University of Toronto
Department of Economics

Working Paper 319

Improving Forecasts of Inflation using the Term Structure of Interest Rates

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May 16, 2008

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Abstract

Many pricing models imply that nominal interest rates contain information on inflation expectations. This has lead to a large empirical literature that investigates the use of interest rates as predictors of future inflation. Most of these focus on the Fisher hypothesis in which the interest rate maturity matches the inflation horizon. In general forecast improvements have been modest and often fail to improve on autoregressive benchmarks. Rather than use only monthly interest rates that match the maturity of inflation, this paper advocates using the whole term structure of daily interest rates and their lagged values to forecast monthly inflation. Principle component methods are employed to combine information from interest rates across both the term structure and time series dimensions. We find robust forecasting improvements in general as compared to both an augmented Fisher equation and autoregressive benchmarks.

JEL Classification: E31,E37,C53,C32
Keywords: inflation, inflation forecast, Fisher equation, term structure, principal components

*Maheu is grateful for financial support from SSHRCC.
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1 Introduction

There has been a growing empirical literature that finds a statistical relationship between interest rates and future inflation. Papers by Mishkin 1990a, 1990b, 1991, Jorion and Mishkin (1991), Estrella and Mishkin (1997), and Kozicki (1997) document the predictive power of interest rates for future inflation. In general, these papers investigate the statistical relationship between a yield spread that matches an inflation spread. This is motivated by the Fisher equation which states that the nominal interest rate is composed of the real interest rate and expected inflation. The stability of this relationship is investigated in Estrella, Rodrigues, and Schich (2003). For the U.S. they find evidence of a structural break in 1979 and 1982 for short horizon regressions. Estrella (2005) discusses the reasons why the yield curve contains predictive content for both real and nominal variables, and argues that monetary policy plays a large role in this relationship.

Nevertheless, the practical forecast improvements that come from employing the Fisher equation sometimes appear modest relative its importance as a theoretical relationship. The literature finds poor predictive power at the short end of the yield curve but improved prediction around 12 months and the best performance from 3 to 5 years out. Stock and Watson (2003) also note that the Fisher equation often loses its predictive content after controlling for lagged inflation.

The failure of the Fisher equation to consistently beat autoregressive benchmarks has two possible implications for inflation forecasting. One possible implication, as argued by Stock and Watson (2003), is that, despite their theoretical appeal, interest rates may have limited practical value for inflation forecasting. An alternative interpretation is that the performance of the Fisher equation is hindered by its rigid restrictions, in which only the information in a single interest rate spread with maturities matching the inflation spread is employed in the forecast. While theoretically appealing, using only one source of information goes against some of the more recent trends in forecasting, in which improvements are found from combing information from multiple predictors or forecasts (Bernanke, Boivin, and Eliasz (2005), Stock and Watson (2002), Favero, Marcellino, and Neglia (2005)).

Recent research on macro-finance models, including Ang and Piazzesi (2003), Chernov and Biokbov (2006), Dewachter, Lyrio, and Maes (2006), and Diebold, Rudebusch, and Aruoba (2006), demonstrates the important role that macro aggregates and monetary policy play in determining the shape of the term structure and its dynamics.

In this paper we contribute to the literature on inflation forecasting in several ways. First, we investigate whether, for a given inflation spread, additional forecasting information can be extracted from the entire interest rate term structure. We also investigate if information in daily lags of the term structure are useful for prediction. In contrast to previous work, we focus exclusively on the out-of-sample predictive performance relative to autoregressive type models, and we work with readily available interest rates on government T-bill and bonds.[1] Our focus is on the empirical forecasting content of interest rates.

One reason why multiple interest rates may improve inflation forecasts is that we face a signal extraction problem. For example, suppose that the Fisher equation holds as in $i_t^k = r_t^k + E_t\pi_{t+k}^k$, where i_t^k is the k period nominal interest rate, r_t^k is the matching real interest rate, $E_t\pi_{t+k}^k$ is the expected inflation over this period, and $\pi_{t+k}^k = \log(p_{t+k}/p_t)$, where p_t denotes the price level. If real interest rates are unobserved and stochastic then i_t^k provides a noisy measure of $E_t\pi_t^k$. However, the interest rate i_t^l, $l > k$, also contains information on $E_t\pi_{t+k}^k$, since we can decompose the longer inflation rate as $\pi_{t+l}^l = \pi_{t+k}^k + \pi_{t+l}^{l-k}$ to get $i_t^l = r_t^l + E_t\pi_{t+k}^k + E_t\pi_{t+l}^{l-k}$. Therefore, i_t^k and i_t^l have $E_t\pi_{t+k}^k$ as a common factor. This suggests additional information on $E_t\pi_{t+k}^k$ may be available in other interest rates and the term structure as a whole. If inflation expectations are persistent then similar reasoning suggest that there may be benefits to using lags of the term structure.

By employing multiple interest rates we may also allow for a more robust predictive relationship with inflation. For instance, the information content of the term structure may be constant, but the location of inflation expectations may be easier to extract at different maturities, depending on the stance and expectation of monetary policy.

The use of the whole term structure and lags of the term structure results in a dimensionality problem. To extract the predictive content but retain parsimony we follow the diffusion index method of Stock and Watson (2002). We extract principle components from both current term structures and lagged term structures. We select the principle components using a variance criteria and a correlation criteria. The latter is based on the correlation between the principle components and regression residuals from an AR model of infla-

[1]The majority of research in this area uses zero coupon yields. This requires estimation of the yield curve at each point in time.

tion. Therefore, they pick up remaining structure not captured by the AR model. We investigate several variable selection methods and report results on a model average over different principle component specifications.

To gauge the success of our methods we include, as benchmarks, an autoregressive type model, a Fisher equation model augmented with lags of inflation and a Phillips curve. To allow for changes in the model relationship we use a rolling window for estimation.

In general, our results show that an AR type benchmark is better than an augmented Fisher model. Our principle component methods improve upon these results. The forecasting improvements come from two dimensions. The term structure (current term structure) dimension and the time (lagged term structures) dimension. For the 12 month ahead predictive regressions, only the term structure dimension improves forecasts, while for the 36 month regressions both the term structure and time dimension are useful. The relative performance of the variance and correlation criteria used to select principle components criteria is mixed, and depends on the subsample and the forecast horizon. Our recommended approach is a model average over specifications that have between 3 and 5 principle components from both the term structure and time dimensions. This approach provides good results for all time periods and forecast horizons.

Our results are supportive of the broad implication of the Fisher equation that interest rates provide a useful tool in inflation forecasting. At the same time, we find that employing the whole term structure and its recent lags provides clear improvements over the restrictions of the Fisher equation. This is consistent with recent developments in forecasting which emphasize the value of combining information and forecasts from multiple sources.

While this paper focuses on predictive content of the term structure, it is not our intention to suggest that interest rates be used in isolation to forecast inflation. There is a large literature on inflation forecasting and many useful techniques have been developed using information other than interest rates that could potentially be combined with term and lagged term structure variables considered here. Examples, include methods based on structural relationships (Fisher, Liu, and Zhou 2002, Orphanides and van Norden 2005, Stock and Watson 1999), the use of asset prices, (Ang, Bekaert, and Wei 2005, Stock and Watson 2003), and factor models (Banerjee and Marcellino 2006, Camba-Mendez and Kapetanios 2005, Stock and Watson

2002).[2].

This paper is organized as follows. Section 2 reviews the data, Section 3 discusses the benchmark models, while the new principle components models are introduced in Section 4. Results are found in Section 5 and conclusions in Section 6.

2 Data

Our data set comprise daily interest rates and monthly data on consumer price indexes, and the total civilian unemployment rate. The daily interest rates included in our panel are U.S. Treasury yields with maturities of 3-months, 6-months, 1-year, 3-years, 5-years, and 10-years. Inflation was computed as the log difference of the seasonally adjusted consumer price index for all urban items. Interest rates and consumer price indices were obtained from the Federal Reserve of St. Louis FRED data base. The unemployment rate was obtained from the Citibase data base. The sample period spans from March 1962 to December 2004. This yields a sample size of 514 for the monthly inflation rate data and a sample size of 11,175 for the daily interest rate data. Out-of-sample forecasts are computed from September 1974 to December 2004, giving a total of 364 monthly out-of-sample forecasts, with the proceeding 150 months reserved for the training sample.

The top panel of Figure 1 presents the annual inflation rate for the whole sample. Two major episodes are observed during the post-war U.S. history. The first one is characterized by a period of high inflation from the early 1960s through the mid 1980s, and a second period of low inflation runs from the mid 1980s to the present.

We define the annualized j-th term inflation rate observed at time t as:

$$\pi_t^j = (1200/j)\ln(p_t/p_{t-j}).$$

Following Stock and Watson (1999), we will focus on forecasting annualized inflation percentage spreads of the form:

$$\pi_{t+k}^k - \pi_{t+1}^1 = (1200/k)\ln(p_{t+k}/p_t) - 1200\ln(p_{t+1}/p_t)$$

[2]Recent work on time series models of inflation emphasize the changing inflation dynamics (Cogley and Sargent 2002, Dossche and Everaert 2005, Pivetta and Reis 2006, Stock and Watson 2006).

where $k = \{12, 36\}$.

