFC period spanning October 2007 through June 2009, and the GPC period spanning March 2020 through June 2020. For the latter, i.e., the GPC period, we go only through June 2020 because at the time of compiling results, the available data end in June 2021, which we need to evaluate the 12-months-ahead forecast.

Figure 6, panel (a) plots the forecast errors over the GFC period from three models: the benchmark gap AR(3)-PCE, the BVAR: PCE + Skew (K), and the BVAR: PCE + Median. (The plot for BVAR: PCE + Median + Skew (K) is almost identical to that for the BVAR: PCE + Median; therefore, we do not show it. As is evident by big misses, all three models generate forecasts that poorly track the actual PCE inflation during the GFC period. However, the model that includes median PCE inflation experiences relatively smaller errors than the univariate benchmark. During that period, actual PCE inflation came in well below the models' projections, resulting in large errors. Panel (b) in Figure 6 plots the forecast errors from the BVAR: PCE + Trim model alongside the PCE + Median model. Both models performed comparably during this period.

Figure 7, panel (a) plots the forecast errors over the GPC period from the same three models. Again, there is evidence of big misses: all three models generate forecasts during the GPC period that do an inferior job of tracking the actual PCE inflation. However, the model that includes median PCE inflation experiences relatively smaller errors than the univariate benchmark. During this period, actual PCE inflation came in well above the models' projections, resulting in large errors. Panel (b) in Figure 7 plots the forecast errors from the BVAR: PCE + Trim model alongside the PCE + Median model. Both models performed comparably during this period, with the model that includes the trimmed-mean measure performing slightly better than the model with the median measure. It is worth noting that the models' forecast errors during the GPC period are smaller in magnitude than during the GFC period. Overall, the forecast results for the GFC and GPC periods highlight the difficulties in accurately forecasting aggregate PCE inflation. Having said that, one is better off incorporating information from trimmed-mean estimators (and possibly Kelly skewness) in constructing forecasts of PCE inflation using popular time-series models.

[Figure 6 here]

[Figure 7 here]

Breakdown by Goods and Services

Table 3 reports point forecast evaluation results for goods PCE inflation. Shown are the results for the full sample and two sub-samples. In each panel, the numbers reported in the first row are the RMSE from the univariate model of goods PCE inflation, denoted "*AR(3)-Goods PCE.*"[21] And the three rows below it are ratios that report relative MSEs (relative to the MSE from the AR(3)-Goods PCE). Thus, a ratio of more than 1 indicates that the univariate model is more accurate on average than the model being compared. The other three models shown are: the BVAR: G. PCE + Skew (K), which is a bi-variate VAR model of goods PCE inflation and a skewness measure computed from disaggregate components belonging to the goods PCE category; the BVAR: G. PCE + Median, which is a bi-variate VAR model of goods PCE inflation and median goods inflation computed from the disaggregate goods components' inflation rates; the BVAR: G. PCE + Median + Skew(K), which is a tri-variate VAR model of goods PCE inflation, median goods PCE inflation, and a skewness measure based on goods PCE inflation.

As is evident from Table 3, most entries for the full sample and financial crisis and onward sample are below one, suggesting the usefulness of the robust measures in improving the point forecast accuracy of goods PCE inflation. However, most of the gains are statistically significant only for the financial crisis and onward period, and that too for models that include the median goods PCE inflation. Similar to the results for headline PCE inflation, the addition of skewness only helps marginally, which suggests that the forecasting prowess of median goods PCE inflation is due to its ability to signal the underlying trend in goods inflation. In contrast to

[21] Tallman and Zaman (2017), among others, document the superior forecasting properties of the univariate model of goods PCE (and CPI) inflation.

the results for headline PCE inflation, the addition of robust measures worsens the forecast accuracy of goods PCE inflation over the pre-financial crisis period, though the losses are statistically insignificant.

Table 4 reports the corresponding results for services PCE inflation. Similar to the results for goods PCE inflation and headline PCE inflation, the evidence suggests that the addition of robust measures to the univariate gap model of services PCE inflation improves the point forecast accuracy of services PCE inflation. Improvements in accuracy are achieved over the financial crisis and onward period, and the bulk of the gains come from the addition of the median services PCE inflation measures with only marginal improvements from the skewness measure. A comparison between Tables 4 and 5 (bottom panels) suggests that skewness's marginal contribution to improving forecast accuracy is greater for services PCE inflation than for goods PCE inflation.

6. The Usefulness of Skewness for Stochastic Volatility Modeling

As noted in Section 2 above (and in Verbrugge, 1999), asymmetry in the cross-sectional distribution is associated with the underlying (time-varying) conditional variance-covariance structure. This leads to a natural curiosity about whether estimates of skewness could help improve the (quarterly) estimates of stochastic volatility in model equations defining inflation dynamics. To help answer this question, we use the state-of-the-art stochastic volatility in mean model developed in Chan (2017). Keeping the same notation as in Chan, we list the model equations below.

$$y_t = \tau_t + \alpha_t e^{h_t} + \varepsilon_t^y, \qquad \varepsilon_t^y \sim N(0, e^{h_t}) \tag{7}$$

$$h_t = \mu + \phi(h_{t-1} - \mu) + \beta X + \varepsilon_t^h, \qquad \varepsilon_t^h \sim N(0, \sigma^2) \tag{8}$$

$$\gamma_t = \gamma_{t-1} + \varepsilon_t^\gamma, \qquad \varepsilon_t^\gamma \sim N(0, \Omega) \tag{9}$$

where y_t refers to the observed variable of interest (e.g., inflation), h_t refers to the log-volatility, $\gamma_t = (\alpha_t, \tau_t)'$, and Ω is a 2 x 2 covariance matrix. Because the model allows for time-varying parameters and volatility feedback (that is, estimated volatility could affect the level of inflation (equation 7), the literature refers to the above model as a time-varying parameter stochastic volatility in mean model (TVP-SVM).

In Chan (2017), the variable X in equation (8) is one-period lagged inflation to capture the potential influence of past inflation on current inflation volatility. In our exercise, we estimate the above model by replacing past inflation with the skewness measure in variable X. We estimate the above model separately for aggregate PCE inflation, services PCE inflation, and goods PCE inflation, along with their corresponding skewness measures.[22]

Our objects of interest are the estimates of the parameters β and e^{h_t}. To assess whether skewness provides timely and useful information for estimates of stochastic volatility, we would require the estimate of the parameter β to be significant (when assessed using 68 percent credible intervals), and visual evidence indicating some difference in the estimate of stochastic volatility e^{h_t} relative to the estimate of SV coming from the (default) model specification, which includes past inflation in variable X.

Table 5 reports the estimates of the parameter beta for various model runs. We report the

[22] To conserve space, we refer the reader to Chan (2017) for model estimation details. The Matlab code to estimate the TVP-SVM model is available to download from Joshua Chan's website.

model runs with the Bowley skewness measure because it was found to be notably more influential compared to the Kelly skewness measure in the estimation of SV. A few observations stand out. First, in all three cases (headline PCE, services PCE, and goods PCE), for the default setting, i.e., where X contains one-quarter lagged inflation, the estimates of beta are trivial and insignificant. Second, for goods PCE inflation, the estimate of the beta is of non-trivial magnitude and significant. However, in the case of services PCE inflation, the beta is insignificant, though the magnitude of the posterior mean estimate is larger than the estimate based on the default setting. With a significant estimate of beta for goods PCE and an insignificant estimate for services PCE, on net, the estimate of beta for headline PCE inflation is significant and non-trivial. Third, whereas in the case of goods PCE inflation, the posterior mean estimate of beta is highly positive, in the case of services PCE inflation, it is negative. This suggests that an increase in the skewness of goods PCE inflation is associated with increased volatility in goods PCE inflation. In contrast, an increase in the skewness of services PCE inflation is associated with reduced volatility of services PCE inflation. Because the services PCE category constitutes a much larger share of the overall PCE compared to the goods PCE category, the estimate of the beta in the case of headline PCE is negative, i.e., the same sign as observed for services PCE inflation.

Figure 8 plots the (full-sample smoothed) estimates of stochastic volatility for goods PCE inflation (panel a) and headline PCE inflation (panel b). Each panel shows two plots: one labeled "Default," which refers to the model estimation that uses lagged inflation, and the other labeled "Skew," which refers to the model estimation that uses skewness measures. A comparison of these two plots within each panel provides us with an assessment of the practical usefulness of the skewness measure for the SV estimation. The plots provide some evidence in support of the skewness measure for goods PCE inflation, as evidenced by improved precision (defined as the width of the 68 percent credible intervals) of the SV estimates and visible differences in the SV estimates from the two approaches during specific periods. Again, in the case of headline PCE inflation, there is some evidence supporting the skewness information, since, during certain periods, which are few, differences in the estimates of SV are observed. However, there is no evidence of improved precision; if anything, there appears to be a slight worsening in the precision of the SV estimates. Overall, there seems to be some evidence in support of skewness for SV estimation, but economically it does not appear to be meaningful.

[Figure 8 here]

7. Conclusion

This paper explores the usefulness of the trimmed-mean estimators and robust skewness statistics in improving the point and density accuracy of aggregate PCE inflation forecasts. Trimmed-mean estimators have been shown to do well in forecasting aggregate inflation, with the forecast accuracy gains thought to be due to their prowess in tracking the underlying trend. We illustrate strong evidence of time variation in the cross-sectional asymmetry (e.g., Bowley skewness and Kelly skewness) computed using the 180+ components of the PCE price index. This asymmetry would suggest additional reasoning supporting the usefulness of trimmed-mean measures for forecasting when added alongside headline PCE because the gap between the two would provide an implicit signal about the skewness. We attempt to ascertain the predictive content of skewness, independent of the information about the future trend embedded within trimmed-mean estimators.

Accordingly, we augment a "hard to beat" benchmark inflation forecasting model of personal consumption expenditures (PCE) price inflation with robust measures: trimmed-mean estimators of inflation (e.g., median PCE; trimmed-mean PCE) and robust measures of the cross-sectional asymmetry (e.g., Bowley skewness and Kelly skewness). We examine both the joint contribution of these measures and their marginal contributions in possibly improving the point and density forecast accuracy of PCE inflation. Among the trimmed-mean estimators, median PCE inflation's ability to forecast future headline PCE inflation has barely been explored. So an important secondary contribution of this paper is to examine the usefulness of median PCE in forecasting aggregate PCE inflation. A third important contribution of this paper is to introduce, and examine the usefulness of, median goods PCE and median services PCE – and their respective robust skewness estimates – for forecasting goods PCE and services PCE. Finally, we explore whether robust measures are useful in stochastic volatility modeling.

