Predicting Inflation without Running Predictive Regressions

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Abstract

Inflation rates are highly persistent and extremely difficult to predict. Most statistical predictions based on predictive regressions fail to outperform the simple assumption of random walk in out-of-sample testing. The poor out-of-sample performance is a common feature of predictive regressions on highly persistent time series. This paper proposes a new approach for inflation forecasting that does not specify or estimate any predictive regressions, but rather starts by estimating a contemporaneous relation between inflation rate and a short-term interest rate, and then relies on the forward interest rate curve to predict future interest rates and accordingly inflation rates over both short and long horizons. Historical analysis with the US inflation series shows that this approach can outperform random walk, out-of-sample, by $30-50\%$ over horizons as far as three to five years.

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1. Introduction

Predicting future inflation rates is important for many economic and financial decisions; yet, inflation rates are notoriously difficult to predict with any accuracy. A recent comprehensive survey by Faust and Wright (2012) shows that, despite the long list of literature on inflation forecasting, virtually all predictive regression specifications considered in the literature fail to outperform random walk out-of-sample in predicting future inflation rates. The issues with predictive regressions, especially on highly persistent time series, are well documented.[1] In this paper, we propose a new approach for inflation rate prediction that does not rely on specifying and estimating any predictive regressions. Instead, we start by estimating a contemporaneous relation between inflation rate and a short-term interest rate. Then, we rely on the forward interest rate curve to generate predictions on future short-term interest rates and accordingly future inflation rates. Historical analysis on US inflation series shows that this approach can outperform random walk, out-of-sample, by $30-50\%$ over horizons as far as three to five years.

One of the most important objectives of monetary policy for central banks is to target inflation (Woodford (2003)). Under such policies, central banks alter their short-term interest rate target in response to their forecast of future inflation rates, thus generating a strong linkage between short-term interest rates and inflation rates. In this paper, we propose to exploit this strong linkage to transform the task of inflation forecasting into the task of forecasting future interest rates. To generate future interest rate forecasts, we rely on the expectation hypothesis and use the current forward rate as prediction of future interest rate. We use a simple historical moving average to remove the average bias of this prediction caused by interest rate risk premiums and convexity effects, but we refrain from running predictive regressions to avoid the well-known pitfalls. Indeed, we show that the simple bias-corrected forward rate predicts future interest rate much better in out-of-sample tests than predictions generated from expectation hypothesis-based predictive regressions.

[1]See, for example, Elliott and Stock (1994) and Stambaugh (1999) on spurious relations and biased coefficient estimates in predictive regressions, Jansson and Moreira (2006) on invalid inferences, Campbell and Yogo (2006) on misspecification, and Phillips (2013) for a general overview of the pitfalls of predictive regressions.

Our approach essentially forecasts future inflation rates using the current forward interest rate curve with a bridge equation that links the interest rates to inflation rates. This approach, while rarely employed in the inflation forecasting literature, has several advantages. First, the contemporaneous link between inflation and interest rates is strong by the virtue of the policy rules, much more so than a predictive relation on a highly persistent time series such as the inflation rate. As a result, the estimates for the contemporaneous link tend to be more stable and less susceptible to out-of-sample deterioration and other pitfalls of predictive regressions. Second, by using forward interest rate as a predictor of future interest rates, we capture forward-looking information from market expectations, which tend to perform better than statistical-regression based forecasts, especially for out-of-sample forecasting applications. Third, utilizing the entire forward rate curve, we are able to produce forecast at much higher frequencies (e.g., daily frequency) and across a wide spectrum of forecasting horizons from one to several years ahead.[2]

To examine the efficacy of this new approach, we perform a historical analysis on US inflation rates. We collect monthly data on four major price indexes over a 50-year period from June 1962 to June 2012. The four indexes are the Consumer Price Index (CPI), the core CPI (CCPI), the Personal Consumption Expenditure (PCE) deflator, and the core PCE deflator (CPCE). From the price indexes, we follow industry common practice to construct year-over-year inflation rates that smooth out the seasonality effects. We link these inflation rates to the continuously compounded spot Treasury rate rate, which are estimated using the Treasury bond price data based on the extended Nelson and Siegel (1987) functional form.[3] The daily coefficient estimates for the extended Nelson-Siegel functional form are available from the Federal Reserve and we can compute the spot and forward rates from these coefficients. In our implementation, we link the inflation rate to the three-month spot interest rate[4] and use h-month forwards of the three-month rate as an h-month ahead forecast of future three-month rate. For the out-of-sample forecasting exercise, at each date,

[2]Forward inflation contracts such as zero-coupon and year-over-year inflation swaps are now traded over the counter. Quotes on these forward contracts should give us more direct forecasts for future inflation. Unfortunately, reliable quotes on these contracts are still difficult to come by; by contrast, one can obtain the very long histories for the interest rate curve.

[3]See Gurkaynak, Sack, and Wright (2007) for details on the data sources and the spot rate curve construction procedures.

[4]We perform an annual average of the daily interest rate to match the period of the year-over-year inflation rate.

we use a ten-year rolling sample to estimate the contemporaneous relation between the three-month spot rate and the inflation rate, as well as the average bias (differences) between forward interest rates at different maturities and the three-month spot rate.

The historical out-of-sample forecasting analysis shows that the inflation rate forecasts generated from our approach can significantly outperform the random walk hypothesis. Over horizons from one to five years, the outperformance against the benchmark random walk model for CPI series, for example, can range from 30% to more than 50%. The averages outperformance over the horizons are about 44%, 40%, 41%, and 30%, respectively for the four inflation rate series. For comparison, we also repeat several commonly employed predictive regression specifications. The results are similar to what have been found in the literature: These predictive regression can hardly outperform the random walk benchmark.

Our approach is largely orthogonal to the existing inflation forecasting literature that rely on predictive regressions.[5] Instead, our new approach builds on two other strands of literature. The first is the recent advancement on monetary policy rules. Taylor (1993) first raises the question on whether central banks should make discretionary monetary policies or follow specific policy rules, and he proposes a particular form of a policy rule that is later popularized as the "Taylor rule," in which the short-term interest rate target is set to be proportional to the expected inflation rate and the output gap, with the coefficient on the expected inflation rate to be around 1.5 and that on the output gap to be 0.5. The more recent development of microeconomic theories on macroeconomic policies shows that such policy rules can be made the optimal decision by the central bank.[6] Associated with the theoretical development, empirical works have been devoted to estimate the policy rule from historical data, e.g., Clarida, Gali, and Gertler (2000) and Taylor (1999). The linkage we strive to build between inflation rates and interest rates is very much in line with this literature, albeit we use it for a new purpose.

[5] There are myriads of predictive regression specifications on inflation forecasting. They are largely motivated by statistical autoregressive behaviors, economic models such as the Phillips (1958) curve, and other economic factors such as factors extracted from the interest rate curve. For a comprehensive survey of all methods up to date, see Faust and Wright (2012).

[6] See, for example, Clarida, Gali, and Gertler (1999) and Woodford (2003).