Finally, note that in the following we use interest rates for T-bills and bonds which may have coupon payments. This has two attractions for our forecasting exercises. First, it avoids the need to estimate a zero-coupon term structure and the associated estimation errors that can arise form this. Second, the interest rates we use are readily available, for example from the St. Louis FRED data base. Throughout the paper we use the terminology Fisher equation even though our rates may not be derived from a zero-coupon instrument.

3 Benchmark Models

In order to obtain the benchmark with the best performance in our sample, a set of competing models were estimated.

1. **Pure autoregression-type benchmark (AR-type)** Our base-line benchmark model for inflation forecasting is the simple autoregressive-type specification given by:

$$\pi_{t+k}^{k} - \pi_{t+1}^{1} = \gamma + \sum_{p=0}^{P-1} \phi_p \pi_{t-p}^{1} + \varepsilon_{t+k}, \tag{1}$$

   where ε_{t+k} is an error term. We also consider two other standard benchmark models in which this AR-type specification is augmented by other predictors suggested by economic models.

2. **Phillips Curve (PhCu)**

   The unemployment-based Phillips curve specification used in this paper is

$$\pi_{t+k}^{k} - \pi_{t+1}^{1} = \gamma + \sum_{p=0}^{P-1} \phi_p \pi_{t-p}^{1} + \sum_{q=0}^{Q-1} \beta_q w_{t-q} + \varepsilon_{t+k}, \tag{2}$$

   where w_t is total civilian unemployment rate *(LHUR)* in month t.

3. **Augmented-Fisher Equation**

Finally, a benchmark that appears as the natural counterpart to the model that includes daily spreads as predictors, is a model that incorporates the Fisher hypothesis. In this case, we extend the autoregressive model by including as an additional predictor the monthly yield spread with the same maturity as the target inflation forecast. The empirical specification of the augmented Fisher equation hypothesis is given by

$$\pi_{t+k}^{k} - \pi_{t+1}^{1} = \gamma + \sum_{p=0}^{P-1} \phi_p \pi_{t-p}^{1} + \beta(i_t^k - i_t^1) + \varepsilon_{t+k}, \tag{3}$$

where i_t^k is the observed treasury yield with maturity k at time t.

All three benchmark models are estimated by OLS, with the number of lagged inflation rates ($1 \leq P \leq 12$) and unemployment rates ($1 \leq Q \leq 12$, PhCu model only) determined recursively using the Bayesian information criterion (BIC). For the Phillips curve, P is selected first and then conditional on that value Q is selected. This process of lag selection is repeated recursively as new information arrives.

The benchmark models above were estimated under the assumption of an I(1) price index. We also compared these to the equivalent benchmark models that hold under the assumption that prices are I(2), in which case the terms involving π_{t-p}^{1} are replaced by $\Delta\pi_{t-p}^{1}$. As in Stock and Watson (1999, 2002) we find little difference between the I(1) and I(2) specifications with respect to the accuracy of the inflation forecasts. Thus we present only the results that hold when prices are modelled as I(1) variables. Generally speaking, we found that the forecasts using the pure AR-type model with prices modelled as I(1) provided the best benchmark forecasts.

4 Principal Components Models

Models that use interest rate spreads as predictors of future inflation are based on a version of the Fisher's hypothesis. The empirical specification of Fisher's hypothesis includes only monthly spreads with the same maturity as the target inflation rate. Thus, Fisher's specification discards any other potential information contained in the term structure of interest rates or its daily lags. In this paper, we propose forecasting inflation by incorporating information contained in both dimensions of the interest rate data: the term structure dimension and the time dimension. The time series dimension is incorporated via the use of daily interest rate observations.

The transition from Fisher's specification that includes just one spread of interest rates as predictors to the multivariate case that incorporates different terms for different dates raises the important problem of parsimony. In order to mitigate overfitting and poor forecast performance we proceed by constructing a small number of factors from the large set of daily spreads using principal components. The methodology is based on the premise that the most useful information for forecasting purposes can be summarized by the first few principal components.

4.1 Incorporating Term Structure and Time Series Information

We denote by X_t the full vector of interest rates used as inflation predictors. In our main forecast results the interest rates included in X_t span both the maturity and time series dimensions. However, in order to better understand the source of the forecast improvements, we first consider the two dimensions separately.

Let $sp_t^{k,j} = i_t^k - i_t^j$ denote the spread at time t between yields with a maturity of k and j respectively. To simplify notation, the length of every month is assumed to be of 22 business days. We use integer subindices to denote monthly frequencies, whereas for daily data subindices we use the conventional notation in which $t + h/22$ for $h = 0, ..., 22 - 1$ refers to business day h in month t. Time t refers to the first business day of month t. Inflation rates are assumed to be observed the first business day of every month. Following the above notation, and to avoid the use of information not available to the econometrician, the information set available at time t is given by inflation rates observed up to time t, and interest rate spreads observed up to time $t - 1/22$.

4.1.1 Term Structure Dimension

In this case, we extend the augmented Fisher equation in the term structure dimension by including the full set of interest interest rate spreads as predictors for future inflation. The matrix of predictors, X_t, is therefore given by

$$\begin{aligned} X_t' &= \Big[sp_{t-1/22}^{12,3}, sp_{t-1/22}^{36,3}, sp_{t-1/22}^{36,12}, sp_{t-1/22}^{60,3}, sp_{t-1/22}^{60,12}, sp_{t-1/22}^{60,36}, sp_{t-1/22}^{120,3}, \\ & \quad sp_{t-1/22}^{120,12}, sp_{t-1/22}^{120,36}, sp_{t-1/22}^{120,60} \Big] \end{aligned}$$

such that only the interest rate spreads observed on the last business day of month $t-1$ are included in the information set I_t.

4.1.2 Time Series Dimension

This case extends the augmented Fisher specification in the time series dimension by including m daily lags of the interest rate spread with the same maturity as the target inflation spread as predictors. In other words, for the target inflation forecast period $\pi_{t+k}^k - \pi_{t+j}^j$, $k > j$, X_t is given by,

$$X_t' = \Big[sp_{t-1/22}^{k,j}, sp_{t-2/22}^{k,j}, ..., sp_{t-m/22}^{k,j} \Big].$$

4.1.3 Combined term structure and time series information

In this case both dimensions, the term structure and time dimension, are pooled together to construct predictors to forecast future inflation. The predictors' matrix, X_t, is formed as

$$\begin{aligned} X_t' &= [x_{1t}', x_{2t}', \ldots, x_{mt}'] \\ x_{ht} &= \Big[sp_{t-h/22}^{12,3}, sp_{t-h/22}^{36,3}, sp_{t-h/22}^{36,12}, sp_{t-h/22}^{60,3}, sp_{t-h/22}^{60,12}, \\ & \quad sp_{t-h/22}^{60,36}, sp_{t-h/22}^{120,3}, sp_{t-h/22}^{120,12}, sp_{t-h/22}^{120,36}, sp_{t-h/22}^{120,60} \Big], \ h \in \{1, ..., m\}. \end{aligned}$$

Unfortunately, there is little guidance as to the number of days, m, that should be included in X_t. To measure the relative information content in daily data, we constructed three matrices of predictors by setting different values for m. The first matrix sets m equal to 20, including four weeks of daily data. In the second matrix m is set equal to 10, and finally, the last case includes only a week of daily data setting m equal to 5. In the following let n denote the number of columns in X_t.

From the above definitions the information set available for forecasting at time t, I_t, is given by lag values of inflation rates and X_t,

$$I_t = \{\pi_t, \pi_{t-1}, \pi_{t-2}, ..., X_t\}.$$

4.2 Dimension Reduction via Principal Components

Following Stock and Watson (2002), forecasting is performed in a two-step procedure. First, the principal components of the set of interest spreads are computed; second, the estimated factors are used as predictors to forecast future inflation.

As discussed above, we denote by X_t the vector of n daily interest rate predictors, potentially varying across both the time series and maturity dimensions, that are observed up until the last day of time $t-1$. Because the dimension of X_t is large, it is impractical to use all n predictors. Instead, we employ the principle component decomposition

$$X_t = AZ_t + A^c Z_t^c = AZ_t + v_t, \qquad v_t \equiv A^c Z_t^c \tag{4}$$

where $Z_t' = \left(z_{t,(1)}, z_{t,(2)}, \ldots, z_{t,(F)}\right)$ denotes the first $F < n$ (sorted) principal components, and Z_t^c contains the remaining $n - F$ components. The factor loading matrices for Z_t and Z_t^c are denoted by A and A^c respectively. This allows us to achieve dimension reduction by extracting only the first F factors Z_t for inclusion as regressors in our forecasting equation for inflation, together with the lagged values of inflation. Thus our forecasting model becomes

$$\pi_{t+k}^k - \pi_{t+1}^1 = \gamma + \sum_{p=0}^{P-1} \phi_p \pi_{t-p}^1 + \sum_{f=1}^{F} \alpha_f z_{t,(f)} + \varepsilon_{t+k}, \tag{5}$$

All of the regression coefficients in (5), including the coefficients α_f on the first F principal components are estimated by OLS. Since the lagged values of inflation already enter (5) parsimoniously, we do not include them in the principal component analysis. As in the benchmark models, the number of lagged inflation rates is chosen using the Bayesian Information Criteria (BIC), with a maximum of 12 ($1 \leq P \leq 12$). We discuss the choice of F in Section 4.3.2 below.

The advantage of this approach is that we have reduced the number of term structure regressors from n down to F, while allowing the factor decomposition to pick out what we expect to be the most important components in Z_t for forecasting inflation. This potentially allows us to incorporate substantially more information on inflation than in the augmented Fisher regressions, while still maintaining parsimony.

