On the Relative Performance of Inflation Forecasts

Julie K. Bennett and Michael T. Owyang

Inflation expectations constitute important components of macroeconomic models and monetary policy rules. We investigate the relative performance of consumer, professional, market-based, and model-based inflation forecasts. Consistent with the previous literature, professional forecasts most accurately predict one-year-ahead year-over-year inflation. Both consumers and professionals overestimate inflation over their respective sample periods. Market-based forecasts as measured by the swap market breakeven inflation rates significantly overestimate actual inflation; Treasury Inflation-Protected Securities market breakeven inflation rates exhibit no significant bias. We find that none of the forecasts can be considered rationalizable under symmetric loss. We also find that each forecast has predictive information that is not encompassed within that of another. (JEL E31, E37)

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1 INTRODUCTION

Pandemic-related product and labor supply shortages have led to an uptick in inflation that represents some of the fastest price growth since the beginning of the Great Recession. This uptick has renewed interest in forecasts of future inflation. Moreover, in some macroeconomic models, expectations of inflation (or, alternatively, forecasts of inflation) can be nearly as important as realizations of inflation. For example, in models with a short-run Phillips curve, unemployment and expectations of inflation are assumed to have a negative relationship. In some monetary policy rules, the policymaker sets the interest rate, in part, as a function of the deviation between inflation expectations and the inflation target.

Long periods of relatively low and steady price growth had apparently made inflation forecasting easier, where simple random walk models' performance belied their computational ease (Atkeson and Ohanian, 2001, and Stock and Watson, 2007). Still, during that low-inflation period, professional forecasters seemingly still held an advantage over pure model-based forecasts (Faust and Wright, 2013). Here, we investigate the relative performance of consumer, professional, market-based, and model-based forecasts of inflation over a few different forecasting horizons.

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Macroeconomists use various measures of inflation expectations. In the absence of a sophisticated econometric model, consumers could construct forecasts based on information from outside sources with simple models, heuristics, personal experience, or some combination of these. Professional survey consensus forecasts such as the Blue Chip Economic Indicators (hereafter Blue Chip) are an amalgam of individual forecasts. Market-based forecasts are breakeven inflation rates (BEIs) derived from the Treasury Inflation-Protected Securities (TIPS) and inflation swap markets. We include a few simple model-based forecasts as a baseline for comparison.

How well do agents forecast inflation? That question lies at the root of a vast literature comparing consumer, professional, financial market, and model-based forecasts (Gramlich, 1983; Thomas, 1999; Mehra, 2002; Ang, Bekaert, and Wei, 2007; Gil-Alana, Moreno, and Pérez de Gracia, 2012; Wright, 2009; Faust and Wright, 2013; and Trehan, 2015, among others). Inflation forecasts are often evaluated for (i) accuracy, (ii) bias (whether the forecaster exhibits a tendency to overestimate or underestimate actual inflation), (iii) rationality (whether forecasts were made using relevant information known to the forecaster), and (iv) encompassing (whether one forecast has additional predictive information relative to another).

We evaluate forecasts for one-year-ahead year-over-year inflation (consumer, professional, and model-based) and five-year average inflation (market-based and model-based) with regard to these four metrics. We define five-year average inflation as the average year-over-year inflation rate over a five-year span, consistent with the inflation rate that five-year TIPS and swaps BEIs are interpreted to forecast. In terms of accuracy, professional forecasts most accurately predict actual one-year-ahead year-over-year inflation, while market-based forecasts and simple model-based forecasts perform similarly well in forecasting actual five-year average inflation. In terms of bias, both professional and consumer forecasts significantly overestimate one-year-ahead year-over-year inflation, while model-based forecasts do not exhibit any significant bias. Market-based forecasts of five-year average inflation as measured by the swaps BEI significantly overestimate inflation, while those measured by the TIPS BEI do not exhibit significant bias. This difference likely arises because of inflation and risk premia embedded in the rates. For rationality, none of the forecasts evaluated can be considered rational under the assumption of a symmetric loss function and an information set consisting of the unemployment rate (UR), federal funds rate (FFR), and lagged inflation rate available at the forecasting origin. Last, for encompassing, all forecasts have predictive information that is not fully contained within that of another forecast.

2 INFLATION FORECASTS

We consider a few examples of four types of forecasts: (i) consumer forecasts; (ii) professional forecasts; (iii) financial market implied forecasts; and (iv) econometric model-based forecasts, each described in more detail below. Consumer forecasts are taken from the University of Michigan Surveys of Consumers (Michigan Surveys). Professional forecasts are from the Blue Chip consensus forecasts. While forecasts from individual firms are available, these forecasts vary in their samples, have missing observations, and may not always be trying to minimize the squared forecast error. Thus, we consider only consensus-level forecasts. Survey of Professional Forecasters (SPF) forecasts are also commonly cited professional forecasts of inflation; however, we do not use these in our analysis, as SPF forecasts are published on a quarterly basis and thus more difficult to compare with monthly forecasts. Financial market implied forecasts are breakeven inflation rates computed from the TIPS and inflation swap markets. We employ two simple types of model-based forecasts: (i) the Atkeson-Ohanian-type (hereafter AO) random walk forecast (Atkeson and Ohanion, 2001) and (ii) a simple vector autoregression- (VAR-) based forecast. We evaluate these forecasts in reference to inflation rates calculated using the seasonally adjusted consumer price index (CPI) from the Bureau of Labor Statistics (BLS).

2.1 Consumer Expectations

To examine the performance and formation of consumer inflation forecasts, researchers often employ the consumer inflation expectations data series from the Michigan Surveys. These monthly surveys ask regular people about their outlook on current and future economic conditions. The results of the surveys help assess how the average consumer processes economic data in forming expectations of future outcomes. Questions in the surveys include the following:

- During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?
- By about what percent do you expect prices to go (up/down) on the average, during the next 12 months?

Using responses to these questions, the Michigan Surveys constructs a data series of consumers' median expectations of year-over-year inflation.[1] This data series is available going back to January 1978 and is available in the Federal Reserve Bank of St. Louis FRED® database.[2]

When taken on their own, consumer inflation forecasts are often evaluated in the context of determining what factors influence the formation of inflation expectations. Ehrmann, Pfajar, and Santoro (2015) use the Michigan Surveys microdata from 1980 to 2011 and find that consumers with current or expected financial difficulties, pessimistic attitudes about major purchases, or expectations that income will go down tend to have a stronger upward bias compared with other households. Consumer inflation expectations have also been found to be responsive to media reporting (Carroll, 2003) and influenced by price changes in frequently purchased items such as gasoline (Coibion and Gorodnichenko, 2015).