The second strand of related literature is the long list of studies that predict future interest rates with the current shape of the term structure.[7] Assuming zero risk premium and ignoring the convexity effect, one can regard the forward interest rate as the expectation of future interest rate. The literature has formulated various forms of predictive regressions to test the validity of the expectation hypothesis. The general consensus of the literature is that the interest rate curve indeed contains useful information about future interest rate movements, but the slope coefficient estimates on these predictive regressions seem to deviate from the expectation hypothesis assumption, indicating the presence of time-varying risk premium.[8] Nevertheless, it is also well recognized that such predictive regressions can generate biased slope coefficient estimates due to, for example, small sample problems (Bekaert, Hodrick, and Marshall (2001)) and errors-in-variable problems (Stambaugh (1988)). In our application, to avoid the pitfalls of predictive regressions, we do not predict the future short rates via a predictive regression, but simply set it to the corresponding forward rate, with an average bias correction estimated from a rolling window capturing potential risk premiums and convexity effects. We show that while the various predictive regressions formulated around the expectation hypothesis may reveal insights on the behavior of risk premium and provide guidance for term structure modeling, they do not necessarily generate better out-of-sample forecasting performance than our simple formulation.

The remainder of the paper is organized as follows. The next section lays out the theoretical basis for our approach of predicting inflation rates without using predictive regressions. Section 3 describes the data behaviors and implementation details. Section 4 discuss the results. Section 5 concludes.

[7]The literature dates back to the 1970s, e.g., Roll (1970). More recent studies include Fama (1984), Fama and Bliss (1987), Mishkin (1988), Stambaugh (1988), Campbell and Shiller (1991), Evans and Lewis (1994), Hardouvelis (1994), Campbell (1995), Bekaert, Hodrick, and Marshall (1996), Longstaff (2000), and Bekaert and Hodrick (2001).

[8]Various term structure models have been proposed to accommodate time-varying risk premium. See, for example, Backus, Foresi, Mozumdar, and Wu (2001), Duffee (2002), and Dai and Singleton (2002).

2. Theoretical Basis for Inflation Prediction Without Predictive Regressions

An economy's inflation is normally measured via some price index. Realized inflation rate over a certain historical period can be measured as log changes in the price index over that period, whereas expected inflation rate is more a measure of the expected trend of the price index. Specifically, if we use P_t to denote the price index level at time t, the annualized realized inflation rate over the time horizon $(t-\tau, t)$ can be calculated as $p_t^\tau = \frac{1}{\tau}\ln(P_t/P_{t-\tau})$, where we use the lower-case p to denote the annualized realized inflation rate, the subscript t to denote the time line of the most recent information, and the superscript τ to denote the length of the horizon over which the realized inflation rate is computed upon. To avoid seasonality effects, realized inflation rates are often computed over a year, $\tau = 1$. In our analysis, we focus on year-over-year realized inflation rates and drop the superscript to reduce notation clustering.

To differentiate from the year-over-year realized inflation rate $p_t \equiv \ln(P_t/P_{t-1})$, we use π_t to denote the time-t expected instantaneous inflation rate π_t, which determines the instantaneous growth rate of the price index. In a one-factor diffusion world, we can represent the relation between the price level and the instantaneous expected inflation rate as,

$$dP_t/P_t = \pi_t dt + \sigma_p dW_t, \tag{1}$$

where W_t denotes a standard Brownian motion and σ_p captures the volatility in the price index variation around the expected inflation rate π_t. Accordingly, the year-over-year realized inflation rate over the next year is related to the expected inflation rate by,

$$p_{t+1} = \int_t^{t+1} \pi_s ds - \frac{1}{2}\sigma_p^2 + \sigma_p(W_{t+1} - W_t), \tag{2}$$

which consists of (i) the average expected inflation rate over the next year $\int_t^{t+1}\pi_s ds$, (ii) a convexity bias, $-\frac{1}{2}\sigma_p^2$, and (iii) a random error term, which by assumption is normally distributed with a zero mean and a variance of σ_p^2.

Monetary policy rules provide a theoretical basis to link the expected inflation rate π_t to the short-term interest rate r_t, the level of which can be manipulated by the central bank via open market operations. In particular, one can write the policy rule as,

$$r_t = \alpha + \beta \pi_t + x_t, \tag{3}$$

where β denotes the response of the interest rate to per unit shocks in the expected inflation rate, and x_t denotes other policy considerations (such as output gap and employment rate) or policy surprises. We sometimes refer to r_t as the "policy rate," highlighting the fact that policy makers strive to manipulate this rate to achieve certain economic objectives.

To set the monetary policy based on the policy rule in (3), policy makers must generate an expected inflation rate forecast first, highlighting the importance of forecasting future expected inflation rates. Our application turns the problem around by assuming that the policy makers have the appropriate expectation on the inflation rate and respond consistently to expected inflation rate changes. We propose to identify the policy response via the following regression,

$$p_t = a + b\bar{r}_t + e_t. \tag{4}$$

Since we do not observe the expected inflation rate but only observe the price index, from which we can compute a realized inflation rate, we use the year-over-year realized inflation rate p_t as a noisy measurement of the average expected inflation rate over the yearly time period $(t-1, t)$. According to the monetary policy rule in (3), this average expected inflation rate is related to a corresponding average of a policy rate, $\bar{r}_t = \int_{t-1}^{t} r_s ds$, which we can approximate using averages of daily observations of some short-term interest rate.

Although the monetary policy rules in (3) alters the short-term interest rate as a function of the expected inflation rate, we turn the relation the other way around and regress the realized inflation rate on the corresponding average short-term interest rate. This reversion not only fits our purpose of inflation forecasting better, but also mitigates the impact of errors-in-variables experienced when one regresses the policy rate against a realized inflation rate as a proxy for expected inflation rate.

Through the estimated linkage in (4), we convert the problem of forecasting future inflation rates into the problem of forecasting future interest rates,

$$\mathbb{E}_t\left[p_{t+h}\right] = a + b\mathbb{E}_t\left[\overline{r}_{t+h}\right], \tag{5}$$

where $\mathbb{E}_t\left[\cdot\right]$ denotes the expectation operator conditional on time-t information.

We rely on the forward interest rate curve to generate the forecast on the future short-term interest rate via the following specification,

$$\mathbb{E}_t\left[r_{t+h}\right] = f(t,t+h) - \mathbb{E}_t\left[f(t,t+h) - r_t\right], \tag{6}$$

where $f(t,t+h)$ denotes the time-t h-period ahead forward of the short rate, and $\mathbb{E}_t\left[f(t,t+h) - r_t\right]$ denotes the expected difference between the forward rate and the short rate due to risk premiums and convexity effects. We estimate this expected difference via a simple historical average over a rolling window.

As such, we can generate future inflation rate forecasts by exploiting the information in the interest rate term structure. The forecasting horizon h can be as long as the maturity spectrum of the term structure allows.

