Phillips Curve Inflation Forecasts

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Abstract

This paper surveys the literature since 1993 on pseudo out-of-sample evaluation of inflation forecasts in the United States and conducts an extensive empirical analysis that recapitulates and clarifies this literature using a consistent data set and methodology. The literature review and empirical results are gloomy and indicate that Phillips curve forecasts (broadly interpreted as forecasts using an activity variable) are better than other multivariate forecasts, but their performance is episodic, sometimes better than and sometimes worse than a good (*not* naïve) univariate benchmark. We provide some preliminary evidence characterizing successful forecasting episodes.

Key words: Inflation forecasting, time-varying parameters

JEL codes: C53, E37

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1. Introduction

Inflation is hard to forecast. There is now considerable evidence that Phillips curve forecasts do not improve upon good univariate benchmark models. Yet the backward-looking Phillips curve remains a workhorse of many macroeconomic forecasting models and continues to be the best way to understand policy discussions about the rates of unemployment and inflation.

After some preliminaries in Section 2, this paper begins in Section 3 by surveying the past fifteen years of literature (since 1993) on inflation forecasting, focusing on papers that conduct a pseudo out-of-sample forecast evaluation.[1] A milestone in this literature is Atkeson and Ohanian (2001), who consider a number of standard Phillips curve forecasting models and show that none improve upon a four-quarter random walk benchmark over the period 1984-1999. As we observe in this survey, Atkeson and Ohanian (2001) deserve the credit for forcefully making this point, however their finding has precursors dating back at least to 1994. The literature after Atkeson-Ohanian (2001) finds that their specific result depends rather delicately on the sample period and the forecast horizon. If, however, one uses other univariate benchmarks (in particular, the unobserved components-stochastic volatility model of Stock and Watson (2007)), the broader point of Atkeson-Ohanian (2001) – that, at least since 1985, Phillips curve forecasts do not outperform univariate benchmarks on average – has been confirmed by several studies. The development of this literature is illustrated empirically using six prototype inflation forecasting models: three univariate models, Gordon's (1990) "triangle" model, an autoregressive-distributed lag model using the unemployment rate, and a model using the term spread.

It is difficult to make comparisons across papers in this literature because the papers use different sample periods, different inflation series, and different benchmark

[1] Experience has shown that good in-sample fit of a forecasting model does not necessarily imply good out-of-sample performance. The method of pseudo out-of-sample forecast evaluation aims to address this by simulating the experience a forecaster would have using a forecasting model. In a pseudo out-of-sample forecasting exercise, one simulates standing at a given date *t* and performing all model specification and parameter estimation using only the data available at that date, then computing the *h*-period ahead forecast for date *t*+*h*; this is repeated for all dates in the forecast period.

models, and the quantitative results in the literature are curiously dependent upon these details. In Section 4, we therefore undertake an empirical study that aims to unify and to assess the results in the literature using quarterly U.S. data from 1953:I – 2008:I. This study examines the pseudo out of sample performance of a total of 192 forecasting procedures (157 distinct models and 35 combination forecasts), including the six prototype models of Section 3, applied to forecasting five different inflation measures (CPI-all, CPI-core, PCE-all, PCE-core, and the GDP deflator). This study confirms the main qualitative results of the literature, although some specific results are found not to be robust. Our study also suggests an interpretation of the strong dependence of conclusions in this literature on the sample period. Specifically, one of our key findings is that the performance of Phillips curve forecasts is episodic: there are times, such as the late 1990s, when Phillips curve forecasts improved upon univariate forecasts, but there are other times (such as the mid-1990s) when a forecaster would have been better off using a univariate forecast. This provides a rather more nuanced interpretation of the Atkeson-Ohanian (2001) conclusion concerning Phillips curve forecasts, one that is consistent with the sensitivity of findings in the literature to the sample period.

A question that is both difficult and important is what this episodic performance implies for an inflation forecaster today. On average, over the past fifteen years, it has been very hard to beat the best univariate model using any multivariate inflation forecasting model (Phillips curve or otherwise). But suppose you are told that next quarter the economy would plunge into recession, with the unemployment rate jumping by two percentage points. Would you change your inflation forecast? The literature is now full of formal statistical evidence suggesting that this information should be ignored, but we suspect that an applied forecaster would nevertheless reduce their forecast of inflation over the one- to two-year horizon. In the final section, we suggest some reasons why this might be justified.

2. Notation, Terminology, Families of Models, and Data

This section provides preliminary details concerning the empirical analysis and gives the six prototype inflation forecasting models that will be used in Section 3 as a guide to the literature. We begin by reviewing some forecasting terminology.

2.1 Terminology

h-period inflation. Inflation forecasting tends to focus on the one-year or two-year horizons. We denote h-period inflation by $\pi_t^h = h^{-1}\sum_{i=0}^{h-1}\pi_{t-i}$, where π_t is the quarterly rate of inflation at an annual rate, that is, $\pi_t = 400\ln(P_t/P_{t-1})$ (using the log approximation), where P_t is the price index in quarter t. Four-quarter inflation at date t is $\pi_t^4 = 100\ln(P_t/P_{t-4})$, the log approximation to the percentage growth in prices over the previous four quarters.

Direct and iterated forecasts. There are two ways to make an h-period ahead model-based forecast. A direct forecast has π_{t+h}^h as the dependent variable and t-dated variables (variables observed at date t) as regressors, for example π_{t+h}^h could be regressed on π_t^h and the date-t unemployment rate (u_t). At the end of the sample (date T), the forecast of π_{T+h}^h is computed "directly" using the estimated forecasting equation. In contrast, an iterated forecast is based on a one-step ahead model, for example π_{t+1} could be regressed on π_t, which is then iterated forward to compute future conditional means of π_s, $s > T+1$, given data through time t. If predictors other than past π_t are used then this requires constructing a subsidiary model for the predictor, or alternatively modeling π_t and the predictor jointly (for example as VAR) and iterating the joint model forward.

Pseudo out-of-sample forecasts; rolling and recursive estimation. Pseudo out-of-sample forecasting simulates the experience of a real-time forecaster by performing all model specification and estimation using data through date t, making a h-step ahead forecast for date t+h, then moving forward to date t+1 and repeating this through the sample.[2] Pseudo out-of-sample forecast evaluation captures model specification uncertainty, model instability, and estimation uncertainty, in addition to the usual uncertainty of future events.

Model estimation can either be rolling (using a moving data window of fixed size) or recursive (using an increasing data window, always starting with the same observation). In this paper, rolling estimation is based on a window of 10 years, and recursive estimation starts in 1953:I or, for series starting after 1953:I, the earliest possible quarter.

Root mean squared error and rolling RMSE. The root mean squared forecast error (RMSE) of h-period ahead forecasts made over the period t_1 to t_2 is

$$RMSE_{t_1,t_2} = \sqrt{\frac{1}{t_2 - t_1 + 1}\sum_{t=t_1}^{t_2}\left(\pi_{t+h}^{h} - \pi_{t+h|t}^{h}\right)^2} \quad (1)$$

where $\pi_{t+h|t}^{h}$ is the pseudo out-of-sample forecast of π_{t+h}^{h} made using data through date t. This paper uses rolling estimates of the RMSE, which are computed using a weighted centered 15-quarter window:

$$\text{rolling } RMSE(t) = \sqrt{\sum_{s=t-7}^{t+7} K(|s-t|)\left(\pi_{s+h}^{h} - \pi_{s+h|s}^{h}\right)^2 \Big/ \sum_{s=t-7}^{t+7} K(|s-t|)}\ , \quad (2)$$

where K is the biweight kernel, $K(x) = (15/16)(1 - x^2)^2\mathbf{1}(|x|\leq 1)$.

2.2 Prototypical Inflation Forecasting Models

Single-equation inflation forecasting models can be grouped into four families: (1) forecasts based solely on past inflation; (2) forecasts based on activity measures ("Phillips curve forecasts"); (3) forecasts based on the forecasts of others; and (4)

[2] A strict interpretation of pseudo out-of-sample forecasting would entail the use of real-time data (data of different vintages), but we interpret the term more generously to include the use of final data.

forecasts based on other predictors. This section lays out these families and provides prototype examples of each.

(1) *Forecasts based on past inflation*. This family includes univariate time series models such as ARIMA models and nonlinear or time-varying univariate models. We also include in this family forecasts in which one or more inflation measure, other than the series being forecasted, is used as a predictor; for example, past CPI core inflation or past growth in wages could be used to forecast CPI-all inflation.

Three of our prototype models come from this family and serve as forecasting benchmarks. The first is a direct autoregressive (AR) forecast, computed using the direct autoregressive model,

$$\pi_{t+h}^h - \pi_t = \mu^h + \alpha^h(\mathrm{L})\Delta\pi_t + v_{t+h}^h \qquad \text{(AR(AIC))} \tag{3}$$

where μ^h is a constant, $\alpha^h(\mathrm{L})$ is a lag polynomial written in terms of the lag operator L, v_{t+h}^h is the h-step ahead error term (we will use v generically to denote regression error terms), and the superscript h denotes the quantity for the h-step ahead direct regression. In this prototype AR model, the lag length is determined by the Akaike Information Criterion (AIC) over the range of 1 to 6 lags. This specification imposes a unit autoregressive root.

The second prototype model is the Atkeson-Ohanian (2001) random walk model, in which the forecast of the four-quarter rate of inflation, π_{t+4}^4, is the average rate of inflation over the previous four quarters, π_t^4 (Atkeson and Ohanian only considered four-quarter ahead forecasting). The Atkeson-Ohanian model thus is,

$$\pi_{t+4}^4 = \pi_t^4 + v_{t+4}^4 \qquad \text{(AO).} \tag{4}$$

The third prototype model is the Stock-Watson (2007) unobserved components-stochastic volatility (UC-SV) model, in which π_t has a stochastic trend τ_t, a serially uncorrelated disturbance η_t, and stochastic volatility:

$$\pi_t = \tau_t + \eta_t, \quad \text{where } \eta_t = \sigma_{\eta,t}\zeta_{\eta,t} \qquad \text{(UC-SV)} \qquad (5)$$

$$\tau_t = \tau_{t-1} + \varepsilon_t, \quad \text{where } \varepsilon_t = \sigma_{\varepsilon,t}\zeta_{\varepsilon,t} \qquad (6)$$

$$\ln \sigma^2_{\eta,t} = \ln \sigma^2_{\eta,t-1} + \nu_{\eta,t} \qquad (7)$$

$$\ln \sigma^2_{\varepsilon,t} = \ln \sigma^2_{\varepsilon,t-1} + \nu_{\varepsilon,t} \qquad (8)$$

where $\zeta_t = (\zeta_{\eta,t}, \zeta_{\varepsilon,t})$ is i.i.d. $N(0, I_2)$, $\nu_t = (\nu_{\eta,t}, \nu_{\varepsilon,t})$ is i.i.d. $N(0, \gamma I_2)$, and ζ_t and ν_t are independently distributed, and γ is a scalar parameter. Although η_t and ε_t are conditionally normal given $\sigma_{\eta,t}$ and $\sigma_{\varepsilon,t}$, unconditionally they are random mixtures of normals and can have heavy tails. This is a one-step ahead model and forecasts are iterated.

This model has only one parameter, γ, which controls the smoothness of the stochastic volatility process. Throughout, we follow Stock and Watson (2007) and set $\gamma = 0.04$.

(2) *Phillips curve forecasts*. We interpret Phillips curve forecasts broadly to include forecasts produced using an activity variable, such as the unemployment rate, an output gap, or output growth, perhaps in conjunction with other variables, to forecast inflation or the change in inflation. This family includes both backwards-looking Phillips curves and new Keynesian Phillips curves, although the latter appear infrequently (and only recently) in the inflation forecasting literature.

We consider two prototype Phillips curve forecasts. The first is Gordon's (1990) "triangle model," which in turn is essentially the model in Gordon (1982) with the minor modifications.[3] In the triangle model, inflation depends on lagged inflation, the unemployment rate u_t, and supply shock variables z_t:

$$\pi_{t+1} = \mu + \alpha^G(L)\pi_t + \beta(L)u_{t+1} + \gamma(L)z_t + v_{t+1}. \qquad \text{(triangle)} \qquad (9)$$

[3] The specification in Gordon (1990), which is used here, differs from Gordon (1982, Table 5, column 2) in three ways: (a) Gordon (1982) uses a polynomial distributed lag specification on lagged inflation, while Gordon (1990) uses the step function; (b) Gordon (1982) includes additional intercept shifts in 1970Q3-1975Q4 and 1976Q1-1980Q4, which are dropped in Gordon (1990); (c) Gordon (1982) uses Perry-weighted unemployment whereas here we use overall unemployment.

The prototype triangle model used here is that in Gordon (1990), in which (9) is specified using the contemporaneous value plus four lags of u_t (total civilian unemployment rate ages 16+, seasonally adjusted), contemporaneous value plus four lags of the rate of inflation of food and energy prices (computed as the difference between the inflation rates in the deflator for "all-items" personal consumption expenditure (PCE) and the deflator for PCE less food and energy), lags one through four of the relative price of imports (computed as the difference of the rates of inflation of the GDP deflator for imports and the overall GDP deflator), two dummy variables for the Nixon wage-price control period, and 24 lags of inflation, where $\alpha^G(L)$ imposes the step-function restriction that the coefficients are equal within the groups of lags 1-4, 5-8, …, 21-24, and also that the coefficients sum to one (a unit root is imposed).

Following Gordon (1998), multiperiod forecasts based on the triangle model (9) are iterated using forecasted values of the predictors, where those forecasts are made using subsidiary univariate AR(8) models of u_t, food and energy inflation, and import inflation.

The second prototype Phillips curve model is direct version of (9) without the supply shock variables, specifically, the autoregressive distributed (ADL) lag model in which forecasts are computed using the direct regression,

$$\pi_{t+h}^h - \pi_t = \mu^h + \alpha^h(L)\Delta\pi_t + \beta^h(L)u_t + v_{t+h}^h, \qquad \text{(ADL-}u\text{)} \qquad (10)$$

where the degrees of $\alpha^h(L)$ and $\beta^h(L)$ are chosen separately by AIC (maximum lag of 4), and (like the triangle model) the ADL-*u* specification imposes a unit root in the autoregressive dynamics for π_t.

(3) ***Forecasts based on forecasts of others***. The third family computes inflation forecasts from explicit or implicit inflationary expectations or forecasts of others. These forecasts include regressions based on implicit expectations derived from asset prices, such as forecasts extracted from the term structure of nominal Treasury debt (which by the Fisher relation should embody future inflation expectations) and forecasts extracted from the TIPS yield curve. This family also includes forecasts based on explicit forecasts of others, such as median forecasts from surveys such as the Survey of Professional Forecasters.

Our prototypical example of forecasts in this family is a modification of the Mishkin (1990) specification, in which the future change in inflation is predicted by a matched-maturity spread between the interest rates on comparable government debt instruments, with no lags of inflation. Here we consider direct four-quarter ahead forecasts based on an ADL model using as a predictor the interest spread, $spread1\_90_t$, between 1-year Treasury bonds and 90-day Treasury bills:

$$\pi_{t+4}^{4} - \pi_t = \mu + \alpha(\mathrm{L})\Delta\pi_t + \beta(\mathrm{L})spread1\_90_t + v_{t+4}^{4}. \quad \text{(ADL-spread)} \qquad (11)$$

We emphasize that Mishkin's (1990) regressions appropriately use term spread maturities matched to the change in inflation being forecasted, which for (11) would be the change in inflation over quarters t+2 to t+4, relative to t+1. (A matched maturity alternative to $spread1\_90_t$ in (11) would be the spread between 1-year Treasuries and the Fed Funds rate, however those instruments have different risks.) Because the focus of this paper is Phillips curve regressions we treat this regression simply as an example of this family and provide references to recent studies of this family in Section 3.3.

(4) ***Forecasts based on other predictors***. The fourth family consists of inflation forecasts that are based on variables other than activity or expectations variables. An example is a 1970s-vintage monetarist model in which M1 growth is used to forecast inflation. Forecasts in this fourth family perform sufficiently poorly relative to the three other approaches that they play negligible roles both in the literature and in current practice, so to avoid distraction we do not track a model in this family as a running example.

2.3 Data and transformations

The data set is quarterly for the United States from 1953:I – 2008:I. Monthly data are converted to quarterly by computing the average value for the three months in the quarter prior to any other transformations; for example quarterly CPI is the average of the three monthly CPI values, and quarterly CPI inflation is the percentage growth (at an annual rate, using the log approximation) of this quarterly CPI.

We examine forecasts of five measures of price inflation: the GDP deflator (PGDP), the CPI for all items (CPI-all), CPI excluding food and energy (CPI-core), the personal consumption expenditure deflator (PCE-all), and the personal consumption expenditure deflator excluding food and energy (PCE-core).

In addition to the six prototype models, in Section 4 we consider forecasts made using a total of 15 predictors, most of which are activity variables (GDP, industrial production, housing starts, the capacity utilization rate, etc.). The full list of variables and transformations is given in Appendix A.

Gap variables. Consistent with the pseudo out-of-sample forecasting philosophy, the activity gaps used in the forecasting models in this paper are all one-sided. Following Stock and Watson (2007), gaps are computed as the deviation of the series (for example, log GDP) from a symmetric two-sided MA(80) approximation to the optimal lowpass filter with pass band corresponding to periodicities of at least 60 quarters. The one-sided gap at date t is computed by padding observations at dates $s > t$ and $s < 1$ with iterated forecasts and backcasts based on an AR(4), estimated recursively through date t.

3. An Illustrated Survey of the Literature on Phillips Curve Forecasts, 1993-2008

This section surveys the literature during the past fifteen years (since 1993) on inflation forecasting in the United States. The criterion for inclusion in this survey is providing empirical evidence on inflation forecasts (model- and/or survey-based) in the form of a true or pseudo out-of-sample forecast evaluation exercise. Such an evaluation can use rolling or recursive forecasting methods based on final data; it can use rolling or recursive methods using real-time data; or it can use forecasts actually produced and recorded in real time such as survey forecasts. Most of the papers discussed here focus on forecasting at horizons of policy relevance, one or two years. Primary interest is in forecasting overall consumer price inflation (PCE, CPI), core inflation, or economy-wide inflation (GDP deflator). There is little work on forecasting producer prices, although a few papers consider producer prices as a predictor of headline inflation.