2.2 Professional Forecasts

When assessing professional inflation forecasts, researchers have used a variety of metrics, including forecasts from the SPF, Livingston Survey, and Blue Chip. The Blue Chip, for example, surveys some of America's top business economists each month and collects their forecasts of various macroeconomic indicators, including inflation. The Blue Chip publishes forecasts from each surveyed economist as well as an average—or consensus—of their forecasts for each variable. These forecasts are often cited by media outlets and used by corporate and government decisionmakers. We use the Blue Chip consensus forecast for one-year-ahead inflation, constructed by Haver Analytics, which is available going back to January 1986.[3]

Numerous earlier studies have evaluated the bias and rationality of professional inflation forecasts. Brown and Maital (1981) find that the average Livingston Survey forecasts of inflation from 1961 to 1977 were not biased, but that information on monetary growth was often underutilized in the forecasts. Figlewski and Watchel (1981) use individual Livingston Survey inflation forecasts from 1947 to 1975 and find that they exhibit a significant downward bias and that forecast errors are positively serially correlated. Keane and Runkle (1989, 1990) use individual price forecasts from the SPF (at the time conducted jointly by the American Statistical Association and National Bureau of Economic Research) and conclude that the forecasts are rational, a contrast to most other studies evaluating professional inflation forecast rationality. Croushore (2010) evaluates the performance of the Livingston Survey and SPF forecasts from 1971 to 2006 in comparison to inflation as measured by the gross domestic product deflator (as opposed to CPI or personal consumption expenditure inflation used in other studies) and finds that there are only short periods where professional forecasters showed persistent and significant bias. Using individual forecasts from the Blue Chip from 1976 to 1986, Batchelor and Dua (1991) find that inflation and unemployment forecasts show the most cases of deviation from rationality, and real gross national product and interest rate forecasts the least; the authors posit, however, that it may not be optimal for individual commercial forecasters to change their forecasts to be rational, as they are attempting to differentiate their products from consensus forecasts.

2.3 Financial Market Forecasts

We use two measures of financial market inflation forecasts: BEIs as measured by the TIPS market and those as measured by the inflation swaps market.

Traders in the TIPS market make implicit forecasts of inflation rates based on the difference between the yield of a nominal bond and the yield of an inflation-linked bond of the same maturity. These forecasts are called *breakeven* inflation rates (BEIs), as an investor would receive the same yield on an inflation or non-inflation-indexed security if inflation averages that level over the course of the maturity. We focus on the five-year TIPS BEI, which is (i) calculated by subtracting the five-year Treasury Inflation-Indexed Constant Maturity Securities yield from the five-year Treasury Constant Maturity Securities yield and (ii) is often interpreted as what market participants expect the year-over-year inflation to be over the next five years, on average. We use monthly averages of daily observations for the five-year TIPS BEI; these data are available going back to January 2003 and are obtained from the Board of Governors of the Federal Reserve System and Haver Analytics.

In the inflation swaps market, two parties negotiate a contract under which inflation risk is transferred through an exchange of fixed cash flows. As both parties are trying to negotiate a fair price under the contract, the inflation swap rate can be seen as the expected BEI over the length of the contract. We focus on the five-year swaps BEI, which is often interpreted as what market participants expect the year-over-year inflation rate to be over the next five years, on average. We use monthly averages of daily observations for the five-year swaps BEI; these data are available going back to August 2004 and are obtained from Bloomberg.

Bauer (2014) finds that both TIPS and swaps BEIs are closely related to movements in the nominal interest rates and are sensitive to macroeconomic data surprises. The TIPS and swaps BEIs are not necessarily straightforward forecasts of inflation, though, as they reflect market participants' inflation expectations as well as inflation and liquidity risk premia. A number of articles decompose the TIPS and swaps BEIs into these components using different methods and find that both the TIPS and swaps BEIs embed nontrivial inflation and liquidity risk premia (Gurkaynak, Sack, and Wright, 2010; Zeng, 2013; Abrahams et al., 2016; D'Amico, Kim, and Wei, 2018; Haubrich, Pennacchi, and Ritchken, 2012; and Casiraghi and Miccoli, 2019; for a full review, see Kupfer, 2018).

Zeng (2013) finds that TIPS BEIs tend to underestimate inflation due to the liquidity risk and that model-implied inflation expectations at various horizons outperform the SPF and Michigan

Surveys forecasts. For TIPS BEIs, Abrahams et al. (2016) find that the estimated inflation risk premium is highly correlated with observable macroeconomic and financial variables, such as disagreement about future inflation among professional forecasters. They also find that the BEIs adjusted for risk and liquidity premia outperform unadjusted BEIs and a random walk in predicting realized inflation in sample and out of sample. Casiraghi and Miccoli (2019) find that swaps BEIs incorporate sizable inflation risk premia and that these premia increase with maturity. They also find that the inflation risk premium was positive before the financial crisis, became negative at the end of 2008 after the bankruptcy of Lehman Brothers, and recovered shortly afterward.

For simplicity, we use BEIs unadjusted for liquidity and inflation risk premia as the financial market forecasts in our analysis.

2.4 Model-Based Forecasts

As a baseline for comparison, we use two model-based forecasts: (i) the AO random walk forecast (Atkeson and Ohanion, 2001) and (ii) a VAR-based forecast.

The AO forecast uses the inflation rate over the previous four quarters as the forecast for what inflation will be over the next four quarters. To fit with our other monthly forecast series, we adapt the AO forecast using the inflation rate over the previous 12 months as the forecast for inflation over the next 12 months.[4] We use a similar model to forecast the five-year average inflation rate to compare with the five-year BEI. In this case, the average year-over-year inflation rate over the previous five years is used to forecast the average year-over-year inflation rate over the next five years.