4.3 Selection of Principal Components

In order to determine which principal components to employ in a principal components model two choices are required. First, one needs a rule for ordering the components from first to last. This involves taking a stand on which components will be most useful for forecasting inflation. Secondly, one needs to decide how many components to use. We discuss these questions separately in the two subsections below.

4.3.1 Ordering the principal components

Two different criteria are employed in the selection of factors. The first criterion, ***Variance Sort***, consists in selecting the principal components that explain the highest percentage of the second moment of the predictors matrix $\{X_t\}$. Regardless of this being the most common practice in the selection of principal components, there is no guarantee that this methodology will result in the set of factors that maximize forecasting power for inflation. Hence, we also propose and compare to a second criterion for selecting factors, ***Correlation Sort***, in which we sort principal components according to their in-sample correlation with the residual from the AR-type benchmark model in (1). The idea consists in selecting the principal components that have the highest in-sample correlation with the residual term from the AR model to capture the component of inflation not explained by the AR model.

4.3.2 Selecting the number of principal components

Once we have decided on a rule for ordering the components, we must next choose the number of components (F) to include. Here we compare three approaches. The first is simply to fix F, the second is to select F by applying a model selection criterion to the forecasting equation, and the third is to model average across forecasts using a range of different choices for F.

Because our primary interest is in forecasting inflation, we apply BIC to the forecasting equation in (5), while treating the principle components $z_t(f)$ as regressors. Thus we measure the (penalized) fit in terms of the explanatory power of the principle components of $z_t(f)$ for inflation $\pi^k_{t+k} - \pi^1_{t+1}$. This is similar to the approach of Stock and Watson (1999). An alternative approach, not pursued here, is to measure the penalized fit based on the explanatory power of the principle components $z_t(f)$ for X_t itself in (4). This is the approach pursued by Bai and Ng (2002) in a more general context, where the primary focus is often on the modeling of X_t itself, rather than on the use of the components of X_t in the forecast of another variable, say y_t. Bai and Ng (2002) provide consistent model selection procedures for the choice of F in (4).

For the model averaging approach, we let $f^{pc}_{t+k,F}$ denote the out-of-sample forecast of the principal component model using F factors. The model average forecasts are then given by

$$f_{a,t+k} = \sum_{F=l}^{u} \omega_{F,t+k} f^{pc}_{F,t+k}, \tag{6}$$

where l and u are the lower and upper bounds for the number of principal components used to forecast inflation. We compare two simple approaches to choosing the weights $\{\omega_{F,t}\}$. In the first approach, we simply weight all forecasts equally, setting $\{\omega_{F,t}\} \equiv 1/(u-l+1)$, so that $f_{a,t+k}$ is just the simple average of all date $t+k$ forecasts. In our second approach, we choose weights using an in-sample regression of the realized inflation rate on the inflation predictions from each model. In other words, the weights are given by the estimated coefficients in the following regression:

$$\pi^k_{t+k} - \pi^1_{t+1} = \sum_{F=l}^{u} \omega_{F,t+k} f^{pc}_{F,t+k} + \varepsilon_{t+k}. \tag{7}$$

5 Results

The ability of the different models, benchmarks and factor models, to forecast inflation is summarized by the mean-squared-error (MSE) and mean-absolute-error (MAE) of their forecasts relative to the MSE and MAE of forecasts based on the autoregressive type model (AR-type) respectively. Table 1 summarizes the results from different tables while results for the competing benchmark models are found in Table 2.

Tables 3-7 present results for the different specifications of the factor models; Term Structure Dimension, Time Series Dimension, and All Information (using both the term structure and time series dimension). For the latter two models results are shown for 5, 10, and 20 days of lagged daily interest rate spreads. As mentioned above, principal components were selected using two different methods: 1) the *variance sort* criteria and 2) the *correlation sort* criteria. We also considered three competing approaches to chose the number of principal components: a) the specification of parsimonious models with fixed numbers of principal components, b) selection by BIC, and c) model averaging across forecasts with different numbers of principal components. Results for the different models are summarized in Tables 3-7 following the organization described in Table 1.

5.1 Benchmark

Table 2 summarizes results for the different benchmark models: the autoregressive-type model (AR-type), the augmented Fisher model, and the Phillips Curve (PhCu) specification. The columns labelled I(1) and I(2) refer to cases where price indices are modelled as I(1) and I(2) respectively. Panel A shows results when the parameters are estimated using recursive least squares[3] and in Panel B rolling windows estimates are presented. In order to make comparisons between the different estimates, the MSE and MAE are computed relative to the recursive least squares AR type model. Results are shown for the 12-month and 36-month inflation forecasts, and are divided in two forecast sub-samples: 1974-1983, 1984-2004, and for the whole period.

There are important differences in the forecasting performance between recursive least squares estimates and rolling windows estimates. Both, MSE and MAE deteriorate dramatically when parameters are estimated using rolling windows, especially the 36-month inflation rate forecasts. The MSE for the 12-month inflation forecasts over the period 1974-2004 using the AR model when prices are modelled as I(1) increases by 14 percent when estimated by rolling windows (1.144, panel B.1, AR) compared to the least square estimation (1.000, panel A.1). For the 36-month inflation forecasts, least squares estimation outperforms rolling windows forecasts by 68 percent measured by MSE (1.684, panel B.2, AR) and by 20 percent in terms of the MAE (1.206, panel B.2, AR). The augmented Fisher representation and Phillips Curve benchmarks exhibit the same pattern. In the case of the Fisher's representation, the MSE for the 12-month inflation rate goes from 0.847 (panel A.2, Fisher) in the least square case to 1.480 (panel B.2, Fisher) in the rolling windows case. Therefore, in the results that follow we concentrate exclusively on recursive least squares estimates.

The AR type model and the augmented Fisher specification outperform

[3]In other words the model is re-estimated and a forecast computed as each new observation arrives.

the rest of the benchmarks. In the case of the 12-month inflation period, the AR type model with an I(1) specification performs the best in both sub-samples.[4] For the 36-months inflation rate, forecasts using Fisher's model outperform the rest of the benchmarks with a relative MSE of 0.847 (panel A.2, Fisher) compared to 1.000 and 1.203 for the AR model and Phillips Curve model respectively. Modelling price indexes as I(1) result in better forecasts than I(2) specifications in the 1974-1983 sub-sample for both the 12 and 36-month inflation terms. However, for the 36-period inflation, the AR-type and Fisher's representation with price indices modelled as I(2) outperform the I(1) specification in the 1984-2004 sub-sample. Despite this result, benchmarks using the I(1) specification have a smaller MSE and MAE than the I(2) specification for the whole sample.

Although no-single benchmark model dominated in all cases, we concluded that the AR-type model provided the best overall benchmark model. The comparisons in the proceeding tables (Tables 3-7) all employ this benchmark when presenting the relative MSEs and MAEs. Since the Fisher model provided the starting point for the term structures models proposed here, Tables 3-6 also include a column with the results from the augmented Fisher model as an additional point of comparison.

5.2 Fixed Number of Principal Components

Tables 3 and 6 present the results for different specifications of the factor model using a fixed number of principal components (from one to five) for the variance and correlation sort criteria respectively. In Panel A the results for the 12-period inflation period are shown and in Panel B results for the 36-period inflation are presented. The columns labelled "Term Structure" refer to the factor model that includes as predictors the current term structure. The columns labelled "Time" present results for the model that incorporates lags of daily spreads with the same maturity as the target inflation. Finally, both are combined in the columns labelled "5 days", "10 days" and "20 days" for a factor model that respectively include 5, 10 and 20 lags of the daily term structure as predictors.

Several findings come out from these tables. All factor models, except the time dimension model, outperform the AR type benchmark uniformly

[4]We compared I(1) and I(2) specifications in which the left-hand side variable is identical annualized inflation differences, but the right hand side inflation variables where I(1) (π^1_{t-p}) or I(2) (first differences of π^1_{t-p}).

in the 1974-1983 sub-sample. Important differences in forecasting performance between models are observed depending on the target inflation rate. Forecast errors are smaller when factors are selected using the correlation approach than the variance approach in the 1974-1983 sub-sample. However, in the 1984-2004 sub-sample, the variance sort produce smaller MSE for the 12-month inflation period. For example, the relative MSE for the Term Structure model using three principal components is 0.820 (Table 3, panel A.3, Term Structure) in the case of the variance sort and 0.805 (Table 4, panel A.3, Term Structure) in the correlation sort for the 1974-1983 subsample, however for the 1984-2004 subsample the results for the variance and correlation sort are 0.933 and 1.300 respectively.

The term structure model outperforms the rest of the factor models when forecasting the 12-month inflation rate for the whole sample. However, there is an improvement in forecasts during the 1984-2004 sub-sample when including the time dimension into the model. Forecasts that use 5 or 10 lags of the daily term structure of interest rates with three principal components perform the best, with a relative MSE of 0.930 and 0.899 (Table 3, panel A.3, 5 and 10 days) respectively. In general, models with three or more principal components improve upon the more parsimonious representations with only one or two principal components.

For the 36-month inflation rate, the correlation sort criteria produces superior forecasts than the variance sort. In contrast with the 12-month inflation, we observe that the time dimension contains information on future inflation beyond the AR-type specification, and uniformly outperforms the AR-type model in all sub-samples. Forecasts with one principal component outperform higher dimension models that include more than one principal component.

