Predictive Abilities of Inflation-Forecasting Models Using Real-Time Data

C. James Hueng
University of Alabama

Ka-fu Wong
Chinese University of Hong Kong

Correspondence to:
C. James Hueng
Department of Economics, Finance, and Legal Studies
University of Alabama, Box 870224
Tuscaloosa, AL 35487
Phone: 205-348-8971
Fax: 205-348-0590
Email: chueng@cba.ua.edu

Predictive Abilities of Inflation-Forecasting Models Using Real-Time Data

ABSTRACT

The information sets used for forecasting inflation in surveys and in econometric models are different. To correctly compare the performances of these two types of forecasts, we use real-time data to reevaluate the out-of-sample predictions from several ARIMA models and a structural model. We find that (1) all the forecasts under-predict the inflation rates in the volatile 1970s and over-predict them after 1980; (2) the survey forecasts are more accurate than those from the econometric models; (3) the ARIMA models beat the structural model; and (4) the invalid use of revised data in forecasting models does not affect the above conclusions very much.

JEL classification: E37.

Keywords: real-time data, out-of-sample prediction.

1. Introduction

What is the best way to forecast inflation? Which release of data should we use to estimate the model and the forecast? The relatively large literature on forecasting inflation generally divides forecasts into one of the following three categories: (i) forecasts from structural macroeconomic models, (ii) forecasts from atheoretical time series models, and (iii) forecasts from surveys.

The out-of-sample prediction performances of the econometric models [i.e., (i) and (ii)] and the survey forecasts are often compared. The results, however, are mixed. For example, Hafer and Hein (1985) find that survey forecasts provide the most accurate inflation forecasts when compared with a univariate time-series model and an interest rate model. Carlson (1977) makes adjustments to survey data and finds that surveys yield more accurate forecasts than the regression-based forecasts. Pearce (1979), however, compares the forecast errors from a rational expectations model with those from survey data and finds that the constructed rational expectations model always produces substantially more accurate predictions. But Croushore (1998) argues that the surveys examined in Pearce (1979) perform badly only because Pearce's sample consists mostly of the data from the volatile 1970s, when forecasting was extremely difficult. Croushore (1998) shows that forecasts from surveys are not as bad during the 1980 and 1990s as they were in the 1970s.

These comparisons between the forecasts from survey data and those from econometric models are, however, subject to a flaw. The information sets used in making these two types of forecasts are often different. Survey participants are making inflation forecasts using only the information available to them at the time of the survey. But researchers computing forecasts from econometric models in retrospect are often using the final, revised historical data available from government statistical agencies at the time they do their research. Obviously, the information contained in revised data is usually different from that in real-time data, which are available to participants in inflation forecast surveys at the time they make their forecasts. Previous forecast comparison exercises are valid only if the data are never revised. However, macroeconomic data have often been revised frequently and irregularly, even years after they were initially released. For details of these revisions, see Croushore and Stark (1999).

We contribute to the inflation forecasting literature by evaluating different inflation forecast models based on real-time data, instead of on revised data. A systematic data source of this nature was not available until recently. The real-time data constructed by the Federal Reserve Bank of Philadelphia enable us to overcome the informational problem.

The results show that first, all the forecasts, from either survey or econometric models, under-predict the inflation rates in the volatile 1970s and over-predict the inflation rates after 1980. Second, the survey forecasts are more accurate than the forecasts from the econometric models. Third, the ARIMA models perform better than a structural model. Finally, data revisions change the magnitudes of the forecast errors but do not affect the above conclusions.

The remainder of the paper is organized into four sections. Section 2 describes the data and the forecasting method. The comparisons of the forecasts are discussed in Section 3. Section 4 concludes the paper.

