

# Monetary Policy Rule as a Bridge: Predicting Inflation Without Predictive Regressions

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## Abstract

Predictive regressions on inflation rates often fail to outperform the simple random walk hypothesis out of sample. This paper proposes a novel approach of inflation forecasting that does not rely on predictive regressions. The approach starts with a monetary policy rule as a bridge between inflation rates and short-term interest rates, and then relies on the forward interest rate curve to generate interest rate forecasts. Historical analysis with US inflation series shows that this approach can outperform random walk out of sample by 30% – 50% over horizons from one to five years. The superior performance extends to other economies.

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Forecasting inflation rates plays a central role in monetary policy decision making (Svensson (2003, 2005)); yet, it is notoriously difficult to predict inflation rates with accuracy (Stock and Watson (2007, 2010)). Predictive regressions on inflation rates often fail to outperform the simple random walk assumption out of sample (Faust and Wright (2013)). The issues concerning predictive regressions, especially on highly persistent time series, are well documented.<sup>1</sup> Poor out-of-sample performance of predictive regressions has also been observed in other financial series, such as interest rates (Duffee (2002, 2013)) and exchange rates (Engel and West (2005)).

In this paper, we propose a new approach of predicting inflation without relying on predictive regressions. Our approach starts by estimating a contemporaneous relation between the inflation rate and a short-term interest rate, motivated by monetary policy rules. Then, we rely on the forward interest rate curve to generate predictions of future short-term interest rates and accordingly future inflation rates, without performing a predictive regression. A historical analysis on US inflation series shows that this approach can outperform random walk out of sample by 30% – 50% over horizons from one to five years. The outperformance extends well to other economies, and is robust to variations in performance metrics, rolling window size choices, and short rate proxies.

One of the most important objectives of modern monetary policy is to target and control inflation (Woodford (2003)). Central banks alter their short-term interest rate targets in response to their forecast of future inflation rates, explicitly or implicitly following some version of policy rules such as the one suggested by Taylor (1993). These monetary policy rules establish a strong linkage between short-term interest rates and expected inflation rates. Our approach exploits this strong linkage to transform the task of forecasting inflation to the task of forecasting short-term interest rates.

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<sup>1</sup>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.

To forecast interest rates, we rely on the information content in the current forward interest rate curve. The forward interest rate curve combines information from three sources: (i) expectation of future short rates, (ii) risk premium, and (iii) convexity effect induced by interest rate volatility. To separate the expectation from the other two components, we do not perform predictive regressions as suggested by the vast literature on expectation hypothesis, but propose to use a simple historical rolling-window moving average to remove the bias induced by the risk premium and the convexity effect, thus avoiding issues associated with predictive regressions. Through historical out-of-sample analysis, we show that this simple average bias correction approach generates substantially better out-of-sample interest rate forecasts than the traditionally specified expectation hypothesis based predictive regressions.

Combining the monetary policy rule with information from the forward interest rate curve, we arrive at a simple predictive relation that predicts future inflation rate changes with the current forward-spot interest rate differential. Such a predictive relation is nothing new by itself as interest rates have been used to predict inflation rates in a long list of studies.<sup>2</sup> What is new is our proposal of *estimating* the predictive relation without resorting to predictive regressions. To highlight how estimation methods affect the out-of-sample performance, we estimate the same predictive relation by running predictive regressions and show that estimating the relation using predictive regressions generates significantly deteriorated out-of-sample performance. Therefore, to achieve superior out-of-sample forecasting performance, it is not only important to search for predictively informative variables, but also equally important, if not more so, to find robust ways of determining the coefficients that govern the predictive relation. Although predictive regressions are the most apparent way of estimating the relation, they are often the least likely to generate stable estimates and robust out-of-sample forecasting performance.

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<sup>2</sup>See, for example, Mishkin (1990), Jorion and Mishkin (1991), Frankel and Lown (1994), Stock and Watson (2003), Diebold, Rudebusch, and Aruba (2006), and Ang, Bekaert, and Wei (2007).

To perform 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 construct year-over-year inflation rates. In addition, we construct continuously compounded spot Treasury rates from Treasury bond price data based on the extended Nelson and Siegel (1987) functional form. We link the inflation rates to the three-month spot interest rate and use  $h$ -month forwards of the three-month rate as an  $h$ -month ahead forecast of the future three-month rate, while removing the average bias induced by risk premiums and convexity effects via a rolling-window moving average.

The out-of-sample forecasting analysis shows that the inflation rate forecasts generated from our approach significantly outperform the random walk hypothesis. The average outperformance over horizons from one to five years are about 44%, 40%, 41%, and 30% for CPI, CCPI, PCE, and CPCE, respectively. The outperformances for the four series are statistically significant at several horizons. Extending the analysis to UK inflation rates generates similarly superior forecasting performance. Robustness analysis further shows that the superior performance of our approach is robust to variations in performance metrics, rolling-window size, and benchmark short rate proxies.

The remainder of the paper is organized as follows. The next section reviews different strands of literature that form the background of our study. Section II lays out the theoretical basis for our inflation forecasting approach. Section III describes the data behavior and the empirical implementation details. Section IV discusses the estimation results. Section V extends the analysis to UK inflation rates. Section VI performs robustness analysis by examining an alternative loss function, the effects of rolling-window size, and benchmark interest rate maturity choices on the out-of-sample inflation forecasting performance. Section VII provides concluding remarks and suggestions for future research.

## I. Background

The existing inflation forecasting literature relies mainly on predictive regressions. There are myriads of predictive regression specifications on inflation forecasting, motivated by statistical autoregressive behaviors, the Phillips (1958) curve, or other economic factors such as factors extracted from the interest rate curve. See Faust and Wright (2013) for a recent survey on this literature.

By contrast, our 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. More recent theoretical works provide microeconomic foundations for such macroeconomic policy rules (Clarida, Gali, and Gertler (1999) and Woodford (2003)). Associated with the theoretical development, empirical works have also been devoted to estimate policy rules from historical data, e.g., Clarida, Gali, and Gertler (2000), Taylor (1999), Orphanides (2001, 2002), and Nikolsko-Rzhevskyy and Papell (2012). The linkage we strive to build between inflation rates and interest rates is in line with this literature, albeit we use it for a new purpose.

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. 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). The forward rate curve combines contribution from three sources: the expectation

of future interest rates, risk premium, and convexity effects induced by interest rate volatility. 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 estimates on these predictive regressions seem to deviate from the expectation hypothesis assumption, indicating the presence of time-varying risk premium. 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). Diebold and Li (2006), Bali, Heidari, and Wu (2009), Duffee (2011a, b), Joslin, Singleton, and Zhu (2011), and Adrian, Crump, and Moench (2013) explore interest rate forecasting based on term structure models. Several recent studies explore the potentials and challenges of predicting time-varying bond risk premium (Cochrane and Piazzesi (2005) and Thornton and Valente (2012)), as well as its relation with expected inflation (Wright (2011)) and Cieslak and Povala (2013)).

In our application, we strive to exploit the information in the forward curve while avoiding the pitfalls of predictive regressions. Instead of performing a predictive regression, we apply a simple average bias correction to the forward-spot interest rate differential via a rolling-window moving average calculation. The moving average captures the average bias induced by risk premium and convexity.

Our paper is also related to the growing macro-finance literature that strives to link the inflation and real output dynamics to the interest rate term structure via no-arbitrage arguments. Examples include Ang and Piazzesi (2003), Gallmeyer, Hollifield, and Zin (2005), Diebold, Rudebusch, and Aruba (2006), Rudebusch and Wu (2008), Lu and Wu (2009), Backus, Chernov, and Zin (2014), Duffee (2014), and Joslin, Priebsch, and Singleton (2014). This literature has so far focused more

on contemporaneous linkages than on out-of-sample forecasts; nevertheless, the strong performance from our exercise highlights the potentials of this macro-finance literature for inflation forecasting.

## II. Monetary policy as a bridge to inflation forecasting

This section elaborates our idea of levering the monetary policy rule as a bridge to inflation forecasting. The idea relies on two key components. First, we rely on the strength of monetary policy rules to build a bridge between inflation rates and short-term interest rates. Second, we exploit the information content in the forward interest rate curve to predict the future path of short-term interest rate and accordingly future inflation rate movements.

### A. Monetary policy rule as a bridge between inflation and interest rates

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 represents the expected drift of the price index process. We use  $P_t$  to denote the price index level at time  $t$ ,  $p_{t+1} = \ln(P_{t+1}/P_t)$  to denote the realized inflation rate over the next year, and  $\pi_t$  to denote the time- $t$  expectation of the future inflation rate realization, hence the expected inflation rate.

Monetary policy rules provide a theoretical basis to link the expected inflation rate  $\pi_t$  to the short-term interest rate  $r_t$ , the level of which can be targeted by the central bank via open market

operations. We can write the policy rule as,

$$r_t = \alpha + \beta \pi_t + x_t, \quad (1)$$

where  $\beta$  denotes the response of the interest rate target to per unit shocks in the expected inflation rate, and  $x_t$  denotes other policy considerations, such as output gap and unemployment rate, and policy surprises. We refer to  $r_t$  as the “policy rate,” highlighting the fact that policy makers strive to target this rate to achieve certain economic objectives.

To set the monetary policy based on the policy rule in (1), policy makers must generate an expected inflation rate forecast first, highlighting the importance of forecasting inflation rates. Our application turns the problem around by assuming that the policy makers have the appropriate expectation of the inflation rate and respond consistently to expected inflation rate changes. We propose to identify the policy response via the following regression,

$$p_t = a + b r_t + e_t. \quad (2)$$

Since we do not observe the expected inflation rate but only observe the price index, we compute the year-over-year realized inflation rate  $p_t$  as a noisy measurement of the average expected inflation rate over the time period  $(t - 1, t)$ . According to the monetary policy rule in (1), this average expected inflation rate is related to the corresponding average policy rate,  $r_t$ , which we approximate using averages of daily observations of a short-term interest rate series.