Based on a forecast evaluation sample covering the period from January 1994 through June 2021, a period that includes large volatility in oil prices, a financial crisis and deep recession, and a severe global pandemic, our results indicate significant gains in the point and density accuracy of PCE inflation forecasts for horizons 18 months ahead and longer. Most of the improvements come from the inclusion of trimmed-mean estimators, with only marginal improvements from the addition of robust skewness estimators. A split sample examination suggests that most of the gains in accuracy are concentrated in the sample spanning the Great Recession and onward, i.e., January 2008 through June 2021.

We find slightly stronger support for median PCE over trimmed-mean PCE, and both outperform the exclusion estimator, core PCE. We find strong support for Kelly skewness over Bowley skewness; furthermore, it matters whether skewness measures are constructed using the disaggregate components' month-over-month inflation rates or 12-month trailing inflation rates. In our empirical exercises, skewness measures constructed based on components' month-over-month rates proved useful; in contrast, skewness measures based on 12-month rates marginally worsened accuracy, even though aggregate PCE and trimmed-mean estimators enter the models as 12-month trailing rates.

Asymmetry (skewness) in the cross-sectional distribution is associated with the underlying (time-varying) conditional variance-covariance structure, suggesting that a direct estimate of a skewness measure may aid in estimating stochastic volatility in equations describing inflation dynamics. Using a state-of-the-art stochastic volatility in the mean model, we illustrate the modest efficacy of the skewness measure in refining the *contemporaneous* estimates of stochastic volatility in the innovations to the equation defining the goods PCE inflation and, in turn, headline PCE inflation. In contrast, we find limited use for the skewness measure in refining the estimates of stochastic volatility for services PCE inflation.

Over time, the reliance on trimmed-mean inflation estimators as a means of obtaining a signal about both the underlying trend in inflation and future inflation has increased globally. Hence, we view our empirical findings as useful for a broad swath of practitioners interested in forecasting inflation.

Figure 1: Cross-sectional distribution of inflation in PCE price index components, May 2018

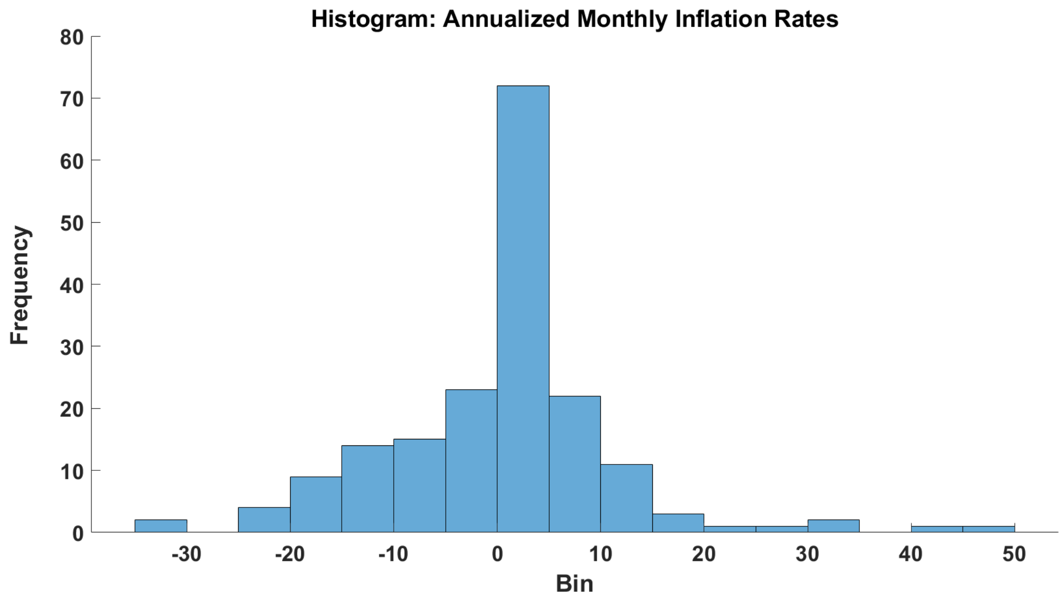
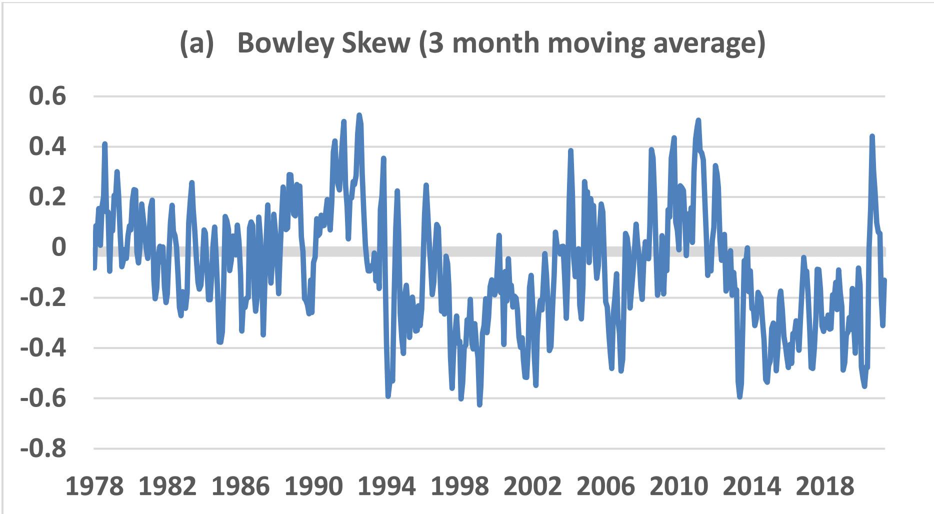


Figure 2: Cross-sectional asymmetry in PCE inflation (month-to-month %)



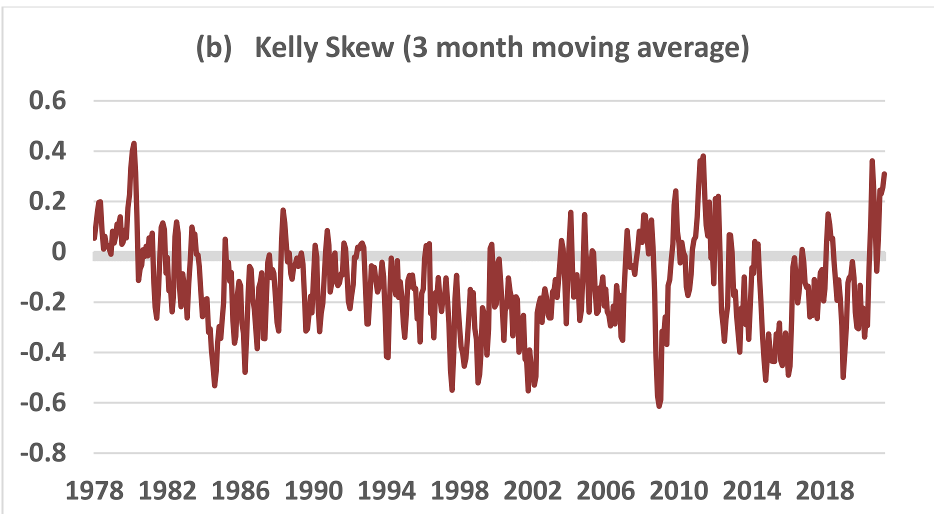


Figure 3: Cross-sectional asymmetry in PCE inflation (12-month %)