2. Data and forecasting methodology

Surveys that are useful to the public and readily available include *the Survey of Professional Forecasters*, *the Livingston Survey*, *Blue Chip Economic Indicators*, and *the National Association of Business Economists Outlook*. Among them, *the Survey of Professional Forecasters*, formerly known as *the ASA/NBER Economic Outlook Survey*, is likely the most accurate [Keane and Runkle (1990) and Croushore (1998)]. As the title suggests, the respondents are mostly people who produce regular forecasts of economic variables as part of their job responsibilities in the business world or on Wall Street. They receive a monetary reward for producing accurate forecasts and report to the survey the same forecasts they sell on the market. The survey asks for detailed quarterly forecasts on a wide variety of macroeconomic variables and thus requires far more effort on the part of participants than do the other surveys. In addition, compared to *the Survey of Professional Forecasters*, *the Livingston Survey* only provides forecasts over six-month periods, while *the National Association of Business Economists Outlook* only forecasts annual averages for most variables. Furthermore, the *Blue Chip Economic Indicators* does not begin until 1976. Therefore, we focus on the quarterly forecasts from *the Survey of Professional Forecasters.*

Both the real-time data and the data from *the Survey of Professional Forecasters* are available from the Federal Reserve Bank of Philadelphia web site. The *Survey of Professional Forecasters* reports both the mean and the median points of the forecasts. The inflation forecasts are constructed by the deflator forecasts. In both data sets, the deflator variable switched from GNP to GDP in 1992, and changed again in 1996 from GDP deflator to chain-weighted GDP deflator. However, the GNP deflator, GDP deflator, and chain-weighted GDP deflator behave quite similarly, and there is no apparent break in the series in either 1992 or 1996 [Croushore (1998)]. Therefore, we do not try to introduce any adjustment to account for these changes in our analysis. For additional descriptive information about the construction of the real-time data, see Croushore and Stark (1999); for *the Survey of Professional Forecasters*, see Croushore (1996).

We emphasize that comparisons of forecasts depend crucially on the timing when the forecasts are made. Forecasts made with more information are usually more accurate. In the real-time data set, each data point contains information that is available on the 15th day of the middle month of the quarter. While in *the Survey of Professional Forecasters* data set, the survey is released at the end of the middle month of each quarter (or early the next month) but the survey deadline is generally a week before the release date. Therefore, the information available when the real-time data are collected and the information available when the survey is conducted are very close.

We compare the forecasts from the survey to those from a single-equation structural economic model and a batch of univariate time series (ARIMA) models. Univariate time series models are often used as a basis for comparing alternative forecasts because the forecasts from these models are derived solely from past inflation rates and are inexpensive. Failure to improve on forecasts from these models poses a serious challenge to the structural model and the survey participants. We experiment with ARIMA(p,I,q) models with fixed orders (I = 0 or 1, p, q =0, 1, 2, or 3, and $p+I+q\neq 0$) and with dynamic ARIMA models whose orders are chosen by AIC and SBC criteria in each regression.

The availability of real-time data limits our selections of structural economic models. We are restricted to choose a model formerly used by Hafer and Hein (1990) and Fama and Gibbons (1984). The model (denoted as the "H&H model" in this paper) is based on Fisher's (1930) hypothesis: with perfect foresight and a well-functioning capital market, the one-period nominal interest rate is the equilibrium real return plus the expected rate of inflation:

$$i_t = E_t(r_{t+1}) + E_t(\pi_{t+1}), \qquad (1)$$

where E_t is the expectation based on the information available at time t; i_t is the nominal rate of return from t to t+1; r_{t+1} is the real rate of return over the same period; and π_{t+1} is the inflation rate over the same period. Equation (1) implies that the ex-post real rate of return can be expressed as

$$i_t - \pi_{t+1} = E_t(r_{t+1}) + e_t, \tag{2}$$

where $e_t = E_t(\pi_{t+1}) - \pi_{t+1}$ is the inflation forecast error. If the expected real rate behaves as a random walk, as suggested by Hafer and Hein (1990) and Fama and Gibbons (1984), then changes in the ex-post real interest rate can be modeled as a simple moving-average model:

$$(i_t - \pi_{t+1}) - (i_{t-1} - \pi_t) = a_t - \theta a_{t-1}, \tag{3}$$

where θ is the moving-average parameter and a_t is an i.i.d. shock. Using equation (3) one can obtain a forecast of real rate of return, $E_t(r_{t+1}) = E_t(i_t - \pi_{t+1}) = E_t[(i_{t-1} - \pi_t) + a_t - \theta a_{t-1}] = (i_{t-1} - \pi_t) - \theta a_{t-1}$. Since i_t is observed at time t, the inflation forecast is

$$E_t(\pi_{t+1}) = i_t - E_t(r_{t+1}) = i_t - (i_{t-1} - \pi_t) + \theta a_{t-1}. \tag{4}$$

Therefore, to forecast inflation, the first difference of the ex-post real interest rate in equation (3) is estimated as an MA(1) process. The rate on U.S. three-month Treasury bills is used as the nominal interest rate.