3. Data and Implementation Details

To gauge the efficacy of our proposed approach, we perform historical analysis on four major price indexes on the US economy: the Consumer Price Index (CPI), the core CPI (CCPI), the Personal Consumption Expenditure (PCE) deflator, and the core PCE deflator (CPCE). The CPI measures the average change in the prices of a basket of goods and services bought by a typical urban household. The PCE deflator measures the average change in the prices of a basket of goods and services purchased by a typical consumer. Their respective core measures exclude food and energy, the prices of which tend to be highly volatile. We obtain the price index time series from the Federal Reserve Bank of Saint Louis. The data span a 50-year sample period, monthly from June 1962 to June 2012. From the price indices, we construct year-over-year realized inflation rates.

We link the inflation rates to the continuously compounded spot Treasury rates. The data sources and spot rate curve construction details are described in Gurkaynak, Sack, and Wright (2007). The daily coefficient estimates for the extended Nelson and Siegel (1987) functional form are available from the Federal Reserve and we can compute the spot and forward rates from these coefficients. In our implementation, we use three-month spot rate as a proxy for the short rate r_t and compute h-month forwards of the 3-month rate from $h = 1$ to 5 years. At each date, we compute the yearly averages of the spot and forward rates to match the time period of the year-over-year inflation rates.

3.1. Summary statistics

Table 1 reports the summary statistics of the year-over-year inflation rates of the four prices indices and the corresponding average spot and forward three-month rate at selected forward horizons of one, two, three, and five years. The inflation rates and the interest rates show similar average magnitude (mean), similar variation (standard deviation), and similar persistence (annual non-overlapping autocorrelation). The inflation rates are also highly correlated with the three-month interest rate, showing potential for a strong linkage between the two.

Among the four inflation rate measures in panel A, the inflation rates defined on PCE deflators show smaller variation and higher persistence than that defined on the CPI index. The two classes of indices have some subtle differences in their definitions. The CPI represents the price paid by urban customers, whereas the PCE deflator is a broader measure that covers both urban and rural customers. Furthermore, the PCE deflator is a chain-weighted index that captures shifting spending patterns, whereas the CPI is a fixed-weight index that relies on spending patterns several years ago. It is possible that the broader base and the chain-weighting contribute to the smaller variation and higher persistence of the PCE deflator. Among each index class, the core inflation rate shows smaller variation and higher persistence due to the exclusion of the more volatile energy and food price component. Overall, the market regards the core PCE deflator as more indicative of the underlying inflation of the economy.

Comparing the spot rate with the forward rates at different forward horizons in panel B, we observe an upward sloping mean term structure. As convexity effect drives the term structure downward sloping, the upward sloping mean term structure is an indication of the presence of non-zero risk premium. The longer-term forward rates also show less variation and more persistence.

Figure 1 plots the time series of the four inflation rates and the corresponding average three-month interest rate. The four inflation rates move very closely together, with a few spikes here and there for the two raw inflation measures. The interest rate series follow closely the movement of the inflation rates.

[Fig. 1 about here.]

3.2. Rolling-window estimation and performance measures

We use a ten-year rolling window in estimating the relation between the year-over-year inflation rate and the average three-month interest rate and in estimating the average difference between forward and spot interest rates. The window length choice balances the need for a sample long enough to include several business cycles and enough inflation variation for effective identification, with the need to allow structural variation caused by potential regime changes.

Given the estimated relations, we generate forecast of future inflation rates and compare the forecasting accuracy relative to the random walk benchmark. Specifically, the random walk assumption defines the forecast of future inflation rate as the most recent realized year-over-year inflation rate,

$$\mathbb{E}_t\left[p_{t+h}\right] = p_t. \tag{7}$$

Thus, we can think of the random walk assumption as predicting a zero change in realized inflation rate, whereas the predicted inflation rate change from our approach can be written as,

$$\mathbb{E}_t\left[p_{t+h}\right] - p_t = \widehat{b}_t\left(\overline{f}(t,t+h) - \overline{r}_t - \eta_t\right), \tag{8}$$

where $\widehat{b}_t$ denotes the time-t rolling-window estimate of the slope coefficient of the relation between inflation rate and the average three-month interest rate, η_t denotes the time-t rolling-window estimate of the average bias (difference) between the corresponding forward rate and the spot three-month rate. This forecast is purely out-of-sample because the estimates on both the inflation-interest rate relation and the forward-spot bias are based on rolling windows up to the forecasting time.

Based on the forecasts generated at each time, we compute the forecasting R-squared relative to the random walk hypothesis as a performance measure,

$$R^2 = 1 - \frac{\sum\left(p_{t+h} - \mathbb{E}_t\left[p_{t+h}\right]\right)^2}{\sum\left(p_{t+h} - p_t\right)^2}. \tag{9}$$

Since the denominator $\sum\left(\overline{p}_{t+h} - \overline{p}_t\right)^2$ is essentially the sum squared forecasting error from the random walk hypothesis, the R-squared estimate will be greater than zero as long as the forecast is more accurate than the random walk hypothesis.

3.3. Comparison to the predictive regression literature

For comparison, we also generate inflation forecasts based on commonly proposed predictive regressions. Given the existence of exhaustive surveys such as Faust and Wright (2012), we do not try to be comprehensive in the comparison, but rather simply highlight the general performance of commonly proposed predictive regressions in our data sample.

Under our setting and notations, we can summarize the predictive regression approach by the following generic specification,

$$p_{t+h} - p_t = C^\top \left(X_t - \overline{X}\right) + e_{t+h}, \tag{10}$$

where X_t denote the predictive variables and $\overline{X}$ denotes its sample average. We consider the following examples for comparison:

1. AR(1): $X_t = p_t$.
2. AR(2): $X_t = [p_t, p_{t-1}]$.
3. One interest rate: X_t being the three-month rate.
4. Two interest rates: X_t being the three-month rate and the five-year rate capturing both the interest rate level and term structure slope.

To be comparable with our approach, we use the same ten-year rolling window for all estimations. Furthermore, the predictive regressions are re-estimated at each forecasting horizon h.

Autoregressive regressions are popular starting points for forecasting exercises. Interest rates and the term structure information have been used to predict inflation rates in a long list of studies.[9] We choose

[9] See, for example, Mishkin (1990), Jorion and Mishkin (1991), Frankel and Lown (1994), Stock and Watson (2003), Diebold, Rudebusch, and Aruoba (2006), and Ang, Bekaert, and Wei (2007).

two examples with interest rates as predictors to highlight both the linkage to and the difference from our approach. Similar to this literature, we rely heavily on the term structure information in generating our inflation forecasts, but different from this literature, we do not directly use interest rates, interest rate factors, or interest rate spreads as our predictors of future inflation rates, but rather we build a contemporaneous link between inflation rates and interest rates and then rely on the forward curve to generate predictions of future interest rates, thus completely circumventing the need to estimate a forecasting regression.

4. Empirical Findings

The success of our inflation forecasting depends on two crucial elements: (i) a strong and robust contemporaneous relation between inflation rates and short-term interest rates, (ii) forward rate as a strong out-of-sample predictor of future interest rates. In this section, we first analyze the estimated relation between inflation and short-term interest rates. Then, we examine the effectiveness of forward rates as predictors of future short rates. We compare the out-of-sample performance of our simple forward rate prediction with a bias correction with the widely investigated expectation hypothesis regressions. Finally, we report the out-of-sample forecasting performance on future inflation rates from our approach and compare it to the performance from several commonly specified predictive regressions.