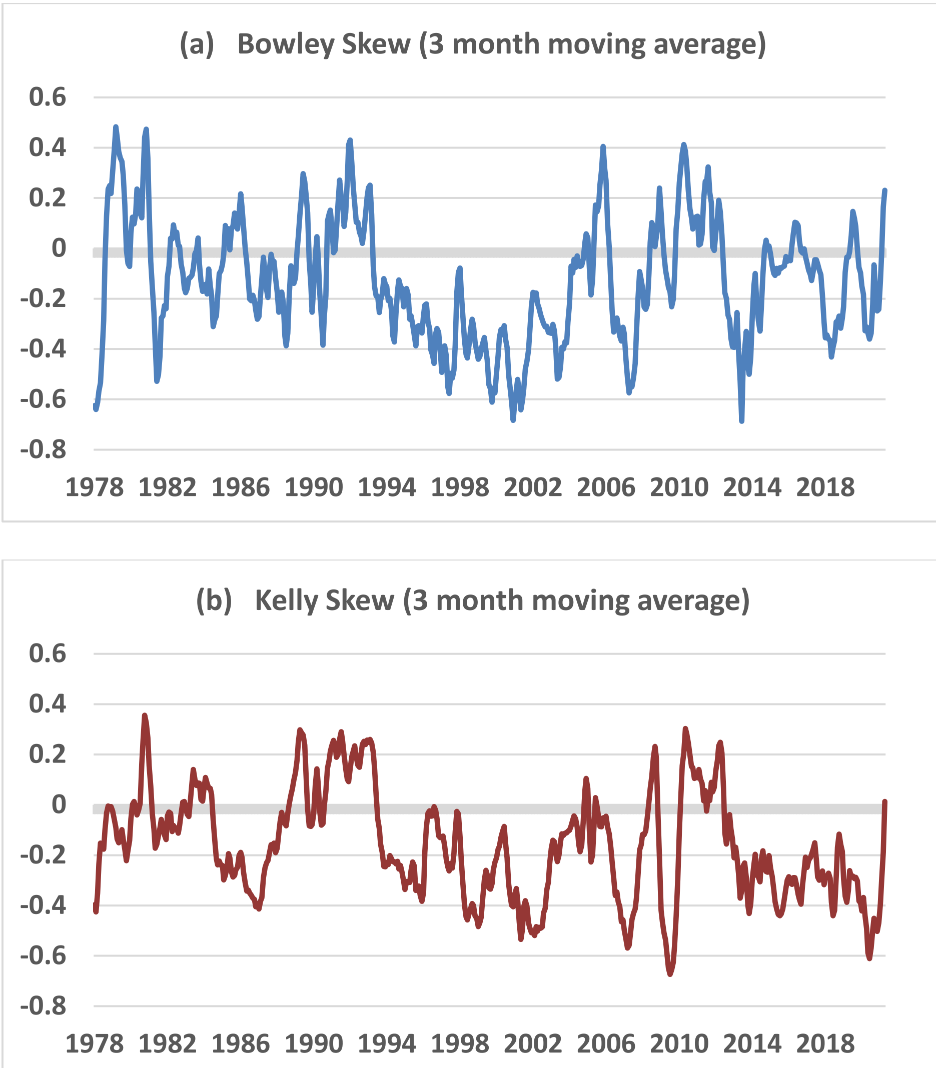


Figure 4: Median by goods and services

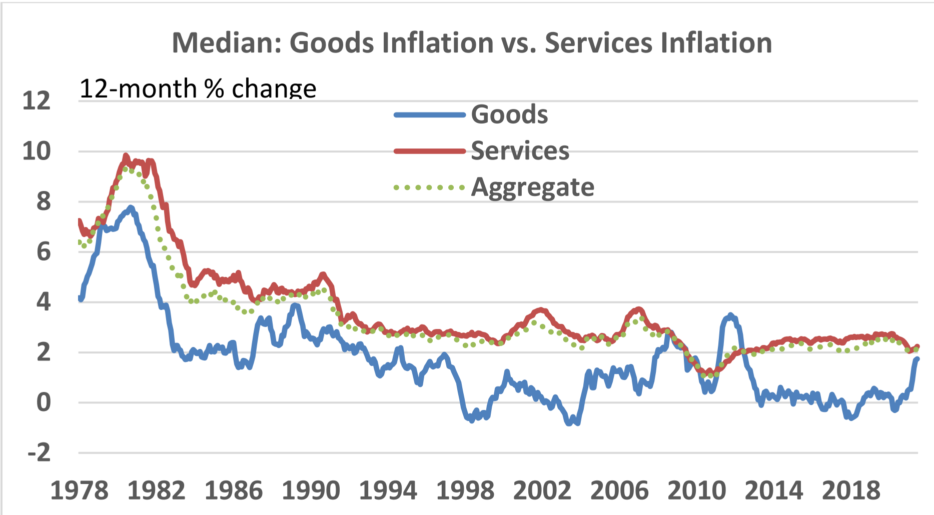


Figure 5: (Kelly) Skew by goods and services

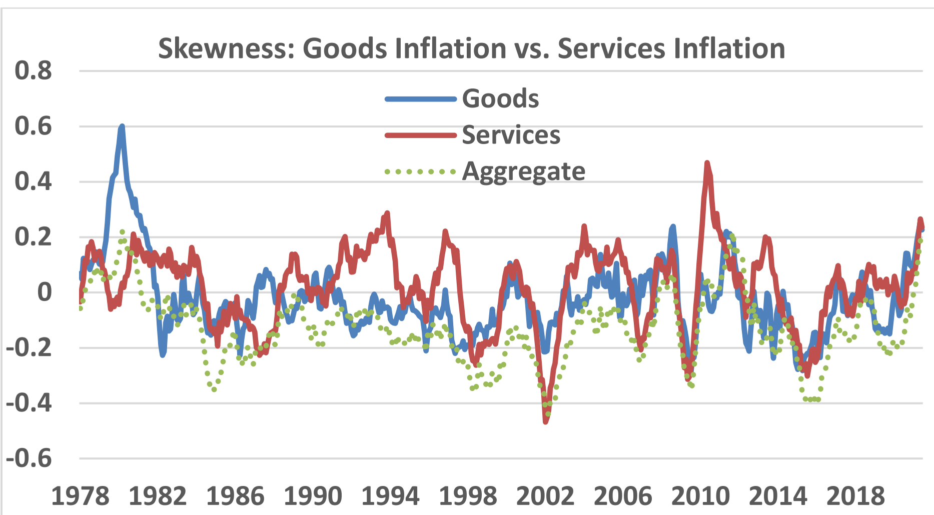


Figure 6: Forecast errors during the Great Recession

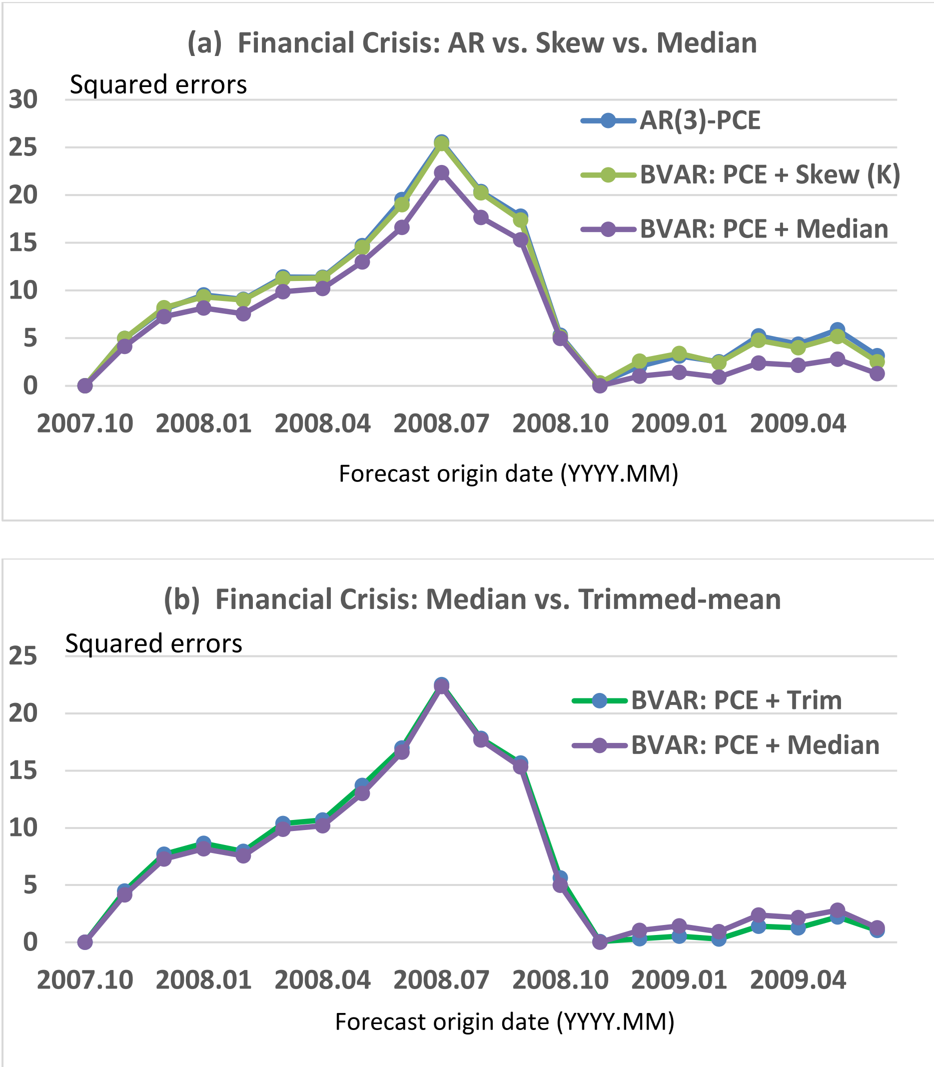


Figure 7: Forecast errors during the Great Pandemic (COVID-19)