The time series models and the interest rate model are estimated using the quarterly real-time data. We estimate the models based on both the recursive and the rolling schemes. Both schemes have been used in previous out-of-sample model evaluation exercises. Under the recursive scheme, all past data available are used to estimate the model. Under the rolling scheme, only a fixed number (also known as the window size) of most recent observations are used to estimate the model. When the model parameters do not vary over time, the recursive scheme is often preferred because it uses all the available data up to the time of estimation and hence yields more precise estimates of the model parameters. Therefore, it is likely to yield a more precise forecast. However, when the model parameters are suspected to vary over time, the rolling scheme is preferred because the fixed window size helps to avoid the influence of the early observations.

After the estimation, one-step-ahead forecasts are computed based on these estimated models. Since the survey forecasts start in the fourth quarter of 1968, we also start the model forecasts in the fourth quarter of 1968. Under both the recursive and the rolling schemes, the first model estimation uses data from 1947:2 to 1968:3, which would have been available to the researcher on November 15, 1968. The estimated models are then used to generate the forecast of the inflation rate in 1968:4. The recursive and the rolling schemes differ from the second estimation and onwards. Under the recursive scheme, the second estimation uses the data from 1947:2 to 1968:4, i.e., all the data that would have been available to the researcher on February 15, 1969, to estimate the models. Under the rolling scheme, the second estimation uses the data from 1947:3 to 1968:4. Thus, under a rolling scheme, the researchers do not use all the data available on February 15, 1969.[1] The results show that the conclusions drawn from the recursive and the rolling schemes are very similar.

[1] In the first quarter of 1996, the data of 1995:4 are not available because of a delay in the release of statistical data caused by the federal government shutdown. In our analysis, we assume the 1996:2 releases of the 1995:4 data were also known at 1996:1. As a check, we had used the corresponding model and the data prior to 1995:3 to generate the forecast of the inflation rate in 1995:4. This forecast and the data prior to 1995:3 are then used to forecast the inflation rate in 1996:1 using the same model. This more involved approach turns out to yield the same conclusion as the simpler procedure. In this paper, we report only the results based on the former procedure.

Therefore, we only report the results from the recursive scheme in Section 3. The results based on the rolling scheme are in an appendix and available upon request.

The inflation rate forecasts from the survey data are calculated as the difference between the log GDP (GNP) deflator forecast of the current quarter and the realized log GDP (GNP) deflator in the preceding quarter (the quarter before the survey date). To calculate the forecast errors, we assume that the initial releases of inflation rates are the "true" inflation rates. That is, for example, the 1968:4 inflation rate released in 1969:1 is used to calculate the forecast error made on November 15, 1968. This assumption is reasonable because the performances of most forecasters are often evaluated immediately after the initial release. The obvious alternative assumption is to use the "final" release as the true inflation, after which there is no more data revision. This approach is impractical because data are known to be revised irregularly even years after the initial release and, therefore, a stable release has not been reached for the most recent data.