4.1. Linkage between inflation rates and short-term interest rates

We regress the year-over-year inflation rates on the three-month interest rate to determine the linkage between the two and to generate an expected inflation rate estimate as a function of the short-term interest rate. Table 2 reports the full-sample regression estimates on the four inflation rate series in panel A. The R-squared of the regressions ranges from 46.48% for the PCE deflator series to 62.33% for the core CPI series. The two core series generate higher R-squared estimates than their corresponding original series, highlighting the noise in the food and energy prices excluded from the core measures.

The slope coefficient estimates range from 0.53 for the two CPI series to 0.62 and 0.66 for the CPI and core CPI series, respectively. The estimates suggest that for each percentage change in the short-term interest rate, the expected inflation rate changes by 0.52-0.66 percentage points. Reversely, from the policy rule perspective, each percentage point of expected inflation change leads to 1.52-1.89 percentage points of action on the short-term interest rate. The estimates are very close to the rule of thumb suggestion by Taylor (1993).

Monetary policies in the United States have experienced significant shifts during our historical sample period. Walsh (2003) describes the Fed policy changes based on differences in Fed operating procedures. More closely related to our purpose, Taylor (1999) and Clarida, Gali, and Gertler (2000) divide the sample based on the responsiveness of interest rates to the expected inflation variation.[10] They divide the sample into two main sub-periods with a transition period in between. The first is the pre-Volcker period up until September 1979. Paul Volcker became the 12th Chairman of the Federal Reserve on August 6, 1979, but the policy shift started in October, when as part of a policy shift to lower inflation, the Fed moved to a non-borrowed reserves operating procedure. An operating procedure that focused on a reserve quantity was viewed as more consistent with reducing money growth rates to bring down inflation. Before that, the Fed is usually described as having followed a federal-funds-rate operating procedure, under which the Fed allowed non-borrowed reserves to adjust automatically to stabilize the funds rate within a narrow band around its target level. This funds-rate operating procedure came under intense criticism during the 1970s because of the Fed's tendency to stabilize interest rates for long period time. Such interest-rate smoothing behavior can have important implications for price-level behavior (Goodfriend (1987)). Because a rise in the price level will increase the nominal demand for bank deposits as private agents attempt to maintain their real money holdings, periods of inflation will lead to increases in the nominal demand for bank reserves. If the central bank holds the non-borrowed reserves fixed, the rising demand for reserves pushes up interest rates,

[10]In other related literature, Goodfriend (2002) provides a detailed analysis of various phases of the monetary policy since 1987. Sims and Zha (2006) strive to identify regime shifts in U.S. monetary policies via statistical analysis. Boivin and Giannoni (2006) investigate the implications of changes in the structure of the U.S. economy for monetary policy effectiveness over the pre- and post-1980 periods.

thereby moderating the rise in money demand and real economic activity. If the central bank instead attempts to prevent interest rate from rising, it must allow the reserve supply to expand to accommodate the rising demand for reserves. Thus, interest-rate-stabilizing policies can automatically accommodate increases in the price level, contributing to ongoing inflation. Empirical analysis by both Taylor (1999) and Clarida, Gali, and Gertler (2000) confirms the interest-rate-stabilizing behavior as they both find low responsiveness of interest rates to inflation variation during the pre-Volcker period. New theoretical developments in monetary policy rules, .e.g., Woodford (1999) and Clarida, Gali, and Gertler (1999) have shown that the monetary policies are inflationary unless the interest rate responses to inflation variation are above one.

Since Volcker, the Fed's operating procedures have experienced a series of changes, from targeting non-borrowed reserves in October 1979 to targeting borrowed-reserves after 1982 and then to directly targeting the Fed fund rate again since Greenspan. Nevertheless, the commonality underlying these different operating procedures is an enhanced interest rate response to inflation variation and hence a more stationary monetary policy.

Following Taylor (1999) and Clarida, Gali, and Gertler (2000), we also divide our sample into two main sub-periods and perform policy rule estimation, except that our estimation reverses the relation by regressing inflation rates on interest rates instead of the other way around. The first main sub-period is from the start of our sample to September 1979, and the second main sub-period is from November 1982 to the present, with the intermediate high-inflation period from 1979 to 1982 as a transition. Panel B reports the sub-sample estimates for the pre-volker period from June 1962 to September 1979. The slope estimates are between 1.15 and 1.62, much higher than the full sample estimates. From the policy rule perspective, these estimates suggest that for each percentage point inflation increase, the short interest rate raises by 0.62-0.87 of a percentage point. This interest rate smoothing behavior has been identified as a key reason for the observed high inflation and inflation variation during this period.

Panel C reports the sub-sample estimates from October 1979 to June 2012. The slope estimates are from 0.43 to 0.57, suggesting a must more responsive policy rule since Volcker. When we re-estimate the relations with data from November 1982 forward in panel D, thus excluding the Volcker disinflation period, the slope estimates become even smaller at 0.23-0.35. The strong response contributes to the low and stable inflation rate ever since.

Using the CPI index to define the inflation, Clarida, Gali, and Gertler (2000) estimate the interest rate response to the inflation at 0.68 for the pre-Volcker period and 2.14 after that. The reciprocal of these estimates are 1.47 and 0.47, very close to our estimates at 1.62 for the period from 1962 to 1979 and 0.50 for the period after. With GDP deflator as the inflation measure, Taylor (1999) generates slightly higher responses at 0.813 for the 1960-1979 period, and slightly lower responses at 1.533 for the 1987-1997 period. The pattern is nevertheless the same.

For our out-of-sample forecasting exercise, we perform the regression with a ten-year rolling window. Figure 2 plots the rolling-window slope coefficient estimates. The rolling-window estimates are above one in the 1970s, which imply that the short rate response to expected inflation changes is less than one. Such response has been shown to be nonstationary and cannot achieve the objective of stabilizing inflation. The response has been corrected since the early 1980s. Since Greenspan, monetary policy has been very successful in containing the inflation rate (especially the core inflation rates) into a low and stable level. As a result of this success, the inflation rate has shown declining response to interest rate changes.

[Fig. 2 about here.]

4.2. Out-of-sample prediction of future interest rates based on the forward curve

By establishing a relation between the expected inflation rate and short-term interest rate, we have essentially transformed the task of forecasting inflation into the task of forecasting short-term interest rate. The literature on interest-rate forecasting dates back to the 1970s and has been repeated reviewed ever since. The main idea of the literature is to forecast future short-term interest rate changes with the current slope of the interest rate term structure, based on the expectation hypothesis that current forward rate is an expectation of future interest rates.