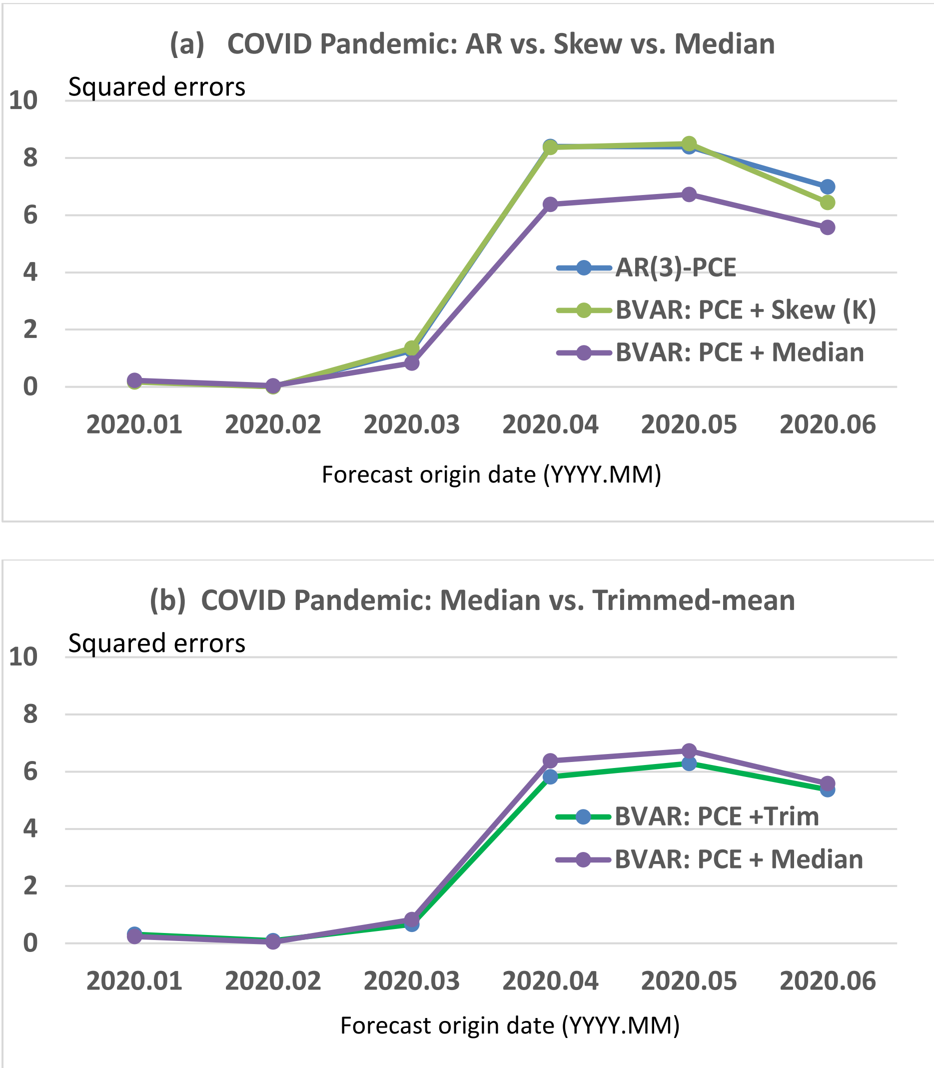
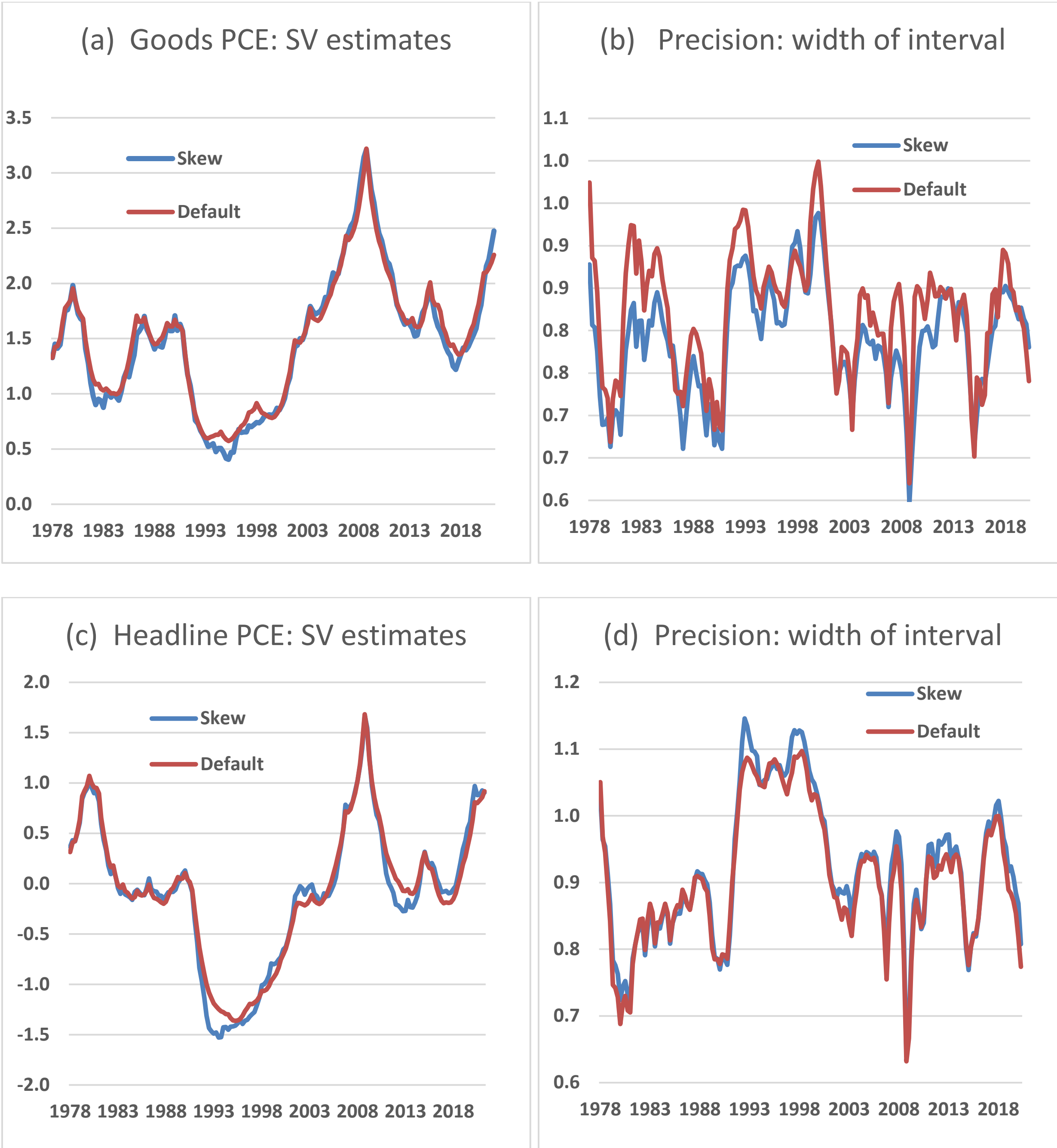


Figure 8: Estimates of SV and precision



Notes: Panels (a) and (c) plot the posterior mean estimates of the parameter beta from the TVP-SVM model specification with lagged inflation (denoted Default), and from the model specification with Bowley skewness (denoted Skew). Panels (b) and (d) plot the corresponding beta parameters' precision estimates (defined as the width of 68% credible intervals).

Table 1: PCE inflation out-of-sample point forecasting comparison
[Skew constructed based on month-over-month inflation rates]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.265	0.858	1.126	1.064	1.075	1.077	1.044
Relative MSE							
BVAR: PCE + Skew (K)	1.028	0.957*	0.988	0.976	0.959*	0.959*	0.967*
BVAR: PCE + Median	1.046*	0.991	0.893	0.882*	0.879*	0.898*	0.887*
BVAR: PCE + Median + Skew (K)	1.008	0.909	0.889	0.887*	0.876*	0.897*	0.885*
BVAR: PCE + Trim	1.045*	0.997	0.891	0.918	0.913	0.916	0.913*
BVAR: PCE + Trim + Skew (K)	1.011	0.916	0.885	0.922	0.906	0.911	0.911*
BVAR: PCE + Core	1.045*	1.010	1.008	0.997	0.980	0.967*	0.973
BVAR: PCE + Core + Skew (K)	1.045	1.010	1.008	0.997	0.980	0.967*	0.973
BVAR: PCE + UR	1.109*	1.181	1.320*	1.485*	1.628*	1.634*	1.612*

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.245	0.553	0.806	0.870	0.941	0.955	0.930
Relative MSE							
BVAR: PCE + Skew (K)	1.009	1.006	0.998	0.989	0.980	0.981	0.995
BVAR: PCE + Median	1.024*	1.053	0.883	0.815	0.787*	0.795*	0.796*
BVAR: PCE + Median + Skew (K)	1.007	1.037	0.888	0.830	0.798*	0.804*	0.802*
BVAR: PCE + Trim	1.019	1.076	0.951	0.910	0.860	0.838*	0.814*
BVAR: PCE + Trim + Skew (K)	0.999	1.052	0.955	0.921	0.866	0.844*	0.818*
BVAR: PCE + Core	1.005	1.030	1.031	1.018	1.004	0.997	1.006
BVAR: PCE + Core + Skew (K)	1.008	1.045	1.046	1.032	1.012	1.000	1.007
BVAR: PCE + UR	1.016	1.220	1.375	1.602*	1.648*	1.769*	1.979*

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.285	1.087	1.359	1.097	0.975	0.972	0.833
Relative MSE							
BVAR: PCE + Skew (K)	1.043*	0.943*	0.982	0.953	0.908*	0.924*	0.947*
BVAR: PCE + Median	1.063*	0.976	0.906	0.932	0.793*	0.742*	0.790*
BVAR: PCE + Median + Skew (K)	1.009	0.877	0.901	0.931	0.771*	0.731*	0.781*
BVAR: PCE + Trim	1.065*	0.980	0.883	0.933	0.774*	0.709*	0.808
BVAR: PCE + Trim + Skew (K)	1.021	0.884	0.875	0.929	0.747*	0.697*	0.802*
BVAR: PCE + Core	1.076*	1.004	0.997	0.974*	0.946*	0.942*	0.954*
BVAR: PCE + Core + Skew (K)	1.055	0.955	0.999	0.958*	0.910*	0.927*	0.939*
BVAR: PCE + UR	1.180*	1.179	1.347*	1.603	1.913	1.807	1.894

Notes: The numbers reported in the first row of each panel are the root mean squared error (RMSE) from the univariate AR PCE inflation in gaps (3-lag specification), while the rows below it are ratios that report relative MSEs (relative to MSE from the AR(3) PCE inflation in gaps). Thus, a ratio of more than 1 indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample). * indicates statistical significance up to 10% level and is based on Diebold-Mariano West test

Table 2: PCE inflation out-of-sample density forecasting comparison
[Skew constructed based on month-over-month inflation rates]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE LPS	-0.096	-1.302	-1.600	-1.516	-1.526	-1.543	-1.545
Relative LPS							
BVAR: PCE + Skew (K)	-0.013	0.027*	0.009	0.010*	0.019*	0.025*	0.027*
BVAR: PCE + Median	-0.019*	0.004	0.073*	0.072*	0.069*	0.065*	0.074*
BVAR: PCE + Median + Skew (K)	-0.001	0.057	0.070	0.068*	0.069*	0.065*	0.075*
BVAR: PCE + Trim	-0.017	0.004	0.055	0.051	0.054	0.061*	0.071*
BVAR: PCE + Trim + Skew (K)	0.000	0.052	0.060	0.047	0.057	0.063*	0.074*
BVAR: PCE + Core	-0.017	0.003	0.008	0.011*	0.017*	0.025*	0.027*
BVAR: PCE + Core + Skew (K)	-0.011	0.026	0.007	0.009	0.018*	0.025*	0.028*

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE LPS	-0.010	-0.875	-1.235	-1.335	-1.426	-1.471	-1.494
Relative LPS							
BVAR: PCE + Skew (K)	-0.015	0.001	0.003	0.011*	0.018*	0.023*	0.028*
BVAR: PCE + Median	-0.017	-0.011	0.059	0.086*	0.099*	0.097*	0.099*
BVAR: PCE + Median + Skew (K)	-0.010	-0.005	0.057	0.081*	0.095*	0.094*	0.095*
BVAR: PCE + Trim	-0.015	-0.015	0.038	0.062	0.084*	0.095*	0.104*
BVAR: PCE + Trim + Skew (K)	-0.009	-0.005	0.035	0.057	0.082*	0.092*	0.102*
BVAR: PCE + Core	-0.010	-0.008	-0.010	-0.003	0.004	0.011*	0.017*
BVAR: PCE + Core + Skew (K)	-0.009	-0.012	-0.014	-0.007	0.002	0.010	0.016*

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE LPS	-0.183	-1.748	-1.948	-1.565	-1.445	-1.467	-1.429
Relative LPS							
BVAR: PCE + Skew (K)	-0.008	0.075*	0.039	0.017*	0.028*	0.027*	0.028*
BVAR: PCE + Median	-0.024	0.041	0.073	0.050	0.105*	0.116*	0.097*
BVAR: PCE + Median + Skew (K)	0.009	0.130	0.076	0.050	0.111*	0.119*	0.104*
BVAR: PCE + Trim	-0.026	0.021	0.071	0.049	0.118*	0.133*	0.100*
BVAR: PCE + Trim + Skew (K)	-0.003	0.110	0.070	0.048	0.124*	0.137*	0.105*
BVAR: PCE + Core	-0.023*	0.015	0.035*	0.034*	0.033*	0.035*	0.035*
BVAR: PCE + Core + Skew (K)	-0.013	0.064*	0.035*	0.031*	0.035*	0.034*	0.035*

Notes: The numbers reported in the first row of each panel are the logarithmic predictive score (LPS) from the univariate AR PCE inflation in gaps (3-lag specification), while the rows below it are relative logarithmic predictive scores (relative to LPS from the AR(3) PCE inflation in gaps). Thus, a relative LPS that is negative indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. Similarly, the positive value of relative LPS indicates the model being compared is more accurate on average. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample). * indicates statistical significance up to 10% level and is based on the LR test of Amisano and Giacomini (2007).