The monetary policy rule in (1) alters the short-term interest rate as a function of the expected inflation rate. Equation (2) turns the policy rule the other way around and regresses the realized inflation rate on the corresponding average short-term interest rate. This reversion not only serves

our purpose of inflation forecasting, but also mitigates the impact of errors-in-variables problem experienced when one regresses the policy rate against a noisy realized inflation rate as a proxy for expected inflation rate (Orphanides (2002)). The regression slope coefficient  $b$  is equal to the reciprocal of the policy response coefficient  $\beta$ ,

$$b = 1/\beta. \quad (3)$$

Through the estimated linkage in (2), we transform the task of forecasting inflation rates to the task of forecasting short rates,

$$\hat{p}_{t+h|t} - p_t = b (\hat{r}_{t+h|t} - r_t), \quad (4)$$

where  $\hat{p}_{t+h|t}$  and  $\hat{r}_{t+h|t}$  denote the time- $t$  forecast of the time- $(t + h)$  inflation rate and interest rate, respectively, with  $h$  denoting the forecasting horizon.

## B. Forecasting the future path of interest rates via the forward rate curve

We use the forward interest rate curve to forecast the future path of the short rate. The forward curve combines contributions from three distinct sources: (i) the expectation of future short rate, (ii) risk premium, and (iii) convexity effect. As an illustrating example, if the instantaneous interest rate follows a simple random walk process with Gaussian innovation, constant volatility  $\sigma$ , and constant market price of risk  $\gamma$ , as a special case of the classic Vasicek (1977) model, the instantaneous forward rate can be written as,

$$f_t^h = r_t - \gamma\sigma h - \frac{1}{2}\sigma^2 h^2, \quad (5)$$

where the three terms capture the expectation, the risk premium, and the convexity effect, respectively. Under the random walk assumption, the expectation of future short rate is equal to the current level of the short rate. The risk premium increases linearly with the horizon  $h$ , and helps generate an upward mean term structure as the market price of interest rate risk  $\gamma$  is often estimated to be negative. The convexity effect is quadratic in the time horizon and contributes more significantly to longer horizons. Different term structure models lead to different forms for each component, but the three-way decomposition remains valid as a general rule. Hence, to use the forward rate curve to predict future interest rates, one must find an effective way to separate the interest rate expectation component from the other two components, i.e., the risk premium and the convexity effect.

The interest-rate forecasting literature mostly relies on the so-called expectation hypothesis that the forward rate represents an expectation of future short rate, thus assuming zero risk premium and ignoring the convexity effect. Depending on how the expectation hypothesis is formulated, the literature proposes different forms of forecasting regressions. The one that is particularly relevant to our purpose is the forecasting regression based on forward interest rate,

$$r_{t+h} - r_t = c^h + d^h(f_t^h - r_t) + e_{t+h}. \quad (6)$$

Under the null of the expectation hypothesis, the regression should generate an intercept of zero and a slope of one:  $c^h = 0, d^h = 1$ . Most studies find the slope estimate to deviate from one and interpret the deviation as evidence for time-varying risk premium.

While it is possible that the convexity effect and/or the risk premium component are time-varying, it is 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 and

capture the combined effects of the risk premium and the convexity effect via a simple moving average, thus avoiding a predictive regression altogether. Compared to the expectation hypothesis-based forecasting regression in (6), we can write our forecasting specification analogously as,

$$r_{t+h} - r_t = c^h + \left( f_t^h - r_t \right) + e_{t+h}, \quad (7)$$

where we impose a slope of one and estimate the intercept  $c^h$  not by performing a forecasting regression with restriction, but by simply setting it to the rolling-window historical moving average of the forward-spot interest rate differential,  $\hat{c}^h = -\overline{(f_t^h - r_t)}$ , thus generating the interest rate prediction without running a predictive regression:

$$\hat{r}_{t+h|h} - r_t = \left( f_t^h - r_t \right) - \overline{(f_t^h - r_t)}, \quad (8)$$

### C. Predicting inflation rates without running predictive regressions

Equations (2) and (8) form the basis of our inflation forecasting, with equation (2) building a linkage between inflation rates and short-term interest rates and equation (8) predicting future short rates using the current forward rate curve with an average bias correction. Given contemporaneous coefficient estimate  $\hat{b}$  and the moving average estimate of the forward-spot interest rate differential, we can generate the inflation rate forecasts ( $\hat{p}_{t+h|t}$ ) as

$$\hat{p}_{t+h|t} - p_t = \hat{b} \left( f_t^h - r_t - \overline{(f_t^h - r_t)} \right). \quad (9)$$

Equation (9) predicts future inflation rate changes with the current forward-spot interest rate differential. In principle, we could estimate this predictive relation via a straightforward predictive

regression:

$$\hat{p}_{t+h} - p_t = \eta + b(f_t^h - r_t) + e_{t+h}. \quad (10)$$

Instead, we propose to avoid such a predictive regression, but determine the slope of the predictive relation via a contemporaneous regression and determine the intercept via the simple moving average of the forward-spot interest rate differential. Our contribution lies not only in the choice of the forward-spot interest rate differential as the predictive variable for the future inflation rate variation over the corresponding horizon, but also, even more crucially, in proposing a new way to determining the predictive relation without performing predictive regressions.

### III. Data and implementation details

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 indexes, 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 principle, one can construct spot rates at any maturities from the estimated functional form, but we find that the constructed spot rates with maturities less than three months show some stability issues. In our implementation, we use three-month spot rate as a proxy for the short rate  $r_t$  and compute  $h$ -period forwards of the 3-month rate from  $h = 1$  to 5 years. The robustness section considers using other maturities to proxy the short rate. 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.

## A. Summary statistics

Table I reports the summary statistics for the year-over-year inflation rates of the four price indexes and the corresponding average spot and forward three-month interest rates at selected forward horizons of one to 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).

[Table I about here.]

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 indexes 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 based 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. Within each index class, the core inflation rate shows smaller variation and higher persistence due to the exclusion of the more volatile energy and food component.

Comparing the spot three-month interest rate with the forward rates at different forward horizons in Panel B, we observe an upward-sloping average term structure, as is commonly found in the literature. As the 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.

The last row of the table measures the cross-correlation of each series with the three-month spot interest rate. The correlation estimates between the four inflation rates and the three-month interest rate are high, ranging from 0.68 for the two raw measures to 0.76 for the core PCE inflation rate and 0.79 for the core CPI inflation rate. As expected, the correlation between forward and spot interest rates are even higher.

Figure 1 plots the time series of the four inflation rates and the corresponding average three-month interest rate. Despite the scattering, the four inflation rates and the interest rate share similar trends. There has been extensive interest in understanding inflation trends, including its dynamics (Clark and Doh (2011)), as well as its relations to monetary policy (Cogley and Sbordone (2008)) and the interest rate term structure (Ferris De Graeve and Wouters (2008), Cieslak and Povala (2013)). Our approach amounts to infer future inflation trends from the current interest rate term structure.

[Figure 1 about here.]

## B. Rolling-window estimation and out-of-sample prediction

We perform out-of-sample forecasting based on rolling-window estimation. At each date, we use a ten-year rolling window to estimate the contemporaneous relation between the year-over-year inflation rate and the three-month interest rate and to estimate the average difference between forward and spot interest rates. The window size 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 for structural variations caused by potential regime changes. The robustness analysis section examines the effects of different window size choices on the forecasting performance.

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

$$\hat{p}_{t+h|t} = p_t. \quad (11)$$

By comparison, the time- $t$  out-of-sample inflation rate forecast from our approach is given by,

$$\hat{p}_{t+h|t} = p_t + \hat{b}_t \left( f_t^h - r_t - \overline{(f_t^h - r_t)} \right), \quad (12)$$

where  $\hat{b}_t$  denotes the time- $t$  rolling-window estimate of the slope coefficient of the relation between inflation rate and the average three-month interest rate from equation (2) and  $\overline{(f_t^h - r_t)}$  denotes the time- $t$  rolling-window estimate of the average difference between the corresponding forward rate and the spot three-month interest rate.

## C. Performance measures and test statistics

From out-of-sample inflation rate forecasts  $\hat{p}_{t+h|h}$ , we define the ex post out-of-sample forecasting error  $e_{t+h}$  as,

$$e_{t+h} = p_{t+h} - \hat{p}_{t+h|t}. \quad (13)$$

We use squared forecasting error to define the loss function and compare the loss of each forecast with the loss from the random walk benchmark, the forecasting error of which is given by  $e_{0,t+h} = p_{t+h} - p_t$ . The robustness section considers using absolute forecasting error as an alternative loss function.

We compute the mean squared forecasting error (MSFE) of each forecast,

$$MSFE = \frac{1}{T} \sum_{t=1}^T e_{t+h}^2, \quad (14)$$

with  $T$  denoting the number of out-of-sample observations. We define an  $R^2$  measure against the random walk benchmark,

$$R^2 = 1 - MSFE/MSFE_0, \quad (15)$$

where  $MSFE_0$  denotes the mean squared forecasting error from the random walk benchmark. The literature often uses the MSFE ratio to represent the relative performance. The  $R^2$  transformation has a more intuitive interpretation of percentage improvement over the random walk benchmark, positive when the forecast outperforms the random walk benchmark and negative when the forecast underperforms.

To test the statistical significance of the forecasting performance difference, we compute the Diebold and Mariano (1995) (DM)  $t$ -statistics on the squared forecasting error difference,  $\delta_{t+h} =$

$$e_{0,t+h}^2 - e_{t+h}^2, \\ DM = \frac{\bar{\delta}}{s_\delta} \left( \frac{T+1-2(h+1)+h(h+1)/T}{T} \right)^{0.5}, \quad (16)$$

where  $\bar{\delta}$  denotes the sample mean of the difference,  $s_\delta$  denotes the Newey and West (1987) standard error estimate, computed with a lag equal to the forecasting horizon. The statistics adjust for the small-sample size bias according to Harvey, Leybourne, and Newbold (1997). Under the null hypothesis that each rolling-window estimated model and the random walk benchmark have equal finite-sample forecast accuracy,<sup>3</sup> Clark and McCracken (2012) find that the thus-computed Diebold and Mariano (1995) test statistic can be compared to standard normal critical values.

## IV. 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 bias-correction based forward rate prediction to 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 obtained from the same predictive relation estimated with predictive regressions.

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<sup>3</sup>See Inoue and Kilian (2004) for a discussion on the distinction between population and finite-sample predictive accuracy, and Clark and McCracken (2012) for a thorough review on forecast performance evaluation.