To see whether the timing of the data availability affects the relative performance of different forecasts, we also compute the forecasts based on revised data, as usually done in the literature. In this case, for example, the revised data from 1947:2 to 1968:3 that were available when this paper was first written (the first quarter of 2000), are used to estimate the models and to forecast the inflation rate in 1968:4. Previous studies using revised data often assume that the most recently available data are the "true" inflation rates and use them to calculate the forecast errors. To compare our real-time forecasts with these studies, we also use the data released in 2000:1 as the "true" inflation in both real-time and revised data sets and compare their forecast errors. That is, the revised 1968:4 inflation rate available in 2000:1 is used to calculate the forecast error for 1968:4.[2]

3. Forecasting results

Table 1 reports the results from the survey, the structural model, and some selected ARIMA models using real-time data. The selected ARIMA models include the random walk model, the best fixed-order ARIMA models chosen by AIC and SBC in the first regression, the fixed-order ARIMA model yielding the lowest RMSPE, and the ARIMA models with dynamic orders chosen by AIC and SBC in each regression. First we show the mean prediction errors (MPEs) for volatile pre-1980 period and the post-1980 period. It can be seen that the survey forecasts under-predict the inflation rates (positive MPE) before 1980 and over-predict them (negative MPE) after 1980. This observation is consistent with Croushore (1998), who also observed this pattern in the annual forecasts of the *Livingston Survey*. This conclusion of under-prediction before 1980 and over-prediction after 1980 is also prevalent in all time-series models. However, for the H&H model, the opposite is true. The MPE from the H&H model is closer to zero than most of the other time-series models. This result suggests that this model is likely to generate "unbiased" forecasts on average but will create a great deal of variability in terms of forecast accuracy.

[2] We believe that most researchers who compare the out-of-sample performances of models based on revised data would likely define the "true inflation" as the "final release" instead of the "initial release". This is because if the researcher is willing to go through the trouble of digging out the initial release as the "true inflation", he/she would likely use real-time data to compute the forecasts as well.

Second, the RMSPEs are generally higher prior to and lower after 1980. The only exception to this pattern is the H&H model, but its forecast errors are much bigger than the others. Thus, it appears that it is more difficult to predict the inflation before 1980, even if researchers were using a time series model to make predictions.

Third, for the whole sample period, the survey forecasts have the lowest RMSPEs, and the H&H model has the highest RMSPE. This result is not too surprising because the professional forecasts are not restricted by some pre-selected models and are more flexible to take into account of information ignored by the econometric models. In the last two columns of the Table, we show the relative performances of the models. The performance is measured by the ratio of the RMSPE of the model to that of the survey and to that of the random walk model. For example, the best time-series model [ARIMA(2,1,0)] has a 21.42% higher RMSPE than the survey forecast (Pro_mean). The RMSPE of the H&H model is 231.55% higher than that of the survey forecast.

Finally, the random walk model not only beats the structural model, but also performs better than other ARIMA models that are chosen by the model selection criteria (AIC and SBC), no matter whether the criteria are used in the first regression of the fixed-order models or are used in the dynamic models.

Will the conclusions drawn from Table 1 be different if we use the revised data, as the previous research usually did? The answer is: not very much. Table 2 reports the results using the revised data. It shows that first, the general under-prediction before 1980 and over-prediction after 1980 still exist. Second, the RMSPEs are generally higher before 1980 than after 1980. Third, for the whole sample period, the survey forecasts have the lowest RMSPEs and the H&H model has the highest RMSPE. Finally, the use of the revised data does not affect our best choices of models using the criteria AIC, BIC or RMSPEs.

However, the relative performances of the other models to the random walk model, which is the benchmark model we use to evaluate the other models, are slightly different from those in Table 1. It can be seen that the last column in Table 2 is generally higher than that in Table 1. That is, compared to other models, the random walk model looks better and may be overvalued when the revised data are used.

Note that when the revised data are used for forecasting, the forecast errors are computed as the most recent release of inflation rate minus the inflation forecast, i.e., the "true inflation" is assumed to be the 2000:1 release of inflation rate. While in Table 1, the "true inflation" is assumed to be the initial release of inflation rate. To directly compare the forecasting performances from using the real-time data and using the revised data, in Table 3, we use the 2000:1 release of inflation rate as the "true inflation" and recalculate the forecasting errors in Table 1, even though it is not very impressive to assume that the performances of the forecasters are evaluated years after the initial release.

The general conclusions in Tables 1 and 2 carry over to Table 3. However, compared to Table 2, the performances of the ARIMA models, measured by the RMSPEs for the full sample, are generally worse when the real-time data are used than when the revised data are used. The only exception is the fixed-order model chosen by AIC. Therefore, when one tries to compare the survey with the time series models and mistakenly uses the revised data for the time series models, he would probably overvalue the time series models.