Table 3: Goods PCE inflation out-of-sample point forecasting comparison
[Skew constructed based on month-over-month inflation rates]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Goods PCE RMSE	0.644	1.952	2.470	2.334	2.467	2.505	2.407
Relative MSE							
BVAR: G.PCE + Skew (K)	1.025	0.962	0.983	1.022	1.026	1.061	1.136*
BVAR: G.PCE + Median	1.050	0.934	0.888	0.944	0.905	0.925	1.004
BVAR: G.PCE + Median + Skew(K)	1.042	0.911	0.886	0.941	0.902	0.930	1.009

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Goods PCE RMSE	0.588	1.278	1.769	1.880	2.051	2.076	1.961
Relative MSE							
BVAR: G.PCE + Skew (K)	1.006	1.017	1.045	1.090	1.103	1.181	1.363
BVAR: G.PCE + Median	1.021	0.923	0.961	1.021	1.023	1.071	1.171
BVAR: G.PCE + Median + Skew(K)	1.017	0.916	0.956	1.015	1.024	1.078	1.185

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Goods PCE RMSE	0.697	2.448	2.948	2.478	2.628	2.690	2.485
Relative MSE							
BVAR: G.PCE + Skew (K)	1.039	0.948	0.974	1.002	0.946	0.973	1.059
BVAR: G.PCE + Median	1.072	0.936	0.856	0.899*	0.792*	0.790*	0.904*
BVAR: G.PCE + Median + Skew(K)	1.061	0.909	0.857	0.897*	0.778*	0.790*	0.907*

Notes: The numbers reported in the first row of each panel are the root mean squared error (RMSE) from the univariate AR PCE inflation in gaps (3-lag specification), while the rows below it are ratios that report relative MSEs (relative to MSE from the AR(3) PCE inflation in gaps). Thus, a ratio of more than 1 indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample).
* indicates statistical significance up to 10% level and is based on Diebold-Mariano West test

Table 4: Services PCE inflation out-of-sample point forecasting comparison
[Skew constructed based on month-over-month inflation rates]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Services PCE RMSE	0.174	0.466	0.661	0.683	0.704	0.728	0.752
Relative MSE							
BVAR: S.PCE + Skew (K)	0.968*	0.935	0.968	0.983	0.991	0.983	0.982
BVAR: S.PCE + Median	1.026	1.022	0.979	0.991	0.997	0.997	1.000
BVAR: S.PCE + Median + Skew(K)	0.998	0.954	0.989	1.003	1.005	0.995	0.995

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Services PCE RMSE	0.187	0.375	0.555	0.622	0.668	0.692	0.732
Relative MSE							
BVAR: S.PCE + Skew (K)	0.949*	0.982	1.018	1.053	1.084	1.108*	1.107*
BVAR: S.PCE + Median	1.006	1.067	1.016	1.026	1.046	1.072	1.079*
BVAR: S.PCE + Median + Skew(K)	1.005	1.010	1.033	1.056	1.080	1.104	1.103*

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-Services PCE RMSE	0.159	0.552	0.767	0.672	0.484	0.482	0.466
Relative MSE							
BVAR: S.PCE + Skew (K)	0.994	0.911	0.940*	0.929*	0.898*	0.921	0.972
BVAR: S.PCE + Median	1.054*	1.001	0.958*	0.964*	0.949*	0.945	0.983
BVAR: S.PCE + Median + Skew(K)	0.986	0.927	0.963	0.957*	0.924*	0.946	0.996

Notes: The numbers reported in the first row of each panel are the root mean squared error (RMSE) from the univariate AR PCE inflation in gaps (3-lag specification), while the rows below it are ratios that report relative MSEs (relative to MSE from the AR(3) PCE inflation in gaps). Thus, a ratio of more than 1 indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample). * indicates statistical significance up to 10% level and is based on Diebold-Mariano West test

Table 5: Estimates of parameter beta

Model	Posterior Mean	68% Credible Bands
Headline PCE inflation		
Default (past inflation)	0.002	-0.005, 0.009
B. Skew	**-0.199**	**-0.330, -0.068**
Services PCE inflation		
Default (past services inflation)	0.001	-0.006, 0.007
Services B. Skew	-0.121	-0.260, 0.017
Goods PCE inflation		
Default (past inflation)	0.003	-0.005, 0.011
Goods B. Skew	**0.320**	**0.116, 0.525**

Notes: The numbers reported under the column labeled "Posterior Mean" refer to posterior mean estimates of the parameter beta obtained by estimating the TVP-SVM model using quarterly data. "B. Skew" refers to the Bowley skewness measure, "Services B. Skew" refers to the Bowley skewness measure constructed using the components underlying the services PCE category, and "Goods B. Skew" refers to the Bowley skewness measure constructed using the components underlying the goods PCE category. Quarterly values of the skewness measures are computed by averaging the monthly estimates of the skewness. The numbers in bold indicate significant values.

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Appendix

A.1. List of disaggregate components

Table A1

1	Personal Consumption Expenditures: New Domestic Autos (SAAR, Mil.$)
2	Personal Consumption Expenditures: New Foreign Autos (SAAR, Mil.$)
3	Personal Consumption Expenditures: New Light Trucks (SAAR, Mil.$)
4	Personal Consumption Expenditures: Used Autos (SAAR, Mil.$)
5	Personal Consumption Expenditures: Used Light Trucks (SAAR, Mil.$)
6	Personal Consumption Expenditures: Tires (SAAR, Mil.$)
7	Personal Consumption Expenditures: Accessories and Parts (SAAR, Mil.$)
8	Personal Consumption Expenditures: Furniture (SAAR, Mil.$)
9	PCE: Clocks, Lamps, Lighting Fixtures & Other HH Decorative Items(SAAR, Mil.$)
10	PCE: Carpets & Other Floor Coverings(SAAR, Mil.$)
11	Personal Consumption Expenditures: Window Coverings (SAAR, Mil.$)
12	Personal Consumption Expenditures: Major Household Appliances (SAAR, Mil.$)
13	Personal Consumption Expenditures: Small Elec Household Appliances (SAAR, Mil.$)
14	Personal Consumption Expenditures: Dishes and Flatware (SAAR, Mil.$)
15	PCE: Nonelectric Cookware & Tableware (SAAR, Mil.$)
16	Personal Consumption Expenditures: Tools, Hardware, and Supplies (SAAR, Mil.$)
17	Personal Consumption Expenditures: Outdoor Equipment and Supplies (SAAR, Mil.$)
18	Personal Consumption Expenditures: Televisions (SAAR, Mil.$)
19	Personal Consumption Expenditures: Other Video Equipment (SAAR, Mil.$)
20	Personal Consumption Expenditures: Audio Equipment (SAAR, Mil.$)
21	PCE: Audio Discs, Tapes, Vinyl and Permanent Digital Downloads (SAAR, Mil.$)
22	PCE: Video Discs, Tapes and Permanent Digital Downloads (SAAR, Mil.$)
23	Personal Consumption Expenditures: Photographic Equipment (SAAR, Mil.$)
24	PCE: Personal Computers/Tablets and Peripheral Equip (SAAR, Mil.$)
25	PCE: Computer Software & Accessories (SAAR, Mil.$)
26	PCE: Calculators, Typewriters & Other Info Processing Equip (SAAR, Mil.$)
27	PCE: Sporting Equip, Supplies, Guns & Ammunition (SAAR, Mil.$)
28	Personal Consumption Expenditures: Motorcycles (SAAR, Mil.$)
29	Personal Consumption Expenditures: Bicycles and Accessories (SAAR, Mil.$)
30	Personal Consumption Expenditures: Pleasure Boats (SAAR, Mil.$)
31	Personal Consumption Expenditures: Pleasure Aircraft (SAAR, Mil.$)
32	Personal Consumption Expenditures: Other Recreational Vehicles (SAAR, Mil.$)
33	Personal Consumption Expenditures: Recreational Books (SAAR, Mil.$)
34	Personal Consumption Expenditures: Musical Instruments (SAAR, Mil.$)
35	Personal Consumption Expenditures: Jewelry (SAAR, Mil.$)
36	Personal Consumption Expenditures: Watches (SAAR, Mil.$)
37	Personal Consumption Expenditures: Therapeutic Medical Equipment (SAAR, Mil.$)
38	PCE: Corrective Eyeglasses & Contact Lenses (SAAR, Mil.$)