Different numbers of lags of daily spreads, m, in the predictors matrix, X for the All Information model are tested. In general, forecasts using 5 daily lags of interest rate spreads perform better than when 10 or 20 lags are included.

5.3 Bayesian Information Criteria

Table 5 shows the results when the number of principal components is selected recursively using BIC. The results are qualitatively similar to those presented in Tables 3 and 6. Overall, the term structure dimension appears more informative than the time dimension, specially for the 12-month inflation rate. The time dimension of interest rates adds information relative to the AR-type model for the 36-month inflation, but not for the 12-month inflation. In contrast to the results obtained in Tables 2 and 3, we obtain mixed results regarding the forecast performance between the correlation and variance sorts. The specification that performs the best for the 12-month inflation includes only the term structure dimension and has a relative MSE of 0.908 (panel A, Term Structure) and 0.907 (panel B, Term Structure) for the correlation and variance sort respectively.

5.4 Model Averaging

Finally, Tables 6 and 7 present results for model averaging. Important improvements in forecasting performance are observed from model averaging. Two different methods are employed to compute forecast averages. The first method is a simple average across models with different number of principal components. The second method is a weighted average across models where weights are obtained by regressing in-sample inflation realizations on forecasts with different numbers of principal components. OLS averaging outperform simple averages. Consistent with the results observed in Tables 3 and 6, averages of models with 3 to 5 principal components perform the best when forecasting the 12-period inflation; and for the 36-period inflation, averages from 1 to 3, and from 1 to 5 principal components are the best. The variance criteria outperforms the correlation criteria for the 12-month inflation rate. The opposite is true for the 36-period inflation rate.

5.5 Significance of Forecast Improvements

Tables 8 and 9 show the results of the Diebold and Mariano (1995) tests used to assess the significance of the out-of-sample improvements of the forecasts using the regression based model average relative to the autoregressive benchmark. In order to generate a sufficient sample size for reliable out-of-sample testing, the tests are based on the full sample period.

Since the forecast horizons, ($k = 12$ and $k = 36$ months) exceed the monthly sampling period, the errors from even an unbiased forecast would follow a moving average process of order $k - 1$ and it would therefore be unrealistic to expect uncorrelated errors in either forecast model. Thus to implement the Diebold and Mariano (1995) test we require a kernel estimator for the long-run variance of the difference in the squared forecast errors.

To this end, we employ the Newey-West (Bartlett) kernel, with a baseline bandwidth choice of $k-1$. While $k-1$ seems a natural choice in the context of a k-period forecast, our relatively large values of k may result in a noisy variance estimator. For this reason, and to assess the robustness of our findings, we also provide test results using several smaller bandwidth values.

The results from the Diebold and Mariano (1995) tests confirm the statistical significance of the forecast improvements relative to our baseline model. In fact, all the t-statistics shown in Tables 8 and 9 exceed the standard critical values by a substantial margin. This strong significance appears robust across the bandwidth choice, forecast horizon (k =12,36), the collection of principal component models included in the average (1 to 3, 3 to 5, 1 to 5), and the choice of term structure and lag information used for the principle components (columns 3-7). On the other hand, the tests do not adjust for the effects of parameter estimation (West 1996), model encompassing (McCracken 2007), or potential data snooping concerns (White 2000). This would be of particular concern in the case of marginally significant results. However, any resulting distortions would have to be quite large in order to overturn the very highly significant results shown in Tables 8 and 9.

5.6 Summary of results

In summary, the AR type model outperforms all benchmarks for the 12-month inflation rate, and the augmented Fisher model outperforms all benchmarks when forecasting the 36-period inflation. Forecasts improvements over the benchmark model for the 12-month inflation rate come from the term structure dimension, with better results obtained when using the variance sort criteria than the correlation sort.

For the 36-period inflation both dimensions, the term structure and time dimension improve upon the benchmark model, with the correlation criteria performing better than the variance criteria. However, model averaging provide robust forecasting improvements as compared with both the Fisher model and autoregressive type models.

6 Conclusion

This paper proposes a new approach to forecasting inflation using daily interest rate data. We consider a large number of potential interest rates predictors and organize them along a term structure and time series dimension. Principal component methods are used to extract useful predictors. For 12 month predictive regressions, only the term structure dimension improves forecasts, while for the 36 month regressions both the term structure and time dimension are useful. We find robust forecasting improvements in general as compared to the augmented Fisher equation and autoregressive benchmarks.

The performance of variance and correlation criteria used to select principle components criteria is mixed, and depends on the subsample and the forecast horizon. Our recommended approach is the model average across models using between 3 to 5 principle components from both term structure and time dimensions. This approach provides good results for all time periods and forecast horizons.

Table 1: Location of Forecast Summary Results for Various Models

Number of Principal Components	**Selection of Principal Components**	
	Variance Sort	Correlation Sort
Fixed from 2 to 6	Table 3	Table 6
BIC	Table 5	Table 5
Model Averaging	Tables 6 and 7	Tables 6 and 7

Table 2: **Benchmark Models:** Relative MSE and MAE for different benchmarks compared to the autoregressive type model (AR-type) estimated by recursive least squares. The columns labelled "PhCu" and "Fisher" refer to the Phillips Curve model and to the augmented Fisher specification. Labels I(1) and I(2) refer to the cases where price indices are modelled as either I(1) or I(2). In Panel A results using Recursive Least Squares are shown. Panel B present results using rolling estimates with a window of 10 years.

Panel A. Recursive Least Squares

Sample	Relative MSE						MAE					
	AR		Fisher		PhCu		AR		Fisher		PhCu	
	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)
1. $\pi^{12}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	1.000	1.056	1.036	1.028	1.001	1.084	1.000	1.009	1.019	**0.997**	1.013	1.029
1984-2004	1.000	1.038	1.075	1.208	1.212	1.213	1.000	**0.935**	1.028	1.014	1.112	1.037
1974-2004	1.000	1.050	1.049	1.087	1.071	1.127	1.000	**0.973**	1.023	1.005	1.061	1.033
2. $\pi^{36}_{t+36} - \pi^{1}_{t+1}$												
1974-1983	1.000	1.999	**0.827**	1.931	**0.825**	1.886	1.000	1.395	**0.903**	1.305	**0.872**	1.353
1984-2004	1.000	**0.690**	**0.882**	**0.737**	1.848	1.175	1.000	**0.672**	**0.936**	**0.702**	1.362	**0.927**
1974-2004	1.000	1.516	**0.847**	1.490	1.203	1.624	1.000	1.027	**0.920**	**0.998**	1.122	1.136

Panel B. Rolling Windows

Sample	Relative MSE						MAE					
	AR		Fisher		PhCu		AR		Fisher		PhCu	
	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)	I(1)	I(2)
1. $\pi^{12}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	1.078	1.159	1.060	1.111	1.119	1.101	1.030	1.053	1.037	1.024	1.031	1.031
1984-2004	1.279	1.007	1.395	1.049	1.500	1.391	1.137	**0.946**	1.151	**0.971**	1.247	1.070
1974-2004	1.144	1.108	1.170	1.091	1.245	1.197	1.082	1.001	1.093	**0.998**	1.136	1.050
2. $\pi^{36}_{t+36} - \pi^{1}_{t+1}$												
1974-1983	1.167	2.041	**0.918**	2.059	1.056	1.658	1.094	1.407	**0.932**	1.274	1.010	1.258
1984-2004	2.567	**0.762**	2.440	**0.764**	3.756	2.322	1.314	**0.719**	1.403	**0.700**	1.741	1.285
1974-2004	1.684	1.569	1.480	1.581	2.053	1.903	1.206	1.056	1.172	**0.981**	1.383	1.272

Table 3: **Out-of-Sample Forecasting for Competing Models, Variance Sort.** Relative MSE and MAE for different specifications are presented. All results are relative to the AR-type benchmark model. The columns labelled “Fisher” present results for the model that incorporates as predictors the monthly yield spread with the same maturity as the forecasted inflation difference. The columns labelled “Term Structure” present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled “Time,” results for the model that uses daily spreads with the same maturity as inflation are presented. The last three columns show the results principal component model incorporating both the time and term structure dimensions, with either 5, 10, or 20 days of daily interest rate lags.