We also produce simple VAR-based forecasts for both one-year-ahead inflation and five-year average inflation. We estimate three different VAR forecasts for one-year-ahead CPI inflation: (i) a VAR including lags of year-over-year CPI inflation and lags of year-over-year industrial production (IP) growth; (ii) a VAR including lags of year-over-year inflation and lags of the UR; and (iii) a VAR including lags of year-over-year inflation, lags of IP growth, and lags of the UR.[5] We use the same three VARs to forecast five-year average inflation using lags of five-year average inflation rather than lags of year-over-year inflation.

For the one-year-ahead inflation model-based forecasts, the first forecast origin is March 1960, corresponding to the first available vintage of UR data that can be used to estimate the VAR. For the five-year average inflation model-based forecasts, the first forecast origin is June 1966, corresponding to the first forecast origin whose VAR model can be estimated with at least 100 observations given the available data.

3 FORECAST EVALUATION

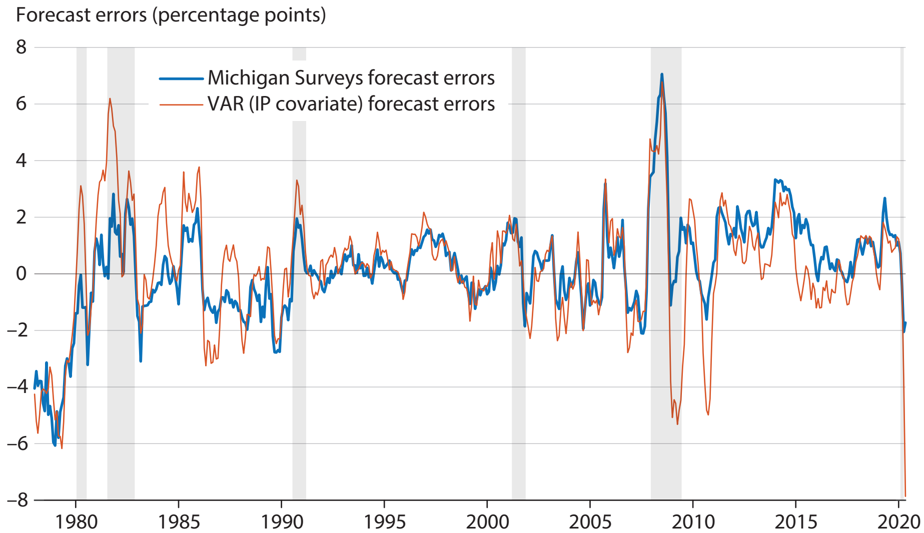
Figure 1 shows forecast errors corresponding to a few of the forecasts we discuss.[6] Panel A shows forecast errors for one-year-ahead year-over-year inflation forecasts. Panel B shows forecast errors for five-year average inflation forecasts. For each panel, the date on the x-axis corresponds to the date the forecast was made. The forecast errors (and, thus, the forecasts themselves) generally move together, with the one-year-ahead year-over-year inflation forecasts tracking each other more closely than the five-year average inflation forecasts.

Some notation will facilitate discussion of the properties of the forecasts. At a forecast origin t, suppose the forecaster has information X_t to construct the h-period-ahead forecast, denoted $Y_{t+h|t}$. Each forecast produces an error relative to the realization, Y_{t+h}, defined as

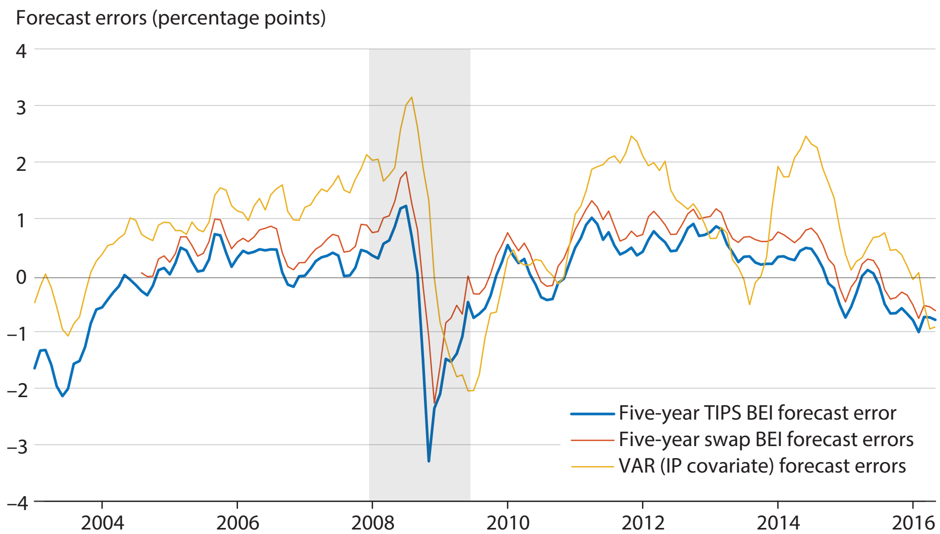
Figure 1

Inflation Forecast Errors

A. One-year-ahead year-over-year inflation forecast errors



B. Five-year average inflation forecast errors



NOTE: This figure shows the forecast errors for both one-year-ahead year-over-year inflation forecast metrics (Panel A) and five-year average inflation forecast metrics (Panel B). The date on the *x*-axis corresponds to the forecast origin. Gray shaded regions indicate NBER recessions.

$$\epsilon_{t+h} = Y_{t+h} - Y_{t+h|t}. \tag{1}$$

We can evaluate these forecasts using a number of measures described in detail below.

3.1 Accuracy

One way to evaluate forecasts is to examine their relative accuracy. We first compute the root mean squared error (RMSE) as

$$RMSE = \sqrt{\frac{1}{P}\sum_{t=1}^{P}\epsilon_{t+h}^{2}}, \tag{2}$$

where P is the number of forecasts being evaluated. Squaring the error focuses on the magnitude of the forecast's deviation from the realized value rather than on whether the forecast is underestimated or overestimated. We compare the relative accuracy of two forecasts by computing the ratio of one forecast's RMSE to another's. A relative RMSE less (greater) than 1 indicates that the forecast represented in the numerator (denominator) is relatively more accurate over the sample period.

While the relative RMSEs provide some suggestion of which of the two forecasts is more accurate, statistical tests are required to determine whether we can assert that one forecast is significantly "better" than another. These tests (e.g., Diebold and Mariano, 1995) are typically formulated with the null of equal predictive ability and require assumptions about the data generating process and how the forecasts were constructed. We forgo formal statistical testing of equal predictive ability here and refer the reader to the literature.