39	Personal Consumption Expenditures: Educational Books (SAAR, Mil.$)
40	PCE: Luggage & Similar Personal Items (SAAR, Mil.$)
41	PCE: Telephone and Related Communication Equipment (SAAR, Mil.$)
42	Personal Consumption Expenditures: Cereals (SAAR, Mil.$)
43	Personal Consumption Expenditures: Bakery Products (SAAR, Mil.$)
44	Personal Consumption Expenditures: Beef and Veal (SAAR, Mil.$)
45	Personal Consumption Expenditures: Pork (SAAR, Mil.$)
46	Personal Consumption Expenditures: Other Meats (SAAR, Mil.$)
47	Personal Consumption Expenditures: Poultry (SAAR, Mil.$)
48	Personal Consumption Expenditures: Fish and Seafood (SAAR, Mil.$)
49	Personal Consumption Expenditures: Fresh Milk (SAAR, Mil.$)
50	Personal Consumption Expenditures: Processed Dairy Products (SAAR, Mil.$)
51	Personal Consumption Expenditures: Eggs (SAAR, Mil.$)
52	Personal Consumption Expenditures: Fats and Oils (SAAR, Mil.$)
53	Personal Consumption Expenditures: Fresh Fruit (SAAR, Mil.$)
54	Personal Consumption Expenditures: Fresh Vegetables (SAAR, Mil.$)
55	Personal Consumption Expenditures: Processed Fruits and Vegetables (SAAR, Mil.$)
56	Personal Consumption Expenditures: Sugar and Sweets (SAAR, Mil.$)
57	PCE: Food Products, Not Elsewhere Classified (SAAR, Mil.$)
58	PCE: Coffee, Tea & Other Bev Mtls (SAAR, Mil.$)
59	PCE: Mineral Waters, Soft Drinks & Vegetable Juices (SAAR, Mil.$)
60	Personal Consumption Expenditures: Spirits (SAAR, Mil.$)
61	Personal Consumption Expenditures: Wine (SAAR, Mil.$)
62	Personal Consumption Expenditures: Beer (SAAR, Mil.$)
63	PCE: Food Produced & Consumed on Farms (SAAR, Mil.$)
64	Personal Consumption Expenditures: Women's and Girls' Clothing (SAAR, Mil.$)
65	Personal Consumption Expenditures: Men's and Boys' Clothing (SAAR, Mil.$)
66	PCE: Children's & Infants' Clothing (SAAR, Mil.$)
67	Personal Consumption Expenditures: Clothing Materials (SAAR, Mil.$)
68	PCE: Standard Clothing Issued to Military Personnel (SAAR, Mil.$)
69	Personal Consumption Expenditures: Shoes and Other Footwear (SAAR, Mil.$)
70	Personal Consumption Expenditures: Gasoline and Other Motor Fuel (SAAR, Mil.$)
71	Personal Consumption Expenditures: Lubricants and Fluids (SAAR, Mil.$)
72	Personal Consumption Expenditures: Fuel Oil (SAAR, Mil.$)
73	Personal Consumption Expenditures: Other Fuels (SAAR, Mil.$)
74	Personal Consumption Expenditures: Prescription Drugs (SAAR, Mil.$)
75	Personal Consumption Expenditures: Nonprescription Drugs (SAAR, Mil.$)
76	Personal Consumption Expenditures: Other Medical Products (SAAR, Mil.$)
77	Personal Consumption Expenditures: Games, Toys, and Hobbies (SAAR, Mil.$)
78	Personal Consumption Expenditures: Pets and Related Products (SAAR, Mil.$)
79	PCE: Flowers, Seeds & Potted Plants (SAAR, Mil.$)
80	Personal Consumption Expenditures: Film and Photographic Supplies (SAAR, Mil.$)
81	Personal Consumption Expenditures: Household Cleaning Products (SAAR, Mil.$)

82	Personal Consumption Expenditures: Household Paper Products (SAAR, Mil.$)
83	Personal Consumption Expenditures: Household Linens (SAAR, Mil.$)
84	Personal Consumption Expenditures: Sewing Items (SAAR, Mil.$)
85	PCE: Miscellaneous Household Products (SAAR, Mil.$)
86	PCE: Hair, Dental, Shaving & Misc Personal Care Prods ex Elec Prods (SAAR, Mil.$)
87	PCE: Cosmetic/Perfumes/Bath/Nail Preparations & Implements (SAAR, Mil.$)
88	PCE: Elec Appliances for Personal Care (SAAR, Mil.$)
89	Personal Consumption Expenditures: Tobacco (SAAR, Mil.$)
90	Personal Consumption Expenditures: Newspapers and Periodicals (SAAR, Mil.$)
91	Personal Consumption Expenditures: Stationery & Misc Printed Materials (SAAR, Mil.$)
92	Personal Consumption Expenditures: Tenant-Occupied Mobile Homes (SAAR, Mil.$)
93	PCE: Tenant-Occupied Stationary Homes (SAAR, Mil.$)
94	Personal Consumption Expenditures: Tenant Landlord Durables (SAAR, Mil.$)
95	Personal Consumption Expenditures: Owner-Occupied Mobile Homes (SAAR, Mil.$)
96	Personal Consumption Expenditures: Owner-Occupied Stationary Homes (SAAR, Mil.$)
97	Personal Consumption Expenditures: Rental Value Of Farm Dwellings (SAAR, Mil.$)
98	Personal Consumption Expenditures: Group Housing (SAAR, Mil.$)
99	PCE: Water Supply & Sewage Maintenance(SAAR, Mil.$)
100	Personal Consumption Expenditures: Garbage and Trash Collection (SAAR, Mil.$)
101	Personal Consumption Expenditures: Electricity (SAAR, Mil.$)
102	Personal Consumption Expenditures: Natural Gas (SAAR, Mil.$)
103	Personal Consumption Expenditures: Physician Services (SAAR, Mil.$)
104	Personal Consumption Expenditures: Dental Services (SAAR, Mil.$)
105	Personal Consumption Expenditures: Paramedical Services (SAAR, Mil.$)
106	PCE: Nonprofit Hospitals' Services to Households (SAAR, Mil.$)
107	Personal Consumption Expenditures: Proprietary Hospitals (SAAR, Mil.$)
108	Personal Consumption Expenditures: Government Hospitals (SAAR, Mil.$)
109	Personal Consumption Expenditures: Nursing Homes (SAAR, Mil.$)
110	PCE: Motor Vehicle Maintenance & Repair (SAAR, Mil.$)
111	Personal Consumption Expenditures: Motor Vehicle Leasing (SAAR, Mil.$)
112	Personal Consumption Expenditures: Motor Vehicle Rental (SAAR, Mil.$)
113	Personal Consumption Expenditures: Parking Fees and Tolls (SAAR, Mil.$)
114	Personal Consumption Expenditures: Railway Transportation (SAAR, Mil.$)
115	Personal Consumption Expenditures: Intercity Buses (SAAR, Mil.$)
116	Personal Consumption Expenditures: Taxicabs (SAAR, Mil.$)
117	Personal Consumption Expenditures: Intracity Mass Transit (SAAR, Mil.$)
118	PCE: Other Road Transportation Service (SAAR, Mil.$)
119	Personal Consumption Expenditures: Air Transportation (SAAR, Mil.$)
120	Personal Consumption Expenditures: Water Transportation (SAAR, Mil.$)
121	PCE: Membership Clubs & Participant Sports Centers (SAAR, Mil.$)
122	PCE: Amusement Parks, Campgrounds & Related Recreational Services (SAAR, Mil.$)
123	Personal Consumption Expenditures: Motion Picture Theaters (SAAR, Mil.$)
124	Personal Consumption Expenditures: Live Entertainment, excl Sports (SAAR, Mil.$)

125	Personal Consumption Expenditures: Spectator Sports (SAAR, Mil.$)
126	Personal Consumption Expenditures: Museums and Libraries (SAAR, Mil.$)
127	PCE: Audio-Video, Photographic & Info Processing Services (SAAR, Mil.$)
128	Personal Consumption Expenditures: Casino Gambling (SAAR, Mil.$)
129	Personal Consumption Expenditures: Lotteries (SAAR, Mil.$)
130	Personal Consumption Expenditures: Pari-Mutuel Net Receipts (SAAR, Mil.$)
131	PCE: Veterinary & Other Services for Pets (SAAR, Mil.$)
132	Personal Consumption Expenditures: Package Tours (SAAR, Mil.$)
133	PCE: Maintenance & Repair of Recreational Vehicles & Sports Equip (SAAR, Mil.$)
134	PCE: Elementary & Secondary School Lunches (SAAR, Mil.$)
135	Personal Consumption Expenditures: Higher Education School Lunches (SAAR, Mil.$)
136	Personal Consumption Expenditures: Other Purchased Meals (SAAR, Mil.$)
137	Personal Consumption Expenditures: Alcohol In Purchased Meals (SAAR, Mil.$)
138	Personal Consumption Expenditures: Food Supplied To Civilians (SAAR, Mil.$)
139	Personal Consumption Expenditures: Food Supplied To Military (SAAR, Mil.$)
140	Personal Consumption Expenditures: Hotels and Motels (SAAR, Mil.$)
141	Personal Consumption Expenditures: Housing At Schools (SAAR, Mil.$)
142	Personal Consumption Expenditures: Commercial Banks (SAAR, Mil.$)
143	PCE: Other Depository Institutions & Regulated Investment Companies (SAAR, Mil.$)
144	Personal Consumption Expenditures: Pension Funds (SAAR, Mil.$)
145	PCE: Financial Service Charges, Fees & Commissions (SAAR, Mil.$)
146	Personal Consumption Expenditures: Life Insurance (SAAR, Mil.$)
147	Personal Consumption Expenditures: Net Household Insurance (SAAR, Mil.$)
148	Personal Consumption Expenditures: Net Health Insurance (SAAR, Mil.$)
149	PCE: Net Motor Vehicle & Other Transportation Insurance (SAAR, Mil.$)
150	Personal Consumption Expenditures: Communication (SAAR, Mil.$)
151	PCE: Proprietary & Public Higher Education (SAAR, Mil.$)
152	PCE: Nonprofit Pvt Higher Education Services to Households (SAAR, Mil.$)
153	PCE: Elementary & Secondary Schools(SAAR, Mil.$)
154	Personal Consumption Expenditures: Day Care and Nursery Schools (SAAR, Mil.$)
155	PCE: Commercial & Vocational Schools(SAAR, Mil.$)
156	Personal Consumption Expenditures: Legal Services (SAAR, Mil.$)
157	PCE: Tax Preparation & Other Related Services (SAAR, Mil.$)
158	Personal Consumption Expenditures: Employment Agency Services (SAAR, Mil.$)
159	PCE: Other Personal Business Services(SAAR, Mil.$)
160	Personal Consumption Expenditures: Labor Organization Dues (SAAR, Mil.$)
161	Personal Consumption Expenditures: Professional Association Dues (SAAR, Mil.$)
162	Personal Consumption Expenditures: Funeral and Burial Services (SAAR, Mil.$)
163	PCE: Hairdressing Salons & Personal Grooming Establishments (SAAR, Mil.$)
164	Personal Consumption Expenditures: Misc Personal Care Services (SAAR, Mil.$)
165	PCE: Laundry & Dry Cleaning Services (SAAR, Mil.$)
166	PCE: Clothing Repair, Rental & Alterations (SAAR, Mil.$)
167	Personal Consumption Expenditures: Repair and Hire Of Footwear (SAAR, Mil.$)