This survey also discusses some papers in related literatures, however we do not attempt a comprehensive review of those related literatures. One such literature concerns the large amount of interesting work that has been done on inflation forecasting in countries other than the U.S.; see Rünstler (2002), Hubrich (2005), Canova (2007), and Diron and Mojon (2008) for recent contributions and references. Another closely related literature concerns in-sample statistical characterizations of changes in the univariate and multivariate inflation process in the U.S. (e.g. Taylor (2000), Brainard and Perry (2000), Cogley and Sargent (2002, 2005), Levin and Piger (2004), and Pivetta and Reis (2007)) and outside the U.S. (e.g. the papers associated with the European Central Bank Inflation Persistence Network (2007)). There is in turn a literature that asks whether these changes in the inflation process can be attributed, in a quantitative (in-sample) way, to changes in monetary policy; papers in this vein include Estrella and Fuhrer (2003), Roberts (2004), Sims and Zha (2004) and Primiceri (2006). A major theme of this survey is time-variation in the Phillips curve from a forecasting perspective, most notably at the end of the disinflation of the early 1980s but more subtly throughout the post-1984 period. This time-variation is taken up in a great many papers (for example estimation of a time-varying NAIRU and time variation in the slope of the Phillips curve), however those papers are only discussed in passing unless they have a pseudo out-of-sample forecasting component.

3.1 The 1990s: Warning Signs

The great inflation and disinflation of the 1970s and the 1980s was the formative experience that dominated the minds and models of inflation forecasters through the 1980s and early 1990s, both because of the forecasting failures of 1960s-vintage ("non-accelerationist") Phillips curves and, more mechanically, because most of the variation in the data comes from that period. The dominance of this episode is evident in Figure 1, which plots the three measures of headline inflation (GDP, PCE-all, and CPI-all) from 1953Q1 to 2007Q4, along with the unemployment rate.

By the early 1980s, despite theoretical attacks on the backwards-looking Phillips curve, Phillips curve forecasting specifications had coalesced around the Gordon (1982) type triangle model (9) and variants. Figure 2 plots the rolling RMSE of the four-quarter ahead pseudo out-of-sample forecast of CPI-all inflation, computed using (2), for the recursively estimated AR(AIC) benchmark (3), the triangle model (9), and the ADL-*u* model (10). As can be seen in Figure 2, these "accelerationist" Phillips curve specifications (unlike their non-accelerationist ancestors) did in fact perform well during the 1970s and 1980s.

The greatest success of the triangle model and the ADL-*u* model was forecasting the fall in inflation during the early 1980s subsequent to the spike in the unemployment rate in 1980, but in fact the triangle and ADL-*u* models improved upon the AR benchmark nearly uniformly from 1965 through 1990. The main exception occurred around 1986, when there was a temporary decline in oil prices. Figure 3 shows the four-quarter ahead pseudo out-of-sample forecasts produced by the AR(AIC), triangle, and ADL-*u* models are shown respectively in panels A-C of Figure 3. As can be seen in Figure 3, the triangle model initially failed to forecast the decline in inflation in 1986, then incorrectly predicted to last longer than it did. Interestingly, unlike the AR(AIC) and ADL-*u* models, triangle model forecasts did not over-extrapolate the decline in inflation in the early 1980s.

Stockton and Glassman (1987) documented the good performance of a triangle model based on the Gordon (1982) specification of the triangle model over the 1977-1984 period (they used the Council of Economic Advisors output gap instead of the unemployment rate and a 16-quarter, not 24-quarter, polynomial distributed lag). They reported a pseudo out-of-sample relative RMSE of the triangle model, relative to an AR(4) model of the change in inflation, of 0.80 (eight quarter ahead iterated forecasts of inflation measured by the Gross Domestic Business Product fixed-weight deflator)[4]. Notably, Stockton and Glassman (1987) also emphasized that there seem to be few good competitors to this model: a variety of monetarist models, including some that incorporate expectations of money growth, all performed worse – in some cases, much

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[4] Stockton and Glassman (1987), Table 6, ratio of PHL(16,FE) to ARIMA RMSE for average of four intervals.

worse – than the AR(4) benchmark. This said, the gains from using a Phillips curve forecast over the second half of the 1980s were slimmer than during the 1970s and early 1980s.

The earliest documentation of this relative deterioration of Phillips curve forecasts of which we are aware is a little-known (2 Google Scholar cites) working paper by Jaditz and Sayers (1994). They undertook a pseudo out-of-sample forecasting exercise of CPI-all inflation using industrial production growth, the PPI, and the 90-day Treasury Bill rate in a VAR and in a vector error correction model (VECM), with a forecast period of 1986-1991 and a forecast horizon of one month. They reported a relative RMSE of .985 for the VAR and a relative MSE in excess of one for the VECM, relative to an AR(1) benchmark.

Cecchetti (1995) also provided early evidence of instability in Phillips curve forecasts, although that instability was apparent only using in-sample break tests and did not come through in his pseudo out-of-sample forecasting evaluation because of his forecast sample period. He considered forecasts of CPI-all at horizons of 1-4 years based on 18 predictors, entered separately, for two forecast periods, 1977-1994 (10 year rolling window) and 1987-1994 (5 year rolling window). Inspection of Figure 2 indicates Phillips curve forecasts did well on average over both of these windows, but that the 1987-1994 period was atypical of the post-1984 experience in that it is dominated by the relatively good performance of Phillips curve forecasts during the 1990 recession. Despite the good performance of Phillips curve forecasts over this period, using in-sample break tests Cecchetti (1990) found multiple breaks in the relation between inflation and (separately) unemployment, the employment/population ratio, and the capacity utilization rate. He also found that good in-sample fit is essentially unrelated to future forecasting performance.

Stock and Watson (1999) undertook a pseudo out-of-sample forecasting assessment of CPI-all and PCE-all forecasts at the one-year horizon using (separately) 168 economic indicators, of which 85 were measures of real economic activity (industrial production growth, unemployment, etc). They considered recursive forecasts computed over two subsamples, 1970-1983 and 1984-1996. The split sample evidence indicated major changes in the relative performance of predictors in the two subsamples, for example the RMSE of the forecast based on the unemployment rate, relative to the AR benchmark, was .89 in the 1970-1983 sample but 1.01 in the 1984-1996 sample. Using in-sample test statistics, they also found structural breaks in the inflation – unemployment relation, although interestingly these breaks were more detectable in the coefficients on lagged inflation in the Phillips curve specifications than on the activity variables.

Cechetti, Chu and Steindel (2000) examined CPI inflation forecasts at the two-year horizon using (separately) 19 predictors, including activity indicators. They reported dynamic forecasts in which future values of the predictors are used to make multi-period ahead forecasts (future employment is treated as known at the time the forecast is made, so these are not psueduo out-of-sample). Notably, they found that over this period the activity-based forecasts (unemployment, employment-population ratio, and capacity utilization rate) typically underperformed the AR benchmark over this period at the one-year horizon.

A final paper documenting poor Phillips curve forecasting performance, contemporaneous with Atkeson-Ohanian (2001), is Camba-Mendezand and Rodriguez-Palenzuela (2003; originally published as ECB working paper April 2001). They showed that inflation forecasts at the one-year horizon based on realizable (that is, backwards-looking) output gap measures, for the forecast period 1980 – 1999, underperform the AR benchmark.

In short, during the 1990s a number of papers provided results that activity-based inflation forecasts provided a smaller advantage relative to an AR benchmark since the mid-1980s than they had before. Ambiguities remained, however, because this conclusion seemed to depend on the sample period and specification, and in any event one could find predictors which were exceptions in the sense that they appeared to provide improvements in the later sample, even if their performance was lackluster in the earlier sample.

3.2 Atkeson-Ohanian (2001)

Atkeson and Ohanian (2001) (AO) resolved the ambiguities in this literature of the 1990s by introducing a new, simple univariate benchmark: the forecast of inflation over the next four quarters is the value of four-quarter inflation today. AO showed that this four-quarter random walk forecast improved substantially upon the AR benchmark over 1984-1999. Figure 4 plots the moving RMSE of four-quarter ahead forecasts of CPI-all inflation for three univariate forecasts: the AR(AIC) forecast (3), the AO forecast (4), and the UC-SV forecast (5) - (8). Because the AO benchmark improved over the 1984-1999 period on the AR forecast, and because the AR forecast had more or less the same performance as the unemployment-based Phillips curve on average over this period (see Figure 2), it is not surprising that the AO forecast outperformed the Phillips curve forecast over the 1984-1999 period. As AO dramatically showed, across 264 specifications (three inflation measures, CPI-all, CPI-core, and PCE-all, 2 predictors, the unemployment rate and the CFNAI, and various lag specifications), the relative RMSEs of a Phillips curve forecast to the AO benchmark ranged from 0.99 to 1.94: gains from using a Phillips curve forecast were negligible at best, and some Phillips curve forecasts went badly wrong. AO went one step further and demonstrated that, over the 1984-1999 period, Greenbook forecasts of inflation also underperformed their four-quarter random walk forecast.

As Figures 2 and 4 demonstrate, one important source of the problem with Phillips curve forecasts was their poor performance in the second half of the 1990s, a period of strong, but at the time unmeasured, productivity growth that held down inflation. The apparent quiescence of inflation in the face of strong economic growth was puzzling at the time (for example, see Lown and Rich (1997)).

An initial response to the AO was to check whether their claims were accurate; with a few caveats, by and large they were. Fisher, Liu, and Zhou (2002) used rolling regressions with a 15-year window and showed that Phillips curve models outperformed the AO benchmark in 1977-1984, and also showed that for some inflation measures and some periods the Phillips curve forecasts outperform the AO benchmark post-1984 (for example, Phillips curve forecasts improve upon AO forecasts of PCE-all over 1993-2000). They also pointed out that Phillips curve forecasts based on the CFNAI achieve 60-70% accuracy in directional forecasting of the change of inflation, compared with 50% for the AO coin flip. Fisher, Liu, and Zhou (2002) suggested that Phillips curve forecasts do relatively poorly in periods of low inflation volatility and after a regime shift.

Stock and Watson (2003) extended the AO analysis to additional activity predictors (as well as other predictors) and confirmed the dominance of the AO forecast over 1985-1999 at the one-year horizon. Brave and Fisher (2004) extended the AO and Fisher, Liu, and Zhou (2002) analyses by examining additional predictors and combination forecasts. Their findings are broadly consistent with Fisher, Liu, and Zhou (2002) in the sense that they found some individual and combination forecasts that outperform AO over 1993-2000, although not over 1985-1992. Orphanides and van Norden (2005) focused on Phillips curve forecasts using real-time gap measures, and they concludeed that although ex-post gap Phillips curves fit well using in-sample statistics, when real-time gaps and pseudo out-of-sample methods are used these too improve upon the AR benchmark prior to 1983, but fail to do so over the 1984-2002 sample.

There are three notable recent studies that confirm the basic AO finding and extend it, with qualifications. First, Stock and Watson (2007) focused on univariate models of inflation and pointed out that the good performance of the AO random walk forecast, relative to other univariate models, is specific to the four-quarter horizon and (as can be seen by comparing the AO and UC-SV rolling RMSEs in Figure 4) to the AO sample period. At any point in time, the UC-SV model implies an IMA(1,1) model for inflation, with time-varying coefficients. The forecast function of this IMA(1,1) closely matches the implicit AO forecast function over the 1984-1999 sample, however the models diverge over other subsamples. Moreover, the rolling IMA(1,1) is in turn well approximated by a ARMA(1,1) because the estimated AR coefficient is nearly one.[5] Stock and Watson (2007) also reported some (limited) results for bivariate forecasts using activity indicators (unemployment, one-sided gaps, and output growth) and confirmed the

[5] The UC-SV model imposes a unit root in inflation so is consistent with the Pivetta-Reis (2007) evidence that the largest AR root in inflation has been essentially one throughout the postwar sample. But the time-varying relative variances of the permanent and transitory innovation allows for persistence to change over the course of the sample and for spectral measures of persistence to decline over the sample, consistent with Cogley and Sargent (2002, 2005).

AO finding that these Phillips curve forecast fail to improve systematically on the AO benchmark or the UC-SV benchmark.

Second, Canova (2007) undertook a systematic evaluation of 4- and 8-quarter ahead inflation forecasts for G7 countries using recursive forecasts over 1996-2000, using a variety of activity variables (unemployment, employment, output gaps, GDP growth) and other indicators (yield curve slope, money growth) as predictors. He found that, for the U.S., bivariate direct regressions and trivariate VARs and BVARs did not improve upon the univariate AO forecast. (Generally speaking, Canova (2007) also did not find consistent improvements for multivariate models over univariate ones for the other G7 countries, and he reported evidence of instability of forecasts based on individual predictors.) Canova (2007) also considered combination forecasts and forecasts generated using a new Keynesian Phillips curve. Over the 1996-2000 sample, the combination forecasts in the U.S. provided a small improvement over the AO forecast, and the new Keynesian Phillips curve forecasts were never best and generally fared poorly. In the case of the U.S., at least, these findings are not surprising in light of the poor performance of Phillips curve forecasts during the low-inflation boom of the second half of the 1990s.

Third, Ang, Bekaert, and Wei (2007) conducted a thorough assessment of forecasts of CPI, CPI-core, CPI ex housing, and PCE inflation, using ten variants of Phillips curve forecasts, 15 variants of term structure forecasts, combination forecasts, and ARMA(1,1) and AR(1)-regime switching univariate models in addition to AR and AO benchmarks. They too confirmed the basic AO message that Phillips curve models fail to improve upon univariate models over forecast periods 1985-2002 and 1995-2002, and their results constitute a careful summary of the current state of knowledge of inflation forecasting models (both Phillips curve and term structure) in the U.S. One finding in their study is that combination forecasts do not systematically improve on individual indicator forecasts, a result that is puzzling in light of the success reported elsewhere of combination forecasts (we return to this puzzle below). Ang, Bekaert, and Wei (2007) also considered survey forecasts, and their most striking result is that survey forecasts (the Michigan, Livingston, and Survey of Professional Forecasters surveys) perform very well: for the inflation measures that the survey respondents are asked to forecast, the survey forecasts nearly always beat the ARMA(1,1) benchmark, their best-performing univariate model over the 1985-2002 period.[6] Further study of rolling regressions led them to suggest that the relatively good performance of the survey forecasts might be due to the ability of professional forecasters to recognize structural change more quickly than automated regression-based forecasts.[7]

An alternative forecast, so far unmentioned, is that inflation is constant. This forecast works terribly over the full sample but Diron and Mojon (2008) found out that, for PCE-core from 1995Q1-2007Q4, a forecast of a constant 2.0% inflation rate outperforms AO and AR forecasts at the 8-quarter ahead horizon, although the AO forecast is best at the 4-quarter horizon. They choose 2.0% as representative of an implicit inflation target over this period, however because the U.S. does not have an explicit ex-ante inflation target and this value was chosen retrospectively, this choice does not constitute a psueduo out-of-sample forecast.

All these papers – from Jaditz and Sayers (1994) through Ang, Bekaert, and Wei (2007) – point to time variation in the underlying inflation process and in Phillips curve forecasting relations. Most of this evidence is based on changes in relative RMSEs, in some cases augmented by Diebold-Mariano (1995) or West (1996) tests using asymptotic critical values. As a logical matter, the apparent statistical significance of the changes in the relative RMSEs between sample periods could be a spurious consequence of using a poor approximation to the sampling distribution of the relevant statistics. Accordingly,

[6] Koenig (2003, Table 3) presented in-sample evidence that real-time markups (nonfinancial corporate GDP divided by nonfinancial corporate employee compensation), in conjunction with the unemployment rate, significantly contribute to a forecast combination regression for 4-quarter CPI inflation over 1983-2001, however he did not present pseudo out-of-sample RMSEs. Two of Ang, Bekaert, and Wei's (2007) models (their PC9 and PC10) include the output gap and the labor income share, specifications similar to the Koenig's (2003), and the pseudo out-of-sample performance of these models is poor: over the two Ang, Bekaert, and Wei's (2007) subsamples and four inflation measures, the RMSEs, relative to the ARMA(1,1) benchmark, range from 1.17 to 3.26. These results suggest that markups are not a solution to the poor performance of Phillips curve forecasts over the post-85 samples.

[7] Cecchetti et. al. (2007, Section 7) provided in-sample evidence that survey inflation forecasts are correlated with future trend inflation, measured using the Stock-Watson (2007) UC-SV model. Thus a different explanation of why surveys perform well is that survey inflation expectations anticipate movements in trend inflation.

Clark and McCracken (2006) undertook a bootstrap evaluation of the relative RMSEs produced using real-time output gap Phillips curves for forecasting the GDP deflator and CPI-core. They reached the more cautious conclusion that much of the relatively poor performance of forecasts using real-time gaps could simply be a statistical artifact that is consistent with a stable Phillips curve, although they found evidence of instability in coefficients on the output gap. One interpretation of the Clark-McCracken (2006) finding is that, over the 1990-2003 period, there are only 14 nonoverlapping observations on the four-quarter ahead forecast error, and estimates of ratios of variances with 14 observations inevitably have a great deal of sampling variability.

3.3 Attempts to Resuscitate Multivariate Inflation Forecasts, 1999 - 2007

One response to the AO findings has been to redouble efforts to find reliable multivariate forecasting models for inflation. Some of these efforts used statistical tools, including dynamic factor models, other methods for using a large number of predictors, time-varying parameter multivariate models, and nonlinear time series models. Other efforts exploited restrictions arising from economics, in particular from no-arbitrage models of the term structure. Unfortunately, these efforts have failed to produce substantial and sustained improvements over the AO or UC-SV univariate benchmarks.

Many-predictor forecasts I: dynamic factor models. The plethora of activity indicators used in Philips curve forecasts indicates that there is no single, most natural measure; in fact, these indicators can all be thought of as different ways to measure underlying economic activity. This suggests modeling the activity variables jointly using a dynamic factor model (Geweke (1977), Sargent-Sims (1977)), estimating the common latent factor (underlying economic activity), and using that estimated factor as the activity variable in Phillips curve forecasts. Accordingly, Stock and Watson (1999) examined different activity measures as predictors of inflation, estimated (using principal components, as justified by Stock and Watson (2002)) as the common factor among 85 monthly indicators of economic activity, and also as the first principal component of 165 series including the activity indicators plus other series. In addition to using information in a very large number of series, Stock and Watson (2002) showed that principal components estimation of factors can be robust to certain types of instability in a dynamic factor model. Stock and Watson's (1999) empirical results indicated that these estimated factors registered improvements over the AR benchmark and over single-indicator Phillips curve specifications in both 1970-1983 and 1984-1996 subsamples.

A version of the Stock-Watson (1999) common factor, computed as the principal component of 85 monthly indicators of economic activity, has been published in real time since January 2001 as the Chicago Fed National Activity Index (CFNAI) (Federal Reserve Bank of Chicago, various). Hansen (2006) confirmed the main findings in Stock and Watson (1999) about the predictive content of these estimated factors for inflation, relative to a random walk forecast over a forecast period of 1960-2000.