3.2 Bias

A forecast is considered biased if the average forecast error over the sample period is statistically different from zero. Thus, we compute the average forecast error over all available forecast origins for each inflation forecast metric and test whether this average is statistically different from zero using a standard z-statistic.

Forecasts might be biased for a number of reasons. A forecaster may prefer to underestimate the variable they are forecasting (rather than overestimate it). For example, say a firm is forecasting demand for its product and there is a high carrying cost for extra inventory. In this case, the forecaster might prefer to underestimate demand, leading to underproduction so that no goods need to be stored in inventory.

3.3 Rationality

Keane and Runkle (1989) define rational (or rationalizable) forecasts as those whose forecast errors are unpredictable given what the forecaster knew at the time they made the forecast. Rationality is evaluated conditional on both a loss function and a fixed information set. The loss function implicit in Keane and Runkle (1989) is quadratic loss, where the loss is an increasing function of the forecast error, regardless of the direction of the error. The information set consists of potentially relevant variables known to the forecaster at the forecast origin. If not taken into account (i.e., incorporated into the forecast), a variable could explain the realization but not the forecast, making the forecast error a function of the variable.

We can test the rationalizability of inflation forecasts by determining whether the forecast errors can be predicted by factors known to the forecaster at the forecast origin, t. To do this, we regress the forecast error on a constant, the forecaster's prediction ($Y_{t+h|t}$), and a set of variable(s), X_t, in the forecaster's information set:

$$Y_{t+h} - Y_{t+h|t} = \alpha_0 + \alpha_1 Y_{t+h|t} + \alpha_2 X_t + u_{t+h}. \tag{3}$$

For the forecasts to be rationalizable given information X_t, the values of α_1 and α_2 should not be significantly different from zero; otherwise, the forecast error could be predicted by X_t. Thus, we consider a forecast rationalizable if we cannot reject the null hypothesis that α_1 and α_2 are jointly zero using an F-test.[7]

We test rationality in this way for each inflation forecast series, using all available forecasting origins for each series. The information set, X_t, for each rationality test consists of past data that are common in macroeconomic models of the inflation rate: the UR, effective FFR, and most recent value of inflation (either year-over-year or five-year average inflation).[8] The composition of X_t varies slightly across rationality tests for different forecasts. The tests for the VAR forecasts and the AO forecasts do not include the most recent value of inflation in X_t, as that lagged inflation value is inherently part of the forecast for both of those models. The VAR forecasts that include the UR as a covariate also do not include the UR in X_t, as that value is incorporated into the forecast for those models.

3.4 Encompassing

Comparing the relative RMSEs of two forecasts may determine which is more accurate on its own. However, a substantial literature has shown that combining forecasts can lead to improved accuracy. Tests for forecast encompassing determine whether one forecast has additional predictive information relative to another. Another way of interpreting this statement asks whether one forecast would have any weight in a forecast combination with the other. For example, previous studies have examined the hypothesis that the Fed's forecasts encompass those made by the private sector.

To conduct an encompassing test, we follow similar methodology to that used by Fair and Shiller (1989) and Romer and Romer (2000). We regress the realized values, Y_{t+h}, on a constant and the two forecasts, $Y_{1,t+h|t}$ (Forecast 1) and $Y_{2,t+h|t}$ (Forecast 2):

$$Y_{t+h} = \alpha + \beta_1 Y_{1,t+h|t} + \beta_2 Y_{2,t+h|t} + \eta_{t+h}, \tag{4}$$

and we test the null hypothesis that $(\alpha, \beta_1, \beta_2)' = (0,1,0)'$. The null assumes that Forecast 2 has no significant predictive information not already contained in Forecast 1. Previous studies have found that forecasts of the inflation rate and output growth rates are biased (see Caunedo et al., 2020); thus, a test could reject this joint null hypothesis because $\alpha \neq 0$. Therefore, we also conduct the encompassing test, omitting the unbiasedness condition, and test only the null $(\beta_1, \beta_2)' = (1,0)'$.

We conduct encompassing tests for all pairs of inflation forecast metrics that are forecasting the same inflation metric (i.e., one-year-ahead year-over-year inflation or five-year average inflation), using a Wald test to test the null hypotheses posited in the preceding paragraph. The encompassing tests use data from the forecasting origins that are available for both Forecasts 1 and 2.

Table 1

Relative RMSEs

A. One-year-ahead inflation

	Michigan Surveys	Blue Chip	AO	VAR (IP covariate)	VAR (UR covariate)	VAR (IP and UR covariates)
Michigan Surveys	1.000	1.342	0.869	0.824	0.771	0.780
Blue Chip		1.000	0.697	0.634	0.590	0.606
AO			1.000	0.908	0.859	0.847
VAR (IP covariate)				1.000	0.946	0.933
VAR (UR covariate)					1.000	0.986
VAR (IP and UR covariates)						1.000

B. Five-year average inflation

	Five-year TIPS BEI	Five-year swaps BEI	AO	VAR (IP covariate)	VAR (UR covariate)	VAR (IP and UR covariates)
Five-year TIPS BEI	1.000	0.908	1.027	0.577	0.608	0.662
Five-year swaps BEI		1.000	0.980	0.533	0.563	0.619
AO			1.000	0.630	0.597	0.610
VAR (IP covariate)				1.000	0.948	0.969
VAR (UR covariate)					1.000	1.022
VAR (IP and UR covariates)						1.000

NOTE: This table displays the RMSEs for each combination of relevant forecasts. Each relative RMSE is the RMSE of the forecast indicated in the row divided by the RMSE of the forecast indicated in the column. For each entry, the two RMSEs are calculated using the date range of whichever forecast of the two has the smallest available date range. A relative RMSE < 1 indicates that the row forecast is more accurate than the column forecast over the evaluated date range. A relative RMSE > 1 indicates that the column forecast is more accurate than the row forecast over the evaluated date range.

4 RESULTS

4.1 Accuracy

Table 1 compares the forecasts' accuracy, reporting the RMSE of the forecast indicated in the row relative to the RMSE of the forecast indicated in the column. For each entry, the two RMSEs are calculated using the common date range of the two forecasts. A relative RMSE < 1 (> 1) indicates that the row forecast is more (less) accurate than the column forecast over the evaluated date range.