Num.	Sample	Augmented		Term Structure		Time		Both Dimensions (Time & Term Structure)					
of	Period	Fisher		Dimension		Dimension		5 Days		10 Days		20 Days	
PCs		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Panel A. $\pi^{12}_{t+12} - \pi^{1}_{t+1}$													
1	1974-1983	1.036	1.019	**0.916**	**0.841**	1.034	1.020	**0.921**	**0.843**	**0.960**	**0.855**	**0.959**	**0.865**
	1984-2004	1.075	1.028	1.174	1.058	1.093	1.040	1.156	1.054	1.129	1.044	1.129	1.046
	1974-2004	1.049	1.023	1.001	**0.946**	1.053	1.030	**0.999**	**0.946**	1.016	**0.946**	1.015	**0.952**
2	1974-1983			**0.954**	**0.883**	1.051	1.018	**0.964**	**0.889**	1.002	**0.903**	1.032	**0.928**
	1984-2004			1.136	1.068	1.072	1.036	1.124	1.064	1.110	1.058	1.091	1.057
	1974-2004			1.014	**0.973**	1.058	1.026	1.017	**0.974**	1.038	**0.978**	1.051	**0.991**
3	1974-1983			**0.820**	**0.798**	1.060	1.019	**0.827**	**0.801**	**0.860**	**0.820**	**0.960**	**0.901**
	1984-2004			**0.933**	**0.960**	1.051	1.022	**0.930**	**0.966**	**0.899**	**0.941**	1.089	1.045
	1974-2004			**0.857**	**0.877**	1.057	1.020	**0.861**	**0.881**	**0.873**	**0.879**	1.003	**0.971**
4	1974-1983			**0.810**	**0.810**	1.072	1.026	**0.833**	**0.808**	**0.857**	**0.817**	**0.900**	**0.851**
	1984-2004			1.102	1.028	1.053	1.022	1.187	1.057	1.053	1.019	**0.918**	**0.958**
	1974-2004			**0.906**	**0.916**	1.066	1.024	**0.950**	**0.929**	**0.922**	**0.915**	**0.906**	**0.903**
5	1974-1983			**0.773**	**0.790**	1.096	1.027	**0.844**	**0.808**	**0.886**	**0.829**	**0.891**	**0.829**
	1984-2004			1.081	1.017	1.055	1.023	1.134	1.041	1.136	1.043	1.257	1.076
	1974-2004			**0.875**	**0.900**	1.083	1.025	**0.940**	**0.921**	**0.969**	**0.933**	1.012	**0.949**
Panel B. $\pi^{36}_{t+36} - \pi^{1}_{t+1}$													
1	1974-1983	**0.827**	**0.903**	**0.831**	**0.904**	**0.869**	**0.922**	**0.847**	**0.843**	**0.960**	**0.855**	**0.921**	**0.843**
	1984-2004	**0.882**	**0.936**	**0.750**	**0.845**	**0.896**	**0.943**	**0.759**	1.054	1.129	1.044	1.156	1.054
	1974-2004	**0.847**	**0.920**	**0.801**	**0.874**	**0.879**	**0.933**	**0.815**	**0.946**	1.016	**0.946**	**0.999**	**0.946**
2	1974-1983			1.061	**1.000**	**0.842**	**0.903**	1.081	**0.889**	1.002	**0.903**	**0.964**	**0.889**
	1984-2004			**0.850**	**0.843**	**0.893**	**0.941**	**0.870**	1.064	1.110	1.058	1.124	1.064
	1974-2004			**0.983**	**0.920**	**0.861**	**0.923**	1.003	**0.974**	1.038	**0.978**	1.017	**0.974**
3	1974-1983			**0.723**	**0.793**	**0.880**	**0.924**	**0.763**	**0.801**	**0.860**	**0.820**	**0.827**	**0.801**
	1984-2004			1.176	1.049	**0.895**	**0.942**	1.194	**0.966**	**0.899**	**0.941**	**0.930**	**0.966**
	1974-2004			**0.890**	**0.924**	**0.886**	**0.933**	**0.922**	**0.881**	**0.873**	**0.879**	**0.861**	**0.881**
4	1974-1983			**0.822**	**0.853**	**0.898**	**0.932**	**0.887**	**0.808**	**0.857**	**0.817**	**0.833**	**0.808**
	1984-2004			**0.848**	**0.878**	**0.888**	**0.938**	**0.848**	1.057	1.053	1.019	1.187	1.057
	1974-2004			**0.832**	**0.865**	**0.895**	**0.935**	**0.872**	**0.929**	**0.922**	**0.915**	**0.950**	**0.929**
5	1974-1983			**0.797**	**0.844**	**0.889**	**0.921**	**0.865**	**0.808**	**0.886**	**0.829**	**0.844**	**0.808**
	1984-2004			**0.932**	**0.919**	**0.904**	**0.943**	**0.856**	1.041	1.136	**1.043**	1.134	1.041
	1974-2004			**0.847**	**0.882**	**0.895**	**0.933**	**0.862**	**0.921**	**0.969**	**0.933**	**0.940**	**0.921**

Table 4: **Out-of-Sample Forecasting for Competing Models, Correlation Sort.**Results for the MSE and MAE for different specifications are presented. All results are relative to the AR benchmark model. The columns labelled "Fisher" present results for the model that incorporates as predictor the monthly yield spread with the same maturity than the forecasted inflation difference. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the model that uses daily spreads with the same maturity as inflation are presented. The last three columns show the results principal component model incorporating both the time and term structure dimensions, with either 5, 10, or 20 days of daily interest rate lags.

Num.	Sample	Augmented		Term Structure		Time		Both Dimensions (Time & Term Structure)					
of	Period	Fisher		Dimension		Dimension		5 Days		10 Days		20 Days	
PCs		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Panel A. $\pi^{12}_{t+12} - \pi^{1}_{t+1}$													
1	1974-1983	1.036	1.019	**0.916**	**0.841**	1.070	1.019	**0.921**	**0.843**	**0.960**	**0.855**	**0.959**	**0.865**
	1984-2004	1.075	1.028	1.174	1.058	1.093	1.040	1.156	1.054	1.129	1.044	1.129	1.046
	1974-2004	1.049	1.023	1.001	**0.946**	1.078	1.029	**0.999**	**0.946**	1.016	**0.946**	1.015	**0.952**
2	1974-1983			**0.877**	**0.814**	1.078	1.028	**0.887**	**0.820**	**0.924**	**0.827**	**0.935**	**0.847**
	1984-2004			1.572	1.197	1.079	1.036	1.682	1.245	1.563	1.211	1.653	1.201
	1974-2004			1.107	**1.000**	1.078	1.032	1.149	1.027	1.135	1.013	1.172	1.019
3	1974-1983			**0.805**	**0.781**	1.091	1.028	**0.814**	**0.782**	**0.831**	**0.795**	**0.883**	**0.828**
	1984-2004			1.300	1.088	1.078	1.033	1.370	1.115	1.331	1.101	1.444	1.126
	1974-2004			**0.969**	**0.930**	1.087	1.030	**0.998**	**0.944**	**0.996**	**0.943**	1.068	**0.972**
4	1974-1983			**0.794**	**0.781**	1.098	1.042	**0.820**	**0.790**	**0.813**	**0.797**	**0.843**	**0.797**
	1984-2004			1.102	1.028	1.064	1.034	1.216	1.061	1.071	1.031	1.245	1.078
	1974-2004			**0.896**	**0.901**	1.087	1.038	**0.950**	**0.922**	**0.898**	**0.911**	**0.976**	**0.933**
5	1974-1983			**0.773**	**0.790**	1.138	1.053	**0.807**	**0.783**	**0.808**	**0.808**	**0.806**	**0.783**
	1984-2004			1.081	1.017	1.045	1.026	1.171	1.026	1.113	1.022	1.199	1.046
	1974-2004			**0.875**	**0.900**	1.107	1.040	**0.927**	**0.901**	**0.909**	**0.912**	**0.936**	**0.911**
Panel B. $\pi^{36}_{t+36} - \pi^{1}_{t+1}$													
1	1974-1983	**0.827**	**0.903**	**0.637**	**0.768**	**0.870**	**0.921**	**0.692**	**0.815**	**0.677**	**0.791**	**0.656**	**0.770**
	1984-2004	**0.882**	**0.936**	**0.677**	**0.803**	**0.929**	**0.959**	**0.687**	**0.798**	**0.773**	**0.849**	**0.723**	**0.815**
	1974-2004	**0.847**	**0.920**	**0.652**	**0.786**	**0.892**	**0.940**	**0.690**	**0.806**	**0.712**	**0.821**	**0.681**	**0.793**
2	1974-1983			**0.662**	**0.756**	**0.936**	**0.960**	**0.684**	**0.794**	**0.725**	**0.792**	**0.628**	**0.743**
	1984-2004			1.325	1.081	**0.932**	**0.956**	1.261	1.029	**0.830**	**0.851**	1.285	1.024
	1974-2004			**0.907**	**0.921**	**0.935**	**0.958**	**0.897**	**0.914**	**0.764**	**0.822**	**0.871**	**0.886**
3	1974-1983			**0.691**	**0.765**	**0.943**	**0.981**	**0.804**	**0.831**	**0.854**	**0.883**	**0.732**	**0.765**
	1984-2004			**0.911**	**0.886**	**0.952**	**0.970**	**0.915**	**0.880**	**0.609**	**0.749**	1.308	1.057
	1974-2004			**0.772**	**0.827**	**0.947**	**0.975**	**0.845**	**0.856**	**0.763**	**0.815**	**0.944**	**0.914**
4	1974-1983			**0.733**	**0.796**	**0.909**	**0.933**	**0.759**	**0.809**	**0.880**	**0.883**	**0.803**	**0.798**
	1984-2004			**0.996**	**0.931**	**0.942**	**0.955**	**0.946**	**0.900**	**0.843**	**0.868**	**0.888**	**0.869**
	1974-2004			**0.830**	**0.865**	**0.921**	**0.944**	**0.828**	**0.855**	**0.867**	**0.876**	**0.834**	**0.834**
5	1974-1983			**0.797**	**0.844**	**0.956**	**0.956**	**0.801**	**0.830**	**0.769**	**0.799**	**0.758**	**0.776**
	1984-2004			**0.932**	**0.919**	**0.940**	**0.948**	**0.964**	**0.908**	**0.770**	**0.815**	**0.924**	**0.882**
	1974-2004			**0.847**	**0.882**	**0.950**	**0.952**	**0.861**	**0.870**	**0.769**	**0.807**	**0.819**	**0.830**

Table 5: **Out-of-Sample Forecasting using BIC to determine the number of principal components:** $\pi^{12}_{t+12} - \pi^{1}_{t+1}$. Relative MSE and MAE for the different specifications are presented. MSE and MAE for each specification is calculated relative to the AR-type model. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the specification that incorporates as predictors principal components of daily matched spreads are shown. The last three columns show the results principal component model incorporating both the time and term structure dimensions, with either 5, 10, 15, or 20 days of daily interest rate lags. Panel A presents the results for the case where the principal components with the largest in-sample correlations between the AR residuals and the estimated principal components are selected. In Panel B shows the results where the principal components with the highest variance are selected are presented.