Recent studies, however, have raised questions about the marginal value of Phillips curve forecasts based on estimated factors, such as the CFNAI, for the post-1985 data. As discussed above, Atkeson and Ohanian showed that the AO forecast outperformed CFNAI-based Phillips curves over the 1984-1999 period; this is consistent with Stock and Watson's (1999) findings because they used an AR benchmark. Banerjee and Marcellino (2006) also found that Phillips curve forecasts using estimated factors perform relatively poorly for CPI-all inflation over a 1991-2001 forecast period. On the other hand, for the longer sample of 1983-2007, Gavin and Kliesen (2008) found that recursive factor forecasts improve upon both the direct AR(12) (monthly data) and AO benchmarks (relative RMSEs are between .88 and .95). In a finding that is inconsistent with AO and with Figure 4, Gavin and Kliesen (2008) also found that the AR(12) model outperforms AO at the 12-month horizon for three of the four inflation series; presumably this surprising result is either a consequence of including earlier and later data than AO or indicates some subtle differences between using quarterly data (as in AO and in Figure 4) and monthly data.

Additional papers which use estimated factors to forecast inflation include Watson (2003), Bernanke, Bovin, and Elias (2005), Boivin and Ng (2005, 2006), D'Agostino and Giannone (2006), Giaccomini and White (2006). In an interesting meta-analysis, Eichmeier and Ziegler (2006) considered a total of 46 studies of inflation and/or output forecasts using estimated factors, including 19,819 relative RMSEs for inflation forecasts in the U.S. and other countries. They concluded that factor model forecasts tend to outperform small model forecasts in general, that the factor inflation forecasts generally improve over univariate benchmarks at all horizons, and that rolling forecasts generally outperform recursive forecasts. One difficulty with interpreting the Eichmeier-Ziegler (2006) findings, however, is that their unit of analysis is a reported relative RMSE, but the denominators (benchmark models) differ across studies; in the U.S. in particular, it matters whether the AR or AO benchmark is used because their relative performance changes over time.

Many-predictor forecasts II: Forecast combination, BMA, Bagging, and other methods. Other statistical methods for using a large number of predictors are available and have been tried for forecasting inflation. One approach is to use leading index methods, in essence a model selection methodology. In the earliest high-dimensional inflation forecasting exercise of which we are aware, Webb and Rowe (1995) constructed a leading index of CPI-core inflation formed using 7 of 30 potential inflation predictors, selected recursively by selecting indicators with a maximal correlation with one-year ahead inflation over a 48 month window, thereby allowing for time variation. This produced a leading index with time-varying composition that improved upon an AR benchmark over the 1970-1994 period, however Webb and Rowe (1995) did not provide sufficient information to assess the success of this index post-83.

A second approach is to use forecast combination methods, in which forecasts from multiple bivariate models (each using a different predictor, lag length, or specification) are combined. Combination forecasts have a long history of success in economic applications, see the review in Timmermann (2006), and are less susceptible to structural breaks in individual forecasting regressions because they in effect average out intercept shifts (Hendry and Clements (2002)). Papers that include combination forecasts (pooled over models) include Stock and Watson (1999, 2003), Clark and McCracken (2006), Canova (2007), Ang, Bekaert, and Wei (2007), and Inoue and Kilian (2008). Although combination forecasts often improve upon the individual forecasts, on average they do not substantially improve upon, and are often slightly worse than, factor-based forecasts.

A third approach is to apply model combination or model averaging tools, such as Bayesian Model Averaging (BMA), bagging, and LASSO, developed in the statistics literature for prediction using large data sets. Wright (2003) applied BMA to forecasts of CPI-all, CPI-core, PCE, and the GDP deflator, obtained from 30 predictors, and finds that BMA tended to improve upon simple averaging. Wright's (2003) relative RMSEs are considerably less than one during the 1987-2003 sample, however this appears to be a consequence of a poor denominator model (an AR(1) benchmark) rather than good numerator models. Inoue and Kilian (2008) considered CPI-all forecasts with 30 predictors using bagging, LASSO, factor-based forecasts (first principal component), along with BMA, pretest, shrinkage, and some other methods from the statistical literature. They reported a relative RMSE for the single-factor forecast of .80, relative to an AR(AIC) benchmark at the 12 month horizon over their 1983-2003 monthly sample. This is a surprisingly low value in light of the AO and subsequent literature, but (like Wright (2003)) this low relative RMSE appears to be driven by the use of the AR (instead of AO or UC-SV) benchmark and by the sample period, which includes 1983. Inoue and Kilian (2008) found negligible gains from using the large data set methods from the statistics literature: the single-factor forecasts beat almost all the other methods they examine, although in most cases the gains from the factor forecasts are slight (the relative RMSEs, relative to the single-factor model, range from .97, for LASSO, to 1.14).

A fourth approach is to model all series simultaneously using high-dimensional VARs with strong parameter restrictions. Bańbura, Gianonne, and Reichlin (2008) performed a pseudo out-of-sample experiment forecasting CPI-all inflation using Bayesian VARs with 3 to more than 100 variables. Over the 1970-2003 sample, they found substantial improvements of medium to large-dimensional VARs relative to very low-dimensional VARs, but their results are hard to relate to the others in this literature because they do not report univariate benchmarks and do not examine split samples.

Eichmeier and Ziegler's (2006) meta-analysis found that the alternative high-dimensional methods discussed in this section slightly outperform factor-based forecasts on average (here, averaging over both inflation and output forecasts for multiple countries), however as mentioned above an important caveat is that the denominators in Eichmeier-Ziegler's (2006) relative RMSEs differ across the studies included in their meta-analysis.

In summary, in some cases (some inflation series, some time periods, some horizons) it appears to be possible to make gains using many predictor methods, either factor estimates or other methods, however those gains are modest and not systematic and do not substantially overturn the negative AO results.

Nonlinear models. If the true time series model is nonlinear (that is, if the conditional mean of inflation given the predictors is a nonlinear function of the predictors) and if the predictors are persistent, then linear approximations to the conditional mean function can exhibit time variation. Thus one approach to the apparent time variation in the inflation-output relation is to consider nonlinear Phillips curves and nonlinear univariate time series models. Papers that do so include Dupasquier and Ricketts (1998), Moshiri and Cameron (2000), Tkacz (2000), Ascari and Marrocu (2003), and Marcellino (2008) (this omits the large literature on nonlinear Phillips curves that reports only in-sample measures of fit, not pseudo out-of-sample forecasts; see Dupasquier and Ricketts (1998) for additional references).

We read the conclusions of this literature as negative. Although this literature detects some nonlinearities using in-sample statistics, the benefits of nonlinear models for forecasting inflation appear to be negligible or negative. Marcellino (2008) examined univariate rolling and recursive CPI-all forecasts (over 1980-2004 and 1984-2004) using logistic smooth transition autoregressions and neural networks (a total of 28 nonlinear models) and found little or no improvement from using nonlinear models. He also documented that nonlinear models can produce outlier forecasts, presumably as a result of overfitting. Ascari and Marrocu (2003) and, using Canadian data, Moshiri and Cameron (2000) also provided negative conclusions.

Structural term structure models. Until now, this survey has concentrated on forecasts from the first two families of inflation forecasts (prices-only and Phillips curve forecasts). One way to construct inflation forecasts in the third family – forecasts based on forecasts of others – is to make inflation forecasts using the term structure of interest rates as in (11). Starting with Barsky (1987), Mishkin (1990a, 1990b, 1991) and Jorion and Mishkin (1991), there is a large literature that studies such forecasting regressions. The findings of this literature, which is reviewed in Stock and Watson (2003), is generally negative, that is, term spread forecasts do not improve over Phillips curve forecasts in the pre-1983 period, and they do not improve over a good univariate benchmark in the post-1984 period.

This poor performance of first-generation term spread forecasts is evident in Figure 5, which plots the rolling RMSE of the pseudo out-of-sample forecast based on the recursively estimated term spread model (11), along with the RMSEs of the AR(AIC) and AO univariate benchmarks. Term spreads are typically one of the variables included in the forecast comparison studies discussed above (Fisher, Liu, and Zhou (2002), Canova (2007), and Ang, Bekaert, and Wei (2007)) and these recent studies also reach the same negative conclusion about unrestricted term spread forecasting regressions, either as the sole predictor or when used in addition to an activity indicator.

Recent attempts to forecast inflation using term spreads have focused on employing economic theory, in the form of no-arbitrage models of the term structure, to improve upon the reduced-form regressions such as (11). Most of this literature uses full-sample estimation and measures of fit; see Ang, Bekaert, and Wei (2007), DeWachter and Lyrio (2006), and Berardi (2007) for references. The one paper of which we are aware that produces pseudo out-of-sample forecasts of inflation is Ang, Bekaert, and Wei (2007), who considered 4-quarter ahead forecasts of CPI-all, CPI-core, CPI-ex housing, and PCE inflation using two no-arbitrage term structure models, one with constant coefficients and one with regime switches. Neither model forecasted well, with relative RMSEs (relative to the ARMA(1,1)) ranging from 1.05 to 1.59 for the four inflation series and two forecast periods (1985-2002 and 1995-2002).

We are not aware of any papers that evaluate the performance of inflation forecasts backed out of the TIPS yield curve, and such a study would be of considerable interest.

Forecasting using the cross-section of prices. Another approach is to try to exploit information in the cross section of inflation indexes (percentage growth of sectoral or commodity group price indexes) for forecasting headline inflation. Hendry and Hubrich (2007) used four high-level subaggregates to forecast CPI-all inflation. They explored several approaches, including combining disaggregated univariate forecasts and using factor models. They found that exploiting the disaggregated information directly to forecast the aggregate improves modestly over an AR benchmark in their pseudo out-of-sample forecasts of CPI-all over 1970-1983 but negligibly over the AO benchmark over 1984-2004 at the 12-month horizon (no single method for using the subaggregates works best). If one uses heavily disaggregated inflation measures, then some method must be used to control parameter proliferation, such as the methods used in the many- predictor applications discussed above. In this vein, Hubrich (2005) presented negative results concerning the aggregation of components forecasts for forecasting the Harmonized Index of Consumer Prices (HICP) in Europe. Reis and Watson (2007) estimated a dynamic factor using a large cross-section of inflation rates but did not conduct any pseudo out-of-sample forecasting.

Rethinking the notion of core inflation suggests different approaches to using the inflation subaggregates. Building on the work of Bryan and Cecchetti (1994), Bryan, Cecchetti and Wiggins (1997) suggested constructing core as a trimmed mean of the cross-section of prices, where the trimming was chosen to provide the best (in-sample) estimate of underlying trend inflation (measured variously as a 24- to 60-month centered moving average). Smith (2004) investigated the pseudo out-of-sample forecasting properties of trimmed mean and median measures of core inflation (forecast period 1990-2000). Smith (2004) reported that the inflation forecasts based on weighted-median core measures have relative RMSEs of .85 for CPI-all and .80 for PCE-all, relative to an exponentially-declining AR benchmark (she does not consider the AO benchmark), although oddly she found that the trimmed mean performed worse than the benchmark.

4. A Quantitative Recapitulation: Changes in Univariate and Phillips Curve Inflation Forecast Models

This section undertakes a quantitative summary of the literature review in the previous section by considering the pseudo out-of-sample performance of a range of inflation forecasting models using a single consistent data set. The focus is on activity-based inflation forecasting models, although some other predictors are considered. We do not consider survey forecasts or inflation expectations implicit in the TIPS yield curve. As Ang, Bekaert and Wei (2007) showed, median survey forecasts perform quite well and thus are useful for policy work; but our task is to understand how to improve upon forecasting systems, not to delegate this work to others.

4.1 Forecasting Models

Univariate models. The univariate models consist of the AR(AIC), AO, and UC-SV models in Section 2.2, plus direct AR models with a fixed lag length of 4 lags (AR(4)) and Bayes Information Criterion lag selection (AR(BIC)), iterated AR(AIC), AR(BIC), and AR(4) models of $\Delta\pi_t$, AR(24) models (imposing the Gordon (1990) step function lag restriction and the unit root in π_t), and a MA(1) model. AIC and BIC model selection used a minimum of 0 and a maximum of 6 lags. Both rolling and recursively estimated versions of these models are considered. In addition some fixed-parameter models were considered: MA(1) models with fixed MA coefficients of 0.25 and 0.65 (these are taken from Stock and Watson (2007)), and the monthly MA model estimated by Nelson and Schwert (1977), temporally aggregated to quarterly data (see Stock and Watson (2007), equation (7)).

Triangle and TV-NAIRU models. Four triangle models are considered: specification (9), the results of which were examined in Section 3; specification (9) without the supply shock variables (relative price of food and energy, import prices, and Nixon dummies); and these two versions with a time-varying NAIRU. The time-varying NAIRU specification introduces random walk intercept drift into (9) following Staiger, Stock, and Watson (1997) and Gordon (1998), specifically, the TV-NAIRU version of (9) is

$$\pi_{t+1} = \alpha^G(L)\pi_t + \beta(L)(u_{t+1} - \bar{u}_t) + \gamma(L)z_t + v_{t+1}, \tag{12}$$

$$\bar{u}_{t+1} = \bar{u}_t + \eta_{t+1}, \tag{13}$$

where v_t and η_t are modeled as independent i.i.d. normal errors with relative variance σ_η^2/σ_v^2 (recall that $\alpha^G(1) = 1$ so a unit root is imposed in (12)). For the calculations here, σ_η^2/σ_v^2 is set to 0.1.

ADL Phillips curve models. The ADL Phillips curve models are direct models of the form,

$$\pi^h_{t+h} - \pi_t = \mu^h + \alpha^h(\mathrm{L})\Delta\pi_t + \beta^h(\mathrm{L})x_t + v^h_{t+h}, \tag{14}$$

where x_t is an activity variable (an output gap, growth rate, or level, depending on the series). Lag lengths for π_t and x_t are chosen separately by AIC or BIC.

ADL models using other predictors. ADL models are specified and estimated the same way as the ADL Phillips curve model (14), but the activity variable x_t is replaced by another predictor (term spreads, core inflation, etc.).

Combination forecasts. Let $\{\hat{\pi}^h_{i,t+h|t}\}$ denote a set of n forecasts of π^h_{t+h}, made using data through date t. Combined forecasts are computed in three ways: by "averaging" (mean, median, trimmed mean); by a MSE-based weighting scheme; or by using the forecast that is most recently best. The MSE-based combined forecasts f_t are of the form $f_t = \sum_{i=1}^{n} \lambda_{it}\hat{\pi}^h_{i,t+h|t}$, where six methods are used to compute the weights $\{\lambda_{it}\}$:

$$\text{(A) } \lambda_{it} = (1/\hat{\sigma}^2_{it})/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt}), \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} 0.9^j e^2_{i,t-j} \tag{15}$$

$$\text{(B) } \lambda_{it} = (1/\hat{\sigma}^2_{it})/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt}), \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} 0.95^j e^2_{i,t-j} \tag{16}$$

$$\text{(C) } \lambda_{it} = (1/\hat{\sigma}^2_{it})/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt}), \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} e^2_{i,t-j} \tag{17}$$

$$\text{(D) } \lambda_{it} = (1/\hat{\sigma}^2_{it})^2/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt})^2, \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} 0.9^j e^2_{i,t-j} \tag{18}$$

$$\text{(E) } \lambda_{it} = (1/\hat{\sigma}^2_{it})^2/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt})^2, \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} 0.95^j e^2_{i,t-j} \tag{19}$$

$$\text{(F) } \lambda_{it} = (1/\hat{\sigma}^2_{it})^2/\sum_{j=1}^{n}(1/\hat{\sigma}^2_{jt})^2, \text{ with } \hat{\sigma}^2_{it} = \sum_{j=0}^{39} e^2_{i,t-j} \tag{20}$$

where $e_{i,t} = \pi_t^h - \hat{\pi}_{i,t|t-h}^h$ is the pseudo out-of-sample forecast error for the i^{th} h-step ahead forecast and the MSEs are estimated using a 10 year rolling window and, for methods (A), (B), (D), and (E), discounting.

Inverse MSE weighting (based on population MSEs) is optimal if the individual forecasts are uncorrelated, and methods (A) – (C) are different ways to implement inverse MSE weighting. Methods (D) – (F) give greater weight to better-performing forecasts than does inverse MSE weighting. Optimal forecast combination using regression weights as in Bates and Granger (1969) is not feasible with the large number of forecasts under consideration. As Timmerman (2006) notes, equal-weighting (mean combining) often performs well and Timmerman (2006) provides a discussion of when mean combining is optimal under squared error loss.

The "recent best" forecasts are the forecasts from the model that has the lowest cumulative MSE over the past 4 (or, alternatively, 8) quarters.

Finally, in an attempt to exploit the time-varying virtues of the UC-SV and triangle models, the recent best is computed using just the UC-SV and triangle model (with time varying NAIRU and z variables).

The complete description of models considered is given in the notes to Table 1.

4.2 Results

The pseudo out-of-sample forecasting performance of each forecasting procedure (model and combining method) is summarized in tabular and graphical form.

The tabular summary consists of relative RMSEs of four-quarter ahead inflation forecasts, relative to the UC-SV benchmark, for six forecast periods; these are tabulated in Tables 1-5 for the five inflation series. The minimum model estimation sample was 40 quarters, and blank cells in the table indicate that for at least one quarter in the forecast period there were fewer than 40 observations for estimation.

The graphical summary of each model's performance is given is Figures 6-11 for the five inflation series. Figure 6 presents the rolling RMSE for the UC-SV benchmark model for the five inflation series, and figures 7-11 show the RMSE of the various forecasts relative to the UC-SV benchmark. Part (a) of Figure 7-11 displays the rolling relative RMSE for the prototype models, where the rolling MSE for each model is computed using (2). Parts (b) – (d) plot the ratio of the rolling RMSE for each category of models, relative to the UC-SV model: univariate models in part (b), Phillips curve forecasts (ADL and triangle) in part (c), and combination forecasts in part (d). In each of parts (b) – (d), leading case models or forecasts are highlighted.

These tables and figures present a great many numbers and facts. Inspection of these results leads us to the following conclusions:

1. There is strong evidence of time variation in the inflation process, in predictive relations, and in Phillips curve forecasts. This is consistent with the literature review, in which different authors reach different conclusions about Phillips curve forecasts depending on the sample period.

2. The performance of Phillips curve forecasts, relative to the UC-SV benchmark, has a considerable systematic component (part (c) of the figures): during periods in which the ADL-*u* prototype model is forecasting well, reasonably good forecasts can be made using a host of other activity variables. In this sense, the choice of activity variable is secondary to the choice of whether one should use an activity-based forecast.