Depending on how the expectation hypothesis is formulated, the literature has proposed different forms of forecasting regressions. The one that is particularly relevant for our purpose is the forecasting regression based on forward interest rate,

$$r_{t+h} - r_t = c^h + d^h(f_{t,h} - r_t) + e_{t+h}. \tag{11}$$

Early studies with this regression include Fama (1984), Fama and Bliss (1987), and Mishkin (1988). The original purpose of this regression is to predict future short-term interest rate with the current forward curve. More recent studies, e.g. Backus, Foresi, Mozumdar, and Wu (2001) and Dai and Singleton (2002) focus more on the implications of the regression slope estimates on the risk premium behavior and on model specifications. In the absence of risk premium and convexity bias induced by interest rate volatility, we would have the forward rate $f_{t,h}$ being the time-t expected value of the short rate at time $t+h$. Thus, the slope estimate would be one and the intercept would be zero. Most literature studies find that the slope estimates are often deviate from one and the estimates have been used as evidence for time-varying risk premium.

While it is very possible that risk premiums are time-varying, it is very difficult to identify them ex ante to generate robust out-of-sample performance. Thus, for our out-of-sample interest rate forecasting, we adopt a more conservative specification, under which we assume that the risk premium (and the convexity bias) is a slowly varying quantity and we can simply remove this bias from the forward rate via a simple moving average without running a forecasting regression. More formally, we can write our forecasting specification as,

$$r_{t+h} - r_t = c_t^h + (f_{t,h} - r_t) + e_{t+h}, \tag{12}$$

where we impose a slope of one and estimate the intercept a_t with a rolling window.

To see how our more conservative approach compares to the expectation hypothesis regression in (11) in out-of-sample forecasting performance, we perform ten-year rolling-window estimation on both relations, from which we generate out-of-sample forecasts on future three-month interest rates. Figure 3 plots the rolling-window expectation hypothesis regression slope estimates ($\widehat{d_t^h}$) at forecasting horizons from one year (solid line) to five years (dashed line). The many dashed lines denote the slope estimates at intermediate horizons. The dash-dotted line denotes the expectation hypothesis benchmark at one. The estimates show large variation around the expectation hypothesis both over time and across different forecasting horizons. The large variation highlights the instability of such regression estimates.

[Fig. 3 about here.]

Figure 4 plots the out-of-sample forecasting R-squared from the two specifications at different forecasting horizons from one to five years. The forecasting R-squared is defined relative to the random walk hypothesis. Thus, a positive estimate indicates that the specification beats random walk out-of-sample whereas a negative estimate indicates that the performance is worse than random walk. The solid line in the graph shows the performance of the expectation hypothesis regression in (11), which generates negative forecasting R-squared for forecasting horizons both below 2.5 years and above 4.5 years. The maximum forecasting R-squared is about 10% at 3.5-year horizon. By contrast, our moving average bias correction specification (dashed line) performs much better. The forecasting R-squared is positive for forecasting horizons longer than 1.5 years and reaches as high as 26% at four-year forecasting horizon. Therefore, regardless of whether the interest rate risk premium is time varying or not, the expectation hypothesis regression itself is not stable enough to generate robust out-of-sample forecasting performance. The simple moving bias correction performs much better.

[Fig. 4 about here.]

Recently, Cochrane and Piazzesi (2005) show that one can regress future bond returns on a portfolio of several forward rates (instead of just a simple slope measure) and generate forecasting R-squared as high as 40% at annual horizon. However, their R-squared estimates only represent the in-sample fitting performance. Whether such multivariate regressions can work robustly out-of-sample is subject to further investigation.

4.3. Out-of-sample inflation prediction without predictive regressions

We combine our rolling-window estimates on the contemporaneous relation between inflation rates and short-term interest rates in (4) with the short rate prediction using forward rates with a moving average bias correction in (12) to generate out-of-sample inflation rate forecasts at horizons from one to five years. Figure 5 plots the out-of-sample forecasting R-squared at different forecasting horizons for the four inflation rate series. The forecasting performance is reasonably uniform across the four inflation series and are strongly positive over long horizons. Over horizons from 1 to 5 years, the outperformance averages at 44%, 40%, 41%, 30%, respectively for the four inflation series.

[Fig. 5 about here.]

For comparison, Figure 6 plots the similarly computed inflation forecasting R-squared from several predictive regression specifications, including a first-order autoregression (panel A), a second-order autoregression (panel B), a forecasting regression against the three-month interest rate (panel C), and a forecasting regression on three-month and five-year interest rates (panel D). As have been found in the literature, the autoregressive regressions generate horrible out-of-sample forecasting performances. The forecasting R-squared estimates are much lower than zero, and the approach performs much worse than the simple random walk assumption.

[Fig. 6 about here.]

Forecasting inflation with interest rates does a little better, but it is still difficult to beat random walk. In all cases, the performances are much worse than our inflation prediction without predictive regressions.

5. Conclusion

In the forecasting literature, the general consensus is that market expectations derived from financial security prices such as forward contracts or collected via surveys perform better than a purely statistical predictive regression specification. This is particularly true for highly persistent series like interest rates and inflation rates. For inflation rate forecasting, the literature has found that most predictive regressions fail to outperform the simple random walk benchmark.

In this paper, we propose to predict inflation rates without running any predictive regressions. Instead, we rely on a strong contemporaneous link between inflation rates and interest rates to transform the task of inflation rate forecasting to the task of interest rate forecasting, and we rely on the forward interest rate curve to generate direct future spot interest rate forecasts across a wide spectrum of forecasting horizons. Our specification is extremely simple, but it generates superb out of sample forecasting performances. The out-of-sample forecasting significantly outperforms a random walk model by an average of 30% to 50% over one to five year horizons.

Our simple empirical implementation illustrates the power of our basic approach, but devils are still in the details and many of them should be further studied in future research. Monetary policies can change over time. Depending on the macroeconomic condition, the policy can be either forward or backward looking. Rolling window estimation can partially accommodate the relational changes due to regime switches, but it is still uncertain what the appropriate size of the rolling window should be. Moreover, different price indices differ in their construction, and hence their timeliness of capturing the actual inflation might require different specifications for different inflation series.

Similar ideas can be applied to the forecast of other macroeconomic variables, such as unemployment rate, real GDP growth, mortgage rates, and bank deposit rates. Unemployment rate is closely related to business cycle and is often another direct target for monetary policy, so a joint exploration of inflation, unemployment (or real GDP growth) and interest rates is possible. Furthermore, many economic indicators are simply noisy representations of the same underlying economic conditions. Linking these economic indicators on the one hand and the interest rate (and credit spread) term structure on the other hand via a low-dimensional economic factor model, one can generate joint predictions on both the underlying economic conditions and the future path of each of these economic indicators.

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Table 1

Summary statistics of inflation rates and Treasury spot rates

Entries report the summary statistics on (A) inflation rates on CPI, core CPI, PCE deflator, and core PCE deflator, and (B) spot and forward three-month interest rates at forward horizons of 1, 2, 3, 4, 5 years. The inflation rates are computed from price indices obtained from the Saint Louis Federal Reserve, and the interest rates are computed from daily Nelson-Siegel coefficients provided by the Federal Reserve on the US Treasuries. The statistics are computed on 501 monthly observations from June 1962 to June 2012. The inflation rates are computed as year-over-year log changes of the four price indices and the corresponding interest rates series are averages of daily observations over the corresponding year. The statistics include the sample average (mean), standard deviation (Std), minimum (Min), maximum (Max), yearly non-overlapping autocorrelation (Auto), and cross-correlation with the three-month spot interest rate (CC).