## A. Policy 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,

$$p_t = a + br_t + e_t, \quad (17)$$

as a reverse of the monetary policy rule,  $r_t = \alpha + \beta\pi_t + x_t$ . From this regression, we generate an expected inflation rate estimate as a function of the short-term interest rate. Table II reports the full-sample regression estimates on the four inflation rate series in Panel A. The R-squared ( $R^2$ ) estimates of the regressions range from 46% for the PCE deflator series to 62% for the core CPI series. The slope estimates range from 0.53 for the two PCE 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. The policy response is the reciprocal of the slope estimates ( $\beta = 1/b$ ): 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 thus close to the rule suggestion by Taylor (1993).

[Table II about here.]

Monetary policies in the US have experienced significant shifts during our sample period. Walsh (2003) describes the Fed policy changes based on differences in Fed operating procedures. Taylor (1999) and Clarida, Gali, and Gertler (2000) divide the sample based on the responsiveness of interest rates to expected inflation variation.<sup>4</sup> 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. During this period, the Fed allowed non-borrowed reserves to adjust automatically to stabilize the

<sup>4</sup>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.

Fed Funds Rate within a narrow band around its target level. Such interest-rate smoothing behavior can have important implications for price-level behavior (Goodfriend (1987)). New theoretical developments in monetary policy rules, e.g., Woodford (1999) and Clarida, Gali, and Gertler (1999), have shown that 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 Funds 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 divide our sample into two main sub-periods and perform sub-period 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 October 1979 to the present. 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 high 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 much more responsive policy rule since Volcker. The strong response contributes to the declining and stabilizing inflation rate ever since.

Using the CPI index to define inflation, Clarida, Gali, and Gertler (2000) estimate the interest rate response to 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, close to our slope 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 patterns are nevertheless similar.

For our out-of-sample forecasting exercise, we perform the regression with a ten-year rolling window. Figure 2 plots the rolling-window slope 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 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 a declining response to interest rate changes.

[Figure 2 about here.]

## B. Out-of-sample interest rate prediction based on the forward curve

By establishing a relation between the expected inflation rate and the short-term interest rate, we transform the task of forecasting inflation into the task of forecasting short-term interest rates. We rely on the forward interest rate curve to generate the forecast on the future path of short-term interest rate movements, while removing the average bias induced by risk premiums and convexity effects via a simple moving average correction,

$$r_{t+h|t} - r_t = \left( f_t^h - r_t \right) - \overline{(f_t^h - r_t)}. \quad (18)$$

Compared to the traditional expectation hypothesis based predictive regression,

$$r_{t+h} - r_t = c^h + d^h(f_t^h - r_t) + e_{t+h}, \quad (19)$$

our approach amounts to imposing a slope to one and estimating the intercept via a rolling-window historical moving average, thus avoiding running a predictive regression altogether.

To see how our moving-average bias removal approach in (18) compares to the predictive regression in (19) 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 ( $\hat{d}_t^h$ ) 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 null of the expectation hypothesis at one. While it is true that the slope estimates often deviate from the null value of one, the deviations themselves also show large sample variation, both above and below the null value, across different sample periods and forecasting horizons. The large variation highlights the inherent instability of the predictive regression slope estimates.

[Figure 3 about here.]

Figure 4 plots the out-of-sample forecasting  $R^2$  estimates from the two specifications at different forecasting horizons from one to five years. The solid line in the graph shows the performance of the expectation hypothesis predictive regression in (19), which generates negative forecasting  $R^2$  estimates for all forecasting horizons. Thus, the expectation hypothesis based predictive regressions cannot beat the simple random walk hypothesis out of sample. By contrast, our moving average bias correction specification (dashed line) performs much better. The forecasting  $R^2$  es-

timates are positive for forecasting horizons longer than 1.5 years and reach as high as 28% at four-year forecasting horizon. Therefore, regardless of whether interest rate risk premium is time varying or not, the expectation hypothesis predictive regression itself is not stable enough to generate robust out-of-sample forecasting performance. Our simple moving average bias correction approach performs much better.

[Figure 4 about here.]

To show the statistical significance of the forecasting performance, Table III reports the out-of-sample forecasting  $R^2$  estimates and the Diebold and Mariano (1995)  $t$ -statistics (DM) against the random walk hypothesis at selected forecasting horizons of one, two, three, four, and five years over the out-of-sample period from June 1972 to June 2012. The DM statistics on the expectation hypotheses regressions are all negative but insignificant. By contrast, our average bias removal approach generates statistically significant outperformance over the random walk benchmark at 10% level at three to four year forecasting horizons.

[Table III about here.]

In related work, 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  $R^2$  estimates as high as 40% at annual forecasting horizon. However, their  $R^2$  estimates only represent the in-sample fitting performance. Whether such multivariate regressions can work robustly out-of-sample is subject to further investigation. More recently, Cieslak and Povala (2013) decompose Treasury yields into inflation expectations and maturity-specific interest rate cycles, construct a time-varying risk premium measure by controlling for the expectation component, and show that this risk premium component can predict excess bond returns. Our specification in (8) allows for time-varying risk premium via the rolling-window moving average estimation, but does not allow

conditional interaction with the forward rates to avoid out-of-sample degeneration. Our approach is similar in spirit to Cieslak and Povala's decomposition in using simple moving averages instead of regressions for out-of-sample stability.

### C. Out-of-sample inflation prediction without predictive regressions

We combine the rolling-window estimates on the contemporaneous relation between inflation rates and short-term interest rates in (17) with the short rate prediction using average-bias corrected forward rates in (18) to generate out-of-sample inflation rate forecasts,

$$\hat{p}_{t+h|t} - p_t = \hat{b}_t \left( f_t^h - r_t - \overline{(f_t^h - r_t)} \right). \quad (20)$$

Figure 5 plots the out-of-sample forecasting  $R^2$  estimates 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 one to five years, the outperformance averages at 44%, 40%, 41%, 30%, respectively for the four inflation series.

[Figure 5 about here.]

Table IV reports both the  $R^2$  estimates and the Diebold and Mariano (1995) test statistics against the random walk hypothesis at selected forecasting horizons of one, two, three, four, and five years. The DM statistics show strong statistical significance at two to three year horizons. At longer horizons, although the  $R^2$  estimates remain high, the statistical significance decline due to the shortening of the effective sample size.

[Table IV about here.]

## D. Out-of-sample performance deterioration with predictive regressions

Given the superior performance of our approach, it is worth investigating further on where such superior performance comes from. Our inflation prediction involves two elements. The first element is an interest-rate prediction based on the average bias corrected forward curve. The second element is the estimation of a contemporaneous relation  $\hat{b}$  between inflation rates and interest rates. Combining these two elements generates a simple predictive relation in (20), except that the intercept and the slope of this predictive relation are not directly estimated from a predictive regression. Therefore, a key difference from the traditional forecasting literature is that we do not estimate the coefficients that govern the predictive relation directly with predictive regressions. Instead, we estimates the coefficients from some other contemporaneous relations, i.e., the contemporaneous average difference between forward and spot interest rates and the contemporaneous relation between inflation rates and short-term interest rates. As such, the superior performance of our approach comes not only from our choice of the forward-spot interest rate differential as the predictive variable, but also from our particular estimation method that does not involve predictive regressions.

To highlight how predictive regressions contribute to the deterioration of out-of-sample performance, we repeat the out-of-sample exercise with the same predictive relation, but using three alternative approaches of estimating the intercept and the slope of the predictive relation:

$$\begin{aligned} A_1 : \quad p_{t+h} - p_t &= c_t^h + b_t^h (f_t^h - r_t) + e_{t+h}, \\ A_2 : \quad p_{t+h} - p_t &= b_t^h \left( f_t^h - r_t - \overline{(f_t^h - r_t)} \right) + e_{t+h}, \\ A_3 : \quad p_{t+h} - p_t &= b_t \left( f_t^h - r_t - \overline{(f_t^h - r_t)} \right) + e_{t+h}, \end{aligned} \tag{21}$$

Approach  $A_1$  directly estimates the intercept and slope of each predictive relation with a rolling-

window predictive regression. This specification acknowledges the information content in the forward rate curve and determines each relation via a straightforward predictive regression. Approach  $A_2$  removes the average forward-spot interest rate bias through a moving average, and then estimates each predictive relation with a rolling-window regression without intercept. This specification acknowledges the existence of an average bias between forward and spot interest rates, but imposes a zero mean on the inflation rate changes, a constraint not imposed in approach  $A_1$ . Approach  $A_3$  imposes the additional constraint that the relation between future inflation rate changes and the corresponding average bias corrected forward-spot interest rate differential is the same across all forecasting horizons, and estimates the common slope coefficient by a stacked predictive regression without intercept. Among the three alternatives,  $A_1$  relies most on the predictive regressions for both the intercept and the slope estimates while  $A_3$  relies the least on the predictive regression by pre-fixing the intercept and by forcing the slope coefficient to be the same across all forecasting horizons. Our proposed approach differs from the three alternatives by avoiding running predictive regressions altogether, and estimating the common slope coefficient  $b$  through a contemporaneous relation between inflation rates and interest rates.

Table V reports the out-of-sample forecasting performance at selected forecasting horizons from the three alternative estimation methods, with one panel for each alternative method. In each panel and for each inflation series, we report the out-of-sample forecasting  $R^2$  defined against the random walk benchmark, as well as two Diebold and Mariano (1995) test statistics, one defined against the random walk hypothesis (DMR) and the other defined against our proposed approach that estimates the predictive relation without running predictive regressions (DMN). A positive estimate for  $R^2$  or equivalently for DMR suggests outperformance over the random walk hypothesis, and a positive estimate of DMN indicates better predictive performance than our proposed method.

[Table V about here.]

The results in Panel  $A_1$  are obtained following approach  $A_1$  of equation (21), in which we estimate both the intercept and the slope of each predictive relation through a rolling-window prediction regression. The forecasting  $R^2$  are negative at both short and long maturities for all four series, and only become positive at intermediate maturities. The DM test statistics against the random walk hypothesis (DMR) are either negative or insignificant. Not surprisingly then, when we compute the DM statistics against our proposed approach (DMN), all the estimates are negative, and many are significantly so.

In Panel  $A_2$  of Table V, we follow the approach  $A_2$  in equation (21) by first removing the average forward-spot interest rate bias via a moving average and then performing predictive regression without intercept for each relation. By relying on the predictive regression only for the slope estimate but not for the intercept, the out-of-sample forecasting performance improves somewhat as the forecasting  $R^2$  estimates become either less negative or more positive.