168	Personal Consumption Expenditures: Child Care (SAAR, Mil.$)
169	Personal Consumption Expenditures: Social Assistance (SAAR, Mil.$)
170	PCE: Social Advocacy & Civic & Social Organizations (SAAR, Mil.$)
171	Receipts From Sales: Religious Organizations' Services to HH(SAAR, Mil.$)
172	Sales Receipts: Foundations & Grant Making & Giving Svcs to HH (SAAR, Mil.$)
173	Personal Consumption Expenditures: Domestic Services (SAAR, Mil.$)
174	PCE: Moving, Storage & Freight Services (SAAR, Mil.$)
175	PCE: Repair of Furniture, Furnishings & Floor Coverings (SAAR, Mil.$)
176	Personal Consumption Expenditures: Repair Of Household Appliances (SAAR, Mil.$)
177	Personal Consumption Expenditures: Other Household Services (SAAR, Mil.$)
178	PCE: Foreign Travel by US Residents (SAAR, Mil.$)
179	PCE: Less: Expenditures in the US by Nonresidents (SAAR, Mil.$)
180	PCE: Expenditures Abroad by US Residents Price Index (SA, 2012=100)
181	PCE: Less: Personal Remittances in Kind to Nonresidents Price Idx (SA, 2012=100)
182	Final Consumption Expenditures of Nonprofit Instns Serving HH (SAAR, Mil.$)

A.2. BVAR Model Details [as in Knotek and Zaman, 2019]

A general representation of a VAR(p) model can be written as:

$$Y_t = A_c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t \tag{A1}$$

where t=1,…,T, $Y_t = [y_{1,t}, y_{2,t}, \ldots, y_{n,t}]$ is an n×1 data vector of n random variables, $A_c = [c_1, c_2, \ldots, c_n]$ is an n×1 vector of constants, $A_1, \ldots, A_p$ are n×n matrices of VAR coefficients, and u_t is an n×1 vector of normally distributed error terms with zero mean and covariance matrix $\Sigma = E u_t u_t'$. In this n dimensional VAR, each equation has m=np+1 regressors, and with n equations, there are n×m parameters to be estimated. In our exercises, n will range from 2 to 3, and we set the number of lags, p, to 3 to be consistent with the benchmark AR(3) model. The system in equation (A1) can be written in a stacked, compact form as:

$$Y = XA + U. \tag{A2}$$

We use Normal-inverse Wishart (N-IW) conjugate priors to characterize our beliefs about the coefficient estimates in $A_1, ..., A_p$ and Σ.[23] The prior beliefs for the mean and variances of the coefficient matrices are:

$$
\begin{aligned}
E[A_k^{(i,j)}] &= \begin{cases} \delta_i & \text{if } i = j,\, k = 1 \\ 0 & \text{otherwise} \end{cases} \\
Var[A_k^{(i,j)}] &= \lambda^2 \frac{1}{k^2} \frac{\sigma_i^2}{\sigma_j^2},\; k = 1, ..., p
\end{aligned}
\tag{1}
$$

We model inflation in gap form using deviations from its long-run trend, based on work by Faust and Wright (2013) and Zaman (2013), among others, that documents improvements in forecast accuracy from following this approach.[24] Since we are working with stationary data (in gaps), we set δ_i=0.0. The scale factor $1/k^2$ helps impose the prior belief that recent lags play a more influential role compared with more distant lags by proportionally shrinking the variances on the more distant lags (centered on a prior mean of zero). The prior parameter σ_i is set equal to the standard deviation of the residuals obtained from regressing the variable y_i on its own p lags and a constant over the sample period up to any point in time t. The hyperparameter λ governs the tightness of our priors. As $\lambda \to 0$, the prior dominates and the posterior equals the prior, i.e., the data have no say. On the other hand, as $\lambda \to \infty$, the prior has no influence and posterior estimates converge to OLS estimates. The prior belief for the residual variance-covariance matrix Σ is set such that the expectation of Σ is equal to $diag(\sigma_1^2, \ldots, \sigma_n^2)$. As in Bańbura, Giannone, and Reichlin (2010), these priors for the coefficient estimates in $A_1, ..., A_p$ and Σ are implemented by augmenting equation (A2) with dummy observations.

[23] The N-IW prior is computationally convenient both for estimation and for performing Bayesian inference compared with other prior choices. Koop (2013) documents the forecast accuracy of BVARs estimated with N-IW priors compared with other families of prior distributions.

[24] As in Knotek, Zaman, and Clark (2015), the long-run trend for inflation comes from splicing the long-term inflation expectations series from the Federal Reserve Board of Governor's FRB/US econometric model, denoted PTR, with the long-run inflation expectations series from the Survey of Professional Forecasters.

The above-mentioned BVAR studies document further gains in forecast accuracy by imposing a "sum of coefficients" (SOC) prior on the equations of the VAR. Although this prior is more relevant when working with data in levels (or log-levels), since it imposes the belief that coefficients on own lags sum to one (or zero when working with stationary data), for purposes of generality, we nevertheless include this prior, but make it very loose. In essence, under the SOC prior, a reasonable forecast of the future level of a variable is the average of that variable's lagged values. The hyperparameter μ governs the tightness of the SOC prior. To implement the SOC prior, letting $\overline{y}_{0i}$ denote the average of the initial lagged p values for variable y_i, we further augment the system in equation (A2) with dummy observations:

$$\begin{aligned} Y^{SOC}(i,j) &= \begin{cases} \overline{y}_{0i} / \mu & \text{if } i = j \\ 0 & \text{otherwise} \end{cases} \\ X^{SOC}(i,r) &= \begin{cases} \overline{y}_{0i} / \mu & \text{if } i = j, r < m \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{A3}$$

where i=1,…,n, j=1,…,n, and r=1,…,m.

Figure A1: Cross-sectional asymmetry (*Bowley*) in PCE inflation (month-to-month %)