Sample	Term Structure		Time		Both Dimensions (Time & Term Structure)							
Period	Dimension		Dimension		5 Days		10 Days		15 Days		20 Days	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Panel A. Correlation Sort												
$\pi^{12}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	**0.799**	**0.786**	1.047	**1.000**	**0.834**	**0.809**	**0.827**	**0.799**	**0.919**	**0.846**	**0.817**	**0.793**
1984-1990	1.494	1.197	1.156	1.045	1.655	1.243	1.507	1.220	1.820	1.351	1.979	1.341
1991-2004	**0.839**	**0.937**	1.164	1.095	**0.810**	**0.929**	**0.811**	**0.924**	**0.849**	**0.948**	**0.854**	**0.951**
1974-2004	**0.908**	**0.909**	1.083	1.035	**0.950**	**0.928**	**0.924**	**0.917**	1.039	**0.974**	**0.993**	**0.945**
$\pi^{36}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	**0.707**	**0.768**	**0.872**	**0.912**	**0.742**	**0.804**	**0.833**	**0.846**	**0.785**	**0.821**	**0.722**	**0.761**
1984-1990	**0.781**	**0.857**	**0.967**	1.008	**0.770**	**0.834**	**0.643**	**0.803**	**0.547**	**0.710**	**0.454**	**0.632**
1991-2004	1.060	**0.980**	**0.960**	**0.961**	1.069	**0.966**	1.152	**0.994**	1.172	1.011	1.124	**0.992**
1974-2004	**0.797**	**0.851**	**0.905**	**0.945**	**0.820**	**0.860**	**0.879**	**0.884**	**0.839**	**0.860**	**0.776**	**0.809**
Panel B. Variance Sort												
$\pi^{12}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	**0.798**	**0.785**	1.018	1.004	**0.851**	**0.828**	**0.880**	**0.840**	**0.934**	**0.878**	**0.882**	**0.831**
1984-1990	1.494	1.197	1.153	1.035	1.792	1.303	1.500	1.225	1.909	1.349	1.950	1.344
1991-2004	**0.839**	**0.937**	1.155	1.096	**0.843**	**0.952**	**0.831**	**0.939**	**0.857**	**0.963**	**0.849**	**0.950**
1974-2004	**0.907**	**0.909**	1.061	1.036	**0.988**	**0.956**	**0.962**	**0.943**	1.063	**0.995**	1.033	**0.965**
$\pi^{36}_{t+12} - \pi^{1}_{t+1}$												
1974-1983	**0.725**	**0.785**	**0.880**	**0.917**	**0.811**	**0.825**	**0.774**	**0.803**	**0.739**	**0.766**	**0.755**	**0.769**
1984-1990	**0.786**	**0.859**	**0.898**	**0.976**	**0.771**	**0.838**	1.057	**0.972**	**0.788**	**0.853**	**0.745**	**0.827**
1991-2004	**0.947**	**0.927**	**0.960**	**0.961**	**0.963**	**0.933**	**0.964**	**0.938**	**0.962**	**0.939**	**0.945**	**0.931**
1974-2004	**0.784**	**0.843**	**0.900**	**0.942**	**0.840**	**0.862**	**0.855**	**0.877**	**0.796**	**0.837**	**0.797**	**0.830**

Table 6: **Model Averaging:** $\pi^{12}_{t+12} - \pi^{1}_{t+1}$. See table note on the next page.

Num.	Sample	Term Structure		Time		Both Dimensions (Time & Term Structure)					
of	Period	Dimension		Dimension		5 Days		10 Days		20 Days	
PCs		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Panel A. Correlation Sort											
Simple Average											
1 to 3	1974-1983	**0.844**	**0.795**	1.059	1.016	**0.857**	**0.804**	**0.883**	**0.811**	**0.899**	**0.824**
	1984-1990	1.905	1.349	1.116	1.022	2.010	1.384	1.868	1.347	2.081	1.418
	1991-2004	**0.861**	**0.942**	1.153	1.087	**0.901**	**0.969**	**0.895**	**0.956**	**0.861**	**0.930**
	1974-2004	1.002	**0.945**	1.083	1.037	1.033	**0.965**	1.029	**0.957**	1.065	**0.970**
3 to 5	1974-1983	**0.781**	**0.780**	1.097	1.036	**0.813**	**0.792**	**0.809**	**0.797**	**0.834**	**0.798**
	1984-1990	1.652	1.268	1.068	1.005	1.811	1.300	1.601	1.245	1.889	1.320
	1991-2004	**0.797**	**0.922**	1.145	1.086	**0.839**	**0.938**	**0.842**	**0.941**	**0.857**	**0.931**
	1974-2004	**0.911**	**0.916**	1.101	1.044	**0.964**	**0.933**	**0.931**	**0.926**	**0.992**	**0.938**
1 to 5	1974-1983	**0.808**	**0.781**	1.068	1.020	**0.828**	**0.785**	**0.842**	**0.800**	**0.857**	**0.805**
	1984-1990	1.732	1.293	1.085	1.010	1.862	1.326	1.696	1.281	1.923	1.346
	1991-2004	**0.822**	**0.926**	1.142	1.084	**0.844**	**0.941**	**0.844**	**0.936**	**0.832**	**0.912**
	1974-2004	**0.946**	**0.923**	1.083	1.036	**0.982**	**0.935**	**0.967**	**0.933**	1.009	**0.941**
Regression based											
1 to 3	1974-1983	**0.771**	**0.777**	1.037	1.001	**0.827**	**0.811**	**0.789**	**0.792**	**0.887**	**0.831**
	1984-1990	1.522	1.172	1.189	1.027	1.332	1.120	1.054	1.107	1.373	1.120
	1991-2004	**0.854**	**0.958**	1.170	1.068	1.027	1.016	1.176	1.132	1.073	1.068
	1974-2004	**0.896**	**0.906**	1.082	1.025	**0.935**	**0.929**	**0.894**	**0.897**	**0.990**	**0.954**
3 to 5	1974-1983	**0.744**	**0.757**	1.060	1.011	**0.770**	**0.789**	**0.820**	**0.780**	**0.799**	**0.812**
	1984-1990	1.375	1.122	1.182	1.026	1.463	1.143	1.322	1.234	1.329	1.130
	1991-2004	**0.936**	**0.967**	1.196	1.075	**0.819**	**0.927**	**0.862**	**0.863**	**0.987**	**0.998**
	1974-2004	**0.869**	**0.888**	1.102	1.032	**0.880**	**0.897**	**0.901**	**0.861**	**0.909**	**0.927**
1 to 5	1974-1983	**0.802**	**0.795**	1.078	1.013	**0.872**	**0.847**	**0.875**	**0.821**	**0.898**	**0.861**
	1984-1990	1.287	1.085	1.187	1.027	1.287	1.087	**0.921**	1.171	1.141	1.034
	1991-2004	**0.768**	**0.908**	1.178	1.068	**0.829**	**0.932**	**0.887**	1.138	**0.956**	1.007
	1974-2004	**0.867**	**0.884**	1.111	1.032	**0.925**	**0.918**	**0.884**	**0.927**	**0.944**	**0.936**
Panel B. Variance Sort											
Simple Average											
1 to 3	1974-1983	**0.879**	**0.828**	1.041	1.016	**0.890**	**0.832**	**0.923**	**0.846**	**0.971**	**0.894**
	1984-1990	1.382	1.148	1.110	1.018	1.355	1.139	1.284	1.103	1.421	1.174
	1991-2004	**0.816**	**0.930**	1.142	1.086	**0.812**	**0.924**	**0.825**	**0.934**	**0.886**	**0.986**
	1974-2004	**0.942**	**0.919**	1.069	1.036	**0.945**	**0.918**	**0.959**	**0.921**	1.022	**0.975**
3 to 5	1974-1983	**0.793**	**0.796**	1.069	1.022	**0.826**	**0.799**	**0.857**	**0.816**	**0.891**	**0.837**
	1984-1990	1.374	1.162	1.096	1.004	1.517	1.222	1.316	1.145	1.360	1.160
	1991-2004	**0.797**	**0.922**	1.124	1.081	**0.828**	**0.943**	**0.830**	**0.942**	**0.835**	**0.947**
	1974-2004	**0.879**	**0.904**	1.082	1.035	**0.928**	**0.923**	**0.920**	**0.916**	**0.950**	**0.932**
1 to 5	1974-1983	**0.826**	**0.795**	1.051	1.019	**0.852**	**0.800**	**0.885**	**0.816**	**0.918**	**0.855**
	1984-1990	1.409	1.168	1.104	1.011	1.473	1.198	1.342	1.146	1.374	1.157
	1991-2004	**0.762**	**0.897**	1.134	1.084	**0.777**	**0.905**	**0.783**	**0.907**	**0.815**	**0.935**
	1974-2004	**0.900**	**0.897**	1.073	1.036	**0.930**	**0.908**	**0.934**	**0.907**	**0.967**	**0.937**
Regression based											
1 to 3	1974-1983	**0.739**	**0.763**	1.028	**1.000**	**0.742**	**0.751**	**0.792**	**0.779**	**0.845**	**0.845**
	1984-1990	1.165	1.037	1.222	1.042	1.202	1.094	1.107	1.014	1.670	1.248
	1991-2004	1.020	1.044	1.165	1.070	1.137	1.100	1.132	1.090	1.056	1.037
	1974-2004	**0.850**	**0.896**	1.080	1.028	**0.877**	**0.917**	**0.897**	**0.913**	1.002	**0.978**
3 to 5	1974-1983	**0.710**	**0.730**	1.027	**0.985**	**0.750**	**0.759**	**0.780**	**0.784**	**0.805**	**0.791**
	1984-1990	1.425	1.120	1.177	1.020	1.269	1.071	1.234	1.027	1.273	1.068
	1991-2004	**0.939**	**0.968**	1.143	1.060	**0.852**	**0.950**	**0.863**	**0.952**	**0.909**	**0.981**
	1974-2004	**0.854**	**0.874**	1.069	1.013	**0.843**	**0.874**	**0.861**	**0.879**	**0.892**	**0.899**
1 to 5	1974-1983	**0.769**	**0.770**	1.076	1.014	**0.766**	**0.760**	**0.821**	**0.807**	**0.804**	**0.816**
	1984-1990	1.210	1.052	1.216	1.034	1.277	1.116	1.171	1.042	1.451	1.148
	1991-2004	1.091	1.057	1.148	1.059	1.172	1.113	1.138	1.095	1.124	1.079
	1974-2004	**0.889**	**0.906**	1.109	1.030	**0.910**	**0.930**	**0.927**	**0.934**	**0.954**	**0.955**