Panel A of Table 1 presents results for one-year-ahead inflation forecasts. In terms of accuracy, the Blue Chip outperforms all other evaluated metrics. The Michigan Surveys forecasts outperform all metrics except those for the Blue Chip. The AO model does better than any of the VARs, and the VARs all perform similarly well. The result that survey-based forecasts outperform simple time-series models is consistent with previous findings (Thomas, 1999; Ang, Bekaert, and Wei, 2007; and Gil-Alana, Moreno, and Pérez de Gracia, 2012).

Panel B of Table 1 presents results for five-year average inflation forecasts. The five-year TIPS BEI outperforms the five-year swaps BEI and the VARs, but the AO model narrowly outperforms

Table 2

Forecast Bias and Rationality Results

	Bias		Rationality: Restrict $\alpha = 0$		Rationality: Allow $\alpha \neq 0$	
	Mean error	*p*-Value	*F*-statistic	*p*-Value	*F*-statistic	*p*-Value
A. One-year-ahead inflation						
Michigan Surveys	–0.187	0.013	15.993	0.000	18.239	0.000
Blue Chip	–0.130	0.016	7.754	0.000	8.140	0.000
AO	0.005	0.950	29.717	0.000	39.621	0.000
VAR (IP covariate)	0.247	0.003	25.848	0.000	31.043	0.000
VAR (UR covariate)	–0.038	0.660	49.379	0.000	73.952	0.000
VAR (IP and UR covariates)	0.098	0.268	55.444	0.000	82.414	0.000
B. Five-year average inflation						
Five-year TIPS BEI	0.056	0.352	53.860	0.000	66.752	0.000
Five-year swaps BEI	–0.424	0.000	157.654	0.000	121.366	0.000
AO	–0.147	0.100	102.665	0.000	135.380	0.000
VAR (IP covariate)	–0.490	0.000	247.684	0.000	319.729	0.000
VAR (UR covariate)	–0.351	0.018	362.431	0.000	535.812	0.000
VAR (IP and UR covariates)	–0.179	0.221	351.027	0.000	524.483	0.000

NOTE: This table presents results for tests of bias and rationality for each of the forecast metrics, separated by whether the metric is forecasting one-year-ahead inflation or five-year average inflation. The two leftmost columns for the rationality results report the *F*-statistics and associated *p*-values corresponding to testing the joint null hypothesis that $(\alpha_0, \alpha_1, \alpha_2) = (0, 0, 0)$. The two rightmost columns for the rationality results report the *F*-statistics and associated *p*-values corresponding to testing the joint null hypothesis that $(\alpha_1, \alpha_2) = (0, 0)$.

the TIPS BEI. The five-year swaps BEI outperforms all metrics except for the five-year TIPS BEI. The TIPS BEI outperforming the swaps BEI, the swaps BEI outperforming the AO model, and the AO model outperforming the TIPS BEI each arise because of the differences in the timespans of data available for the TIPS BEI and the swaps BEI. The AO model does better than any of the VARs, and the VARs all perform similarly well.

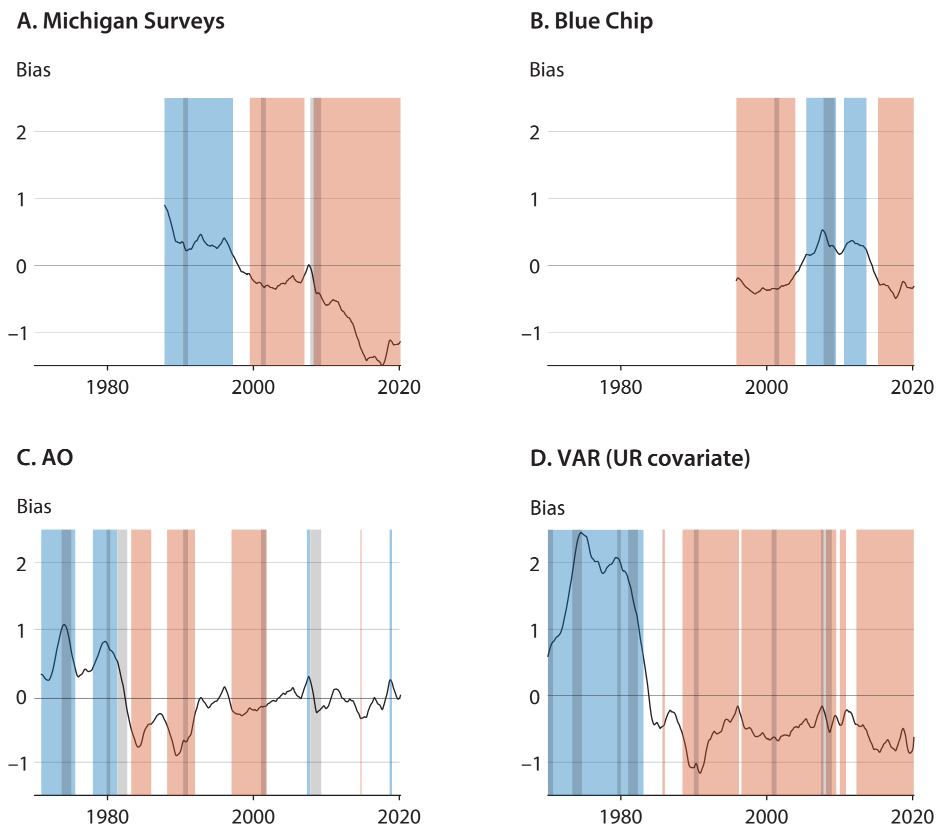
4.2 Bias

The first two columns of Table 2 present the results of evaluating forecast bias over the entirety of each forecast's sample period. A positive (negative) bias value indicates that the forecast systematically underpredicts (overpredicts) actual inflation. For one-year-ahead inflation metrics, both the Michigan Surveys forecasts and the Blue Chip forecasts significantly overestimate actual inflation. Meanwhile, the AO model is not significantly biased. Results for the VARs vary, though they typically do not show significant bias.

The five-year TIPS BEI does not exhibit any significant bias in forecasting actual inflation, while the five-year swaps BEI significantly overestimates it. While they are both financial market forecasts, the distinction may arise from the differences in liquidity and inflation risk premia in the two markets.