3. Among the univariate models considered here, with and without time-varying coefficients, there is no single model, or combination of univariate models, that has uniformly better performance than the UC-SV model. Of the 82 cells in Table 1 that give relative RMSEs for univariate CPI-all forecasts in different subsamples, only 4 have RMSEs less than 1.00, the lowest of which is .95, and these instances are for fixed-parameter MA models in the 1960s and in 1985-1992. Similar results are found for the other four inflation measures. In some cases, the AR models do quite poorly relative to the UC-SV, for example in the 2001-2007 sample the AR forecasts of CPI-all and PCE-all inflation have very large relative MSEs (typically exceeding 1.3). In general, the performance of the AR model, relative to the UC-SV (or AO)

benchmarks, is series- and period-specific. This reinforces the remarks in the literature review about the importance of using a consistently good benchmark: in some cases, apparently good performance of a predictor for a particular inflation series over a particular period can be the result of a large denominator, not a small numerator.

4. Although some of the Phillips curve forecasts improved substantially on the UC-SV model during the 1970s and early 1980s, there is little or no evidence that it is possible to improve upon the UC-SV model on average over the full later samples. This said, there are notable periods and inflation measures for which Phillips curve models do quite well. The triangle model does particularly well during the high unemployment disinflation of the early 1980s for all five inflation measures. For CPI-all, PCE-all, and the GDP deflator, it also does well in the late 1990s, while for CPI-core and PCE-core the triangle model does well emerging from the 1990 recession. This episodically good behavior of the triangle model, and of Phillips-curve forecasts more generally, provides a more nuanced interpretation of the history of inflation forecasting models than the blanket Atkeson-Ohanian (2001) conclusion that "none of the NAIRU forecasts is more accurate than the naïve forecast" (AO abstract).

5. Forecast combining, which has worked so well in other applications (Timmerman (2006)), generally improves upon the individual Phillips-curve forecasts, however the combination forecasts generally do not improve upon the UC-SV benchmark in the post-1993 periods. For example, for PCI-all, the mean-combined ADL-activity forecasts have a relative RMSE of .86 over 1977-1982 and .96 over 1985-1992; these mean-combined forecasts compare favorably to individual activity forecasts and to the triangle model. In the later periods, however, the forecasts being combined have relative RMSEs exceeding one and combining them works no magic and fails to improve upon the UC-SV benchmark. Although some of the combining methods improve upon equal weighting, these improvements are neither large nor systematic.

In addition, consistent with the results in Fisher, Liu, and Zhou (2002), factor forecasts (using the CFNAI) fail to improve upon the UC-SV benchmark on average over the later periods. These results are consistent with the lack of success found by attempts in the literature (before and after Atkeson-Ohanian (2001)) to obtain large gains by using many predictors and/or model combinations.

6. Forecasts using predictors other than activities variables, while not the main focus of this paper, generally fare poorly, especially during the post-1992 period. For example, the relative RMSE of the mean-combined forecast using non-activity variables is at least 0.99 in each subsample in Tables 1-5 for forecasts of all five activity variables. We did not find substantial improvements using alternative measures of core (median and trimmed mean CPI) as predictors.[8] Although our treatment of non-activity variables is not comprehensive, these results largely mirror those in the literature.

5. When Were Phillips Curve Forecasts Successful, and Why?

If the relative performance of Phillips curve forecasts has been episodic, is it possible to characterize what makes for a successful or unsuccessful episode?

The relative RMSEs of the triangle and ADL-*u* model forecasts for headline inflation (CPI-all, PCE-all, and GDP deflator), relative to the UC-SV benchmark, are plotted in Figure 12, along with the unemployment rate. One immediately evident feature is that the triangle model has substantially larger swings in performance than the ADL-*u* model. This said, the dates of relative success of these Phillips curve forecasts bear considerable similarities across models and inflation series. Both models perform

[8] The exceptions are median and trimmed mean rolling forecasts for CPI-core and GDP inflation for the 2001-2007 sample. However, the relative RMSEs exceed one (typically, they exceed 1.15) for other inflation series, other samples, and for recursive forecasts, and we view these isolated cases as outliers. Most likely, the difference between our negative results for median CPI and Smith's (2004) positive results over 1990-2000 are differences in the benchmark model, in her case a univariate AR with exponential lag structure imposed.

relatively well for all series in the early 1980s, in the early 1990s, and around 1999; both models perform relatively poorly around 1985 and in the mid-1990s. These dates of relative success correspond approximately to dates of different phases of business cycles.

Figure 13 is a scatterplot of the quarterly relative RMSE for the triangle (panel (a)) and ADL-*u* (panel (b)) prototype models, vs. the two-sided unemployment gap (the two-sided gap was computed using the two-sided version of the lowpass filter described in Section 2.3), along with kernel regression estimates. The most striking feature of these scatterplots is that the relative RMSE is minimized, and is considerably less than one, at the extremes values of the unemployment gap, both positive and negative. (The kernel regression estimator exceeds one at the most negative values of the unemployment gap for the triangle model in panel (a), but there are few observations in that tail.) When the unemployment rate is near the NAIRU (as measured by the lowpass filter), both Phillips curve models do worse than the UC-SV model. But when the unemployment gap exceeds 1.5 in absolute value, the Phillips curve forecasts improve substantially upon the UC-SV model. Because the gap is largest in absolute value around turning points, this finding can be restated that the Phillips curve models provide improvements over the UC-SV model around turning points, but not during normal times.

Figure 14 takes a different perspective on the link between performance of the Phillips curve forecasts and the state of the economy, by plotting the relative RMSE against the four-quarter change in the unemployment rate. The relative improvements in the Phillips curve forecasts do not seem as closely tied to the change in the unemployment rate as to the gap (the apparent improvement at very high changes of the unemployment rate is evident in only a few observations)

Figures 15-17 examine a conjecture in the literature, that Phillips curve forecasts are relatively more successful when inflation is volatile, by plotting the rolling relative RMSE against the 4-quarter change in 4-quarter inflation. These figures provide only limited support for this conjecture, as do similar scatterplots (not provided here) of the rolling RMSE against the UC-SV estimate of the instantaneous variance of the first difference of the inflation rate. It is true that the quarters of worst performance occur when in fact inflation is changing very little but, other than for GDP deflator, the episodes of best performance do not seem to be associated with large changes in inflation.

As presented here, these patterns cannot yet be used to improve forecasts: the sharpest patterns are ones that appear using two-sided gaps. Still, these results are suggestive, and they seem to suggest a route toward developing a response to the AO conundrum in which real economic activity seems to play little or any role in inflation forecasting. The results here suggest that, if times are quiet – if the unemployment rate is close to the NAIRU – then in fact one is better off using a univariate forecast than introducing additional estimation error by making a multivariate forecast. But if the economy is near a turning point – if the unemployment rate is far from the NAIRU – then knowledge of that large unemployment gap would be useful for inflation forecasting. Further work is needed to turn these observations into formal empirical results.

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Data Appendix

The definitions and sources of the series used in this analysis are summarized in the following table. The "trans" column indicates the transformation applied to the series: logarithm (ln), first difference of logarithm ((1−L)ln), accumulation ($(1-L)^{-1}$), or no transformation (level). When the original series is monthly, quarterly data are constructed as the average of the monthly values in the quarter before any other transformation. Sources are Federal Reserve Bank of St. Louis FRED database (F), the Bureau of Economic Analysis (BEA), and other Federal Reserve banks as indicated.

Short name	Trans	Definition	Mnemonic (Source)
		Inflation series	
CPI-all	(1-L)ln	CPI, all items	CPIAUCSL (F)
CPI-core	(1-L)ln	CPI less food and energy	CPILFESL (F)
PCE-all	(1-L)ln	PCE deflator, all items	PCECTPI (F)
PCE-core	(1-L)ln	PCE deflator, less food and energy	JCXFE (F)
GDP deflator	(1-L)ln	GDP deflator	GDPCTPI (F)
		Predictors	
UR	level	Unemployment rate, total civilian 16+	UNRATE (F)
GDP	ln	Real GDP	GDPC96 (F)
IP	ln	Index of Industrial Production (total)	INDPRO (F)
EMP	ln	Nonagricultural civilian employment (total)	PAYEMS (F)
CapU	level	Capacity utilization rate	TCU (F)
HPerm	ln	Housing permits (starts)	PERMIT (F)
CFNAI	$(1-L)^{-1}$	Chicago Fed National Activity Index (accumulated)	FRB-Chicago
UR-5wk	level	Unemployment rate for unemployed < 5 week	UEMPLT5(F) /CLF160V(F)
AHE	(1-L)ln	Average hourly earnings	AHETPI (F)
Real AHE	(1-L)ln	real average hourly earnings	AHETPI (F)/ GDPCTPI (F)
Labor Share	ln	labor share	AHETPI (F)/ GDPCTPI (F)
CPI-Median	level	Cleveland Fed median CPI inflation "Original" CPI-Median through 2007:7; "Revised" CPI-Median after 2007:7)	FRB-Cleveland
CPI-TrMn	level	Cleveland Fed trimmed mean CPI inflation ("Original" CPI-Trimmed Mean through 2007:7; "Revised" CPI-Trimmed Mean after 2007:7)	FRB-Cleveland
ExRate	level	trade-weighted exchange rate	TWEXMMTH (F)
TB_sp	level	1 Year Treasury bond rate minus 3 Month Treasury bill rate (at annual rate)	Fed Board of Governors
RPFE	(1−L)ln	Relative Price of Food and Energy	PCECTPI (F)/ JCXFE (F)
RPImp	(1−L)ln	Relative Price of Imports	B021RG3(BEA)/ GDPCTPI(F)
Price Control Variable 1	level	0.8 for 1971:III≤ t≤1972:II, 0 otherwise	Gordon (1982)
Price Control Variable 2	level	−0.4 for t = 1974:2 or 1975:I, −1.6 for 1974:III≤ t≤1974:IV, 0 otherwise.	Gordon (1982)

Table 1
RMSEs for Inflation Forecasting Models by Sub-Period, Relative to UC-SV model: CPI-all

Forecast period	**1960Q1 – 1967Q4**	**1968Q1 – 1976Q4**	**1977Q1 - 1984Q4**	**1985Q1 – 1992Q4**	**1993Q1 – 2000Q4**	**2001Q1 – 2007Q4**
No. observations	32	36	32	32	32	25
Root MSE of UC-SV forecast	0.82	1.99	2.35	1.39	0.68	1.05
Forecasting model and relative RMSEs						
Univariate forecasts						
UC-SV	1.00	1.00	1.00	1.00	1.00	1.00
AR(AIC)_rec	.	1.09	1.05	1.12	1.03	1.39
AR(AIC)_iter_rec	.	1.06	1.00	1.12	1.02	1.43
AR(BIC)_rec	.	1.10	1.03	1.10	1.03	1.37
AO	1.01	1.23	1.12	1.00	1.10	1.14
MA(1)_rec	.	1.07	1.01	1.07	1.03	1.37
AR(4)_rec	.	1.12	1.02	1.13	1.02	1.42
AR(AIC)_roll	.	1.10	1.09	1.03	1.21	1.30
AR(AIC)_iter_roll	.	1.08	1.03	1.15	1.11	1.37
AR(BIC)_roll	.	1.09	1.08	1.02	1.14	1.32
AR(4)_roll	.	1.19	1.06	1.07	1.17	1.29
AR(24)_iter	.	.	.	1.30	1.04	1.33
AR(24)_iter_nocon	.	.	1.18	1.25	1.00	1.32
MA(1)_roll	.	1.04	1.02	1.07	1.05	1.13
MA(2) - NS	0.98	1.14	1.13	0.95	1.01	1.12
MA(1), θ=.25	1.12	1.01	1.00	1.11	1.06	1.52
MA(1), θ=.65	0.97	1.15	1.12	0.96	1.03	1.12
Single-predictor ADL forecasts						
UR(Level)_AIC_rec	.	0.96	0.92	0.98	1.28	1.36
UR(Dif)_AIC_rec	.	0.93	0.94	1.04	1.22	1.39
UR(1sdBP)_AIC_rec	.	0.96	0.95	1.00	1.22	1.38
GDP(Dif)_AIC_rec	.	0.88	0.93	1.00	1.09	1.36
GDP(1sdBP)_AIC_rec	.	1.03	0.90	1.00	1.08	1.34
IP(Dif)_AIC_rec	.	0.89	0.93	1.02	1.22	1.43
IP(1sdBP)_AIC_rec	.	0.95	0.93	1.01	1.17	1.40
Emp(Dif)_AIC_rec	.	0.93	0.86	1.01	1.06	1.53
Emp(1sdBP)_AIC_rec	.	0.95	0.87	1.02	1.14	1.49
CapU(Level)_AIC_rec	.	.	.	1.03	1.39	1.56
CapU((Dif)_AIC_rec	.	.	.	1.03	1.30	1.45
CapU(1sdBP)_AIC_rec	.	.	.	0.99	1.21	1.35
HPerm(Level)_AIC_rec	.	.	0.79	1.12	1.14	1.75
HPerm((Dif)_AIC_rec	.	.	0.91	1.29	0.97	1.67
HPerm(1sdBP)_AIC_rec	.	.	0.90	1.02	1.08	1.37
CFNAI(Dif)_AIC_rec	.	.	.	1.01	1.21	1.57
CFNAI(1sdBP)_AIC_rec	.	.	.	0.98	1.18	1.42
UR_5wk(Level)_AIC_rec	.	1.06	0.93	1.05	1.73	1.38
UR_5wk(Dif)_AIC_rec	.	0.94	0.91	1.07	1.34	1.40
UR_5wk(1sdBP)_AIC_rec	.	0.97	0.90	1.06	1.34	1.31
AHE(Dif)_AIC_rec	.	.	1.10	1.19	1.03	1.48
AHE(1sdBP)_AIC_rec	.	.	1.12	1.20	1.01	1.46
RealAHE(Dif)_AIC_rec	.	.	1.10	1.19	1.03	1.48
RealAHE(1sdBP)_AIC_rec	.	.	1.12	1.20	1.01	1.46
LaborShare(Level)_AIC_rec	.	1.06	1.02	1.21	1.76	1.44
LaborShare(Dif)_AIC_rec	.	1.08	1.03	1.12	1.06	1.36
ULaborShare(1sdBP)_AIC_rec	.	1.10	1.01	1.09	1.30	1.36
CPI_Med(Level)_AIC_rec	.	.	.	1.34	1.39	1.54
CPI_Med(Dif)_AIC_rec	.	.	.	1.20	1.11	1.45
CPI_TrMn(Level)_AIC_rec	.	.	.	1.35	1.46	1.47
CPI_TrMn(Dif)_AIC_rec	.	.	.	1.10	1.07	1.45
ExRate(Dif)_AIC_rec	.	.	.	1.43	1.26	1.21
ExRate(1sdBP)_AIC_rec	.	.	.	1.82	1.04	1.28
tb_spr_AIC_rec	.	1.10	1.05	1.21	1.24	1.56
UR(Level)_AIC_roll	.	1.20	1.13	0.99	1.32	1.30
UR(Dif)_AIC_roll	.	1.07	1.00	1.04	1.23	1.28

UR(1sdBP)_AIC_roll	.	1.17	1.07	1.03	1.28	1.30
GDP(Dif)_AIC_roll	.	1.01	1.01	0.98	1.36	1.25
GDP(1sdBP)_AIC_roll	.	1.10	0.91	1.00	1.25	1.25
IP(Dif)_AIC_roll	.	0.95	0.99	1.05	1.26	1.33
IP(1sdBP)_AIC_roll	.	1.07	1.00	1.05	1.30	1.28
Emp(Dif)_AIC_roll	.	1.06	0.97	0.99	1.23	1.24
Emp(1sdBP)_AIC_roll	.	1.19	0.91	1.02	1.26	1.31
CapU(Level)_AIC_roll	.	.	.	0.98	1.38	1.33
CapU((Dif)_AIC_roll	.	.	.	1.02	1.27	1.29
CapU(1sdBP)_AIC_roll	.	.	.	0.97	1.35	1.22
HPerm(Level)_AIC_roll	.	.	0.75	1.27	1.23	1.41
HPerm((Dif)_AIC_roll	.	.	1.14	1.16	1.05	1.55
HPerm(1sdBP)_AIC_roll	.	.	0.94	1.21	1.20	1.32
CFNAI(Dif)_AIC_roll	.	.	.	0.97	1.28	1.25
CFNAI(1sdBP)_AIC_roll	.	.	.	1.02	1.28	1.25
UR_5wk(Level)_AIC_roll	.	1.19	0.93	1.18	1.60	1.34
UR_5wk(Dif)_AIC_roll	.	1.03	0.97	1.03	1.41	1.27
UR_5wk(1sdBP)_AIC_roll	.	1.08	0.85	1.06	1.45	1.31
AHE(Dif)_AIC_roll	.	.	1.10	1.08	1.38	1.24
AHE(1sdBP)_AIC_roll	.	.	1.12	1.07	1.33	1.19
RealAHE(Dif)_AIC_roll	.	.	1.10	1.08	1.38	1.24
RealAHE(1sdBP)_AIC_roll	.	.	1.12	1.07	1.33	1.19
LaborShare(Level)_AIC_roll	.	1.15	1.02	1.12	1.31	1.32
LaborShare(Dif)_AIC_roll	.	1.13	1.09	1.02	1.63	1.32
ULaborShare(1sdBP)_AIC_roll	.	1.18	1.09	1.04	1.31	1.30
CPI_Med(Level)_AIC_roll	.	.	.	1.15	1.34	1.18
CPI_Med(Dif)_AIC_roll	.	.	.	1.01	1.15	1.29
CPI_TrMn(Level)_AIC_roll	.	.	.	1.12	1.38	1.28
CPI_TrMn(Dif)_AIC_roll	.	.	.	1.05	1.15	1.31
ExRate(Dif)_AIC_roll	.	.	.	1.53	1.20	1.28
ExRate(1sdBP)_AIC_roll	.	.	.	1.91	1.16	1.34
tb_spr_AIC_roll	.	1.13	1.23	1.33	1.42	1.37
UR(Level)_BIC_rec	.	0.92	0.91	0.98	1.28	1.36
UR(Dif)_BIC_rec	.	0.88	0.94	1.06	1.16	1.35
UR(1sdBP)_BIC_rec	.	0.91	0.93	0.96	1.17	1.35
GDP(Dif)_BIC_rec	.	0.95	0.99	1.00	1.09	1.36
GDP(1sdBP)_BIC_rec	.	0.99	0.95	0.99	1.05	1.33
IP(Dif)_BIC_rec	.	0.90	0.97	1.03	1.20	1.41
IP(1sdBP)_BIC_rec	.	0.95	0.99	1.00	1.11	1.39
Emp(Dif)_BIC_rec	.	0.90	0.92	0.98	1.05	1.51
Emp(1sdBP)_BIC_rec	.	0.93	0.93	0.99	1.09	1.45
CapU(Level)_BIC_rec	.	.	.	1.02	1.29	1.56
CapU((Dif)_BIC_rec	.	.	.	1.07	1.30	1.46
CapU(1sdBP)_BIC_rec	.	.	.	0.97	1.17	1.30
HPerm(Level)_BIC_rec	.	.	0.82	1.06	1.14	1.75
HPerm((Dif)_BIC_rec	.	.	1.05	1.32	0.97	1.65
HPerm(1sdBP)_BIC_rec	.	.	0.93	1.02	1.08	1.37
CFNAI(Dif)_BIC_rec	.	.	.	0.92	1.18	1.44
CFNAI(1sdBP)_BIC_rec	.	.	.	0.95	1.18	1.42
UR_5wk(Level)_BIC_rec	.	1.03	0.92	1.13	1.62	1.48
UR_5wk(Dif)_BIC_rec	.	0.94	0.96	1.15	1.17	1.49
UR_5wk(1sdBP)_BIC_rec	.	0.94	0.88	1.11	1.27	1.34
AHE(Dif)_BIC_rec	.	.	1.08	1.19	1.10	1.42
AHE(1sdBP)_BIC_rec	.	.	1.10	1.23	1.05	1.37
RealAHE(Dif)_BIC_rec	.	.	1.08	1.19	1.10	1.42
RealAHE(1sdBP)_BIC_rec	.	.	1.10	1.23	1.05	1.37
LaborShare(Level)_BIC_rec	.	1.02	0.99	1.20	1.61	1.44
LaborShare(Dif)_BIC_rec	.	1.08	1.03	1.13	1.07	1.36
ULaborShare(1sdBP)_BIC_rec	.	1.07	0.97	1.13	1.30	1.40
CPI_Med(Level)_BIC_rec	.	.	.	1.22	1.44	1.53
CPI_Med(Dif)_BIC_rec	.	.	.	1.21	1.14	1.51
CPI_TrMn(Level)_BIC_rec	.	.	.	1.23	1.43	1.49
CPI_TrMn(Dif)_BIC_rec	.	.	.	1.10	1.07	1.49
ExRate(Dif)_BIC_rec	.	.	.	1.53	1.19	1.32
ExRate(1sdBP)_BIC_rec	.	.	.	1.87	1.09	1.28
tb_spr_BIC_rec	.	1.09	1.09	1.17	1.06	1.40