The performance improves further in Panel  $A_3$  when we constrain the predictive relations across all forecasting horizons to have the same slope coefficient and estimate the common slope via a stacked predictive regression without intercept. Nevertheless, even in this best alternative case, none of the predictions significantly outperform the random walk hypothesis and all of them perform worse than our approach, significantly so at short forecasting horizons.

What this exercise tells us is that even with the same predictive relation, the out-of-sample forecasting performance can still vary greatly depending on how the predictive relation is estimated. In particular, even if the predictive variable is truly informative, rolling-window predictive regressions tend to generate unstable coefficient estimates that lead to inferior out-of-sample forecasting performance. Thus, to enhance out-of-sample forecasting power, it is important to not only search for informative predictive variables, but also find robust ways of estimating the predictive relation.

Although predictive regressions are often the most apparent way of estimating predictive relations, they are also often the least likely to generate stable coefficient estimates and robust out-of-sample forecasting performance. One of our contributions in this paper is to propose a new, robust way of estimating the inflation forecasting relation without resorting to predictive regressions.

## V. Extension to UK inflation rates prediction

This section extends our forecasting analysis to the UK and examines whether our proposed methodology also generates superior forecasting performance on UK inflation rates.

We collect the UK Retail Price Index (RPI) from the Office for National Statistics, and compute year-over-year inflation rates from the price index. The RPI index measures the change in the cost of a representative sample of retail goods and services. The data sample is monthly from January 1980 to December 2014. We link the inflation rates to the interest rates on UK government bonds. Bank of England provides stripped daily spot interest rates from one year to 20 years.<sup>5</sup> Based on the available data, we use the short end of the data, at one-year maturity, to proxy the policy rate  $r_t$  and compute  $h$ -period forwards of the one-year rate from one to five years.

Figure 6 compares the time series of the UK sterling one-year interest rate (solid line) with the time series of the year-over-year UK inflation rate (dashed line) in Panel A. The inflation rate reached over 20% in the early 1980s, but has come down significantly and has been fluctuating within a narrow range since the early 1990s. The one-year sterling interest rate time series show a similar downward trend. During this sample period, UK monetary policies experienced several structural transformations (Osborne (2013)). From 1976 to 1987, the UK monetary policy aimed to control various monetary aggregates. From 1987 to 1992, the policy was directed to target the

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<sup>5</sup>Spot rate data at shorter maturities are sparse, with large amounts of missing values.

exchange rate, as UK interest rates were set to keep the value of sterling within a certain band relative to the German currency. In the face of large international capital flows and speculation, the monetary authorities could not maintain the exchange rate target, resulting in some instability of both output and prices, as well as a sharp depreciation of sterling in 1992. Following the exit from the exchange rate targeting regime, the monetary policy started to target inflation for the first time. In 1997, the Monetary Policy Committee of the Bank of England was given operational independence, and inflation targeting has been the chief objective since then.

[Figure 6 about here.]

When we regress the UK realized inflation rate on the one-year sterling interest rate over the entire sample period, we obtain a slope estimate of  $b = 0.56$  with a Newey and West (1987) standard deviation of 0.20, and an  $R^2$  of 41%. The estimate corresponds to a strong monetary response of  $\beta = 1/b = 1.78$ . When we perform rolling-window estimation on the relation, the slope coefficient estimates evolve in line with the historical development of the UK monetary policy, as shown in Panel B of Figure 6. The rolling-window slope estimates are high and above one before 1992, suggesting that UK monetary policy during this early period was inflationary. Since the introduction of inflation targeting however, the coefficient estimates have come down to below one.

To forecast UK sterling interest rates with the forward curve, we again compare the expectation hypothesis based predictive regression with our simple moving average bias removal approach. Panel A of Figure 7 plots the rolling-window expectation hypothesis regression slope estimates over different forecasting horizons. The solid line denotes estimates on the one-year ahead forecasting relation, the dashed line denotes estimates on the five-year ahead forecasting relation, and the dotted lines denote estimates for intermediate horizons. Similar to the observation for the US dollar interest rates, the slope estimates often deviate strongly from the null value of one, but the

deviations themselves also vary greatly over time and over different forecasting horizons, ranging from estimates as low as  $-1$  to estimates as high as  $3$ . Again, the large sample variation highlights the inherent instability of the estimates, making them unsuitable for out-of-sample forecasting application.

[Figure 7 about here.]

Panel B of Figure 7 plots the out-of-sample interest rate forecasting  $R^2$  estimates over different horizons for both the expectation hypothesis regression approach (solid line) and our simple moving average bias removal approach (dashed line). The solid line stays far below zero, further highlighting the out-of-sample instability of the expectation hypothesis regressions. Out of sample, the expectation hypothesis regression degenerates, leading to far worse forecasting performance than the simple random walk benchmark. By contrast, our moving average bias removal approach outperforms the random walk benchmark over all horizons. The outperformance is over 20% at three–four year horizon.

Figure 8 plots the out-of-sample forecasting  $R^2$  estimates on the UK inflation rate at different forecasting horizons. Similar to the performance observed for the US, our methodology works equally well for predicting UK inflation rates. The outperformance reaches as high as 40% around three–four year forecasting horizon.

[Figure 8 about here.]

Table VI reports the out-of-sample  $R^2$  estimates and the Diebold and Mariano (1995)  $t$ -statistics at selected forecasting horizons of one, two, three, four, and five years. The shorter sample makes the  $t$ -statistics weaker than those observed on the US data. Nevertheless, the outperformance at

one-year forecasting horizon over the random walk benchmark is statistically significant at the 10% confidence level.

[Table VI about here.]

Several researchers, e.g., Welch and Goyal (2008) and Kelly and Pruitt (2013), stress the importance of testing the performance robustness of a methodology across different samples. The extension to UK inflation analysis shows that our proposed inflation forecasting methodology works well not only over different forecasting horizons, but also across different economies.

## VI. Robustness analysis

To examine the robustness of our proposed forecasting methodology, we consider the effects of alternative loss functions, different rolling-window sizes, and different maturity choices of the policy rate proxies.

### A. Mean absolute error as an alternative loss function

Although squared forecasting error is the most commonly used metric for loss function definition, there are many alternatives (Giacomini and White (2006)). To gauge the robustness of our results, this subsection considers mean absolute error as an alternative loss measure. The relative mean absolute error (*RMAE*) measure is defined as the ratio of the mean absolute forecasting errors of our model against the random walk benchmark. We compute the corresponding Diebold and Mariano (1995) test statistics based on the absolute forecasting error differences. Table VII reports the *RMAE* ratio and the corresponding DM statistics. The overall pattern is quite similar to the  $R^2$  measure. For CPI and PCE, our model statistically outperform the random walk benchmark at

the 2- and 3-year horizons. For CCPI, the outperformance is statistically significant at the 3-year ahead horizon.

[Table VII about here.]

## B. Window size choices

Hansen and Timmermann (2012) discuss how the out-of-sample predictive performance can vary greatly with the window size choice. Rossi and Inoue (2012) propose to use a large range of window sizes to gain robustness. In our view, the window size choice is not a purely statistical issue. Economic considerations are equally important. In our particular application, choosing a window size shorter than the average duration of a business cycle is likely to generate large and spurious variations in the estimated economic linkage between inflation and interest rates. On the other hand, increasing the window size not only reduces the actual number of observations for the out-of-sample tests, thus reducing the statistical power of the test, but also runs the risk of suffering from biases induced by structural regime changes.

To examine how the window size choices affects the inflation forecasting performance, we repeat our out-of-sample forecasting exercise with different window sizes for the rolling-window estimation. Table VIII reports the out-of-sample forecasting performance on the four sets of inflation rates based on different rolling-window sizes: 5-year window in Panel A, 15-year window in Panel B, and recursive in Panel C. With the 5-year window, we start the forecasts in June 1967 and hence obtain more observations for the statistical tests. Thus, although the  $R^2$  estimates become slightly lower than those from the ten-year rolling window estimation in Table IV, the DM statistics remain as strong in most cases. On the other hand, when we use a 15-year window, the number of out-of-sample observations becomes much smaller. Accordingly, the DM statistics

become weaker. Nevertheless, the overall performance patterns are similar across the different window size choices. Using a recursive approach, we start the forecasts in June 1972, which gives the same ten-year initial window, and the  $R^2$  estimates are similar to those from the ten-year rolling window results with somewhat lower DM statistics.

[Table VIII about here.]

## C. Policy rate proxies

Our main analysis uses the three-month spot interest rate as to proxy the policy rate. The rates constructed at shorter maturities from the Nelson-Siegel coefficients show numeric instability. Nevertheless, we can investigate how the forecasting performance varies if we choose a longer maturity interest rate as the policy rate proxy. Table IX reports the out-of-sample forecasting performance on the four sets of inflation rates when we use six-month (Panel A) and 12-month (Panel B) interest rates as the policy rate proxy. Using either six-month or the 12-month interest rate as the workhorse of the inflation forecasting, we observe similar patterns in both  $R^2$  and DM statistics.

[Table IX about here.]

## VII. Concluding remarks

While predictive regressions have been used extensively in the literature to determine the existence and statistical significance of certain predictive relations, they have been found particularly ineffective in generating superior out-of-sample forecasting performance. In predicting common financial series such as inflation rates, interest rates, and exchange rates, predictive regressions often fail to outperform the simple random walk hypothesis in out-of-sample tests. In this paper, within the

context of inflation rate forecasting, we propose a new and much more robust approach of estimating a predictive relation without resorting to predictive regressions. The out-of-sample forecasting performance from our approach is significantly better than the random walk hypothesis, even more so than the performance from estimating the same predictive relation with predictive regressions.

We achieve the superior performance by combining two strands of literature. This first strand is on monetary policy rules, which imply the existence of a strong contemporaneous relation between inflation rates and short-term interest rates. The literature is often about inferring the appropriate level of interest rate target given inflation predictions, but we consider the relation the other way around by inferring the inflation rate expectation from the interest rate level. The second strand of literature is on the information content of the forward interest rate curve about future interest rate movements. While the information content of the forward curve and the behavior of interest rate risk premiums are often investigated by running various predictive regressions, we propose to forecast future interest rate changes with the current forward-spot interest rate differential without running a predictive regression but just with a simple moving average bias correction. Combining the two elements leads to a predictive relation that predicts future inflation rate changes with current bias-corrected forward-spot interest rate differentials, and with the slope coefficient of the predictive relation determined by a contemporaneous regression instead of a predictive regression.