	A. Inflation rates				B. spot and forward three-month rates					
Statistics	CPI	CCPI	PCE	CPCE	0	1	2	3	4	5
Mean	4.04	3.97	3.60	3.52	5.50	6.01	6.35	6.59	6.78	6.94
Std	2.72	2.50	2.34	2.09	3.01	2.90	2.74	2.59	2.47	2.38
Min	-2.01	0.60	-1.10	1.06	0.11	0.25	0.65	1.22	1.83	2.42
Max	13.62	12.76	10.96	9.74	15.53	14.11	13.80	13.55	13.41	13.35
Auto	0.74	0.81	0.79	0.87	0.86	0.91	0.92	0.93	0.94	0.94
CC	0.68	0.79	0.68	0.76	1.00	0.97	0.93	0.90	0.87	0.85

Table 2
Linkage between inflation rates and short-term interest rates
Entries report the coefficient (intercept $\widehat{a}$ and slope $\widehat{b}$) estimates, their Newey-West standard deviations (in parentheses), and the R-squared from regressing year-over-year realized inflation rates on average three-month Treasury interest rates. The regressions in Panel A are performed on 501 monthly observations for each series from June 1962 to June 2012. Panels B, C, and D report regression results over sub-sample periods. Corresponding to each year-over-year inflation rate, the regressor is the average of daily observations on the three-month interest rate over the same yearly period. The Newey-West standard errors are computed with 36 lags.

Price Index	$\widehat{a}$		$\widehat{b}$		R^2, %
			A. June 1962-June 2012		
CPI	0.65	(0.59)	0.62	(0.14)	46.76
CCPI	0.37	(0.45)	0.66	(0.10)	62.33
PCE	0.69	(0.48)	0.53	(0.11)	46.48
CPCE	0.61	(0.36)	0.53	(0.07)	57.93
			B. June 1962-September 1979		
CPI	-3.97	(0.71)	1.62	(0.14)	87.13
CCPI	-3.14	(0.63)	1.43	(0.11)	82.76
PCE	-3.03	(0.90)	1.37	(0.18)	78.77
CPCE	-2.03	(0.86)	1.15	(0.15)	73.72
			C. October 1979-June 2012		
CPI	0.82	(0.60)	0.50	(0.14)	49.49
CCPI	0.47	(0.47)	0.57	(0.11)	71.11
PCE	0.75	(0.50)	0.43	(0.11)	54.47
CPCE	0.59	(0.39)	0.46	(0.07)	72.23
			D. November 1982-June 2012		
CPI	1.80	(0.31)	0.23	(0.06)	26.78
CCPI	1.28	(0.15)	0.35	(0.03)	69.91
PCE	1.46	(0.27)	0.24	(0.05)	35.00
CPCE	1.11	(0.19)	0.32	(0.04)	59.89

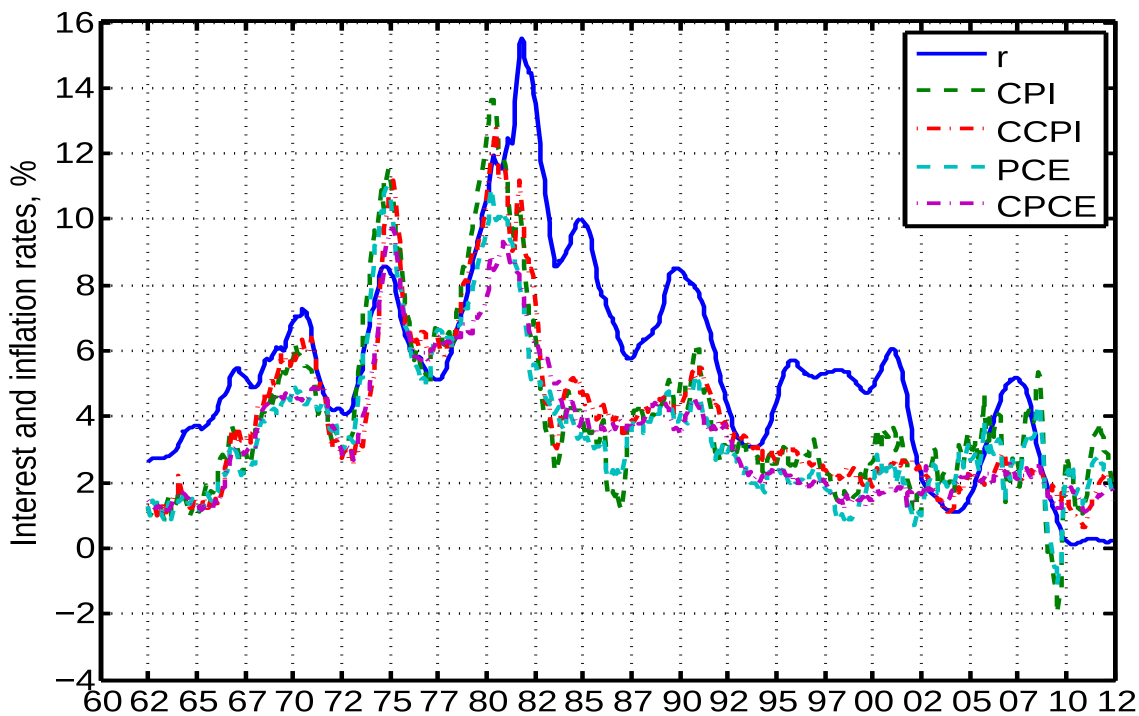

Fig. 1. The time series of inflation rates and three-month Treasury interest rate.
The four dashed lines depict the time series of the year-over-year realized inflation rates computed from the four price indices: CPI, core CPI, PCE deflator, and core PCE deflator. The solid line depicts the time series of the corresponding yearly averages of daily three-month Treasury continuously compounded spot rate. The daily interest rates are computed from the Nelson-Siegel coefficients provided by the Federal Reserve.