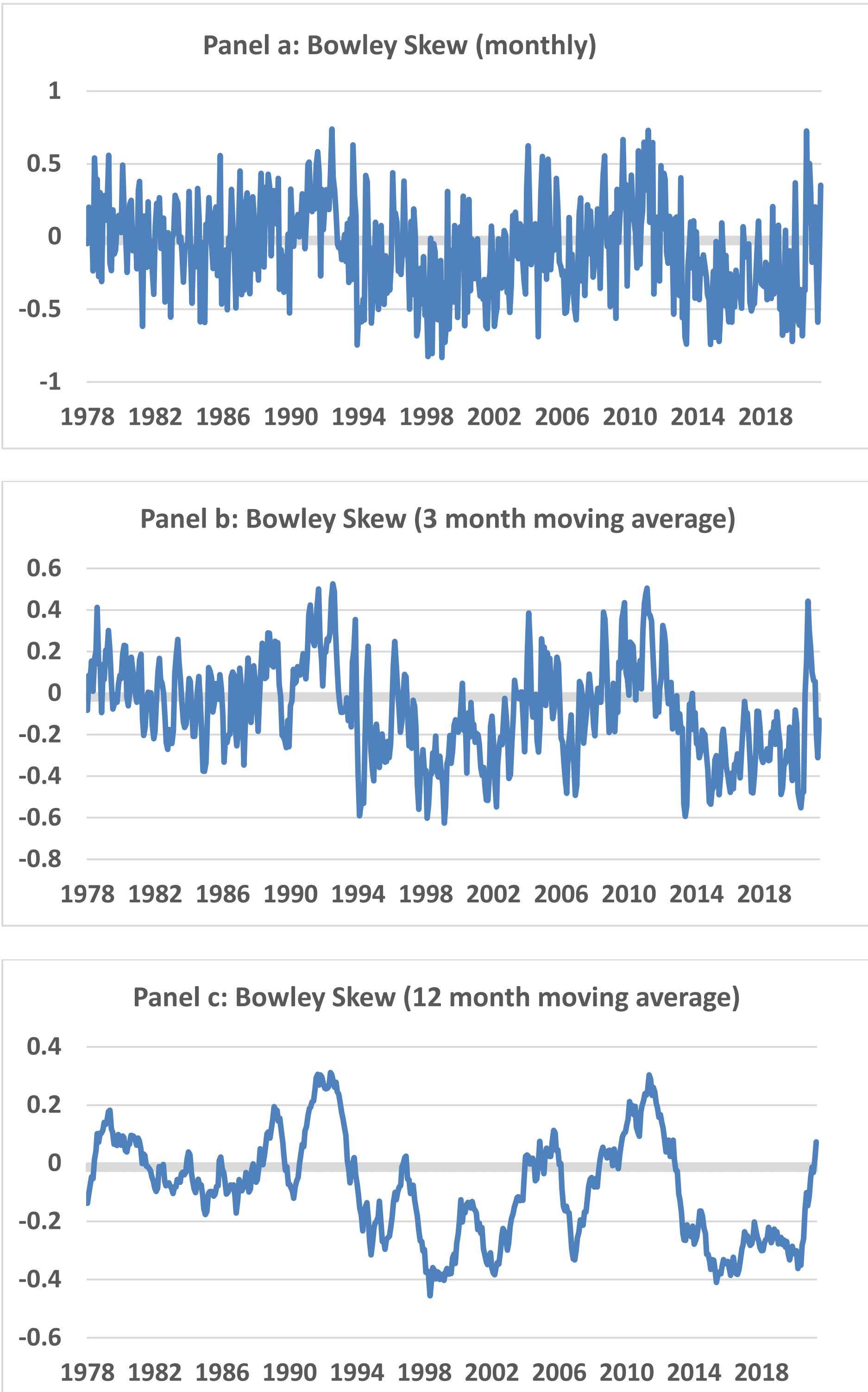

Figure A2: Cross-sectional asymmetry (Kelly Skew) in PCE price index

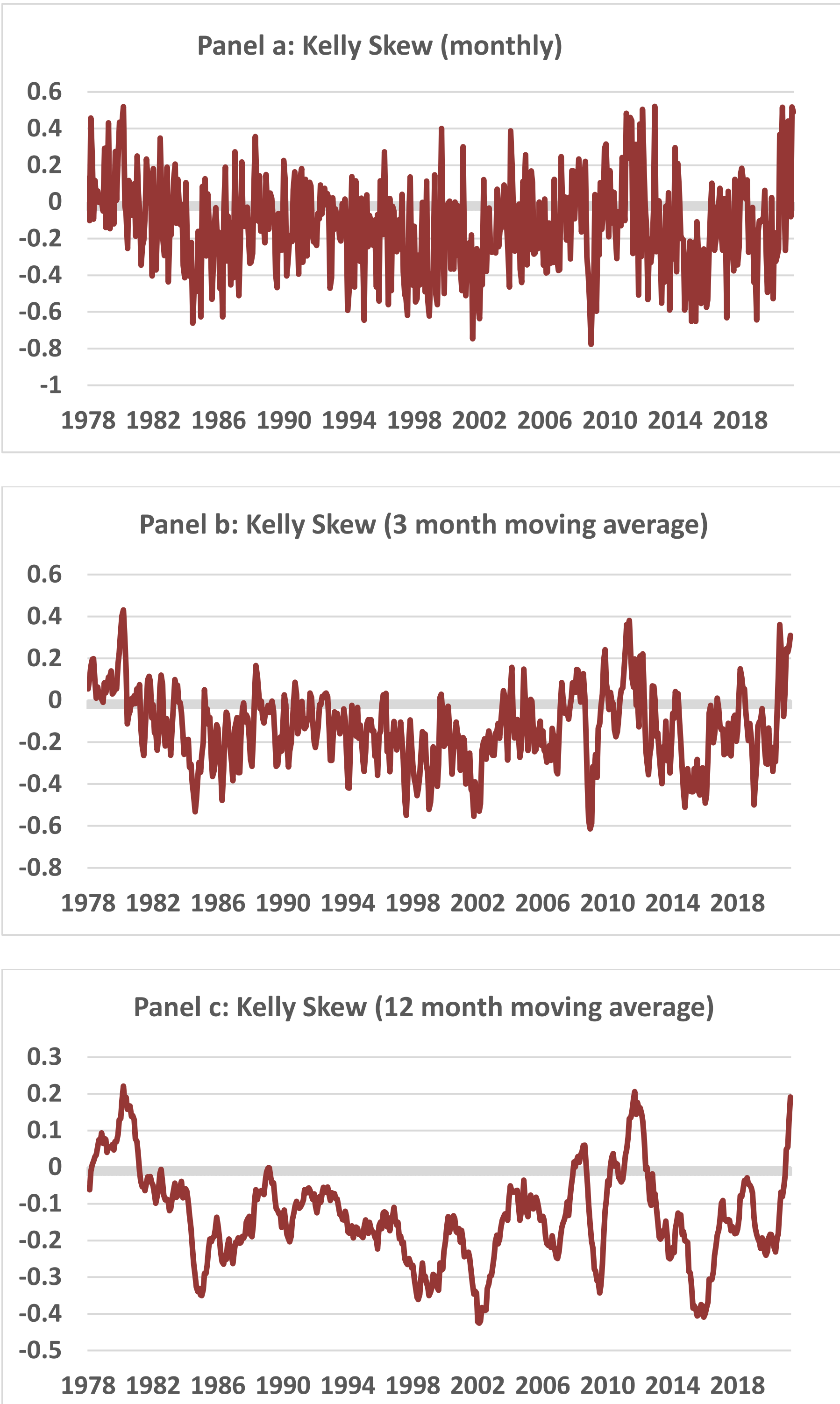

Table A2: PCE inflation out-of-sample Point forecasting comparison
[Skew measures constructed based on month-over-month inflation rates]
[Results using Bowley Skew]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.265	0.858	1.126	1.064	1.075	1.077	1.044
Relative MSE							
BVAR: PCE + Skew (B)	1.043*	0.988	0.988	0.975	0.975	0.964	0.968
BVAR: PCE + Median	1.046*	0.991	0.893	0.882*	0.879*	0.898*	0.887*
BVAR: PCE + Median + Skew (B)	1.039*	0.948	0.881	0.878*	0.883*	0.900*	0.884*
BVAR: PCE + Trim	1.045*	0.997	0.891	0.918	0.913	0.916	0.913*
BVAR: PCE + Trim + Skew (B)	1.040*	0.964	0.884	0.915	0.913	0.911	0.907*
BVAR: PCE + Core	1.045*	1.010	1.008	0.997	0.980	0.967*	0.973
BVAR: PCE + Core + Skew (B)	1.050	1.009	1.015	0.996	0.986	0.963*	0.964
BVAR: PCE + UR	1.109*	1.181	1.320*	1.485*	1.628*	1.634*	1.612*

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.245	0.553	0.806	0.870	0.941	0.955	0.930
Relative MSE							
BVAR: PCE + Skew (B)	1.006	0.988	1.008	1.001	0.994	0.995	1.008
BVAR: PCE + Median	1.024*	1.053	0.883	0.815	0.787*	0.795*	0.796*
BVAR: PCE + Median + Skew (B)	0.998	0.987	0.887	0.817	0.787*	0.794*	0.796*
BVAR: PCE + Trim	1.019	1.076	0.951	0.910	0.860	0.838*	0.814*
BVAR: PCE + Trim + Skew (B)	0.994	1.008	0.948	0.914	0.862	0.839*	0.815*
BVAR: PCE + Core	1.005	1.030	1.031	1.018	1.004	0.997	1.006
BVAR: PCE + Core + Skew (B)	1.006	1.022	1.050*	1.036	1.019	1.008	1.015
BVAR: PCE + UR	1.016	1.220	1.375	1.602*	1.648*	1.769*	1.979*

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.285	1.087	1.359	1.097	0.975	0.972	0.833
Relative MSE							
BVAR: PCE + Skew (B)	1.071*	0.988	0.978	0.941*	0.939*	0.936	0.962
BVAR: PCE + Median	1.063*	0.976	0.906	0.932	0.793*	0.742*	0.790*
BVAR: PCE + Median + Skew (B)	1.070*	0.941	0.893	0.921	0.794*	0.745*	0.792*
BVAR: PCE + Trim	1.065*	0.980	0.883	0.933	0.774*	0.709*	0.808
BVAR: PCE + Trim + Skew (B)	1.075*	0.958	0.875	0.919	0.770*	0.708*	0.808*
BVAR: PCE + Core	1.076*	1.004	0.997	0.974*	0.946*	0.942*	0.954*
BVAR: PCE + Core + Skew (B)	1.084*	1.005	0.998	0.949*	0.941*	0.938*	0.954*
BVAR: PCE + UR	1.180*	1.179	1.347*	1.603	1.913	1.807	1.894

Notes: The numbers reported in the first row of each panel are the root mean squared error (RMSE) from the univariate AR PCE inflation in gaps (3-lag specification), while the four rows below it are ratios that report relative MSEs (relative to MSE from the AR(3) PCE inflation in gaps). Thus, a ratio of more than 1 indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample). * indicates statistical significance up to 10% level and is based on Diebold-Mariano West test.

Table A3: PCE inflation out-of-sample density forecasting comparison

Full sample (January 1994 – June 2021):
[Skew measures constructed based on month-over-month inflation rates]

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE LPS	-0.096	-1.302	-1.600	-1.516	-1.526	-1.543	-1.545
Relative LPS							
BVAR: PCE + Skew (B)	-0.021	0.007	0.010	0.012*	0.014*	0.023*	0.024*
BVAR: PCE + Median	-0.019*	0.004	0.073*	0.072*	0.069*	0.065*	0.074*
BVAR: PCE + Median + Skew (B)	-0.017	0.029	0.077*	0.072*	0.067*	0.062*	0.071*
BVAR: PCE + Trim	-0.017	0.004	0.055	0.051	0.054	0.061*	0.071*
BVAR: PCE + Trim + Skew (B)	-0.015	0.019	0.064	0.051	0.054	0.061*	0.070*
BVAR: PCE + Core	-0.017	0.003	0.008	0.011*	0.017*	0.025*	0.027*
BVAR: PCE + Core + Skew (B)	-0.020	0.005	0.008	0.011	0.014*	0.022*	0.025*

Table A4: PCE inflation out-of-sample point forecasting comparison
[Skew constructed based on month-over-month inflation rates]
[**Two-step algorithm**]

Full sample (January 1994 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.265	0.858	1.126	1.064	1.075	1.077	1.044
Relative MSE							
BVAR: PCE + Skew (K)	1.028	0.957*	0.988	0.976	0.959*	0.959*	0.967*
BVAR: PCE + Median	1.046*	0.991	0.893	0.882*	0.879*	0.898*	0.887*
BVAR: PCE + Median Adjusted	1.045*	0.972	0.881	0.918*	0.924*	0.928	0.924*
BVAR: PCE + Trim	1.045*	0.997	0.891	0.918	0.913	0.916	0.913*
BVAR: PCE + Trim Adjusted	1.044*	0.988	0.900	0.973	0.969	0.953	0.963*

Pre-financial crisis sample (January 1994 – December 2007)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.245	0.553	0.806	0.870	0.941	0.955	0.930
Relative MSE							
BVAR: PCE + Skew (K)	1.009	1.006	0.998	0.989	0.980	0.981	0.995
BVAR: PCE + Median	1.024*	1.053	0.883	0.815	0.787*	0.795*	0.796*
BVAR: PCE + Median Adjusted	1.018	0.979	0.847	0.812*	0.800*	0.807*	0.820*
BVAR: PCE + Trim	1.019	1.076	0.951	0.910	0.860	0.838*	0.814*
BVAR: PCE + Trim Adjusted	1.007	0.970	0.895	0.895	0.878	0.868*	0.866*

Financial crisis and onward sample (January 2008 – June 2021)

	h=1M	h=6M	h=1Y	h=18M	h=2Y	h=30M	h=3Y
AR(3)-PCE RMSE	0.285	1.087	1.359	1.097	0.975	0.972	0.833
Relative MSE							
BVAR: PCE + Skew (K)	1.043*	0.943*	0.982	0.953	0.908*	0.924*	0.947*
BVAR: PCE + Median	1.063*	0.976	0.906	0.932	0.793*	0.742*	0.790*
BVAR: PCE + Median Adjusted	1.052*	0.943	0.893	0.928	0.726*	0.695*	0.757*
BVAR: PCE + Trim	1.065*	0.980	0.883	0.933	0.774*	0.709*	0.808
BVAR: PCE + Trim Adjusted	1.054*	0.947	0.875	0.930	0.718*	0.691*	0.805*

Notes: The numbers reported in the first row of each panel are the root mean squared error (RMSE) from the univariate AR PCE inflation in gaps (3-lag specification), while the rows below it are ratios that report relative MSEs (relative to MSE from the AR(3) PCE inflation in gaps). Thus, a ratio of more than 1 indicates that the univariate inflation in gaps model is more accurate on average than the model being compared. The forecast performance is based on an expanding window of estimation spanning the period January 1994 through June 2021 (full sample), and January 1994 through December 2007 (pre-financial crisis sample). * indicates statistical significance up to 10% level and is based on Diebold-Mariano West test