By estimating the same predictive relation with different methods that rely progressively more heavily on predictive regressions, we show how estimating the relation using predictive regressions can generate unstable coefficient estimates and significantly deteriorated out-of-sample forecasting performance. To achieve high out-of-sample forecasting power, then, it is not only important to search for informative predictive variables, but also equally important, if not more so, to find robust ways of determining the predictive relation. Although predictive regressions are often the most apparent way of estimating the relation, they are often the least likely to generate stable estimates

and robust out-of-sample forecasting performance.

For future research, there are many directions that one can explore to generate more robust estimations of predictive relations. For example, central banks are becoming increasingly vocal about how they plan to target the policy rate. These public communications provide a benchmark on the structural link between expected inflation rates and the interest rate targets and can be used as strong priors on the statistical relation estimation. In particular, when central banks indicate that they plan to change their policy mandates, one can alter the relation in inflation prediction, even before one collects enough data to estimate the new relation.

As another example, the literature often find that surveys from economists, when they are available, often perform well out of sample. The issue is that these surveys are conducted infrequently and only for a few horizons. For future research, instead of trying to use these sparsely observed surveys as additional forecasting variables in a predictive regression, it can potentially be more beneficial to use them as benchmarks for calibrating existing predictive relations.

More recently, the inflation derivatives market has also been developing rapidly, thus providing another source of forward-looking information. For example, zero-coupon inflation swaps and year-over-year inflation swaps are now traded over the counter. Quotes on these forward contracts can give us more direct forecasts for future inflation. While reliable quotes on these contracts are still difficult to come by, let alone long time series, future research can potentially combine the information in these inflation swap contracts with that from the forward interest rate curve to generate more accurately estimated predictive relations and more robust inflation forecasts.

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**Table I**  
**Summary statistics of inflation rates and Treasury spot rates.**

Entries report the summary statistics on inflation rates on CPI, core CPI, PCE deflator, and core PCE deflator in Panel A, and spot and forward three-month interest rates at forward horizons of one, two, three, four, five years in Panel B. The inflation rates are computed from price indexes obtained from the Saint Louis Federal Reserve, and the interest rates are computed from daily Nelson-Siegel model coefficients provided by the Federal Reserve on the US Treasuries. The statistics are computed on 501 monthly observations from 1962:6 to 2012:6. The inflation rates are computed as year-over-year log changes of the four price indexes and the 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).

Statistics	A. Inflation rates				B. Spot and forward three-month rates					
	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 II**  
**Linkage between inflation rates and short-term interest rates.**

Entries report the coefficient (intercept  $\hat{a}$  and slope  $\hat{b}$ ) estimates, their Newey-West standard errors (in parentheses), and the R-squared ( $R^2$ ) from regressing year-over-year realized inflation rates on three-month Treasury interest rates. The regressions in Panel A are performed on 501 monthly observations for each series from 1962:6 to 2012:6. Panels B and C report regression results over sub-sample periods. The Newey-West standard errors are computed with 36 lags.

Price Index	$\hat{a}$	$\hat{b}$	$R^2$
A. 1962:6 – 2012:6			
CPI	0.65 ( 0.59 )	0.62 ( 0.14 )	0.47
CCPI	0.37 ( 0.45 )	0.66 ( 0.10 )	0.62
PCE	0.69 ( 0.48 )	0.53 ( 0.11 )	0.46
CPCE	0.61 ( 0.36 )	0.53 ( 0.07 )	0.58
B. 1962:6 – 1979:9			
CPI	-3.97 ( 0.71 )	1.62 ( 0.14 )	0.87
CCPI	-3.14 ( 0.63 )	1.43 ( 0.11 )	0.83
PCE	-3.03 ( 0.90 )	1.37 ( 0.18 )	0.79
CPCE	-2.03 ( 0.86 )	1.15 ( 0.15 )	0.74
C. 1979:10 – 2012:6			
CPI	0.82 ( 0.60 )	0.50 ( 0.14 )	0.49
CCPI	0.47 ( 0.47 )	0.57 ( 0.11 )	0.71
PCE	0.75 ( 0.50 )	0.43 ( 0.11 )	0.54
CPCE	0.59 ( 0.39 )	0.46 ( 0.07 )	0.72

**Table III**  
**Out-of-sample forecasting performance on future interest rates.**

Entries report the out-of-sample forecasting performance on future interest rates at forecasting horizons of one, two, three, four, and five years, based on two approaches: (A) the expectation hypothesis (EH) regression and (B) the moving average (MV) bias removal. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each method against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on the squared forecasting error differences, which has standard normal critical values. The models are estimated with a ten-year-rolling window. The out-of-sample statistics are computed using data from 1972:6 to 2012:6.

Horizon Years	A. EH regression		B. MV bias correction	
	$R^2$	DM	$R^2$	DM
1	-0.12	-1.06	-0.01	-0.07
2	-0.17	-0.71	0.11	0.72
3	-0.14	-0.28	0.23	1.69
4	-0.27	-0.39	0.28	1.96
5	-0.58	-0.78	0.21	1.25

**Table IV**  
**Out-of-sample forecasting performance on US inflation rates without predictive regressions.**

Entries report the out-of-sample forecasting performance on four US inflation rates series at forecasting horizons of one, two, three, four, and five years under our approach without performing predictive regressions. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on the squared forecasting error differences, which has standard normal critical values. The models are estimated with a ten-year-rolling window. The out-of-sample statistics are computed using data from 1972:6 to 2012:6.

Horizon Years	CPI		CCPI		PCE		CPCE	
	$R^2$	DM	$R^2$	DM	$R^2$	DM	$R^2$	DM
1	0.14	1.36	-0.02	-0.12	0.13	1.10	-0.07	-0.42
2	0.37	2.09	0.31	1.65	0.33	1.95	0.21	1.21
3	0.52	1.83	0.51	1.75	0.49	1.84	0.39	1.69
4	0.51	1.55	0.56	1.52	0.49	1.53	0.44	1.47
5	0.38	1.07	0.40	1.11	0.35	1.06	0.32	1.06

**Table V**  
**Out-of-sample forecasting performance on US inflation rates with predictive regressions.**

Entries report the out-of-sample forecasting performance on four US inflation rates series at forecasting horizons of one, two, three, four, and five years. The prediction is based on three alternative ways of estimation, one in each panel. Panel  $A_1$  determines both the intercept and the slope of the predictive relation via a rolling-window predictive regression. Panel  $A_2$  removes the average forward-spot interest rate bias with a rolling-window moving average and estimates the slope for each relation with a predictive regression without intercept. Panel  $A_3$  stacks predictive relations across all forecasting horizons to estimate one common slope with the pooled predictive regression without intercept. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistics both against the random walk hypothesis (DMR) and against our approach that does not include any predictive regression estimation (DMN). The DM statistics have standard normal critical values. The models are estimated with a ten-year-rolling window. The out-of-sample statistics are computed using data from 1972:6 to 2012:6.

Horizon Years	CPI			CCPI			PCE			CPCE		
	$R^2$	DMR	DMN									
<i>A<sub>1</sub>:</i> Predictive regression estimation of intercept and slope												
1	-0.14	-1.23	-2.30	-0.31	-2.22	-1.29	-0.20	-1.62	-2.36	-0.37	-2.15	-1.07
2	0.04	0.12	-1.43	-0.19	-0.73	-2.11	-0.10	-0.38	-2.10	-0.32	-1.47	-1.93
3	0.14	0.23	-0.87	0.07	0.11	-0.91	0.11	0.21	-1.15	0.03	0.07	-1.27
4	0.06	0.16	-1.98	-0.03	-0.05	-1.37	0.02	0.06	-2.47	-0.00	-0.00	-1.69
5	-0.46	-1.80	-1.47	-0.85	-1.90	-1.57	-0.41	-1.51	-1.82	-0.49	-1.53	-1.66
<i>A<sub>2</sub>:</i> Predictive regression estimation of slope without intercept												
1	-0.08	-0.59	-1.75	-0.14	-1.36	-0.72	-0.13	-0.98	-1.99	-0.21	-1.70	-0.66
2	0.07	0.20	-1.21	-0.07	-0.25	-1.51	-0.08	-0.26	-1.71	-0.24	-0.98	-1.52
3	0.17	0.26	-0.74	0.11	0.18	-0.90	0.14	0.25	-0.87	0.04	0.10	-1.33
4	0.11	0.22	-1.34	-0.01	-0.01	-1.27	0.09	0.18	-1.34	0.01	0.01	-1.31
5	-0.20	-0.83	-2.55	-0.59	-1.18	-2.07	-0.15	-0.40	-2.34	-0.29	-0.66	-2.02
<i>A<sub>3</sub>:</i> Stacked predictive regression estimation of common slope without intercept												
1	-0.23	-1.05	-2.08	-0.27	-1.31	-1.56	-0.28	-1.25	-2.35	-0.39	-1.64	-1.93
2	0.09	0.25	-1.06	-0.04	-0.12	-1.47	0.01	0.05	-1.35	-0.13	-0.59	-1.75
3	0.28	0.58	-0.77	0.19	0.41	-1.13	0.26	0.55	-0.81	0.16	0.44	-1.07
4	0.33	0.66	-0.72	0.26	0.47	-1.02	0.33	0.68	-0.67	0.28	0.67	-0.76
5	0.23	0.43	-0.62	0.14	0.27	-0.91	0.23	0.45	-0.51	0.19	0.44	-0.71

**Table VI**  
**Out-of-sample forecasting performance on UK inflation rates.**

Entries report the out-of-sample forecasting performance on the UK inflation rates series defined on the UK Retail Price Index at forecasting horizons of one, two, three, four, and five years. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on the squared forecasting error differences, which has standard normal critical values. The models are estimated with a ten-year-rolling window. The out-of-sample statistics are computed using data from 1990:1 to 2014:12.

Horizon, Years	1	2	3	4	5
$R^2$	0.15	0.26	0.39	0.30	0.18
DM	1.66	1.06	0.86	0.65	0.34

**Table VII**  
**Out-of-sample forecasting performance on US inflation rates based on mean absolute errors.**

Entries report the out-of-sample forecasting performance on four US inflation rates series at forecasting horizons of one, two, three, four, and five years. The performance measures include both a forecasting relative mean absolute error ( $RMAE$ ) measure, defined as the ratio of the mean absolute forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on the absolute error differences, which has standard normal critical values. The models are estimated with a ten-year-rolling window. The out-of-sample statistics are computed using data from 1972:6 to 2012:6.