UR(Level)_BIC_roll	.	1.16	1.05	0.99	1.33	1.31
UR(Dif)_BIC_roll	.	0.99	0.99	0.99	1.19	1.35
UR(1sdBP)_BIC_roll	.	1.14	0.98	0.96	1.24	1.28
GDP(Dif)_BIC_roll	.	0.96	1.01	0.98	1.28	1.31
GDP(1sdBP)_BIC_roll	.	1.04	0.92	0.98	1.18	1.30
IP(Dif)_BIC_roll	.	0.99	1.01	1.05	1.24	1.29
IP(1sdBP)_BIC_roll	.	1.08	0.96	0.97	1.31	1.32
Emp(Dif)_BIC_roll	.	1.06	0.95	1.02	1.22	1.27
Emp(1sdBP)_BIC_roll	.	1.12	0.92	1.05	1.24	1.27
CapU(Level)_BIC_roll	.	.	.	0.97	1.30	1.30
CapU((Dif)_BIC_roll	.	.	.	1.01	1.26	1.27
CapU(1sdBP)_BIC_roll	.	.	.	0.93	1.23	1.25
HPerm(Level)_BIC_roll	.	.	0.77	1.25	1.22	1.43
HPerm((Dif)_BIC_roll	.	.	1.09	1.21	1.06	1.36
HPerm(1sdBP)_BIC_roll	.	.	0.92	1.21	1.19	1.33
CFNAI(Dif)_BIC_roll	.	.	.	0.96	1.26	1.32
CFNAI(1sdBP)_BIC_roll	.	.	.	1.02	1.22	1.24
UR_5wk(Level)_BIC_roll	.	1.18	0.95	1.19	1.35	1.43
UR_5wk(Dif)_BIC_roll	.	0.96	0.99	1.10	1.19	1.35
UR_5wk(1sdBP)_BIC_roll	.	1.04	0.93	1.09	1.32	1.37
AHE(Dif)_BIC_roll	.	.	1.09	1.03	1.19	1.38
AHE(1sdBP)_BIC_roll	.	.	1.10	1.16	1.12	1.23
RealAHE(Dif)_BIC_roll	.	.	1.09	1.03	1.19	1.38
RealAHE(1sdBP)_BIC_roll	.	.	1.10	1.16	1.12	1.23
LaborShare(Level)_BIC_roll	.	1.09	1.05	1.05	1.23	1.33
LaborShare(Dif)_BIC_roll	.	1.12	1.10	1.11	1.17	1.38
ULaborShare(1sdBP)_BIC_roll	.	1.11	1.06	1.02	1.29	1.36
CPI_Med(Level)_BIC_roll	.	.	.	1.07	1.28	1.24
CPI_Med(Dif)_BIC_roll	.	.	.	1.04	1.15	1.30
CPI_TrMn(Level)_BIC_roll	.	.	.	1.02	1.28	1.30
CPI_TrMn(Dif)_BIC_roll	.	.	.	1.07	1.14	1.36
ExRate(Dif)_BIC_roll	.	.	.	1.56	1.13	1.34
ExRate(1sdBP)_BIC_roll	.	.	.	1.95	1.11	1.36
tb_spr_BIC_roll	.	1.16	1.25	1.32	1.22	1.38
Triangle model forecasts						
Triangle Constant NAIRU	.	.	0.94	1.11	1.14	1.11
Triangle TV NAIRU	.	.	0.95	1.15	1.07	1.16
Triangle Constant NAIRU (no z)	.	.	1.02	1.19	1.34	1.34
Triangle TV NAIRU (no z)	.	.	1.12	1.23	1.10	1.52
Combination forecasts						
Activity Median Combining	.	0.96	0.88	0.96	1.13	1.30
Activity Mean Combining	.	0.97	0.86	0.96	1.11	1.30
Activity Tr. Mean Combining	.	0.97	0.87	0.96	1.11	1.30
Activity MSE(A) Combining	.	.	0.86	0.97	1.12	1.31
Activity MSE(B) Combining	.	.	0.86	0.96	1.12	1.31
Activity MSE(3 Combining	.	.	0.86	0.96	1.11	1.30
Activity MSE(D) Combining	.	.	0.86	0.98	1.14	1.33
Activity MSE(E) Combining	.	.	0.87	0.97	1.13	1.32
Activity MSE(F) Combining	.	.	0.87	0.96	1.12	1.30
Activity Rec. Best(4q) Combining	.	1.12	0.74	0.99	1.38	1.56
Activity Rec. Best(8q) Combining	.	1.07	0.90	1.22	1.48	1.36
OtherADL Median Combining	.	1.07	1.06	1.03	1.11	1.29
OtherADL Mean Combining	.	1.08	1.01	1.06	1.09	1.30
OtherADL Tr. Mean Combining	.	1.08	1.03	1.05	1.09	1.31
OtherADL MSE(A) Combining	.	.	0.98	1.07	1.11	1.30
OtherADL MSE(B) Combining	.	.	0.98	1.07	1.12	1.30
OtherADL MSE(C) Combining	.	.	0.99	1.07	1.12	1.30
OtherADL MSE(D) Combining	.	.	0.98	1.08	1.13	1.31
OtherADL MSE(E) Combining	.	.	0.99	1.07	1.13	1.30
OtherADL MSE(F) Combining	.	.	0.99	1.07	1.14	1.30
OtherADL Rec. Best(4q) Combining	.	1.13	1.05	1.12	1.36	1.37
OtherADL Rec. Best(8q) Combining	.	1.14	1.09	1.21	1.30	1.42
All Median Combining	.	0.98	0.92	0.98	1.10	1.31
All Mean Combining	.	0.99	0.89	0.98	1.07	1.29
All Tr. Mean Combining	.	0.99	0.90	0.98	1.08	1.30
All MSE(A) Combining	.	.	0.87	0.99	1.10	1.30

All MSE(B) Combining	.	.	0.87	0.98	1.10	1.30
All MSE(C) Combining	.	.	0.87	0.98	1.09	1.29
All MSE(D) Combining	.	.	0.87	1.00	1.12	1.31
All MSE(E) Combining	.	.	0.88	0.99	1.12	1.30
All MSE(F) Combining	.	.	0.88	0.98	1.10	1.29
All Rec. Best(4q) Combining	.	1.12	0.74	1.11	1.47	1.63
All Rec. Best(8q) Combining	.	1.08	0.92	1.19	1.51	1.43
UCSV and Triangle Rec. Best(4q) Combining	.	.	.	1.02	1.05	1.01
UCSV and Triangle Rec. Best(8q) Combining	.	.	.	1.06	1.05	1.11

Notes to Table 1: Entries are RMSEs, relative to the RMSE of the UC-SV model, over the indicated sample period. Blanks indicate insufficient data to compute forecasts over the indicated subsample. The abbreviations denote:

- _AIC: AIC lag selection, up to six lags (for ADL models, AIC over the two lag lengths separately)
- _BIC: BIC lag selection, up to six lags (for ADL models, AIC over the two lag lengths separately)
- _rec: recursive estimation
- _roll: rolling estimation
- Level: indicated predictor appears in levels
- Dif: indicated predictor appears in log differences
- 1sdBP: indicated predictor appears in gap form, computed using 1-sided bandpass filter as discussed in the text
- Triangle: Triangle model or TV-triangle model, with or without supply shock ("z") variables
- mean, median, trimmed mean: forecast combining methods, for the indicated group of forecasts
- MSE(A) – MSE(F): MSE-based combining as indicated in (15) - (20).
- Best (4q) and Best (8q): recently best forecast based on cumulative MSE over past 4 (or 8) quarters
- UCSV and Triangle Rec. Best (4q) and (8q) Combining: best of UC-SV and triangle models (constant NAIRU) based on cumulative MSE over past 4 (or 8) quarters
- nocon: constant term is suppressed

Table 2
RMSEs for Inflation Forecasting Models by Sub-Period, Relative to UC-SV model: CPI-core

Forecast period	**1960Q1 – 1967Q4**	**1968Q1 – 1976Q4**	**1977Q1 - 1984Q4**	**1985Q1 – 1992Q4**	**1993Q1 – 2000Q4**	**2001Q1 – 2007Q4**
No. observations	32	36	32	32	32	25
Root MSE of UC-SV forecast	0.82	2.15	2.30	0.58	0.31	0.53
Forecasting model and relative RMSEs						
Univariate forecasts						
UC-SV	1.00	1.00	1.00	1.00	1.00	1.00
AR(AIC)_rec	.	.	1.07	1.07	1.04	1.05
AR(AIC)_iter_rec	.	.	1.08	1.06	1.04	1.06
AR(BIC)_rec	.	.	1.07	1.01	1.06	1.05
AO	1.03	1.14	1.01	1.08	1.04	1.06
MA(1)_rec	.	1.05	1.04	1.00	1.01	1.04
AR(4)_rec	.	.	1.09	1.09	1.03	1.04
AR(AIC)_roll	.	.	1.12	1.05	1.12	1.09
AR(AIC)_iter_roll	.	.	1.21	1.15	1.15	1.11
AR(BIC)_roll	.	.	1.11	1.03	1.11	1.09
AR(4)_roll	.	.	1.15	1.06	1.12	1.10
AR(24)_iter	.	.	1.24	1.57	1.51	0.93
AR(24)_iter_nocon	.	.	1.10	1.23	1.32	0.91
MA(1)_roll	.	1.04	1.03	1.12	1.00	1.07
MA(2) - NS	1.04	1.04	1.01	1.04	1.07	0.98
MA(1), θ=.25	1.05	1.01	0.98	1.02	1.04	1.07
MA(1), θ=.65	1.03	1.06	1.00	1.03	1.04	1.00
Single-predictor ADL forecasts						
UR(Level)_AIC_rec	.	.	0.89	0.83	1.92	1.11
UR(Dif)_AIC_rec	.	.	0.95	0.91	1.43	1.01
UR(1sdBP)_AIC_rec	.	.	0.91	1.01	1.63	1.05
GDP(Dif)_AIC_rec	.	.	1.02	0.91	1.02	0.92
GDP(1sdBP)_AIC_rec	.	.	0.95	1.00	1.17	1.09
IP(Dif)_AIC_rec	.	.	1.03	1.00	1.25	1.16
IP(1sdBP)_AIC_rec	.	.	0.97	0.85	1.54	1.39
Emp(Dif)_AIC_rec	.	.	0.92	0.90	1.18	1.32
Emp(1sdBP)_AIC_rec	.	.	0.91	0.90	1.28	1.27
CapU(Level)_AIC_rec	.	.	.	1.24	2.00	2.19
CapU((Dif)_AIC_rec	.	.	.	1.12	1.21	1.25
CapU(1sdBP)_AIC_rec	.	.	.	1.34	1.26	1.20
HPerm(Level)_AIC_rec	.	.	0.91	1.29	1.46	1.91
HPerm((Dif)_AIC_rec	.	.	1.06	1.10	1.21	1.04
HPerm(1sdBP)_AIC_rec	.	.	0.99	1.07	1.48	0.98
CFNAI(Dif)_AIC_rec	.	.	.	1.16	1.27	1.39
CFNAI(1sdBP)_AIC_rec	.	.	.	1.17	1.29	1.37
UR_5wk(Level)_AIC_rec	.	.	0.86	1.10	3.09	1.32
UR_5wk(Dif)_AIC_rec	.	.	0.91	1.19	1.91	1.08
UR_5wk(1sdBP)_AIC_rec	.	.	0.90	1.22	2.32	1.06
AHE(Dif)_AIC_rec	.	.	1.12	1.08	1.03	1.06
AHE(1sdBP)_AIC_rec	.	.	1.16	1.36	1.10	1.10
RealAHE(Dif)_AIC_rec	.	.	1.12	1.08	1.03	1.06
RealAHE(1sdBP)_AIC_rec	.	.	1.16	1.36	1.10	1.10
LaborShare(Level)_AIC_rec	.	.	1.11	1.37	2.18	1.12
LaborShare(Dif)_AIC_rec	.	.	1.14	1.05	1.27	1.06
ULaborShare(1sdBP)_AIC_rec	.	.	1.14	1.15	1.58	1.07
CPI_Med(Level)_AIC_rec	.	.	.	1.30	2.06	1.10
CPI_Med(Dif)_AIC_rec	.	.	.	1.14	1.81	1.25
CPI_TrMn(Level)_AIC_rec	.	.	.	1.28	1.69	1.23
CPI_TrMn(Dif)_AIC_rec	.	.	.	1.11	1.38	1.20
ExRate(Dif)_AIC_rec	.	.	.	2.97	1.43	0.93
ExRate(1sdBP)_AIC_rec	.	.	.	3.14	1.25	1.24
tb_spr_AIC_rec	.	.	1.10	1.52	2.53	1.32
UR(Level)_AIC_roll	.	.	1.27	1.52	1.34	1.19
UR(Dif)_AIC_roll	.	.	1.02	1.26	1.07	1.07

UR(1sdBP)_AIC_roll	.	.	0.87	1.40	1.12	1.21
GDP(Dif)_AIC_roll	.	.	1.12	1.37	1.12	1.10
GDP(1sdBP)_AIC_roll	.	.	1.00	1.52	1.02	1.10
IP(Dif)_AIC_roll	.	.	1.08	1.48	1.15	1.26
IP(1sdBP)_AIC_roll	.	.	0.89	1.70	1.14	1.39
Emp(Dif)_AIC_roll	.	.	0.94	1.47	1.09	1.31
Emp(1sdBP)_AIC_roll	.	.	0.84	1.57	1.08	1.54
CapU(Level)_AIC_roll	.	.	.	1.59	1.31	1.39
CapU((Dif)_AIC_roll	.	.	.	1.48	1.11	1.17
CapU(1sdBP)_AIC_roll	.	.	.	1.48	1.26	1.26
HPerm(Level)_AIC_roll	.	.	0.89	2.35	1.04	1.24
HPerm((Dif)_AIC_roll	.	.	1.10	1.63	1.12	1.14
HPerm(1sdBP)_AIC_roll	.	.	1.04	1.95	1.05	1.12
CFNAI(Dif)_AIC_roll	.	.	.	1.44	1.03	1.17
CFNAI(1sdBP)_AIC_roll	.	.	.	1.50	0.92	1.25
UR_5wk(Level)_AIC_roll	.	.	1.05	2.12	1.28	1.13
UR_5wk(Dif)_AIC_roll	.	.	1.09	1.44	1.08	1.10
UR_5wk(1sdBP)_AIC_roll	.	.	0.85	1.32	1.33	1.12
AHE(Dif)_AIC_roll	.	.	1.23	1.23	1.13	1.16
AHE(1sdBP)_AIC_roll	.	.	1.22	1.53	1.12	1.15
RealAHE(Dif)_AIC_roll	.	.	1.23	1.23	1.13	1.16
RealAHE(1sdBP)_AIC_roll	.	.	1.22	1.53	1.12	1.15
LaborShare(Level)_AIC_roll	.	.	1.20	1.34	1.83	1.12
LaborShare(Dif)_AIC_roll	.	.	1.41	1.15	1.97	1.10
ULaborShare(1sdBP)_AIC_roll	.	.	1.30	1.16	1.69	1.10
CPI_Med(Level)_AIC_roll	.	.	.	1.37	1.69	0.80
CPI_Med(Dif)_AIC_roll	.	.	.	1.04	1.25	1.15
CPI_TrMn(Level)_AIC_roll	.	.	.	1.30	1.53	1.19
CPI_TrMn(Dif)_AIC_roll	.	.	.	1.08	1.14	1.19
ExRate(Dif)_AIC_roll	.	.	.	3.48	1.19	1.11
ExRate(1sdBP)_AIC_roll	.	.	.	3.58	1.05	1.10
tb_spr_AIC_roll	.	.	1.15	1.61	1.22	1.12
UR(Level)_BIC_rec	.	.	0.97	0.83	1.92	1.11
UR(Dif)_BIC_rec	.	.	1.00	0.91	1.43	1.01
UR(1sdBP)_BIC_rec	.	.	0.88	1.01	1.62	1.05
GDP(Dif)_BIC_rec	.	.	1.04	0.98	1.06	0.91
GDP(1sdBP)_BIC_rec	.	.	0.96	0.96	1.14	1.07
IP(Dif)_BIC_rec	.	.	1.04	0.99	1.11	1.11
IP(1sdBP)_BIC_rec	.	.	1.00	0.90	1.41	1.34
Emp(Dif)_BIC_rec	.	.	0.97	0.90	1.18	1.32
Emp(1sdBP)_BIC_rec	.	.	0.83	0.90	1.28	1.27
CapU(Level)_BIC_rec	.	.	.	1.24	1.83	2.10
CapU((Dif)_BIC_rec	.	.	.	1.06	1.11	1.22
CapU(1sdBP)_BIC_rec	.	.	.	1.22	1.23	1.27
HPerm(Level)_BIC_rec	.	.	0.91	1.27	1.46	1.91
HPerm((Dif)_BIC_rec	.	.	1.05	1.16	1.21	1.04
HPerm(1sdBP)_BIC_rec	.	.	0.99	1.07	1.48	0.98
CFNAI(Dif)_BIC_rec	.	.	.	1.10	1.27	1.29
CFNAI(1sdBP)_BIC_rec	.	.	.	1.17	1.29	1.37
UR_5wk(Level)_BIC_rec	.	.	0.93	1.09	2.88	1.42
UR_5wk(Dif)_BIC_rec	.	.	1.01	1.19	1.94	1.15
UR_5wk(1sdBP)_BIC_rec	.	.	0.87	1.24	2.23	1.05
AHE(Dif)_BIC_rec	.	.	1.13	1.03	1.05	1.09
AHE(1sdBP)_BIC_rec	.	.	1.17	1.24	1.16	1.09
RealAHE(Dif)_BIC_rec	.	.	1.13	1.03	1.05	1.09
RealAHE(1sdBP)_BIC_rec	.	.	1.17	1.24	1.16	1.09
LaborShare(Level)_BIC_rec	.	.	1.08	1.22	1.68	1.09
LaborShare(Dif)_BIC_rec	.	.	1.09	1.02	1.34	1.08
ULaborShare(1sdBP)_BIC_rec	.	.	1.09	1.08	1.27	1.02
CPI_Med(Level)_BIC_rec	.	.	.	1.34	1.66	1.11
CPI_Med(Dif)_BIC_rec	.	.	.	1.02	1.25	1.10
CPI_TrMn(Level)_BIC_rec	.	.	.	1.28	1.71	1.23
CPI_TrMn(Dif)_BIC_rec	.	.	.	1.09	1.38	1.20
ExRate(Dif)_BIC_rec	.	.	.	1.73	1.34	1.09
ExRate(1sdBP)_BIC_rec	.	.	.	2.85	1.10	1.01
tb_spr_BIC_rec	.	.	1.07	1.50	2.40	1.32