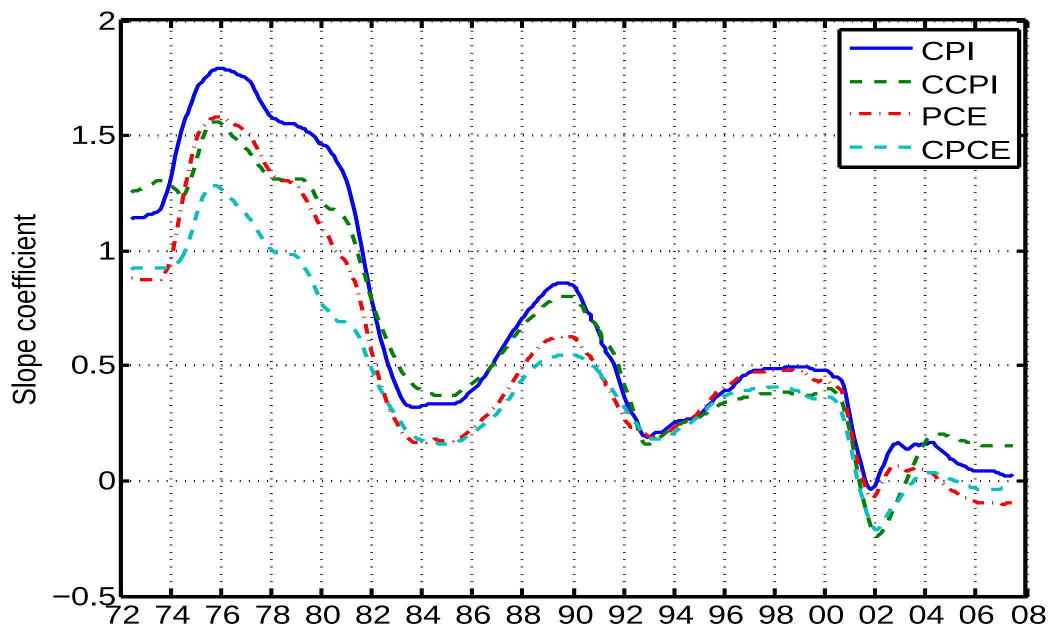

Fig. 2. Rolling-window slope and R-squared estimates on the inflation-interest relation. Lines plot the time series of the ten-year rolling window estimates of the slope coefficient.

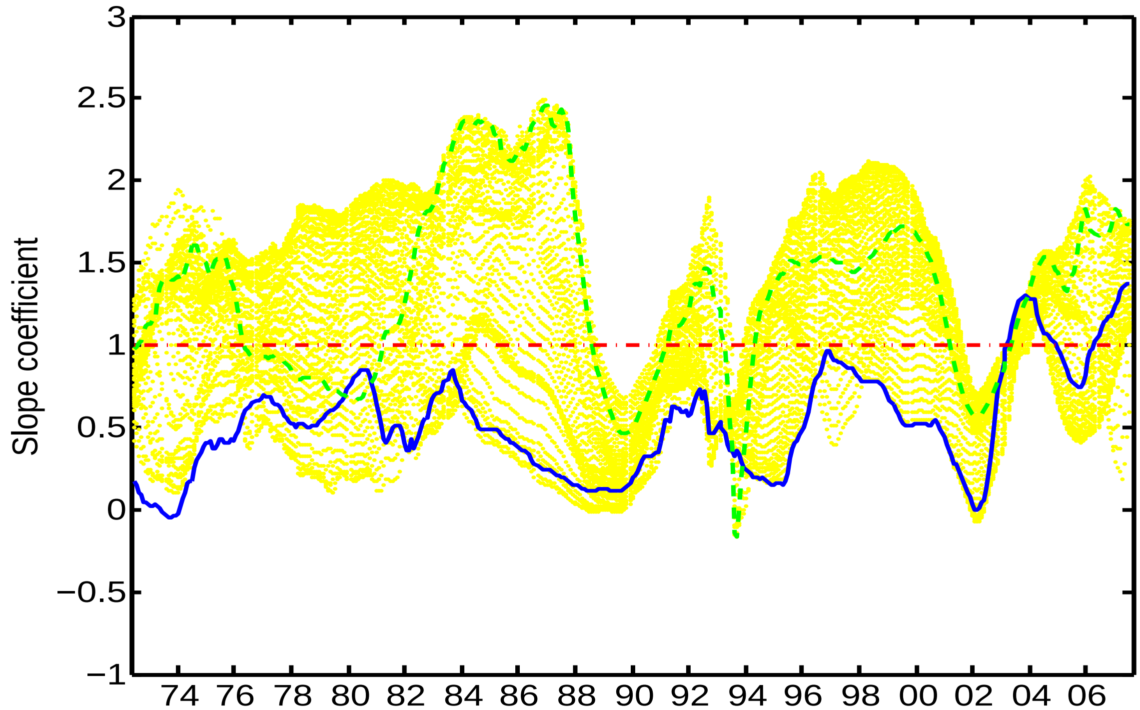

Fig. 3. Rolling-window slope estimates on the expectation hypothesis regression.
The solid line denotes the ten-year rolling-window slope estimates on the expectation hypothesis regression at one-year horizon. The dashed line denotes the rolling-window slope estimates at five-year forecasting horizon. The other dotted lines show estimates at intermediate horizons. The dash-dotted line represents the expectation hypothesis of one.

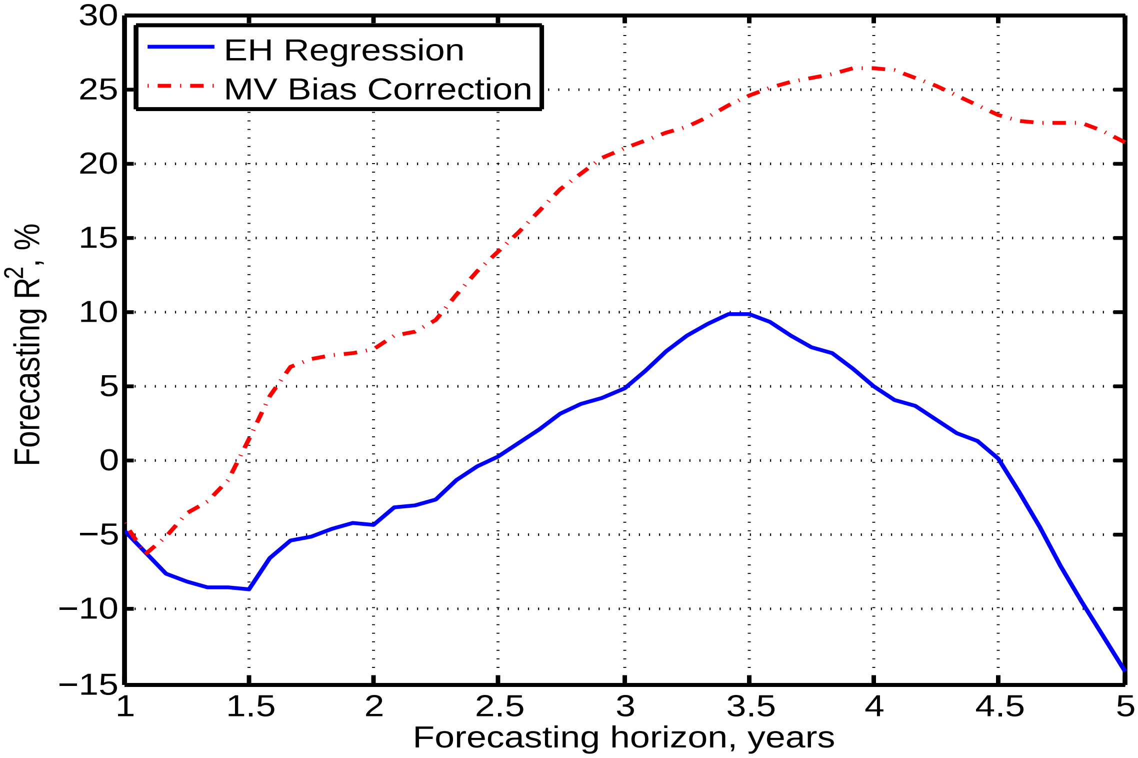

Fig. 4. Out-of-sample forecasting R-squared on future interest rates.