Horizon Years	CPI		CCPI		PCE		CPCE	
	$RMAE$	DM	$RMAE$	DM	$RMAE$	DM	$RMAE$	DM
1	0.95	1.00	1.05	-0.62	0.97	0.53	1.06	-0.77
2	0.83	2.25	0.90	1.17	0.85	1.99	0.97	0.32
3	0.75	2.18	0.77	1.85	0.76	2.01	0.86	1.47
4	0.76	1.59	0.76	1.50	0.80	1.29	0.82	1.12
5	0.89	0.79	0.84	1.08	0.90	0.84	0.92	0.61

**Table VIII**  
**Effects of rolling window size choice on out-of-sample inflation forecasting performance.**

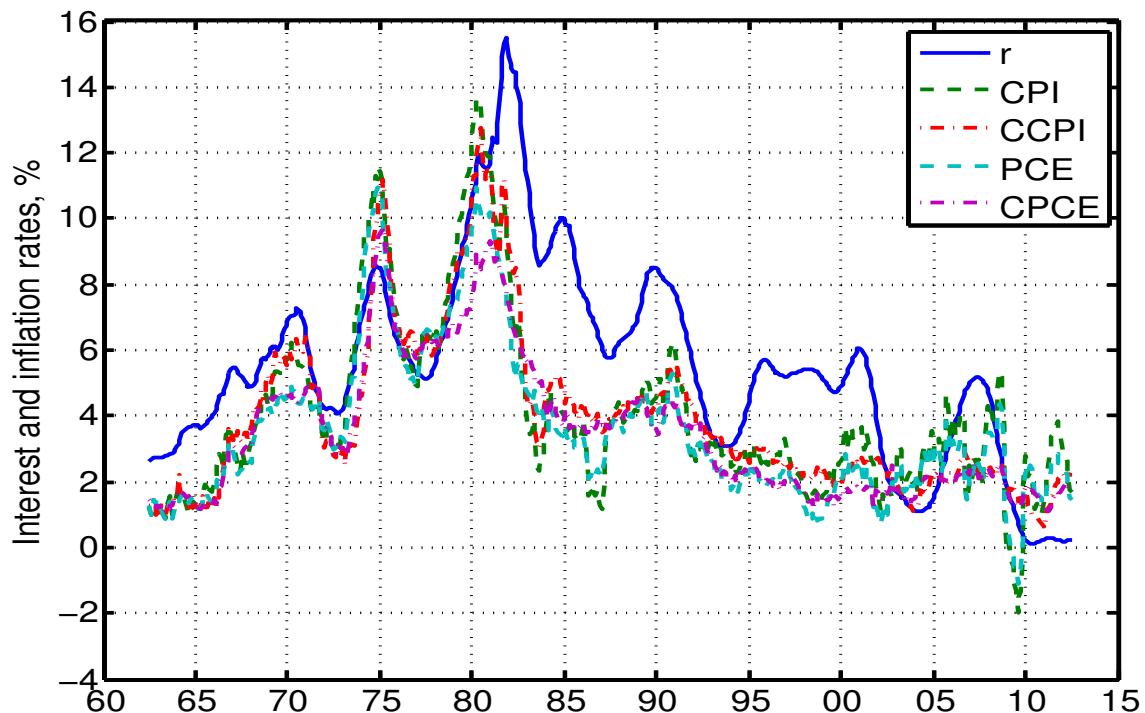
Entries report the out-of-sample forecasting performance on four US inflation rates series at forecasting horizons of one, two, three, four, and five years when we perform the rolling window estimation using different rolling-window sizes. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on the squared forecasting error differences, which has standard normal critical values. The models are estimated with rolling windows of five years in Panel A and 15 years in Panel B. Panel C uses an expanding window starting at ten years.

Horizon Years	CPI		CCPI		PCE		CPCE	
	$R^2$	DM	$R^2$	DM	$R^2$	DM	$R^2$	DM
A. 5-year rolling window								
1	0.04	0.41	-0.18	-1.28	0.06	0.59	-0.13	-1.06
2	0.28	1.88	0.11	0.78	0.24	1.88	0.05	0.43
3	0.45	2.07	0.34	1.67	0.40	2.21	0.24	1.79
4	0.43	1.74	0.43	1.60	0.37	1.83	0.30	1.72
5	0.25	0.95	0.22	0.88	0.19	0.97	0.13	0.88
B. 15-year rolling window								
1	0.12	1.13	0.06	0.30	0.03	0.22	-0.36	-1.04
2	0.32	1.35	0.29	0.98	0.26	1.06	0.03	0.09
3	0.44	1.20	0.44	1.05	0.39	1.08	0.27	0.78
4	0.41	1.02	0.44	0.89	0.34	0.85	0.26	0.60
5	0.32	0.75	0.30	0.60	0.24	0.58	0.14	0.32
C. Recursive approach								
1	0.14	1.33	-0.05	-0.36	0.10	0.80	-0.22	-1.20
2	0.37	1.95	0.27	1.29	0.33	1.74	0.12	0.59
3	0.50	1.70	0.44	1.33	0.49	1.62	0.30	0.98
4	0.45	1.31	0.44	1.04	0.42	1.19	0.31	0.78
5	0.27	0.68	0.20	0.47	0.22	0.57	0.11	0.27

**Table IX**  
**Effects of benchmark rate choice on out-of-sample inflation forecasting performance.**

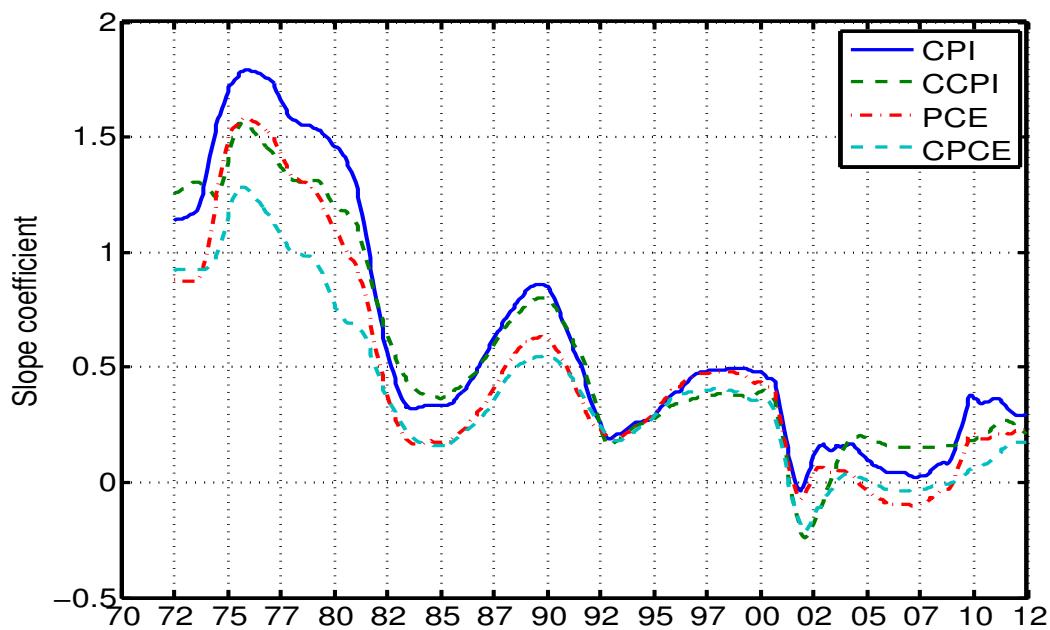
Entries report the out-of-sample forecasting performance on four US inflation rates series at forecasting horizons of one, two, three, four, and five years. The performance measures include both a forecasting R-squared ( $R^2$ ) measure, defined as one minus the ratio of the mean squared forecasting error of each model against the random walk benchmark, and the Diebold-Mariano  $t$ -statistic (DM) defined on squared forecasting error differences, which has standard normal critical values. Panel A reports the statistics using six-month interest rate as the benchmark short rate, and Panel B reports the statistics using one-year interest rate as the benchmark short rate. The forecasts are computed based on ten-year rolling-window estimation. The out-of-sample statistics are computed using data from 1972:6 to 2012:6.

Horizon Years	CPI		CCPI		PCE		CPCE	
	$R^2$	DM	$R^2$	DM	$R^2$	DM	$R^2$	DM
A. Six-month interest rate as benchmark								
1	0.08	0.88	-0.09	-0.64	0.06	0.60	-0.16	-0.93
2	0.34	2.11	0.25	1.58	0.30	1.96	0.16	1.11
3	0.49	1.85	0.45	1.70	0.47	1.87	0.34	1.67
4	0.49	1.55	0.51	1.48	0.46	1.53	0.38	1.42
5	0.36	1.05	0.36	1.04	0.32	1.04	0.27	0.99
B. One-year interest rate as benchmark								
1	0.06	0.77	-0.09	-0.66	0.04	0.46	-0.15	-1.00
2	0.30	2.15	0.22	1.60	0.26	2.00	0.13	1.07
3	0.45	1.85	0.43	1.72	0.43	1.87	0.31	1.70
4	0.45	1.54	0.48	1.49	0.41	1.51	0.35	1.41
5	0.32	1.07	0.34	1.08	0.27	1.03	0.24	0.98