UR(Level)_BIC_roll	.	.	1.16	1.49	1.26	1.16
UR(Dif)_BIC_roll	.	.	1.04	1.18	1.06	1.08
UR(1sdBP)_BIC_roll	.	.	0.88	1.33	1.15	1.10
GDP(Dif)_BIC_roll	.	.	1.01	1.30	1.11	1.04
GDP(1sdBP)_BIC_roll	.	.	0.95	1.47	1.10	1.11
IP(Dif)_BIC_roll	.	.	1.06	1.49	1.15	1.23
IP(1sdBP)_BIC_roll	.	.	0.86	1.67	1.13	1.31
Emp(Dif)_BIC_roll	.	.	1.00	1.45	1.15	1.16
Emp(1sdBP)_BIC_roll	.	.	0.84	1.56	1.15	1.50
CapU(Level)_BIC_roll	.	.	.	1.61	1.32	1.37
CapU((Dif)_BIC_roll	.	.	.	1.48	1.11	1.15
CapU(1sdBP)_BIC_roll	.	.	.	1.46	1.30	1.29
HPerm(Level)_BIC_roll	.	.	0.89	2.29	1.05	1.17
HPerm((Dif)_BIC_roll	.	.	1.10	1.62	1.20	1.13
HPerm(1sdBP)_BIC_roll	.	.	1.05	1.93	1.08	1.11
CFNAI(Dif)_BIC_roll	.	.	.	1.47	1.03	1.13
CFNAI(1sdBP)_BIC_roll	.	.	.	1.53	0.91	1.20
UR_5wk(Level)_BIC_roll	.	.	1.08	1.96	1.19	1.12
UR_5wk(Dif)_BIC_roll	.	.	1.11	1.49	1.11	1.09
UR_5wk(1sdBP)_BIC_roll	.	.	0.85	1.36	1.31	1.08
AHE(Dif)_BIC_roll	.	.	1.12	1.15	1.12	1.13
AHE(1sdBP)_BIC_roll	.	.	1.16	1.32	1.13	1.16
RealAHE(Dif)_BIC_roll	.	.	1.12	1.15	1.12	1.13
RealAHE(1sdBP)_BIC_roll	.	.	1.16	1.32	1.13	1.16
LaborShare(Level)_BIC_roll	.	.	1.10	1.35	1.61	1.11
LaborShare(Dif)_BIC_roll	.	.	1.20	1.21	1.84	1.10
ULaborShare(1sdBP)_BIC_roll	.	.	1.13	1.12	1.56	1.10
CPI_Med(Level)_BIC_roll	.	.	.	1.41	1.47	0.84
CPI_Med(Dif)_BIC_roll	.	.	.	1.05	1.22	1.18
CPI_TrMn(Level)_BIC_roll	.	.	.	1.23	1.47	1.19
CPI_TrMn(Dif)_BIC_roll	.	.	.	1.08	1.15	1.18
ExRate(Dif)_BIC_roll	.	.	.	3.03	1.10	1.14
ExRate(1sdBP)_BIC_roll	.	.	.	3.35	1.06	1.06
tb_spr_BIC_roll	.	.	1.14	1.45	1.28	1.11
Triangle model forecasts						
Triangle Constant NAIRU	.	.	1.32	1.50	1.81	1.44
Triangle TV NAIRU	.	.	1.32	1.46	1.48	1.39
Triangle Constant NAIRU (no z)	.	.	1.05	1.11	2.34	1.17
Triangle TV NAIRU (no z)	.	.	1.07	1.22	1.63	1.23
Combination forecasts						
Activity Median Combining	.	.	0.86	0.86	1.00	1.07
Activity Mean Combining	.	.	0.86	0.89	1.02	1.02
Activity Tr. Mean Combining	.	.	0.86	0.88	1.01	1.04
Activity MSE(A) Combining	.	.	.	0.87	1.05	1.05
Activity MSE(B) Combining	.	.	.	0.88	1.06	1.04
Activity MSE(3 Combining	.	.	.	0.88	1.06	1.04
Activity MSE(D) Combining	.	.	.	0.87	1.09	1.07
Activity MSE(E) Combining	.	.	.	0.87	1.10	1.06
Activity MSE(F) Combining	.	.	.	0.88	1.11	1.05
Activity Rec. Best(4q) Combining	.	.	1.13	1.15	1.22	1.19
Activity Rec. Best(8q) Combining	.	.	0.96	1.40	1.50	1.40
OtherADL Median Combining	.	.	1.08	0.99	1.11	1.06
OtherADL Mean Combining	.	.	1.05	1.04	1.15	1.02
OtherADL Tr. Mean Combining	.	.	1.07	0.96	1.12	1.03
OtherADL MSE(A) Combining	.	.	.	1.02	1.16	1.04
OtherADL MSE(B) Combining	.	.	.	1.00	1.18	1.03
OtherADL MSE(C) Combining	.	.	.	0.99	1.18	1.03
OtherADL MSE(D) Combining	.	.	.	1.07	1.16	1.06
OtherADL MSE(E) Combining	.	.	.	1.02	1.17	1.05
OtherADL MSE(F) Combining	.	.	.	1.00	1.18	1.04
OtherADL Rec. Best(4q) Combining	.	.	1.08	2.06	1.18	1.06
OtherADL Rec. Best(8q) Combining	.	.	1.07	1.54	1.10	1.38
All Median Combining	.	.	0.94	0.83	1.01	1.04
All Mean Combining	.	.	0.91	0.85	1.00	0.98
All Tr. Mean Combining	.	.	0.92	0.82	1.00	1.00
All MSE(A) Combining	.	.	.	0.86	1.03	1.02

All MSE(B) Combining	.	.	.	0.84	1.03	1.01
All MSE(C) Combining	.	.	.	0.84	1.02	1.01
All MSE(D) Combining	.	.	.	0.88	1.05	1.04
All MSE(E) Combining	.	.	.	0.85	1.05	1.03
All MSE(F) Combining	.	.	.	0.84	1.04	1.02
All Rec. Best(4q) Combining	.	.	1.19	1.53	1.17	1.08
All Rec. Best(8q) Combining	.	.	0.96	1.67	1.45	1.50
UCSV and Triangle Rec. Best(4q) Combining	.	.	.	1.37	1.06	1.00
UCSV and Triangle Rec. Best(8q) Combining	.	.	.	1.02	1.16	1.09

Table 3
RMSEs for Inflation Forecasting Models by Sub-Period, Relative to UC-SV model: PCE-all

Forecast period	**1960Q1 – 1967Q4**	**1968Q1 – 1976Q4**	**1977Q1 - 1984Q4**	**1985Q1 – 1992Q4**	**1993Q1 – 2000Q4**	**2001Q1 – 2007Q4**
No. observations	32	36	32	32	32	25
Root MSE of UC-SV forecast	0.73	1.83	1.41	0.88	0.59	0.72
Forecasting model and relative RMSEs						
Univariate forecasts						
UC-SV	1.00	1.00	1.00	1.00	1.00	1.00
AR(AIC)_rec	.	1.14	1.02	1.15	1.06	1.45
AR(AIC)_iter_rec	.	1.04	1.01	1.14	1.04	1.50
AR(BIC)_rec	.	1.12	1.02	1.15	1.07	1.58
AO	1.02	1.20	1.18	1.01	1.10	1.09
MA(1)_rec	.	1.08	1.00	1.08	1.04	1.42
AR(4)_rec	.	1.16	1.03	1.13	1.07	1.46
AR(AIC)_roll	.	1.13	1.06	1.09	1.25	1.28
AR(AIC)_iter_roll	.	1.26	1.06	1.20	1.31	1.35
AR(BIC)_roll	.	1.11	1.07	1.09	1.24	1.33
AR(4)_roll	.	1.23	1.06	1.15	1.22	1.26
AR(24)_iter	.	.	1.23	1.53	1.15	1.34
AR(24)_iter_nocon	.	.	1.10	1.42	1.12	1.33
MA(1)_roll	.	1.04	0.99	1.09	1.03	1.10
MA(2) - NS	1.01	1.09	1.20	1.00	1.01	1.15
MA(1), θ=.25	1.10	1.01	0.99	1.12	1.07	1.59
MA(1), θ=.65	0.99	1.12	1.18	0.99	1.02	1.14
Single-predictor ADL forecasts						
UR(Level)_AIC_rec	.	1.06	0.98	0.99	1.22	1.43
UR(Dif)_AIC_rec	.	1.02	1.04	1.10	1.15	1.47
UR(1sdBP)_AIC_rec	.	1.07	1.09	0.99	1.14	1.42
GDP(Dif)_AIC_rec	.	1.02	0.98	1.04	1.15	1.47
GDP(1sdBP)_AIC_rec	.	1.08	1.02	1.00	1.11	1.43
IP(Dif)_AIC_rec	.	1.01	1.00	1.04	1.24	1.51
IP(1sdBP)_AIC_rec	.	1.06	1.06	1.01	1.21	1.46
Emp(Dif)_AIC_rec	.	1.03	0.96	1.04	1.12	1.66
Emp(1sdBP)_AIC_rec	.	1.04	1.03	1.01	1.13	1.54
CapU(Level)_AIC_rec	.	.	.	1.13	1.31	1.75
CapU((Dif)_AIC_rec	.	.	.	1.21	1.31	1.70
CapU(1sdBP)_AIC_rec	.	.	.	1.13	1.22	1.50
HPerm(Level)_AIC_rec	.	.	0.96	1.05	1.07	1.74
HPerm((Dif)_AIC_rec	.	.	1.11	1.16	1.07	1.61
HPerm(1sdBP)_AIC_rec	.	.	0.99	1.03	1.07	1.43
CFNAI(Dif)_AIC_rec	.	.	.	1.15	1.18	1.76
CFNAI(1sdBP)_AIC_rec	.	.	.	1.12	1.19	1.64
UR_5wk(Level)_AIC_rec	.	1.19	0.95	1.13	1.47	1.44
UR_5wk(Dif)_AIC_rec	.	1.07	1.02	1.14	1.19	1.45
UR_5wk(1sdBP)_AIC_rec	.	1.09	0.98	1.12	1.19	1.38
AHE(Dif)_AIC_rec	.	.	1.10	1.27	1.08	1.59
AHE(1sdBP)_AIC_rec	.	.	1.15	1.26	1.07	1.56
RealAHE(Dif)_AIC_rec	.	.	1.10	1.27	1.08	1.59
RealAHE(1sdBP)_AIC_rec	.	.	1.15	1.26	1.07	1.56
LaborShare(Level)_AIC_rec	.	1.15	0.96	1.28	1.65	1.45
LaborShare(Dif)_AIC_rec	.	1.15	1.01	1.14	1.09	1.40
ULaborShare(1sdBP)_AIC_rec	.	1.18	0.96	1.13	1.32	1.40
CPI_Med(Level)_AIC_rec	.	.	.	1.33	1.34	1.56
CPI_Med(Dif)_AIC_rec	.	.	.	1.22	1.13	1.64
CPI_TrMn(Level)_AIC_rec	.	.	.	1.28	1.34	1.50
CPI_TrMn(Dif)_AIC_rec	.	.	.	1.15	1.10	1.64
ExRate(Dif)_AIC_rec	.	.	.	1.28	1.33	1.31
ExRate(1sdBP)_AIC_rec	.	.	.	1.60	1.15	1.32
tb_spr_AIC_rec	.	1.18	1.31	1.25	1.01	1.51
UR(Level)_AIC_roll	.	1.24	1.53	1.04	1.32	1.25
UR(Dif)_AIC_roll	.	1.10	1.12	1.11	1.26	1.21

UR(1sdBP)_AIC_roll	.	1.29	1.30	1.06	1.29	1.25
GDP(Dif)_AIC_roll	.	1.07	1.14	1.16	1.33	1.19
GDP(1sdBP)_AIC_roll	.	1.24	1.12	1.02	1.33	1.21
IP(Dif)_AIC_roll	.	1.08	0.99	1.19	1.39	1.25
IP(1sdBP)_AIC_roll	.	1.20	1.18	1.14	1.43	1.37
Emp(Dif)_AIC_roll	.	1.10	1.20	1.12	1.34	1.22
Emp(1sdBP)_AIC_roll	.	1.24	1.12	1.15	1.34	1.32
CapU(Level)_AIC_roll	.	.	.	1.10	1.44	1.29
CapU((Dif)_AIC_roll	.	.	.	1.17	1.37	1.30
CapU(1sdBP)_AIC_roll	.	.	.	1.01	1.43	1.30
HPerm(Level)_AIC_roll	.	.	1.00	1.14	1.25	1.33
HPerm((Dif)_AIC_roll	.	.	1.19	1.08	1.11	1.88
HPerm(1sdBP)_AIC_roll	.	.	1.07	1.15	1.28	1.24
CFNAI(Dif)_AIC_roll	.	.	.	1.14	1.38	1.21
CFNAI(1sdBP)_AIC_roll	.	.	.	1.10	1.37	1.28
UR_5wk(Level)_AIC_roll	.	1.32	1.25	1.16	1.43	1.26
UR_5wk(Dif)_AIC_roll	.	1.12	1.06	1.17	1.34	1.28
UR_5wk(1sdBP)_AIC_roll	.	1.20	1.10	1.03	1.43	1.27
AHE(Dif)_AIC_roll	.	.	1.10	1.35	1.33	1.24
AHE(1sdBP)_AIC_roll	.	.	1.15	1.06	1.34	1.14
RealAHE(Dif)_AIC_roll	.	.	1.10	1.35	1.33	1.24
RealAHE(1sdBP)_AIC_roll	.	.	1.15	1.06	1.34	1.14
LaborShare(Level)_AIC_roll	.	1.26	1.01	1.21	1.45	1.27
LaborShare(Dif)_AIC_roll	.	1.16	1.04	1.11	1.32	1.48
ULaborShare(1sdBP)_AIC_roll	.	1.22	1.03	1.09	1.35	1.23
CPI_Med(Level)_AIC_roll	.	.	.	1.16	1.27	1.20
CPI_Med(Dif)_AIC_roll	.	.	.	1.04	1.25	1.32
CPI_TrMn(Level)_AIC_roll	.	.	.	1.23	1.31	1.13
CPI_TrMn(Dif)_AIC_roll	.	.	.	1.07	1.29	1.28
ExRate(Dif)_AIC_roll	.	.	.	1.33	1.25	1.24
ExRate(1sdBP)_AIC_roll	.	.	.	1.64	1.25	1.22
tb_spr_AIC_roll	.	1.18	1.79	1.39	1.38	1.35
UR(Level)_BIC_rec	.	1.05	0.98	1.06	1.22	1.42
UR(Dif)_BIC_rec	.	1.00	1.08	1.11	1.15	1.48
UR(1sdBP)_BIC_rec	.	1.05	1.07	1.06	1.14	1.42
GDP(Dif)_BIC_rec	.	1.03	1.09	1.10	1.15	1.47
GDP(1sdBP)_BIC_rec	.	1.09	0.99	1.07	1.07	1.44
IP(Dif)_BIC_rec	.	1.04	1.03	1.10	1.23	1.50
IP(1sdBP)_BIC_rec	.	1.07	1.02	1.09	1.16	1.47
Emp(Dif)_BIC_rec	.	1.02	0.97	1.02	1.11	1.59
Emp(1sdBP)_BIC_rec	.	1.06	0.98	1.06	1.13	1.54
CapU(Level)_BIC_rec	.	.	.	1.16	1.28	1.75
CapU((Dif)_BIC_rec	.	.	.	1.22	1.31	1.79
CapU(1sdBP)_BIC_rec	.	.	.	1.10	1.20	1.47
HPerm(Level)_BIC_rec	.	.	0.95	1.12	1.07	1.74
HPerm((Dif)_BIC_rec	.	.	1.07	1.21	1.07	1.61
HPerm(1sdBP)_BIC_rec	.	.	0.97	1.09	1.07	1.43
CFNAI(Dif)_BIC_rec	.	.	.	1.16	1.17	1.81
CFNAI(1sdBP)_BIC_rec	.	.	.	1.09	1.18	1.54
UR_5wk(Level)_BIC_rec	.	1.16	0.94	1.15	1.43	1.57
UR_5wk(Dif)_BIC_rec	.	1.02	1.02	1.15	1.12	1.54
UR_5wk(1sdBP)_BIC_rec	.	1.08	0.97	1.13	1.20	1.43
AHE(Dif)_BIC_rec	.	.	1.07	1.29	1.11	1.62
AHE(1sdBP)_BIC_rec	.	.	1.15	1.31	1.08	1.57
RealAHE(Dif)_BIC_rec	.	.	1.07	1.29	1.11	1.62
RealAHE(1sdBP)_BIC_rec	.	.	1.15	1.31	1.08	1.57
LaborShare(Level)_BIC_rec	.	1.15	0.98	1.30	1.51	1.65
LaborShare(Dif)_BIC_rec	.	1.11	1.01	1.14	1.10	1.54
ULaborShare(1sdBP)_BIC_rec	.	1.18	0.99	1.14	1.32	1.64
CPI_Med(Level)_BIC_rec	.	.	.	1.37	1.26	1.63
CPI_Med(Dif)_BIC_rec	.	.	.	1.27	1.13	1.64
CPI_TrMn(Level)_BIC_rec	.	.	.	1.35	1.25	1.61
CPI_TrMn(Dif)_BIC_rec	.	.	.	1.27	1.10	1.64
ExRate(Dif)_BIC_rec	.	.	.	1.38	1.25	1.41
ExRate(1sdBP)_BIC_rec	.	.	.	1.53	1.16	1.46
tb_spr_BIC_rec	.	1.14	1.13	1.16	1.04	1.59