4. Conclusion

Previous studies that compare the accuracy of US inflation forecasts using regression models are often based on the revised data that were available to the researchers at the time the studies were done. We use the real-time data to re-evaluate these models and compare their performances with the survey forecasts, which, of course, are based on real-time information. The results show that all the forecasts under-predict the inflation rates in the volatile 1970s and over-predict the inflation rates after 1980. The survey forecasts are more accurate than the forecasts from regression models. The performance of our only macroeconomic model is lousy in terms of RMSPE. It is the worst among the forecasts considered in this paper. We also investigate whether the invalid use of revised data in the model predictions would have changed our conclusions. It turns out that the general conclusions still hold even if one mistakenly compares the forecasts with different information sets. However, if we want to compare the significance of the relative performances (in terms of RMSPEs) of the forecasts, the use of the revised data can yield misleading results.

We do not conduct any hypothesis tests about the out-of-sample predictions because none of the existing asymptotic theory [e.g., West and McCracken (1998)] is valid when the real-time data are used in the forecasting exercise. None of the existing asymptotic theory for out-of-sample inference is correct because all these theories are based on the assumption that the variables used in the forecasting models are never revised. The asymptotic theory for prediction using real-time data will require an adjustment based on the assumed pattern and properties of data revision.[3] The task of deriving the asymptotic theory in this situation is beyond the scope of the current paper. We believe that, without any statistical test, we can still see the economic significance in forecasting exercise. Future development of asymptotic theory for out-of-sample prediction inference should address the "data revision" issue.

[3] We are very grateful to Mike McCracken and Ken West for pointing out this observation to us.

References:

Carlson, John A. (1977): "A Study of Price Forecasts," *Annals of Economic and Social Measurement*, Vol. 6, No. 1, pp. 27-56.

Croushore, Dean (1996): "Inflation Forecasts: How Good Are They?" *Business Review*, Federal Reserve Bank of Philadelphia, May/June, pp. 15-25.

Croushore, Dean (1998): "Evaluating Inflation Forecasts," *Federal Reserve Bank of Philadelphia Working Paper* No. 98-14.

Croushore, Dean; Stark, Tom (1999): "A Real-Time Data Set for Macroeconomists: Does the Data Vintage Matter?" *Federal Reserve Bank of Philadelphia Working Paper* No. 99-21.

Fama, Eugene F.; Gibbons, Michael R. (1984): "A Comparison of Inflation Forecasts," *Journal of Monetary Economics*; vol. 13, no.3 (May), pp. 327-48.

Fisher, Irving (1930): *The theory of Interest*, New York: Macmillan.

Hafer, R.W.; Hein, Scott E. (1985): "On the Accuracy of Time-Series, Interest Rate, and Survey Forecasts of Inflation," *Journal of Business*, vol. 58, no. 4., pp. 377-398.

Hafer, R.W.; Hein, Scott E. (1990): "Forecasting Inflation Using Interest-Rate and Time-Series Models: Some International Evidence," *Journal of Business*, vol. 63, no. 1., pp. 1-17.

Keane, Michael P.; Runkle, David E. (1990): "Testing the Rationality of Price Forecasts: New Evidence from the Panel Data," *American Economic Review*, vol. 80, no. 4., pp. 714-735.

Pearce, Douglas K. (1979): "Comparing Survey and Rational Measures of Expected Inflation: Forecast Performance and Interest Rate Effects," *Journal of Money, Credit and Banking*, Vol. 11, No. 4, pp. 447-456.

West, Kenneth D.; McCracken, Michael W. (1998): "Regression-based tests of predictive ability," *International Economic Review*, vol. 39, pp.817-840.