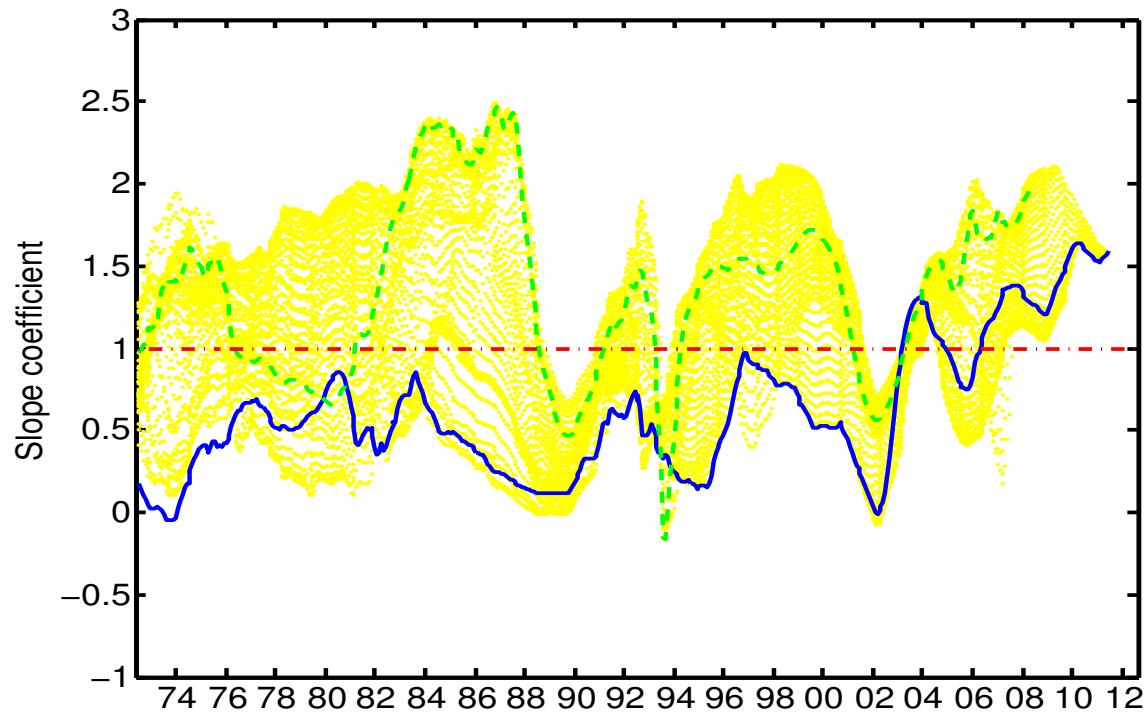
**Figure 1. The time series of inflation rates and three-month Treasury interest rate.**

The four dashed lines depict the time series of the year-over-year realized inflation rates computed from the four price indexes: 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.



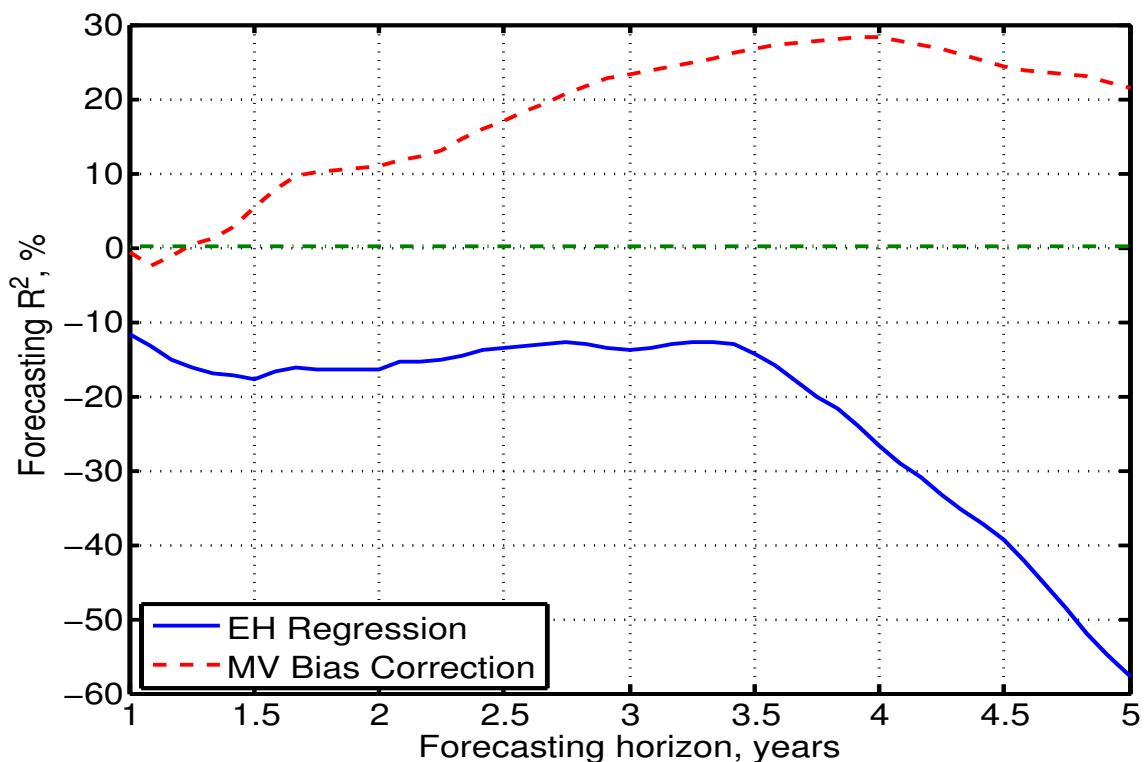
**Figure 2. Rolling-window slope estimates on the inflation-interest relation.**

Lines plot the time series of the ten-year rolling window estimates of the slope coefficient of the inflation-interest rate relation for the four inflation rate series.



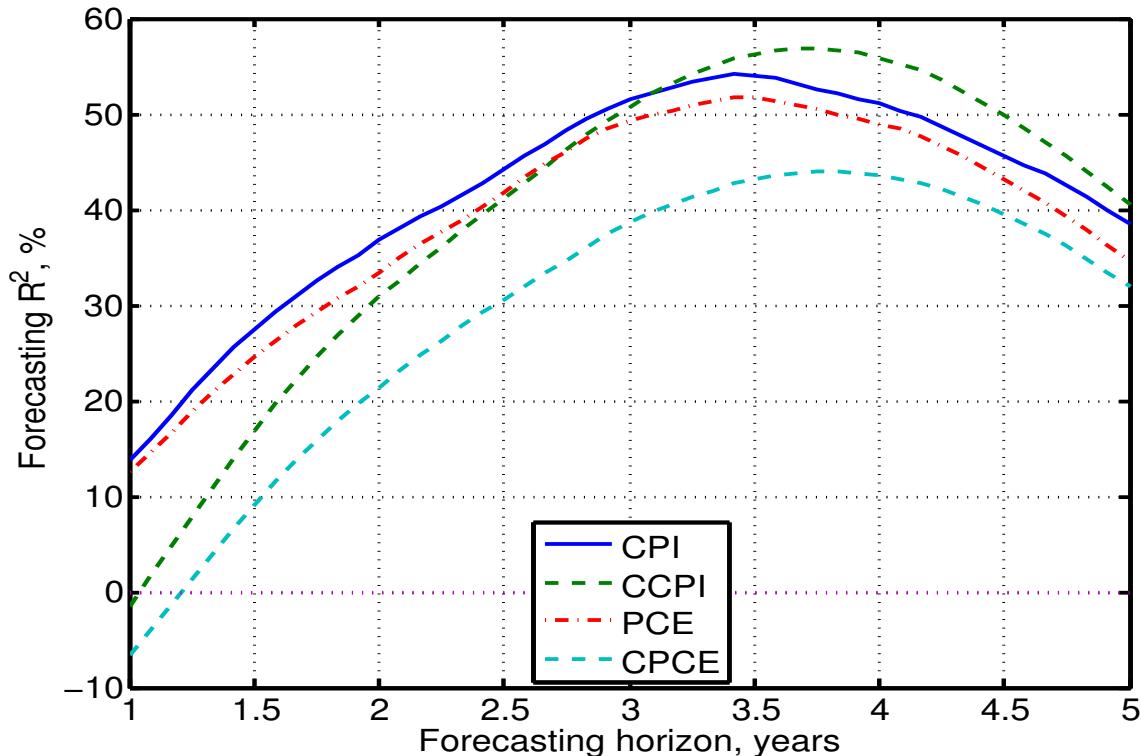
**Figure 3. Rolling-window slope estimates on the expectation hypothesis regressions.**

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 null value of the expectation hypothesis at one.



**Figure 4. Out-of-sample forecasting  $R^2$  on future interest rates.**

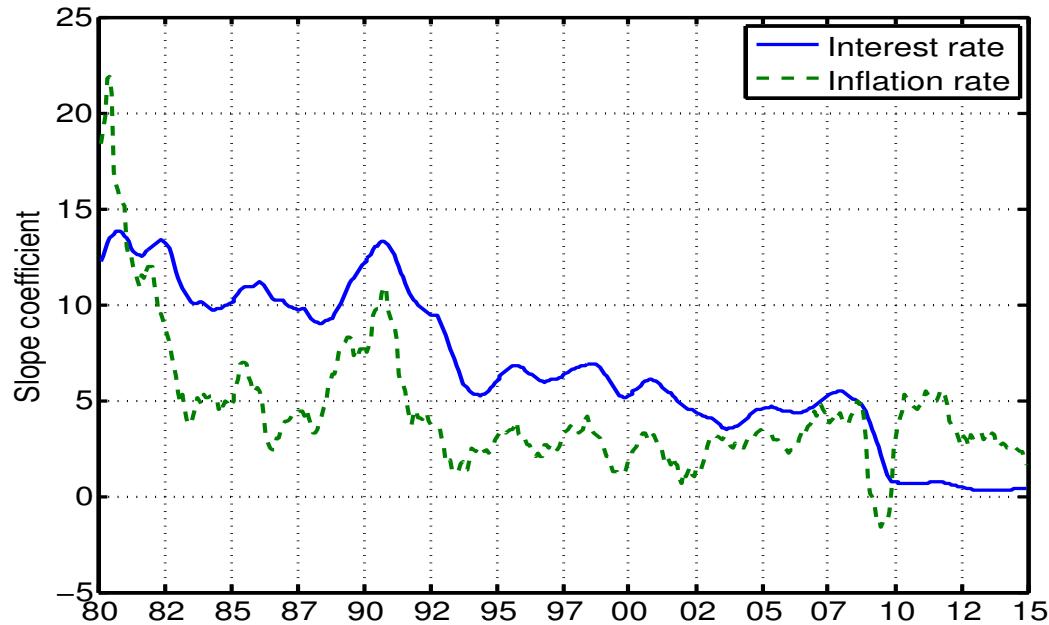
The  $R^2$  estimates are computed as one minus the ratio of mean squared forecasting error of each model against the random walk hypothesis over the period from 1972:6 to 2012:6.