Figure 2

Ten-Year Rolling Bias for One-Year-Ahead Inflation Forecasts



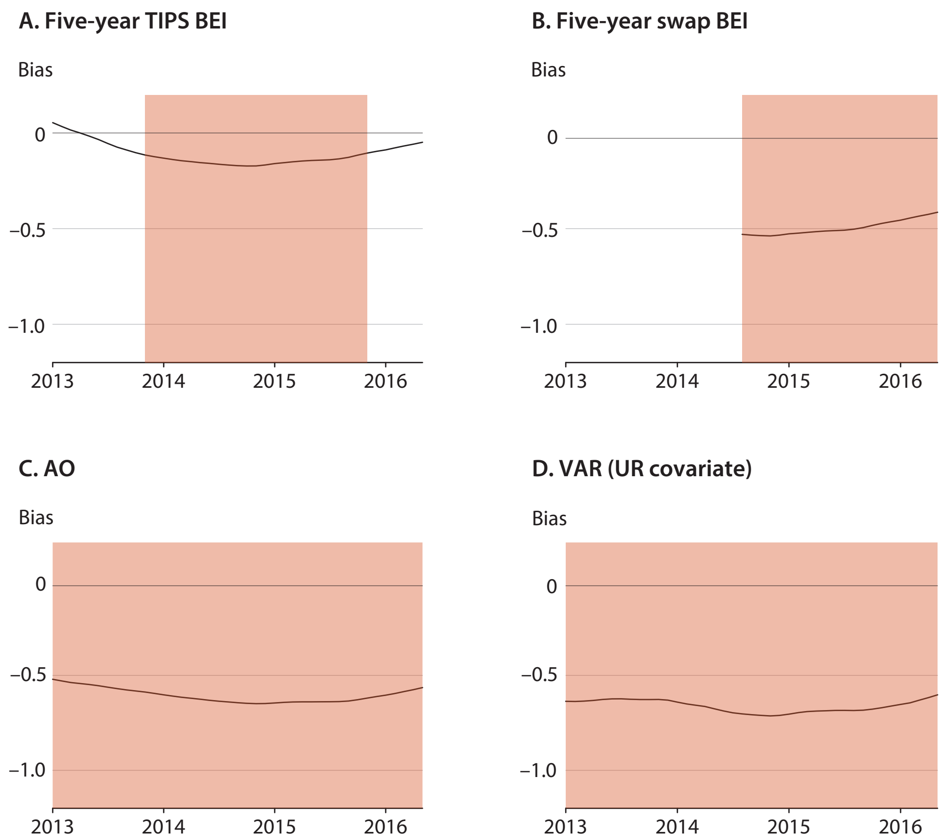
NOTE: The figure shows the average bias of a given one-year-ahead inflation forecast for the 10-year period that ends on the date indicated by the *x*-axis. Orange shaded regions indicate subsamples in which the forecast bias is negative (overestimate) and statistically significant at the 10 percent level. Blue shaded regions indicate subsamples in which the forecast bias is positive (underestimate) and statistically significant at the 10 percent level. Gray shaded regions indicate NBER recessions.

The five-year swaps BEI incorporates an inflation risk premium that is, on average, positive, resulting in overestimation of actual inflation (Casiraghi and Miccoli, 2019). On the other hand, previous research has argued that the TIPS BEI is subject to countercyclical risk premia (Abrahams et al., 2016, and Andreasen, Christensen, and Riddell, 2020). Because these premia are time varying, this variance leads to the overestimation of actual inflation at some points and underestimation at others. Results for the VARs vary.

Previous work suggests that forecast bias results may be sensitive to the time period chosen for evaluation (Croushore, 2010). Therefore, we also look at each forecast's bias over a 10-year rolling window. Figures 2 and 3 display these results for one-year-ahead year-over-year inflation forecasts and five-year average inflation forecasts, respectively. Each line in Figures 2 and 3 shows the average bias of a given forecast for the 10-year period that ends on the date indicated by the *x*-axis. Orange shaded regions indicate subsamples in which the forecast bias is an overestimate and statistically significant at the 10 percent level. Blue shaded regions indicate subsamples in which the forecast

Figure 3

Ten-Year Rolling Bias for Five-Year Average Inflation Forecasts



NOTE: This figure shows the average bias of a given five-year average inflation forecast for the 10-year period that ends on the date indicated by the *x*-axis. Orange shaded regions indicate subsamples in which the forecast bias is negative (overestimate) and statistically significant at the 10 percent level.

bias is an underestimate and statistically significant at the 10 percent level. Gray shaded regions indicate National Bureau of Economic Research (NBER) recessions.

For one-year-ahead inflation forecasts, the sign and significance of the forecast bias varies across the sample periods. For example, at the beginning of the Michigan Surveys forecast sample period, consumers tended to underestimate inflation; however, beginning in the mid-1990s, they tend to overestimate it. Consumers' forecast bias is significant across a majority of the 10-year rolling windows, though there are two short periods in which it is not. On the other hand, Blue Chip forecasters overestimated inflation in the beginning of their sample, underestimated it during the mid-2000s to mid-2010s, and more recently have overestimated it. Similar to that of consumers, professionals' forecast bias is significant across a majority of the 10-year rolling windows, though there are three short periods in which it is not.

For five-year average inflation forecasts, the 10-year rolling-window forecasts overestimate actual inflation, save for a short window at the beginning of the TIPS BEI sample period that is insignificant. Looking at the time period comparable to the BEI forecasts (which is displayed in

Figure 3), the swaps BEI, AO model, and VAR significantly overestimate actual inflation over all 10-year windows, while the TIPS BEI significantly overestimates inflation only for a specific period of windows (window with end date November 2013 to window with end date November 2015). The AO model and VAR model, however, do have periods preceding 2013 in which they do not exhibit significant bias.