Table 1: Mean Prediction Error (MPE) and Root Mean Squared Prediction Error (RMSPE) Based on Real-Time Data[1] ("true inflation" = initial release)

	MODEL	MPE		RMSPE			RMSPE relative to[6]	
		Pre-1980	Post-1980	Pre-1980	Post-1980	Full	Pro_mean	RW
Professional mean forecast	[Pro_mean][2]	0.0722	-0.0926	0.3380	0.2538	0.2870	1	0.7595
Professional median forecast	[Pro_med][2]	0.0873	-0.0977	0.3449	0.2502	0.2879	1.0034	0.7621
Hafer and Hafer	[H&H][3]	-0.0774	0.0351	0.7223	1.0588	0.9514	3.3155	2.5180
Random walk with drift	[ARIMA(0,1,0)]	0.0231	-0.0195	0.4562	0.3256	0.3779	1.3167	1
Fixed-order ARIMA (AIC)[4]	[ARIMA(2,0,2)]	0.3275	-0.0615	0.5331	0.3038	0.4017	1.3997	1.0631
Fixed-order ARIMA (SBC)[4]	[ARIMA(1,0,0)]	0.2756	-0.0762	0.5014	0.3195	0.3948	1.3756	1.0447
Best time series (RMSPE)[4]	[ARIMA(2,1,0)]	0.0229	-0.0422	0.4427	0.2819	0.3484	1.2142	0.9221
Dynamically selected ARIMA (AIC)[5]	[Dyn_aic]	0.3049	-0.0400	0.5239	0.3024	0.3967	1.3824	1.0499
Dynamically selected ARIMA (SBC)[5]	[Dyn_sbc]	0.2549	-0.0969	0.4892	0.3051	0.3818	1.3303	1.0103

Notes:

1. Forecasting period: 1968:4 – 1999:4. MPE and RMSPE are in percentage per quarter. For example, 0.3275 represents a forecast error of 0.3275% inflation rate per quarter.
2. Pro_Mean and Pro_Med are respectively the mean and median predictions from *the Survey of Professional Forecasters*.
3. H&H is the interest rate model proposed by Hafer & Hein (1990). See equations (1) – (4) in the main text.
4. "Fixed-order ARIMA (AIC)" and "Fixed-order ARIMA (SBC)" refer to the fixed-order ARIMA model chosen respectively by the AIC and SBC criterion of the first regression. "Best time series (RMSPE)" refers to the model with the lowest RMSPE.
5. Dynamically selected ARIMA models use the in-sample AIC or SBC in each regression to choose the orders of the models.
6. These columns report the ratio of the RMSPE of a specific model to that of professional mean forecast (Pro_mean) and random walk with drift model (RW), respectively.

Table 2: Mean Prediction Error (MPE) and Root Mean Squared Prediction Error (RMSPE) Based on Revised Data ("true inflation" = 2001:1 release)

	MODEL	MPE		RMSPE			RMSPE relative to	
		Pre-1980	**Post-1980**	**Pre-1980**	**Post-1980**	**Full**	**Pro_mean**	**RW**
Professional mean forecast	[Pro_mean]	0.1665	-0.0985	0.3337	0.2018	0.2572	1	0.8530
Professional median forecast	[Pro_med]	0.1816	-0.1036	0.3522	0.2042	0.2671	1.0385	0.8858
Hafer and Hafer	[H&H]	-0.0804	0.0387	0.6976	1.0261	0.9214	3.5821	3.0557
Random walk with drift	[ARIMA(0,1,0)]	0.0070	-0.0243	0.4002	0.2279	0.3015	1.1723	1
Fixed-order ARIMA (AIC)	[ARIMA(2,0,2)]	0.4251	-0.0452	0.5866	0.2198	0.3934	1.5296	1.3048
Fixed-order ARIMA (SBC)	[ARIMA(1,0,0)]	0.3853	-0.0441	0.5258	0.2436	0.3708	1.4417	1.2298
Best time series (RMSPE)	[ARIMA(2,1,0)]	0.0214	-0.0360	0.3803	0.2115	0.2841	1.1044	0.9421
Dynamically selected ARIMA (AIC)	[Dyn_aic]	0.2807	-0.1034	0.5093	0.2654	0.3721	1.4465	1.2339
Dynamically selected ARIMA (SBC)	[Dyn_sbc]	0.2688	-0.1029	0.4928	0.2639	0.3634	1.4126	1.2050

See the notes in Table 1.