UR(Level)_BIC_roll	.	1.23	1.29	1.10	1.32	1.31
UR(Dif)_BIC_roll	.	1.06	1.13	1.08	1.33	1.30
UR(1sdBP)_BIC_roll	.	1.22	1.29	1.10	1.32	1.31
GDP(Dif)_BIC_roll	.	1.05	1.12	1.09	1.33	1.32
GDP(1sdBP)_BIC_roll	.	1.23	1.09	1.12	1.28	1.30
IP(Dif)_BIC_roll	.	1.05	1.01	1.18	1.43	1.27
IP(1sdBP)_BIC_roll	.	1.23	1.17	1.15	1.46	1.39
Emp(Dif)_BIC_roll	.	1.09	1.12	1.14	1.36	1.30
Emp(1sdBP)_BIC_roll	.	1.18	1.22	1.18	1.39	1.29
CapU(Level)_BIC_roll	.	.	.	1.15	1.48	1.34
CapU((Dif)_BIC_roll	.	.	.	1.16	1.40	1.32
CapU(1sdBP)_BIC_roll	.	.	.	1.09	1.46	1.36
HPerm(Level)_BIC_roll	.	.	1.00	1.10	1.27	1.39
HPerm((Dif)_BIC_roll	.	.	1.09	1.07	1.10	1.33
HPerm(1sdBP)_BIC_roll	.	.	1.00	1.09	1.27	1.33
CFNAI(Dif)_BIC_roll	.	.	.	1.13	1.41	1.27
CFNAI(1sdBP)_BIC_roll	.	.	.	1.06	1.39	1.28
UR_5wk(Level)_BIC_roll	.	1.26	1.24	1.19	1.42	1.33
UR_5wk(Dif)_BIC_roll	.	1.04	1.07	1.12	1.32	1.30
UR_5wk(1sdBP)_BIC_roll	.	1.17	1.10	1.06	1.42	1.27
AHE(Dif)_BIC_roll	.	.	1.08	1.09	1.27	1.30
AHE(1sdBP)_BIC_roll	.	.	1.15	1.13	1.33	1.26
RealAHE(Dif)_BIC_roll	.	.	1.08	1.09	1.27	1.30
RealAHE(1sdBP)_BIC_roll	.	.	1.15	1.13	1.33	1.26
LaborShare(Level)_BIC_roll	.	1.19	0.97	1.20	1.38	1.31
LaborShare(Dif)_BIC_roll	.	1.13	1.04	1.24	1.34	1.44
ULaborShare(1sdBP)_BIC_roll	.	1.17	0.96	1.11	1.35	1.32
CPI_Med(Level)_BIC_roll	.	.	.	1.12	1.29	1.19
CPI_Med(Dif)_BIC_roll	.	.	.	1.09	1.27	1.29
CPI_TrMn(Level)_BIC_roll	.	.	.	1.15	1.27	1.16
CPI_TrMn(Dif)_BIC_roll	.	.	.	1.08	1.28	1.34
ExRate(Dif)_BIC_roll	.	.	.	1.28	1.25	1.40
ExRate(1sdBP)_BIC_roll	.	.	.	1.48	1.26	1.40
tb_spr_BIC_roll	.	1.15	1.76	1.15	1.33	1.37
Triangle model forecasts						
Triangle Constant NAIRU	.	.	1.14	1.18	1.25	1.20
Triangle TV NAIRU	.	.	1.07	1.20	1.04	1.30
Triangle Constant NAIRU (no z)	.	.	0.98	1.33	1.38	1.27
Triangle TV NAIRU (no z)	.	.	0.97	1.48	1.16	1.58
Combination forecasts						
Activity Median Combining	.	1.07	0.97	1.05	1.16	1.32
Activity Mean Combining	.	1.07	0.94	1.05	1.14	1.35
Activity Tr. Mean Combining	.	1.07	0.95	1.05	1.16	1.34
Activity MSE(A) Combining	.	.	0.95	1.04	1.15	1.35
Activity MSE(B) Combining	.	.	0.95	1.04	1.15	1.35
Activity MSE(3 Combining	.	.	0.95	1.04	1.14	1.35
Activity MSE(D) Combining	.	.	0.95	1.05	1.16	1.35
Activity MSE(E) Combining	.	.	0.95	1.04	1.16	1.35
Activity MSE(F) Combining	.	.	0.94	1.04	1.15	1.35
Activity Rec. Best(4q) Combining	.	1.20	1.10	1.25	1.44	1.42
Activity Rec. Best(8q) Combining	.	1.21	0.99	1.19	1.46	1.61
OtherADL Median Combining	.	1.14	1.04	1.15	1.17	1.33
OtherADL Mean Combining	.	1.14	1.02	1.12	1.14	1.35
OtherADL Tr. Mean Combining	.	1.14	1.03	1.13	1.14	1.35
OtherADL MSE(A) Combining	.	.	0.93	1.14	1.15	1.34
OtherADL MSE(B) Combining	.	.	0.93	1.14	1.15	1.34
OtherADL MSE(C) Combining	.	.	0.94	1.14	1.16	1.35
OtherADL MSE(D) Combining	.	.	0.94	1.14	1.16	1.32
OtherADL MSE(E) Combining	.	.	0.93	1.13	1.17	1.34
OtherADL MSE(F) Combining	.	.	0.94	1.13	1.17	1.36
OtherADL Rec. Best(4q) Combining	.	1.29	1.13	1.18	1.32	1.11
OtherADL Rec. Best(8q) Combining	.	1.32	0.98	1.32	1.33	1.26
All Median Combining	.	1.07	0.94	1.07	1.15	1.31
All Mean Combining	.	1.08	0.93	1.06	1.12	1.34
All Tr. Mean Combining	.	1.08	0.93	1.07	1.14	1.33
All MSE(A) Combining	.	.	0.92	1.06	1.14	1.34

All MSE(B) Combining	.	.	0.92	1.06	1.14	1.34
All MSE(C) Combining	.	.	0.92	1.06	1.13	1.34
All MSE(D) Combining	.	.	0.93	1.07	1.16	1.33
All MSE(E) Combining	.	.	0.92	1.06	1.15	1.34
All MSE(F) Combining	.	.	0.92	1.06	1.14	1.34
All Rec. Best(4q) Combining	.	1.25	1.18	1.34	1.44	1.32
All Rec. Best(8q) Combining	.	1.22	1.01	1.30	1.52	1.44
UCSV and Triangle Rec. Best(4q) Combining	.	.	.	1.07	1.18	1.07
UCSV and Triangle Rec. Best(8q) Combining	.	.	.	1.15	1.16	1.07

Table 4
RMSEs for Inflation Forecasting Models by Sub-Period, Relative to UC-SV model: PCE-core

Forecast period	**1960Q1 – 1967Q4**	**1968Q1 – 1976Q4**	**1977Q1 - 1984Q4**	**1985Q1 – 1992Q4**	**1993Q1 – 2000Q4**	**2001Q1 – 2007Q4**
No. observations	32	36	32	32	32	25
Root MSE of UC-SV forecast	0.68	1.56	1.08	0.55	0.36	0.33
Forecasting model and relative RMSEs						
Univariate forecasts						
UC-SV	1.00	1.00	1.00	1.00	1.00	1.00
AR(AIC)_rec	.	.	1.15	1.15	1.21	1.34
AR(AIC)_iter_rec	.	.	1.09	1.17	1.24	1.37
AR(BIC)_rec	.	.	1.13	1.22	1.21	1.34
AO	1.08	1.16	1.12	1.00	0.94	1.18
MA(1)_rec	.	1.03	1.03	1.09	1.16	1.27
AR(4)_rec	.	.	1.15	1.15	1.18	1.29
AR(AIC)_roll	.	.	1.15	1.24	1.18	1.30
AR(AIC)_iter_roll	.	.	1.15	1.31	1.21	1.27
AR(BIC)_roll	.	.	1.15	1.06	1.24	1.28
AR(4)_roll	.	.	1.19	1.25	1.16	1.27
AR(24)_iter	.	.	.	1.85	1.37	1.26
AR(24)_iter_nocon	.	.	1.14	1.32	1.26	1.24
MA(1)_roll	.	1.02	1.03	1.08	1.14	1.06
MA(2) - NS	1.09	1.05	1.14	0.99	1.07	1.06
MA(1), θ=.25	1.01	1.01	0.99	1.11	1.19	1.33
MA(1), θ=.65	1.08	1.07	1.12	0.98	1.03	1.07
Single-predictor ADL forecasts						
UR(Level)_AIC_rec	.	.	1.08	1.01	1.48	1.51
UR(Dif)_AIC_rec	.	.	1.14	1.16	1.42	1.30
UR(1sdBP)_AIC_rec	.	.	1.19	1.08	1.30	1.41
GDP(Dif)_AIC_rec	.	.	1.03	1.17	1.38	1.45
GDP(1sdBP)_AIC_rec	.	.	0.95	1.01	1.06	1.50
IP(Dif)_AIC_rec	.	.	1.01	1.15	1.39	1.29
IP(1sdBP)_AIC_rec	.	.	0.96	1.01	1.25	1.80
Emp(Dif)_AIC_rec	.	.	1.00	1.14	1.26	2.10
Emp(1sdBP)_AIC_rec	.	.	1.14	1.06	1.28	1.70
CapU(Level)_AIC_rec	.	.	.	1.23	1.53	2.81
CapU((Dif)_AIC_rec	.	.	.	1.23	1.39	1.27
CapU(1sdBP)_AIC_rec	.	.	.	1.19	1.17	1.52
HPerm(Level)_AIC_rec	.	.	1.13	1.17	1.30	2.11
HPerm((Dif)_AIC_rec	.	.	1.25	1.17	1.22	1.34
HPerm(1sdBP)_AIC_rec	.	.	1.15	1.04	1.38	1.32
CFNAI(Dif)_AIC_rec	.	.	.	1.15	1.25	1.68
CFNAI(1sdBP)_AIC_rec	.	.	.	1.00	1.12	1.63
UR_5wk(Level)_AIC_rec	.	.	0.96	1.18	1.99	1.73
UR_5wk(Dif)_AIC_rec	.	.	1.14	1.21	1.44	1.21
UR_5wk(1sdBP)_AIC_rec	.	.	1.06	1.22	1.57	1.24
AHE(Dif)_AIC_rec	.	.	1.18	1.24	1.22	1.34
AHE(1sdBP)_AIC_rec	.	.	1.39	1.29	1.27	1.34
RealAHE(Dif)_AIC_rec	.	.	1.18	1.24	1.22	1.34
RealAHE(1sdBP)_AIC_rec	.	.	1.39	1.29	1.27	1.34
LaborShare(Level)_AIC_rec	.	.	0.99	1.39	1.91	1.57
LaborShare(Dif)_AIC_rec	.	.	1.09	1.18	1.40	1.50
ULaborShare(1sdBP)_AIC_rec	.	.	1.05	1.25	1.55	1.59
CPI_Med(Level)_AIC_rec	.	.	.	1.20	1.33	1.37
CPI_Med(Dif)_AIC_rec	.	.	.	1.12	1.17	1.49
CPI_TrMn(Level)_AIC_rec	.	.	.	1.20	1.19	1.32
CPI_TrMn(Dif)_AIC_rec	.	.	.	1.09	1.05	1.28
ExRate(Dif)_AIC_rec	.	.	.	1.29	1.35	1.27
ExRate(1sdBP)_AIC_rec	.	.	.	1.45	1.26	1.28
tb_spr_AIC_rec	.	.	1.40	1.33	1.22	1.49
UR(Level)_AIC_roll	.	.	1.44	1.20	1.03	1.49
UR(Dif)_AIC_roll	.	.	1.22	1.20	1.20	1.31

UR(1sdBP)_AIC_roll	.	.	1.20	0.93	1.01	1.60
GDP(Dif)_AIC_roll	.	.	1.17	1.24	1.23	1.33
GDP(1sdBP)_AIC_roll	.	.	1.00	0.98	1.01	1.55
IP(Dif)_AIC_roll	.	.	1.10	1.35	1.29	1.44
IP(1sdBP)_AIC_roll	.	.	0.98	1.11	1.20	1.73
Emp(Dif)_AIC_roll	.	.	1.08	1.14	1.18	1.58
Emp(1sdBP)_AIC_roll	.	.	1.23	1.17	1.12	2.07
CapU(Level)_AIC_roll	.	.	.	1.21	1.33	1.73
CapU((Dif)_AIC_roll	.	.	.	1.34	1.27	1.44
CapU(1sdBP)_AIC_roll	.	.	.	1.00	1.26	1.60
HPerm(Level)_AIC_roll	.	.	1.27	1.17	1.03	1.51
HPerm((Dif)_AIC_roll	.	.	1.37	1.17	1.26	1.23
HPerm(1sdBP)_AIC_roll	.	.	1.44	1.11	1.15	1.32
CFNAI(Dif)_AIC_roll	.	.	.	1.14	1.20	1.49
CFNAI(1sdBP)_AIC_roll	.	.	.	0.96	1.09	1.73
UR_5wk(Level)_AIC_roll	.	.	1.14	1.44	1.04	1.44
UR_5wk(Dif)_AIC_roll	.	.	1.17	1.06	1.16	1.28
UR_5wk(1sdBP)_AIC_roll	.	.	1.13	1.00	1.26	1.33
AHE(Dif)_AIC_roll	.	.	1.18	1.25	1.21	1.32
AHE(1sdBP)_AIC_roll	.	.	1.36	1.36	1.21	1.61
RealAHE(Dif)_AIC_roll	.	.	1.18	1.25	1.21	1.32
RealAHE(1sdBP)_AIC_roll	.	.	1.36	1.36	1.21	1.61
LaborShare(Level)_AIC_roll	.	.	1.20	1.35	1.56	1.58
LaborShare(Dif)_AIC_roll	.	.	1.32	1.12	1.16	1.63
ULaborShare(1sdBP)_AIC_roll	.	.	1.27	1.23	1.46	1.55
CPI_Med(Level)_AIC_roll	.	.	.	1.37	1.31	1.14
CPI_Med(Dif)_AIC_roll	.	.	.	1.20	1.21	1.31
CPI_TrMn(Level)_AIC_roll	.	.	.	1.34	1.28	1.33
CPI_TrMn(Dif)_AIC_roll	.	.	.	1.15	1.19	1.33
ExRate(Dif)_AIC_roll	.	.	.	1.39	1.21	1.44
ExRate(1sdBP)_AIC_roll	.	.	.	1.43	1.12	1.46
tb_spr_AIC_roll	.	.	1.64	1.26	1.24	1.30
UR(Level)_BIC_rec	.	.	0.96	1.06	1.48	1.58
UR(Dif)_BIC_rec	.	.	1.17	1.16	1.42	1.34
UR(1sdBP)_BIC_rec	.	.	1.10	1.12	1.35	1.39
GDP(Dif)_BIC_rec	.	.	1.10	1.17	1.38	1.47
GDP(1sdBP)_BIC_rec	.	.	0.95	1.07	1.14	1.46
IP(Dif)_BIC_rec	.	.	1.14	1.15	1.40	1.33
IP(1sdBP)_BIC_rec	.	.	0.97	1.03	1.23	1.67
Emp(Dif)_BIC_rec	.	.	1.01	1.15	1.30	2.09
Emp(1sdBP)_BIC_rec	.	.	1.06	1.10	1.27	1.66
CapU(Level)_BIC_rec	.	.	.	1.25	1.45	2.53
CapU((Dif)_BIC_rec	.	.	.	1.23	1.39	1.27
CapU(1sdBP)_BIC_rec	.	.	.	1.20	1.18	1.48
HPerm(Level)_BIC_rec	.	.	1.10	1.13	1.20	1.74
HPerm((Dif)_BIC_rec	.	.	1.15	1.23	1.22	1.34
HPerm(1sdBP)_BIC_rec	.	.	1.11	1.11	1.38	1.38
CFNAI(Dif)_BIC_rec	.	.	.	1.16	1.30	1.68
CFNAI(1sdBP)_BIC_rec	.	.	.	1.09	1.16	1.63
UR_5wk(Level)_BIC_rec	.	.	1.03	1.18	1.98	1.76
UR_5wk(Dif)_BIC_rec	.	.	1.14	1.20	1.21	1.25
UR_5wk(1sdBP)_BIC_rec	.	.	1.04	1.23	1.58	1.31
AHE(Dif)_BIC_rec	.	.	1.19	1.26	1.22	1.34
AHE(1sdBP)_BIC_rec	.	.	1.31	1.37	1.31	1.28
RealAHE(Dif)_BIC_rec	.	.	1.19	1.26	1.22	1.34
RealAHE(1sdBP)_BIC_rec	.	.	1.31	1.37	1.31	1.28
LaborShare(Level)_BIC_rec	.	.	1.07	1.32	1.73	1.40
LaborShare(Dif)_BIC_rec	.	.	1.06	1.14	1.46	1.36
ULaborShare(1sdBP)_BIC_rec	.	.	1.08	1.22	1.66	1.46
CPI_Med(Level)_BIC_rec	.	.	.	1.29	1.36	1.46
CPI_Med(Dif)_BIC_rec	.	.	.	1.19	1.24	1.48
CPI_TrMn(Level)_BIC_rec	.	.	.	1.21	1.28	1.38
CPI_TrMn(Dif)_BIC_rec	.	.	.	1.14	1.19	1.33
ExRate(Dif)_BIC_rec	.	.	.	1.15	1.38	1.31
ExRate(1sdBP)_BIC_rec	.	.	.	1.19	1.26	1.32
tb_spr_BIC_rec	.	.	1.26	1.22	1.12	1.50