Model Averaging: $\pi^{12}_{t+12} - \pi^{1}_{t+1}$**.** Relative MSE and MAE for equally weighted forecasts using 1 to 3 principal components, 3 to 5 principal components, and 1 to 5 principal components. All results are relative to the AR benchmark model. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the model that uses daily spreads with the same maturity as inflation are presented. The last three columns show the results principal component model incorporating both the time and term structure dimensions, with either 5, 10, or 20 days of daily interest rate lags.

Table 7: **Model Averaging:** $\pi^{36}_{t+36} - \pi^{1}_{t+1}$. See table note on the next page.

Num. of PCs	Sample Period	Term Structure Dimension MSE	Term Structure Dimension MAE	Time Dimension MSE	Time Dimension MAE	Both Dimensions (Time & Term Structure) 5 Days MSE	5 Days MAE	10 Days MSE	10 Days MAE	20 Days MSE	20 Days MAE
Panel A. Correlation Sort											
						Simple Average					
1 to 3	1974-1983	**0.623**	**0.739**	**0.916**	**0.947**	**0.779**	**0.828**	**0.708**	**0.797**	**0.635**	**0.734**
	1984-1990	**0.522**	**0.745**	**0.996**	1.029	**0.498**	**0.715**	**0.676**	**0.788**	**0.537**	**0.726**
	1991-2004	1.182	1.041	**0.959**	**0.958**	1.049	**0.974**	**0.715**	**0.813**	1.419	1.127
	1974-2004	**0.735**	**0.835**	**0.937**	**0.966**	**0.801**	**0.853**	**0.705**	**0.801**	**0.798**	**0.856**
3 to 5	1974-1983	**0.740**	**0.798**	**0.938**	**0.948**	**0.766**	**0.806**	**0.810**	**0.834**	**0.751**	**0.767**
	1984-1990	**0.667**	**0.784**	1.014	1.033	**0.640**	**0.753**	**0.551**	**0.756**	**0.579**	**0.728**
	1991-2004	1.146	1.009	**0.960**	**0.947**	1.100	**0.971**	**0.838**	**0.863**	1.311	1.073
	1974-2004	**0.822**	**0.862**	**0.953**	**0.964**	**0.824**	**0.848**	**0.781**	**0.828**	**0.854**	**0.856**
1 to 5	1974-1983	**0.665**	**0.765**	**0.917**	**0.939**	**0.739**	**0.806**	**0.720**	**0.800**	**0.667**	**0.742**
	1984-1990	**0.578**	**0.770**	**0.995**	1.026	**0.529**	**0.723**	**0.576**	**0.756**	**0.487**	**0.680**
	1991-2004	1.149	1.025	**0.956**	**0.952**	1.039	**0.961**	**0.811**	**0.861**	1.293	1.077
	1974-2004	**0.762**	**0.848**	**0.937**	**0.959**	**0.778**	**0.839**	**0.721**	**0.811**	**0.784**	**0.836**
						Regression based					
1 to 3	1974-1983	**0.584**	**0.708**	**0.906**	**0.926**	**0.816**	**0.779**	**0.656**	**0.569**	**0.592**	**0.692**
	1984-1990	**0.475**	**0.689**	1.050	1.042	**0.394**	**0.605**	**0.771**	1.568	**0.547**	**0.728**
	1991-2004	**0.785**	**0.857**	**0.917**	**0.933**	**0.976**	**0.947**	**0.913**	1.054	1.221	1.052
	1974-2004	**0.614**	**0.751**	**0.928**	**0.950**	**0.794**	**0.799**	**0.729**	**0.815**	**0.728**	**0.812**
3 to 5	1974-1983	**0.656**	**0.723**	**0.949**	**0.934**	**0.789**	**0.789**	**0.814**	**0.775**	**0.738**	**0.738**
	1984-1990	**0.770**	**0.860**	1.097	1.055	**0.676**	**0.755**	**0.502**	1.154	**0.779**	**0.878**
	1991-2004	1.250	1.019	**0.908**	**0.912**	1.091	**0.960**	**0.640**	**0.980**	1.214	1.019
	1974-2004	**0.806**	**0.842**	**0.960**	**0.950**	**0.842**	**0.836**	**0.732**	**0.873**	**0.851**	**0.853**
1 to 5	1974-1983	**0.564**	**0.683**	**0.889**	**0.904**	**0.784**	**0.742**	**0.621**	**0.548**	**0.619**	**0.703**
	1984-1990	**0.448**	**0.662**	1.097	1.044	**0.403**	**0.596**	**0.560**	**0.992**	**0.492**	**0.685**
	1991-2004	**0.804**	**0.861**	**0.917**	**0.923**	**0.941**	**0.931**	**0.831**	1.143	1.054	**0.984**
	1974-2004	**0.602**	**0.735**	**0.924**	**0.936**	**0.767**	**0.774**	**0.660**	**0.743**	**0.700**	**0.788**
Panel A. Variance Sort											
						Simple Average					
1 to 3	1974-1983	**0.829**	**0.880**	**0.869**	**0.911**	**0.866**	**0.903**	**0.867**	**0.897**	**0.962**	**0.941**
	1984-1990	**0.971**	**0.973**	**0.888**	**0.976**	1.028	**0.991**	1.123	1.021	1.092	**0.964**
	1991-2004	**0.828**	**0.874**	**0.960**	**0.959**	**0.829**	**0.876**	**0.824**	**0.874**	**0.760**	**0.810**
	1974-2004	**0.848**	**0.896**	**0.892**	**0.938**	**0.880**	**0.911**	**0.892**	**0.913**	**0.934**	**0.904**
3 to 5	1974-1983	**0.787**	**0.825**	**0.897**	**0.922**	**0.830**	**0.838**	**0.782**	**0.811**	**0.789**	**0.807**
	1984-1990	**0.968**	**0.940**	**0.887**	**0.979**	**0.970**	**0.937**	1.187	1.038	1.190	1.040
	1991-2004	1.020	**0.968**	**0.962**	**0.956**	**0.979**	**0.949**	**0.962**	**0.945**	**0.831**	**0.883**
	1974-2004	**0.864**	**0.892**	**0.910**	**0.943**	**0.882**	**0.892**	**0.878**	**0.896**	**0.854**	**0.875**
1 to 5	1974-1983	**0.812**	**0.861**	**0.878**	**0.914**	**0.840**	**0.872**	**0.807**	**0.852**	**0.821**	**0.849**
	1984-1990	**0.832**	**0.898**	**0.886**	**0.978**	**0.859**	**0.902**	**0.991**	**0.957**	1.052	**0.975**
	1991-2004	**0.867**	**0.903**	**0.960**	**0.957**	**0.848**	**0.892**	**0.843**	**0.890**	**0.794**	**0.860**
	1974-2004	**0.827**	**0.881**	**0.897**	**0.940**	**0.844**	**0.884**	**0.840**	**0.884**	**0.847**	**0.876**
						Regression based					
1 to 3	1974-1983	**0.553**	**0.647**	**0.879**	**0.911**	**0.555**	**0.667**	**0.569**	**0.672**	**0.822**	**0.845**
	1984-1990	1.314	1.169	**0.972**	1.000	1.487	1.232	1.568	1.283	**0.764**	**0.879**
	1991-2004	1.116	1.018	**0.930**	**0.936**	1.105	1.014	1.054	**0.998**	**0.863**	**0.888**
	1974-2004	**0.784**	**0.862**	**0.904**	**0.936**	**0.806**	**0.883**	**0.815**	**0.890**	**0.823**	**0.865**
3 to 5	1974-1983	**0.618**	**0.709**	**0.945**	**0.920**	**0.787**	**0.798**	**0.775**	**0.774**	**0.779**	**0.735**
	1984-1990	1.736	1.192	**0.939**	1.001	1.301	1.012	1.154	**0.975**	**0.736**	**0.777**
	1991-2004	1.126	1.000	**0.952**	**0.948**	**0.921**	**0.910**	**0.980**	**0.922**	**0.891**	**0.890**
	1974-2004	**0.885**	**0.891**	**0.946**	**0.944**	**0.887**	**0.873**	**0.873**	**0.858**	**0.798**	**0.791**
1 to 5	1974-1983	**0.492**	**0.621**	**0.915**	**0.909**	**0.543**	**0.642**	**0.548**	**0.667**	**0.488**	**0.609**
	1984-1990	1.426	1.203	**0.997**	1.009	1.256	1.109	**0.992**	**0.973**	1.028	**0.964**
	1991-2004	1.221	1.041	**0.946**	**0.942**	1.144	**1.000**	1.143	**0.988**	1.139	1.008
	1974-2004	**0.784**	**0.863**	**0.933**	**0.938**	**0.776**	**0.843**	**0.743**	**0.825**	**0.709**	**0.801**