Table 3: Mean Prediction Error (MPE) and Root Mean Squared Prediction Error (RMSPE) Based on Real-Time Data ("true inflation" = 2000:1 release)

	MODEL	MPE		RMSPE			RMSPE relative to	
		Pre-1980	**Post-1980**	**Pre-1980**	**Post-1980**	**Full**	**Pro_mean**	**RW**
Professional mean forecast	[Pro_mean]	0.1665	-0.0985	0.3337	0.2018	0.2572	1	0.7406
Professional median forecast	[Pro_med]	0.1816	-0.1036	0.3522	0.2042	0.2671	1.0385	0.7691
Hafer and Hafer	[H&H]	0.0169	0.0292	0.7149	1.0087	0.9139	3.5529	2.6313
Random walk with drift	[ARIMA(0,1,0)]	0.1174	-0.0254	0.4447	0.2780	0.3473	1.3502	1
Fixed-order ARIMA (AIC)	[ARIMA(2,0,2)]	0.4218	-0.0674	0.5375	0.2455	0.3776	1.4680	1.0872
Fixed-order ARIMA (SBC)	[ARIMA(1,0,0)]	0.3699	-0.0821	0.5052	0.2712	0.3728	1.4493	1.0734
Best time series (RMSPE)	[ARIMA(2,1,0)]	0.1172	-0.0482	0.4033	0.2288	0.3034	1.1796	0.8736
Dynamically selected ARIMA (AIC)	[Dyn_aic]	0.1864	-0.0460	0.5389	0.2420	0.3769	1.4652	1.0851
Dynamically selected ARIMA (SBC)	[Dyn_sbc]	0.1745	-0.1029	0.4980	0.2633	0.3656	1.4211	1.0525

See the notes in Table 1.

Additional appendix

In this additional appendix, we report the results analogous to those reported in Tables 1 to 3 but using the rolling scheme to perform the forecasting exercise. We choose to report these tables in this additional appendix instead of the text because the results based on rolling scheme are quite similar to those based on recursive scheme.

Table A1: Mean Prediction Error (MPE) and Root Mean Squared Prediction Error (RMSPE) Based on Real-Time Data[1] ("true inflation" = initial release)

	MODEL	MPE		RMSPE			RMSPE relative to[6]	
		Pre-1980	**Post-1980**	**Pre-1980**	**Post-1980**	**Full**	**Pro_mean**	**RW**
Professional mean forecast	[Pro_mean][2]	0.0722	-0.0926	0.3380	0.2538	0.2870	1	0.7568
Professional median forecast	[Pro_med][2]	0.0873	-0.0977	0.3449	0.2502	0.2879	1.0034	0.7594
Hafer and Hafer	[H&H][3]	-0.0536	0.0542	0.7148	1.0509	0.9438	3.2889	2.4892
Random walk with drift	[ARIMA(0,1,0)]	0.0180	-0.0172	0.4577	0.3268	0.3792	1.3213	1
Fixed-order ARIMA (AIC)[4]	[ARIMA(2,0,2)]	0.1914	-0.0883	0.4953	0.2969	0.3804	1.3257	1.0033
Fixed-order ARIMA (SBC)[4]	[ARIMA(1,0,0)]	0.2049	-0.1058	0.4749	0.3237	0.3850	1.3417	1.0155
Best time series (RMSPE)[4]	[ARIMA(0,1,1)]	0.0159	-0.0465	0.4599	0.2871	0.3590	1.2511	0.9468
Dynamically selected ARIMA (AIC)[5]	[Dyn_aic]	0.1399	-0.0572	0.4733	0.3022	0.3729	1.2996	0.9836
Dynamically selected ARIMA (SBC)[5]	[Dyn_sbc]	0.0991	-0.0440	0.5239	0.2900	0.3907	1.3614	1.0303