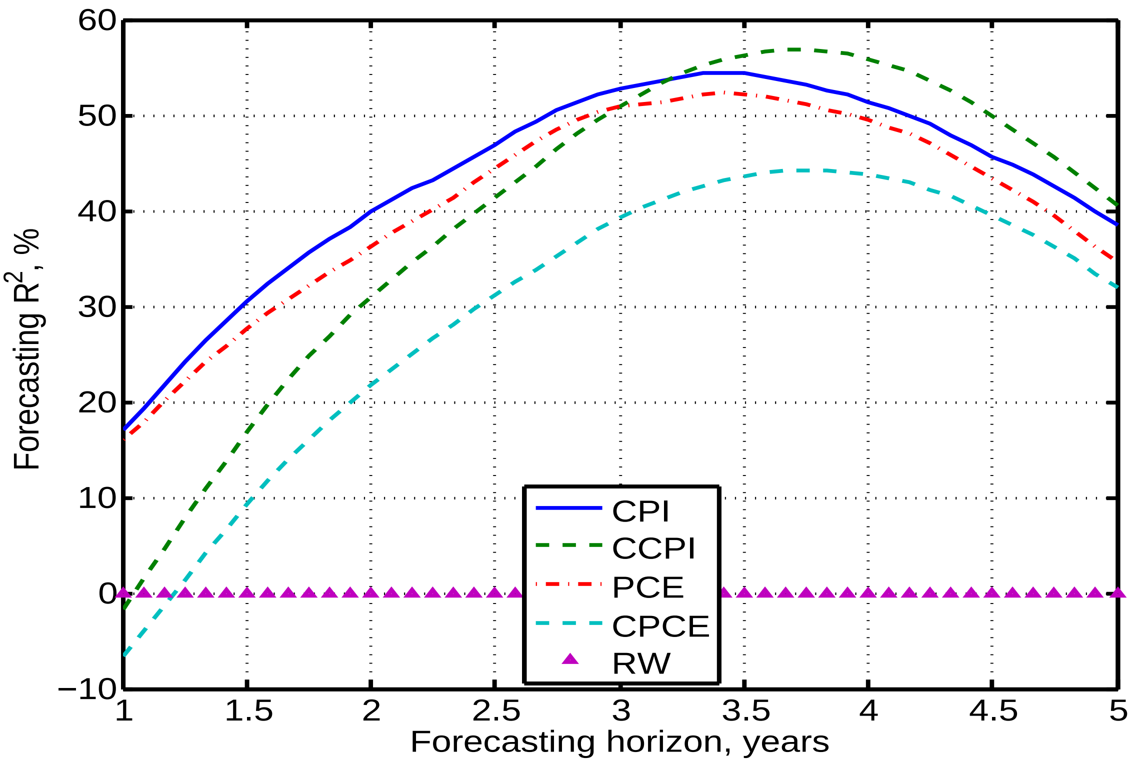

Fig. 5. Out-of-sample forecasting R-squared on future inflation rates.
Lines plot the inflation forecasting R-squared of our approach over the random walk benchmark as a function of the forecasting horizons.

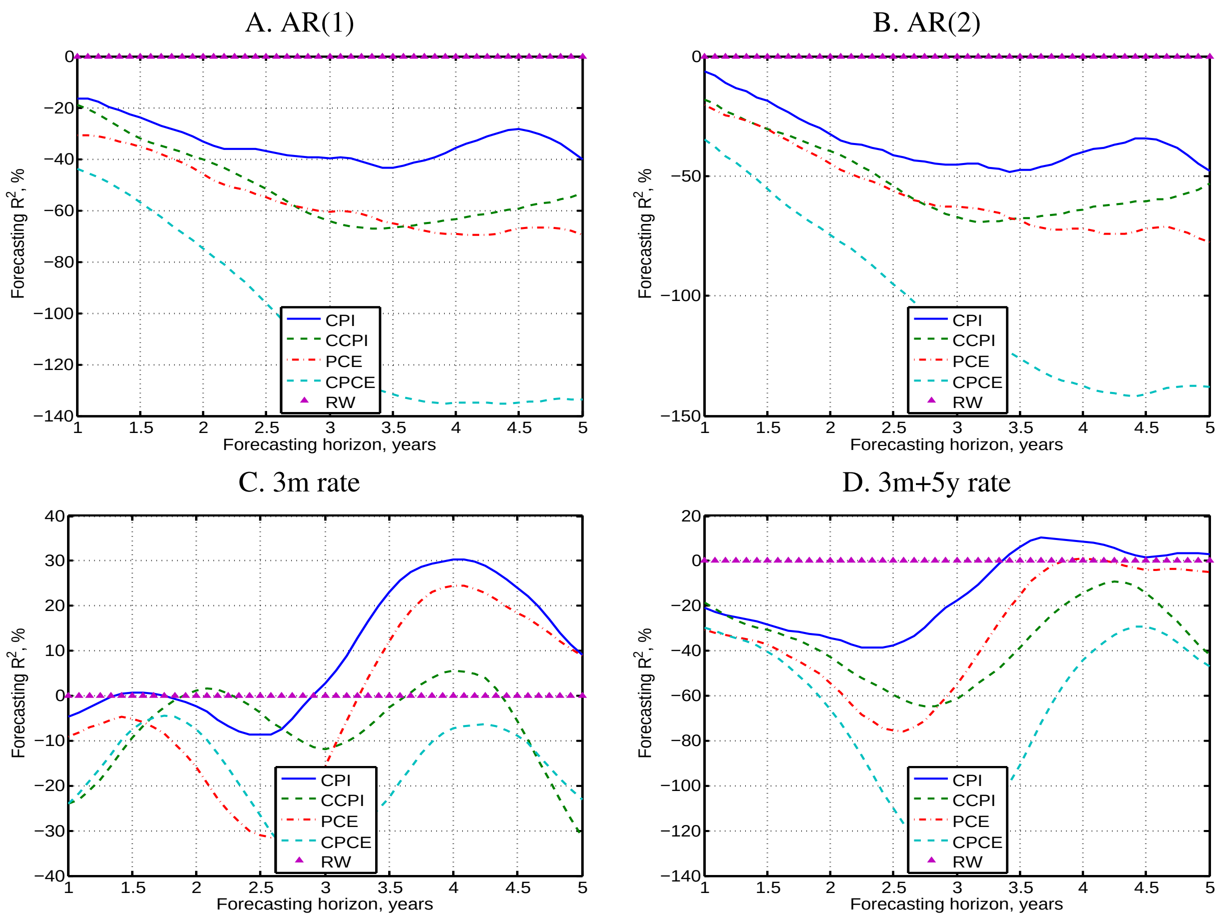

Fig. 6. Out-of-sample inflation forecasting R-squared of predictive regressions.
Lines plot the out-of-sample forecasting R-squared of four sets of predictive regressions as a function of the forecasting horizons.