4.3 Rationality

The four rightmost columns in Table 2 presents the results of the forecast rationality tests described in Section 3.3. Columns 3 and 4 report the F-statistics and associated p-values corresponding to testing the joint null hypothesis that $(\alpha_0, \alpha_1, \alpha_2) = (0,0,0)$ (i.e., restricting the forecast to be unbiased); Columns 5 and 6 report the F-statistics and associated p-values corresponding to testing the joint null hypothesis that $(\alpha_1, \alpha_2) = (0,0)$ (i.e., allowing the forecast to be biased). In either case, failure to reject the null indicates that the forecast is rationalizable. Rejection of the null indicates that the forecast error can be predicted by relevant macroeconomic variables known to the forecaster at the forecast origin; thus, the forecaster did not incorporate all relevant, known information into their forecast.

Based on our results, we reject rationality for all forecasts, regardless of whether the forecast is allowed to be biased. These results fall in line with previous work that rejects rationalizability for consumer, professional, financial market, and model-based forecasts (Brown and Maital, 1981; Batchelor and Dua, 1991; and Thomas 1999, among others).

No particular economic indicator appears unaccounted for across forecasts. Instead, the rejection of the null hypothesis appears to be driven by different factors across types of forecasts. For example, consumers appear to appropriately incorporate the most recent value of inflation into their forecasts, but leave information from the UR and FFR on the table. Meanwhile, five-year TIPS BEIs appropriately incorporate information from the FFR into their forecasts but leave information from the UR and most recent value of inflation underutilized. Professional forecasters underutilize information from all considered regressors. These results suggest that agents make inflation forecasts based on different information sets.

These results on rationalizability are predicated on the selected information set and assumed loss function (quadratic). Previous work finds that forecasts, particularly professional forecasts, are often rationalizable under the assumption of an asymmetric loss function (Elliot, Komunjer, and Timmerman, 2008; and Capistran and Timmerman, 2009; among others).

4.4 Encompassing

Table 3 presents the results of the encompassing tests for one-year-ahead inflation forecast metrics. Panel A displays the p-values associated with testing the joint null hypothesis $(\alpha, \beta_1, \beta_2) = (0,1,0)$ based on the regression described in Section 3.4, and Panel B displays the p-values associated with testing the joint null hypothesis $(\beta_1, \beta_2) = (1,0)$. In either case, a failure to reject the null indicates that the predictive information contained in Forecast 1 encompasses that which is contained in Forecast 2; a rejection of the null indicates that Forecast 2 contains predictive information that is not contained in Forecast 1.

In each of the pairwise combinations evaluated in Table 3—regardless of whether or not the forecasts are allowed to be biased—the null hypothesis is rejected at the 10 percent significance level.

Table 3

One-Year Ahead Inflation Encompassing Results

		Forecast 2					
		Michigan Surveys	Blue Chip	AO	VAR (IP covariate)	VAR (UR covariate)	VAR (IP and UR covariates)
	A. Restrict $\alpha = 0$						
Forecast 1	Michigan Surveys		0.000	0.000	0.000	0.000	0.000
Forecast 1	Blue Chip	0.000		0.002	0.000	0.000	0.000
Forecast 1	AO	0.000	0.000		0.000	0.000	0.000
Forecast 1	VAR (IP covariate)	0.000	0.000	0.000		0.000	0.000
Forecast 1	VAR (UR covariate)	0.000	0.000	0.000	0.000		0.000
Forecast 1	VAR (IP and UR covariates)	0.000	0.000	0.000	0.000	0.000	
	B. Allow $\alpha \neq 0$						
Forecast 1	Michigan Surveys		0.000	0.000	0.000	0.000	0.000
Forecast 1	Blue Chip	0.000		0.013	0.000	0.000	0.000
Forecast 1	AO	0.000	0.000		0.000	0.000	0.000
Forecast 1	VAR (IP covariate)	0.000	0.000	0.000		0.000	0.000
Forecast 1	VAR (UR covariate)	0.000	0.000	0.000	0.000		0.000
Forecast 1	VAR (IP and UR covariates)	0.000	0.000	0.000	0.000	0.000	

NOTE: This table presents results of encompassing tests that test whether Forecast 1 encompasses Forecast 2 for a given row/column pair. Panel A presents results for encompassing tests where the regression constant is tested to be zero in the joint null hypothesis $(\alpha, \beta_1, \beta_2)' = (0,1,0)'$. Panel B presents results for encompassing tests where the regression constant is not tested under the joint null hypothesis, $(\beta_1, \beta_2)' = (1,0)'$ The values reported in both panels are the *p*-values associated with the *F*-statistic testing the relevant joint null hypothesis.

Thus, each of the forecasts has predictive content that is not fully contained within that of another. When the forecast is allowed to be biased (Panel B), we could conclude that Blue Chip forecasts encompass the AO model forecasts if evaluating the results using a 1 percent significance level.

Because professional forecasters likely take the most recent value of inflation into consideration, Blue Chip forecasts nearly encompass the AO model forecasts. One might expect Blue Chip forecasts to nearly encompass the Michigan Surveys forecasts, assuming that professional forecasters have more and better information than the average consumer. That consumer forecasts have predictive information not contained in professional forecasts, however, is consistent with previous findings that households and professionals focus on different factors when making inflation forecasts (Berge, 2018, and Palardy and Ovaska, 2015). Moreover, consumer forecasts have outperformed professional forecasts over some sample periods (Gramlich, 1983, and Mehra, 2002).

Table 4 presents the results of the encompassing tests for five-year average inflation metrics. Analogous to Table 3, Panel A displays the *p*-values associated with restricting Forecast 1 to be unbiased, and Panel B displays the *p*-values associated with allowing Forecast 1 to be biased. As before, the results in Table 4 indicate that, regardless of whether Forecast 1 is allowed to be biased, the null hypothesis is rejected at the 10 percent significance level; thus, each of the forecasts has a distinct information set that is not fully contained within that of another.