Notes:
1. Forecasting period: 1968:4 – 1999:4. MPE and RMSPE are in percentage per quarter. For example, 0.3275 represents a forecast error of 0.3275% inflation rate per quarter.
2. Pro_Mean and Pro_Med are respectively the mean and median predictions from *the Survey of Professional Forecasters*.
3. H&H is the interest rate model proposed by Hafer & Hein (1990). See equations (1) – (4) in the main text.
4. "Fixed-order ARIMA (AIC)" and "Fixed-order ARIMA (SBC)" refer to the fixed-order ARIMA model chosen respectively by the AIC and SBC criterion of the first regression. "Best time series (RMSPE)" refers to the model with the lowest RMSPE.
5. Dynamically selected ARIMA models use the in-sample AIC or SBC in each regression to choose the orders of the models.
6. These columns report the ratio of the RMSPE of a specific model to that of professional mean forecast (Pro_mean) and random walk with drift model (RW), respectively.

Table A2: Mean Prediction Error (MPE) and Root Mean Squared Prediction Error (RMSPE) Based on Revised Data (“true inflation” = 2001:1 release)

	MODEL	MPE		RMSPE			RMSPE relative to	
		Pre-1980	Post-1980	Pre-1980	Post-1980	Full	Pro_mean	RW
Professional mean forecast	[Pro_mean]	0.1665	-0.0985	0.3337	0.2018	0.2572	1	0.8511
Professional median forecast	[Pro_med]	0.1816	-0.1036	0.3522	0.2042	0.2671	1.0385	0.8839
Hafer and Hafer	[H&H]	-0.0476	0.0368	0.6766	1.0117	0.9055	3.5201	2.9961
Random walk with drift	[ARIMA(0,1,0)]	0.0117	-0.0164	0.4014	0.2283	0.3022	1.1749	1
Fixed-order ARIMA (AIC)	[ARIMA(2,0,2)]	0.2034	-0.0630	0.4657	0.2176	0.3292	1.2799	1.0893
Fixed-order ARIMA (SBC)	[ARIMA(1,0,0)]	0.2529	-0.0696	0.4499	0.2291	0.3263	1.2684	1.0796
Best time series (RMSPE)	[ARIMA(0,1,1)]	0.0280	-0.0291	0.3887	0.2210	0.2927	1.1378	0.9684
Dynamically selected ARIMA (AIC)	[Dyn_aic]	0.1520	-0.0484	0.4635	0.2410	0.3384	1.3156	1.1197
Dynamically selected ARIMA (SBC)	[Dyn_sbc]	0.1266	-0.0356	0.4334	0.2314	0.3192	1.2409	1.0561

See the notes in Table A1.

Table A3: Mean Prediction Error (MPE) and Root Mean Squared Prediction Errors (RMSPE) Based on Real-Time Data ("true inflation" = 2000:1 release)

	MODEL	MPE		RMSPE			RMSPE relative to	
		Pre-1980	Post-1980	Pre-1980	Post-1980	Full	Pro_mean	RW
Professional mean forecast	[Pro_mean]	0.1665	-0.0985	0.3337	0.2018	0.2572	1	0.7369
Professional median forecast	[Pro_med]	0.1816	-0.1036	0.3522	0.2042	0.2671	1.0385	0.7653
Hafer and Hafer	[H&H]	0.0407	0.0483	0.6962	1.0225	0.9185	3.5707	2.6313
Random walk with drift	[ARIMA(0,1,0)]	0.1123	-0.0231	0.4459	0.2802	0.3491	1.3570	1
Fixed-order ARIMA (AIC)	[ARIMA(2,0,2)]	0.2857	-0.0942	0.5060	0.2431	0.3605	1.4016	1.0329
Fixed-order ARIMA (SBC)	[ARIMA(1,0,0)]	0.2992	-0.1117	0.4814	0.2805	0.3658	1.4219	1.0479
Best time series (RMSPE)	[ARIMA(0,1,1)]	0.1102	-0.0524	0.4059	0.2407	0.3105	1.2070	0.8895
Dynamically selected ARIMA (AIC)	[Dyn_aic]	0.2342	-0.0631	0.4785	0.2517	0.3507	1.3633	1.0046
Dynamically selected ARIMA (SBC)	[Dyn_sbc]	0.1934	-0.0499	0.5023	0.2429	0.3586	1.3942	1.0274

See the notes in Table A1.