Model Averaging: $\pi^{36}_{t+36} - \pi^{1}_{t+1}$**.** Relative MSE and MAE for equally weighted forecasts using 1 to 3 principal components, 3 to 5 principal components, and 1 to 5 principal components. All results are relative to the AR benchmark model. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the model that uses daily spreads with the same maturity as inflation are presented. The last three columns show the results principal component model incorporating both the time and term structure dimensions, with either 5, 10, or 20 days of daily interest rate lags.

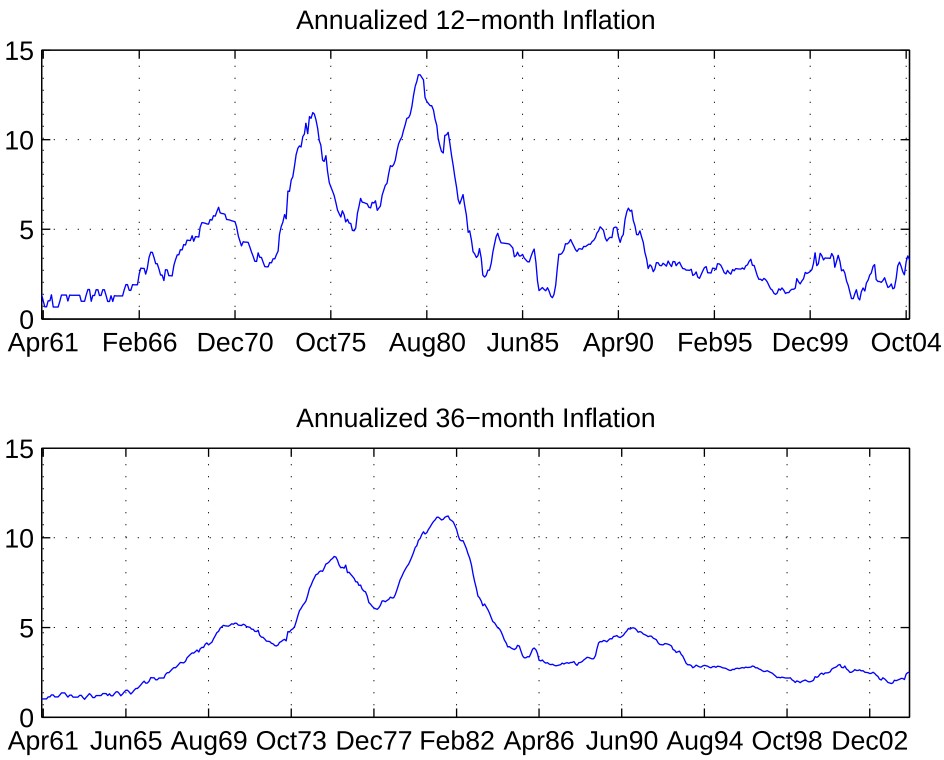
Table 8: **Diebold Mariano Tests on Regression based Model Averages.** Results for the Diebold Mariano test statistic for regression based average forecasts using 1 to 3 principal components, 3 to 5 principal components, and 1 to 5 principal components are presented. All results are relative to the AR benchmark model. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the model that uses daily spreads with the same maturity as inflation are presented. Finally, the columns labelled "5 days", "10 days" and "20 days" present results for the model that incorporates principal components of predictors that incorporate both dimensions: Term-Structure dimension and Time dimension.

Lags NWest	Num. of PC	Term Structure	Time	5 Days	10 Days	20 Days
Panel A. $\pi^{12} - \pi^{1}$						
Correlation Sort						
3	1 to 3	7.08	7.32	7.44	6.71	7.21
	3 to 5	7.23	7.43	7.33	7.24	7.60
	1 to 5	7.18	7.34	7.28	6.41	7.39
6	1 to 3	5.92	6.41	6.34	5.70	6.07
	3 to 5	6.17	6.47	6.29	6.13	6.40
	1 to 5	6.09	6.41	6.25	5.48	6.21
11	1 to 3	5.09	5.74	5.55	4.99	5.26
	3 to 5	5.33	5.73	5.52	5.31	5.49
	1 to 5	5.25	5.72	5.50	4.81	5.35
Variance Sort						
3	1 to 3	6.67	7.24	6.81	6.66	7.48
	3 to 5	7.27	7.24	6.95	6.73	6.58
	1 to 5	6.93	7.19	6.73	6.35	6.84
6	1 to 3	5.15	5.91	5.26	5.13	5.93
	3 to 5	5.67	5.88	5.35	5.10	4.98
	1 to 5	5.44	5.84	5.23	4.88	5.23
11	1 to 3	4.39	5.22	4.48	4.35	5.04
	3 to 5	4.85	5.18	4.58	4.35	4.25
	1 to 5	4.65	5.16	4.45	4.13	4.43

Table 9: **Diebold Mariano Tests on Regression based Model Averages.** Results for the Diebold Mariano test statistic for regression based average forecasts using 1 to 3 principal components, 3 to 5 principal components, and 1 to 5 principal components are presented. All results are relative to the AR benchmark model. The columns labelled "Term Structure" present results for the model that incorporates as predictors the principal components of the monthly term structure spreads. In the columns labelled "Time", results for the model that uses daily spreads with the same maturity as inflation are presented. Finally, the columns labelled "5 days", "10 days" and "20 days" present results for the model that incorporates principal components of predictors that incorporate both dimensions: Term-Structure dimension and Time dimension.

Lags NWest	Num. of PC	Term Structure	Time	5 Days	10 Days	20 Days
Panel A. $\pi^{36} - \pi^{1}$						
Correlation Sort						
3	1 to 3	8.27	7.93	8.14	8.55	9.10
	3 to 5	8.50	8.30	7.77	7.71	8.18
	1 to 5	8.27	8.14	7.15	7.65	8.79
9	1 to 3	5.79	5.55	5.85	5.91	6.34
	3 to 5	6.10	5.82	5.65	5.47	5.69
	1 to 5	5.88	5.68	5.20	5.44	6.05
15	1 to 3	4.91	4.72	4.94	4.97	5.34
	3 to 5	5.26	4.93	4.86	4.58	4.80
	1 to 5	5.02	4.81	4.42	4.57	5.05
20	1 to 3	4.49	4.36	4.52	4.53	4.87
	3 to 5	4.86	4.52	4.46	4.13	4.41
	1 to 5	4.60	4.43	4.04	4.11	4.59
30	1 to 3	4.05	4.03	4.07	4.06	4.41
	3 to 5	4.44	4.12	4.00	3.64	4.01
	1 to 5	4.13	4.05	3.60	3.61	4.11
35	1 to 3	3.91	3.93	3.91	3.90	4.26
	3 to 5	4.27	3.99	3.83	3.47	3.87
	1 to 5	3.96	3.94	3.45	3.45	3.96
Variance Sort						
3	1 to 3	6.86	8.21	6.92	6.99	8.08
	3 to 5	7.82	8.12	8.22	7.27	6.88
	1 to 5	7.04	8.23	6.77	6.74	6.63
9	1 to 3	4.78	5.77	4.79	4.84	5.62
	3 to 5	5.64	5.69	5.76	5.08	4.79
	1 to 5	4.96	5.77	4.70	4.71	4.61
15	1 to 3	4.03	4.91	4.05	4.08	4.77
	3 to 5	4.86	4.84	4.85	4.33	4.06
	1 to 5	4.20	4.91	3.98	4.01	3.90
20	1 to 3	3.67	4.52	3.71	3.72	4.41
	3 to 5	4.46	4.46	4.44	3.97	3.72
	1 to 5	3.82	4.53	3.64	3.69	3.57
30	1 to 3	3.28	4.16	3.36	3.35	4.04
	3 to 5	4.01	4.09	3.99	3.59	3.38
	1 to 5	3.41	4.16	3.29	3.36	3.24
35	1 to 3	3.16	4.05	3.25	3.24	3.91
	3 to 5	3.84	3.97	3.84	3.48	3.28
	1 to 5	3.26	4.05	3.19	3.26	3.15

Figure 1: Inflation



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