Table 4

Five-Year Average Inflation Encompassing Results

		Forecast 2					
		Five-year TIPS BEI	Five-year swaps BEI	AO	VAR (IP covariate)	VAR (UR covariate)	VAR (IP and UR covariates)
	A. Restrict $\alpha = 0$						
Forecast 1	Five-year TIPS BEI		0.000	0.000	0.000	0.000	0.000
	Five-year swaps BEI	0.000		0.000	0.000	0.000	0.000
	AO	0.000	0.000		0.000	0.000	0.000
	VAR (IP covariate)	0.000	0.000	0.000		0.000	0.000
	VAR (UR covariate)	0.000	0.000	0.000	0.000		0.000
	VAR (IP and UR covariates)	0.000	0.000	0.000	0.000	0.000	
	B. Allow $\alpha \neq 0$						
Forecast 1	Five-year TIPS BEI		0.000	0.000	0.000	0.000	0.000
	Five-year swaps BEI	0.000		0.000	0.000	0.000	0.000
	AO	0.000	0.000		0.000	0.000	0.000
	VAR (IP covariate)	0.000	0.000	0.000		0.000	0.000
	VAR (UR covariate)	0.000	0.000	0.000	0.000		0.000
	VAR (IP and UR covariates)	0.000	0.000	0.000	0.000	0.000	

NOTE: This table presents results of encompassing tests that test whether Forecast 1 encompasses Forecast 2 for a given row/column pair. Panel A presents results for encompassing tests where the regression constant is tested to be zero in the joint null hypothesis $(\alpha, \beta_1, \beta_2)' = (0,1,0)'$. Panel B presents results for encompassing tests where the regression constant is not tested under the joint null hypothesis, $(\beta_1, \beta_2)' = (1,0)'$ The values reported in both panels are the *p*-values associated with the *F*-statistic testing the relevant joint null hypothesis.

4.5 Interpretation

Based on these results and the results in previous studies, no single forecast (or forecaster) appears to dominate any other. What does this imply for the comparison of the consumer and professional survey forecasts, both relative to each other and relative to the model-based forecasts?

First, professional forecasters are generally better than consumers and simple models at predicting inflation. This finding aligns with what one might expect, as professionals may have information and resources to make more informed forecasts than the average consumer.

Second, consumers are not bad at predicting inflation. Although they are not generally as accurate as professional forecasters, they outperform simple econometric models. This finding suggests that the average consumer understands inflation trends. Energy prices and food prices are often correlated with headline inflation (energy and headline correlation: 0.68; food and headline correlation: 0.71).[9] Even if consumers rely on heuristics that overemphasize energy and food prices, they may predict the direction of price growth through casual observation of prices in their everyday experiences.

Third, the BEIs cannot be interpreted as straightforward forecasts of inflation. These rates are extracted from financial market instruments, and they embed time-varying liquidity and inflation risk premia that mask market participants' actual inflation expectations. Taken at face value as inflation forecasts, they may be misleading.

Fourth, there appears to be exploitable predictive information in all forecasts. Moreover, it appears that consumers, forecasting professionals, and financial market analysts consider different information sets when constructing forecasts. As none of the forecasts evaluated here are rationalizable under the assumption of a symmetric loss function, it may be relevant to consider whether agents form inflation forecasts based on asymmetric preferences.

5 CONCLUSION

We evaluate the performance of consumer, professional, market-based, and model-based inflation forecasts with regard to accuracy, bias, rationality, and encompassing. Consistent with previous studies, survey-based forecasts are more accurate than model-based forecasts. Consumer, professional, and swap market forecasts all tend to overestimate inflation on average, but the sign of the bias varies across the sample period for consumer, professional, and TIPS market forecasts. Results of rationality tests indicate that none of the forecasts can be considered rationalizable under the assumption of symmetric loss, and economic agents use different information sets when forming their inflation forecasts. Encompassing tests indicate that each forecast contains predictive information that is not encompassed by another forecast. Future work could consider additional survey-based inflation forecast metrics, such as the consumer inflation expectations series from the Federal Reserve Bank of New York, as well as market-based forecasts adjusted for inflation and risk premia. Further tests of equal predictive ability or rationality under asymmetric loss could also provide additional information on the relative performance of various inflation forecasts. ■

NOTES

1 More information regarding the survey questionnaire and the construction of the consumers' median inflation expectation series can be found at https://data.sca.isr.umich.edu/.

2 The Federal Reserve Bank of New York also produces consumer inflation expectations series at one-year and three-year horizons. These data are only available for a relatively short sample (from 2012 to the present); thus, we omit them from our analysis. These series could be used in future work.

3 This series is constructed using the Blue Chip one-year-ahead consumer price index (CPI) consensus forecast four quarters ahead as the monthly value. The quarterly series are aggregated from the monthly series. For example, the one-year-ahead inflation forecast value made in January 2020 is constructed using the CPI forecast for 2021:Q1 in the January 2020 survey. The one-year-ahead inflation forecast value made in February 2020 is constructed using the CPI forecast for 2021:Q1 in the February 2020 survey.

4 For example, at the forecasting origin January 2000, one would use the year-over-year value of inflation measured in December 1999 as the forecast for year-over-year inflation measured in January 2001, as the December 1999 value would be the most recent year-over-year inflation value available to the forecaster in January 2000.

5 The seasonally adjusted CPI from the Bureau of Labor Statistics (BLS) is used to calculate inflation rates; the UR data are produced by the BLS; and the IP data are produced by the Board of Governors of the Federal Reserve System. We use vintages of both IP and UR data obtained from the Federal Reserve Bank of St. Louis ALFRED® database: https://alfred.stlouisfed.org/. These series are subject to frequent and substantial revisions. We do not use CPI vintages to calculate year-over-year inflation rates, as CPI revisions are typically insubstantial.

6 Blue Chip forecasts are proprietary and cannot be depicted here.

[7] Rationality tests often include $\alpha_0 \neq 0$ in the null. In this case, if the forecasts are biased, rationality is rejected. We include results for tests that include or exclude $\alpha_0 \neq 0$ in the null.

[8] The information at month t depends on when the forecast is made within a given month. The University of Michigan typically conducts the Surveys of Consumers in the last week of $t-1$ through approximately the third week of month t. We assume the most recent value of the UR, the FFR, and inflation available to consumers is $t-2$. Blue Chip surveys are conducted in the first week of t. We assume the most recent value of the UR and inflation available to professionals is $t-2$ and the most recent value of the FFR is $t-1$. Both the TIPS and swap market BEIs are monthly averages of daily rates. The information set available to a market forecaster on the first day of the month consists of UR and inflation values from $t-2$ and the FFR from $t-1$. The model-based forecasts all use $t-1$ lagged inflation in their forecast calculation. Those forecasts are made on the CPI release date of t; thus, all regressors are from $t-1$.

[9] These correlations are calculated using CPI inflation data from January 1978 to May 2021, the dates corresponding with the Michigan Surveys inflation forecasts.

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