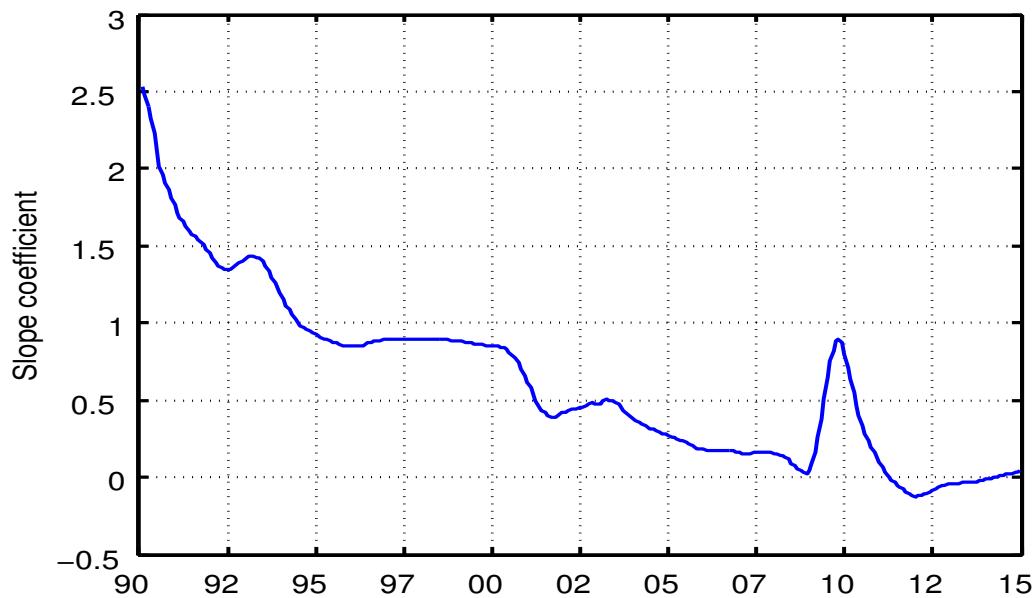
**Figure 5. Out-of-sample forecasting  $R^2$  on future inflation rates.**

The  $R^2$  estimates are computed as one minus the ratio of mean squared forecasting error of each model against the random walk hypothesis over the period from 1972:6 to 2012:6.

Panel A. UK inflation and interest rate time series



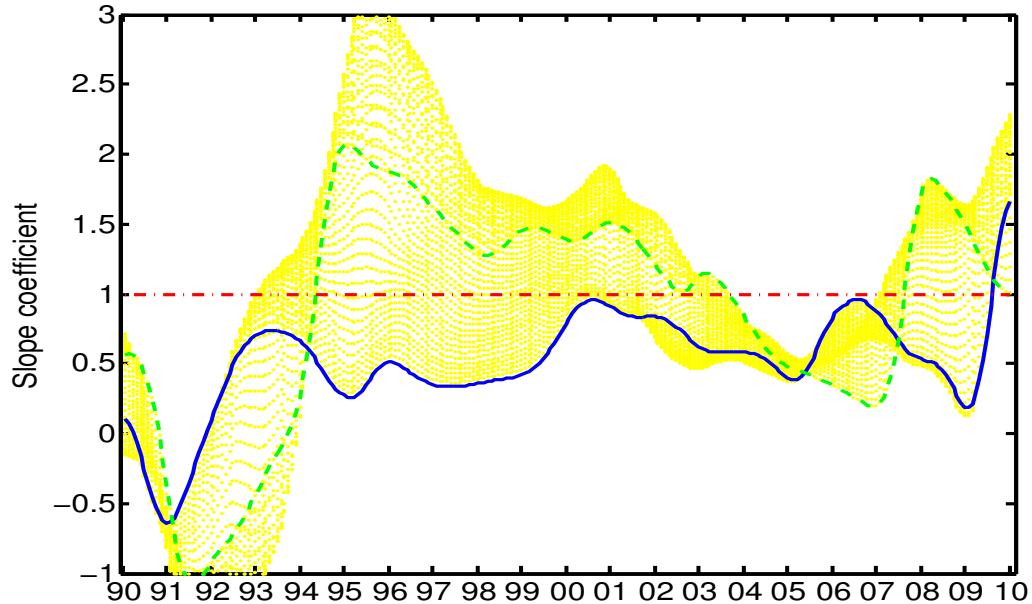
Panel B. Time variation in the UK inflation-interest rate relation



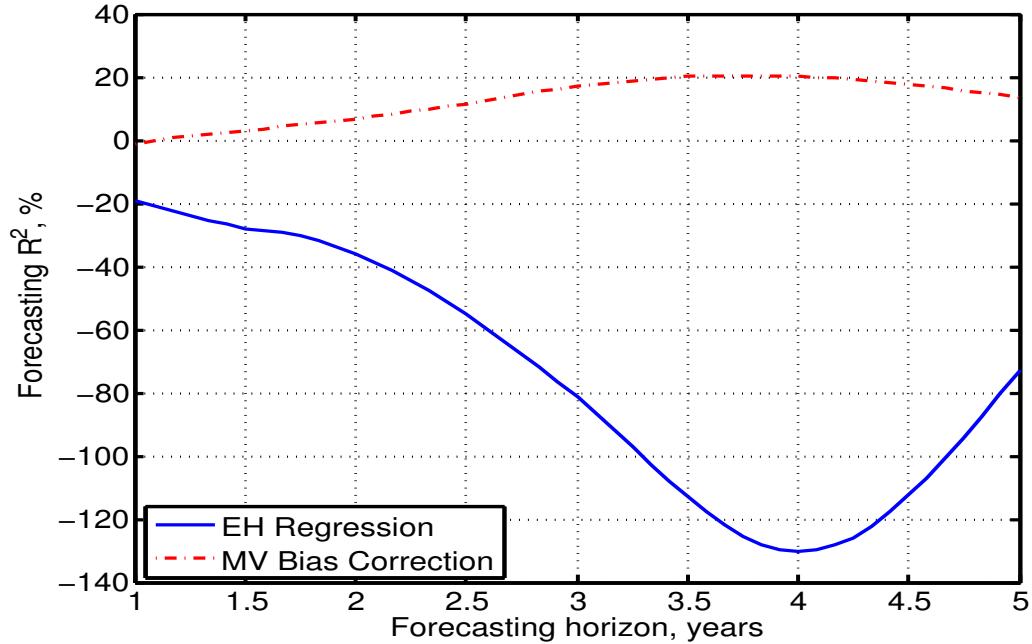
**Figure 6. Time variation in the UK inflation rate, interest rate, and their relation.**

Panel A plots the time series of the one-year UK sterling interest rate (solid line) and the year-over-year UK inflation rate (dashed line) computed from the Retail Price Index. Panel B plots the time series of the ten-year rolling window slope estimates of the UK inflation-interest rate relation.

Panel A. Rolling-window expectation hypothesis slope estimates on UK interest rates

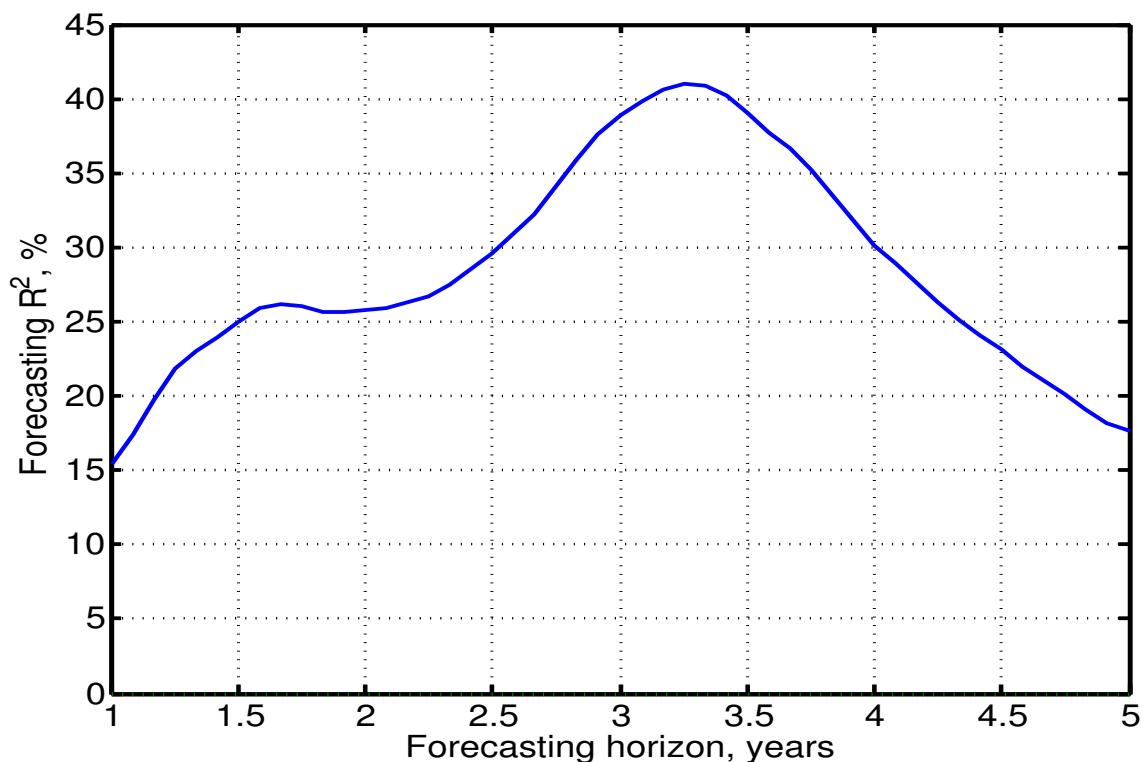


Panel B. Out-of-sample UK interest rate forecasting performance



**Figure 7. UK expectation hypothesis regressions and interest rate forecasting.**

Panel A plots the ten-year rolling-window slope estimates on the expectation hypothesis forecasting regressions, with the solid line denoting the one-year horizon, the dashed line denoting the five-year horizon, and the other dotted lines representing intermediate horizons. The dash-dotted line represents the null value of the expectation hypothesis at one. Panel B plots out-of-sample interest rate forecasting  $R^2$ , computed as one minus the ratio of mean squared forecasting error against the random walk hypothesis over the period from 1990:1 to 2014:12.



**Figure 8. Out-of-sample forecasting  $R^2$  on UK inflation rates.**

The  $R^2$  estimates are computed as one minus the ratio of mean squared forecasting error of each model against the random walk hypothesis over the period from 1990:1 to 2014:12.