UR(Level)_BIC_roll	.	.	1.40	1.18	1.01	1.50
UR(Dif)_BIC_roll	.	.	1.25	1.02	1.21	1.30
UR(1sdBP)_BIC_roll	.	.	1.27	0.97	1.00	1.57
GDP(Dif)_BIC_roll	.	.	1.17	1.10	1.23	1.30
GDP(1sdBP)_BIC_roll	.	.	1.02	1.02	1.00	1.53
IP(Dif)_BIC_roll	.	.	1.24	1.11	1.31	1.34
IP(1sdBP)_BIC_roll	.	.	1.05	1.12	1.18	1.65
Emp(Dif)_BIC_roll	.	.	1.14	1.11	1.24	1.47
Emp(1sdBP)_BIC_roll	.	.	1.17	1.06	1.12	2.04
CapU(Level)_BIC_roll	.	.	.	1.21	1.33	1.44
CapU((Dif)_BIC_roll	.	.	.	1.07	1.28	1.39
CapU(1sdBP)_BIC_roll	.	.	.	1.07	1.24	1.37
HPerm(Level)_BIC_roll	.	.	1.15	1.15	1.00	1.54
HPerm((Dif)_BIC_roll	.	.	1.19	1.08	1.26	1.21
HPerm(1sdBP)_BIC_roll	.	.	1.20	1.12	1.11	1.31
CFNAI(Dif)_BIC_roll	.	.	.	1.08	1.24	1.37
CFNAI(1sdBP)_BIC_roll	.	.	.	0.99	1.09	1.74
UR_5wk(Level)_BIC_roll	.	.	1.14	1.42	1.05	1.45
UR_5wk(Dif)_BIC_roll	.	.	1.20	1.05	1.18	1.28
UR_5wk(1sdBP)_BIC_roll	.	.	1.16	1.01	1.27	1.27
AHE(Dif)_BIC_roll	.	.	1.16	1.11	1.24	1.34
AHE(1sdBP)_BIC_roll	.	.	1.31	1.17	1.22	1.49
RealAHE(Dif)_BIC_roll	.	.	1.16	1.11	1.24	1.34
RealAHE(1sdBP)_BIC_roll	.	.	1.31	1.17	1.22	1.49
LaborShare(Level)_BIC_roll	.	.	1.14	1.22	1.41	1.45
LaborShare(Dif)_BIC_roll	.	.	1.12	1.09	1.26	1.58
ULaborShare(1sdBP)_BIC_roll	.	.	1.24	1.15	1.45	1.46
CPI_Med(Level)_BIC_roll	.	.	.	1.24	1.29	1.14
CPI_Med(Dif)_BIC_roll	.	.	.	1.05	1.22	1.27
CPI_TrMn(Level)_BIC_roll	.	.	.	1.23	1.29	1.30
CPI_TrMn(Dif)_BIC_roll	.	.	.	1.07	1.25	1.31
ExRate(Dif)_BIC_roll	.	.	.	1.14	1.29	1.43
ExRate(1sdBP)_BIC_roll	.	.	.	1.07	1.08	1.41
tb_spr_BIC_roll	.	.	1.62	1.10	1.25	1.27
Triangle model forecasts						
Triangle Constant NAIRU	.	.	1.69	1.06	1.80	1.55
Triangle TV NAIRU	.	.	1.94	0.99	1.37	1.44
Triangle Constant NAIRU (no z)	.	.	1.17	1.64	2.20	1.58
Triangle TV NAIRU (no z)	.	.	1.28	1.58	1.48	2.13
Combination forecasts						
Activity Median Combining	.	.	0.95	1.01	1.07	1.27
Activity Mean Combining	.	.	0.93	1.00	1.07	1.28
Activity Tr. Mean Combining	.	.	0.95	1.01	1.08	1.27
Activity MSE(A) Combining	.	.	.	0.99	1.08	1.31
Activity MSE(B) Combining	.	.	.	0.98	1.08	1.30
Activity MSE(3 Combining	.	.	.	0.98	1.07	1.30
Activity MSE(D) Combining	.	.	.	0.97	1.10	1.34
Activity MSE(E) Combining	.	.	.	0.95	1.08	1.33
Activity MSE(F) Combining	.	.	.	0.95	1.07	1.33
Activity Rec. Best(4q) Combining	.	.	1.01	1.39	1.37	1.95
Activity Rec. Best(8q) Combining	.	.	0.78	1.35	1.29	1.57
OtherADL Median Combining	.	.	1.10	1.11	1.16	1.24
OtherADL Mean Combining	.	.	1.08	1.12	1.14	1.23
OtherADL Tr. Mean Combining	.	.	1.10	1.11	1.14	1.22
OtherADL MSE(A) Combining	.	.	.	1.13	1.16	1.26
OtherADL MSE(B) Combining	.	.	.	1.13	1.16	1.25
OtherADL MSE(C) Combining	.	.	.	1.13	1.16	1.24
OtherADL MSE(D) Combining	.	.	.	1.13	1.18	1.29
OtherADL MSE(E) Combining	.	.	.	1.13	1.17	1.26
OtherADL MSE(F) Combining	.	.	.	1.13	1.17	1.25
OtherADL Rec. Best(4q) Combining	.	.	1.30	1.37	1.51	1.42
OtherADL Rec. Best(8q) Combining	.	.	1.40	1.32	1.49	1.72
All Median Combining	.	.	1.01	1.03	1.09	1.26
All Mean Combining	.	.	0.96	1.03	1.08	1.24
All Tr. Mean Combining	.	.	0.98	1.04	1.09	1.24
All MSE(A) Combining	.	.	.	1.01	1.10	1.27

All MSE(B) Combining	.	.	.	1.01	1.09	1.26
All MSE(C) Combining	.	.	.	1.00	1.08	1.26
All MSE(D) Combining	.	.	.	1.00	1.12	1.30
All MSE(E) Combining	.	.	.	0.98	1.10	1.29
All MSE(F) Combining	.	.	.	0.97	1.08	1.28
All Rec. Best(4q) Combining	.	.	1.20	1.44	1.43	1.93
All Rec. Best(8q) Combining	.	.	0.78	1.35	1.43	1.61
UCSV and Triangle Rec. Best(4q) Combining	.	.	.	1.04	1.13	1.03
UCSV and Triangle Rec. Best(8q) Combining	.	.	.	1.04	1.26	1.13

Table 5
RMSEs for Inflation Forecasting Models by Sub-Period, Relative to UC-SV model: GDP deflator

Forecast period	**1960Q1 – 1967Q4**	**1968Q1 – 1976Q4**	**1977Q1 - 1984Q4**	**1985Q1 – 1992Q4**	**1993Q1 – 2000Q4**	**2001Q1 – 2007Q4**
No. observations	32	36	32	32	32	25
Root MSE of UC-SV forecast	0.72	1.76	1.28	0.70	0.41	0.57
Forecasting model and relative RMSEs						
Univariate forecasts						
UC-SV	1.00	1.00	1.00	1.00	1.00	1.00
AR(AIC)_rec	.	1.03	1.06	1.06	1.02	1.16
AR(AIC)_iter_rec	.	1.11	1.08	1.04	0.99	1.19
AR(BIC)_rec	.	1.03	1.04	1.08	1.07	1.24
AO	0.97	1.10	1.17	1.04	0.95	1.02
MA(1)_rec	.	1.02	1.00	1.04	1.02	1.16
AR(4)_rec	.	1.07	1.07	1.04	0.99	1.17
AR(AIC)_roll	.	1.11	1.05	1.15	1.19	1.16
AR(AIC)_iter_roll	.	1.10	1.06	1.02	1.12	1.11
AR(BIC)_roll	.	1.08	1.05	1.21	1.17	1.11
AR(4)_roll	.	1.15	1.08	1.08	1.14	1.15
AR(24)_iter	.	.	1.42	1.10	1.02	0.99
AR(24)_iter_nocon	.	.	1.34	1.02	0.99	0.99
MA(1)_roll	.	1.03	0.99	1.05	0.98	1.02
MA(2) - NS	0.97	1.02	1.19	1.03	1.02	1.02
MA(1), θ=.25	1.03	1.00	1.00	1.07	1.08	1.25
MA(1), θ=.65	0.96	1.03	1.17	1.02	0.99	1.01
Single-predictor ADL forecasts						
UR(Level)_AIC_rec	.	0.93	0.99	0.91	1.23	1.30
UR(Dif)_AIC_rec	.	0.93	1.11	0.96	1.25	1.22
UR(1sdBP)_AIC_rec	.	0.94	1.12	0.91	1.14	1.19
GDP(Dif)_AIC_rec	.	0.94	1.04	0.91	1.06	1.09
GDP(1sdBP)_AIC_rec	.	0.98	1.01	0.89	0.96	1.15
IP(Dif)_AIC_rec	.	0.90	1.05	0.89	1.25	1.15
IP(1sdBP)_AIC_rec	.	0.93	1.04	0.86	1.18	1.23
Emp(Dif)_AIC_rec	.	0.93	1.03	0.93	1.11	1.42
Emp(1sdBP)_AIC_rec	.	0.94	1.05	0.94	1.19	1.35
CapU(Level)_AIC_rec	.	.	.	1.03	1.54	1.87
CapU((Dif)_AIC_rec	.	.	.	0.96	1.39	1.22
CapU(1sdBP)_AIC_rec	.	.	.	0.91	1.23	1.23
HPerm(Level)_AIC_rec	.	.	1.07	1.05	0.89	1.60
HPerm((Dif)_AIC_rec	.	.	1.17	1.09	1.01	1.13
HPerm(1sdBP)_AIC_rec	.	.	1.18	1.04	1.10	1.09
CFNAI(Dif)_AIC_rec	.	.	.	1.00	1.16	1.54
CFNAI(1sdBP)_AIC_rec	.	.	.	0.89	1.12	1.46
UR_5wk(Level)_AIC_rec	.	1.08	1.01	0.92	1.83	1.32
UR_5wk(Dif)_AIC_rec	.	0.99	1.07	0.93	1.32	1.11
UR_5wk(1sdBP)_AIC_rec	.	0.99	1.04	0.95	1.30	1.14
AHE(Dif)_AIC_rec	.	.	1.09	1.09	1.05	1.16
AHE(1sdBP)_AIC_rec	.	.	1.21	1.19	1.07	1.13
RealAHE(Dif)_AIC_rec	.	.	1.09	1.09	1.05	1.16
RealAHE(1sdBP)_AIC_rec	.	.	1.21	1.19	1.07	1.13
LaborShare(Level)_AIC_rec	.	1.10	0.99	1.18	1.85	1.27
LaborShare(Dif)_AIC_rec	.	1.09	1.06	1.07	1.12	1.14
ULaborShare(1sdBP)_AIC_rec	.	1.10	1.01	1.08	1.47	1.13
CPI_Med(Level)_AIC_rec	.	.	.	1.09	1.38	1.29
CPI_Med(Dif)_AIC_rec	.	.	.	1.02	1.15	1.34
CPI_TrMn(Level)_AIC_rec	.	.	.	1.12	1.17	1.21
CPI_TrMn(Dif)_AIC_rec	.	.	.	1.02	0.96	1.19
ExRate(Dif)_AIC_rec	.	.	.	1.23	1.44	1.06
ExRate(1sdBP)_AIC_rec	.	.	.	1.66	1.25	0.91
tb_spr_AIC_rec	.	1.08	1.23	1.19	0.95	1.27
UR(Level)_AIC_roll	.	1.09	1.43	1.06	1.16	1.11
UR(Dif)_AIC_roll	.	0.97	1.35	1.12	1.25	1.06

UR(1sdBP)_AIC_roll	.	1.03	1.33	1.04	1.25	1.13
GDP(Dif)_AIC_roll	.	1.13	1.21	1.08	1.26	1.05
GDP(1sdBP)_AIC_roll	.	1.15	0.96	1.05	1.21	1.07
IP(Dif)_AIC_roll	.	1.01	1.22	1.10	1.42	1.10
IP(1sdBP)_AIC_roll	.	1.05	1.10	1.12	1.48	1.20
Emp(Dif)_AIC_roll	.	1.04	1.24	1.15	1.23	1.08
Emp(1sdBP)_AIC_roll	.	1.06	1.23	1.17	1.27	1.23
CapU(Level)_AIC_roll	.	.	.	1.12	1.39	1.12
CapU((Dif)_AIC_roll	.	.	.	1.11	1.34	1.10
CapU(1sdBP)_AIC_roll	.	.	.	1.05	1.33	1.06
HPerm(Level)_AIC_roll	.	.	1.18	1.36	0.92	1.35
HPerm((Dif)_AIC_roll	.	.	1.20	1.21	1.12	1.08
HPerm(1sdBP)_AIC_roll	.	.	1.36	1.33	1.07	1.10
CFNAI(Dif)_AIC_roll	.	.	.	1.12	1.29	1.11
CFNAI(1sdBP)_AIC_roll	.	.	.	1.10	1.31	1.16
UR_5wk(Level)_AIC_roll	.	1.28	1.18	1.21	1.86	1.20
UR_5wk(Dif)_AIC_roll	.	1.09	1.11	1.17	1.45	1.14
UR_5wk(1sdBP)_AIC_roll	.	1.08	1.09	0.94	1.38	1.15
AHE(Dif)_AIC_roll	.	.	1.07	1.06	1.18	1.14
AHE(1sdBP)_AIC_roll	.	.	1.19	1.11	1.22	1.06
RealAHE(Dif)_AIC_roll	.	.	1.07	1.06	1.18	1.14
RealAHE(1sdBP)_AIC_roll	.	.	1.19	1.11	1.22	1.06
LaborShare(Level)_AIC_roll	.	1.22	1.39	1.18	1.25	1.14
LaborShare(Dif)_AIC_roll	.	1.11	1.53	1.11	1.60	1.26
ULaborShare(1sdBP)_AIC_roll	.	1.15	1.44	1.13	1.30	1.15
CPI_Med(Level)_AIC_roll	.	.	.	1.14	1.31	0.87
CPI_Med(Dif)_AIC_roll	.	.	.	1.06	1.20	1.14
CPI_TrMn(Level)_AIC_roll	.	.	.	1.16	1.21	0.72
CPI_TrMn(Dif)_AIC_roll	.	.	.	1.07	1.16	1.13
ExRate(Dif)_AIC_roll	.	.	.	1.42	1.15	1.19
ExRate(1sdBP)_AIC_roll	.	.	.	1.67	1.21	1.13
tb_spr_AIC_roll	.	1.09	1.60	1.29	1.16	1.21
UR(Level)_BIC_rec	.	0.94	0.96	0.92	1.21	1.28
UR(Dif)_BIC_rec	.	0.94	1.08	0.97	1.20	1.20
UR(1sdBP)_BIC_rec	.	0.93	1.06	0.94	1.14	1.19
GDP(Dif)_BIC_rec	.	1.00	1.09	0.94	1.08	1.11
GDP(1sdBP)_BIC_rec	.	0.99	1.00	0.93	0.87	1.17
IP(Dif)_BIC_rec	.	0.96	1.06	0.89	1.22	1.11
IP(1sdBP)_BIC_rec	.	0.96	0.99	0.89	1.12	1.22
Emp(Dif)_BIC_rec	.	0.90	0.99	0.90	1.12	1.30
Emp(1sdBP)_BIC_rec	.	0.97	0.99	0.90	1.14	1.31
CapU(Level)_BIC_rec	.	.	.	1.06	1.47	1.83
CapU((Dif)_BIC_rec	.	.	.	1.02	1.39	1.22
CapU(1sdBP)_BIC_rec	.	.	.	0.94	1.19	1.21
HPerm(Level)_BIC_rec	.	.	0.99	1.05	0.89	1.60
HPerm((Dif)_BIC_rec	.	.	1.09	1.08	1.05	1.22
HPerm(1sdBP)_BIC_rec	.	.	1.08	0.99	1.09	1.05
CFNAI(Dif)_BIC_rec	.	.	.	1.00	1.16	1.51
CFNAI(1sdBP)_BIC_rec	.	.	.	0.86	1.08	1.32
UR_5wk(Level)_BIC_rec	.	1.08	1.00	1.01	1.73	1.43
UR_5wk(Dif)_BIC_rec	.	0.98	1.08	1.03	1.17	1.20
UR_5wk(1sdBP)_BIC_rec	.	1.00	1.03	0.98	1.28	1.18
AHE(Dif)_BIC_rec	.	.	1.07	1.17	1.07	1.24
AHE(1sdBP)_BIC_rec	.	.	1.21	1.31	1.11	1.20
RealAHE(Dif)_BIC_rec	.	.	1.07	1.17	1.07	1.24
RealAHE(1sdBP)_BIC_rec	.	.	1.21	1.31	1.11	1.20
LaborShare(Level)_BIC_rec	.	1.09	1.03	1.22	1.68	1.34
LaborShare(Dif)_BIC_rec	.	1.06	1.04	1.06	1.15	1.22
ULaborShare(1sdBP)_BIC_rec	.	1.11	1.03	1.09	1.49	1.23
CPI_Med(Level)_BIC_rec	.	.	.	1.14	1.38	1.29
CPI_Med(Dif)_BIC_rec	.	.	.	1.08	1.18	1.27
CPI_TrMn(Level)_BIC_rec	.	.	.	1.16	1.17	1.21
CPI_TrMn(Dif)_BIC_rec	.	.	.	1.08	0.99	1.22
ExRate(Dif)_BIC_rec	.	.	.	1.12	1.48	1.09
ExRate(1sdBP)_BIC_rec	.	.	.	1.28	1.33	1.11
tb_spr_BIC_rec	.	1.03	1.09	1.11	0.99	1.33

UR(Level)_BIC_roll	.	1.14	1.49	1.04	1.21	1.15
UR(Dif)_BIC_roll	.	1.03	1.33	1.14	1.21	1.10
UR(1sdBP)_BIC_roll	.	0.98	1.36	1.02	1.20	1.17
GDP(Dif)_BIC_roll	.	1.15	1.15	1.17	1.28	1.00
GDP(1sdBP)_BIC_roll	.	1.15	0.98	1.06	1.20	1.10
IP(Dif)_BIC_roll	.	1.05	1.16	1.10	1.34	1.08
IP(1sdBP)_BIC_roll	.	1.09	1.13	1.18	1.43	1.24
Emp(Dif)_BIC_roll	.	1.03	1.21	1.15	1.25	1.11
Emp(1sdBP)_BIC_roll	.	1.04	1.24	1.24	1.27	1.24
CapU(Level)_BIC_roll	.	.	.	1.01	1.37	1.14
CapU((Dif)_BIC_roll	.	.	.	1.10	1.27	1.05
CapU(1sdBP)_BIC_roll	.	.	.	0.96	1.29	1.12
HPerm(Level)_BIC_roll	.	.	1.08	1.25	0.94	1.37
HPerm((Dif)_BIC_roll	.	.	1.08	1.25	1.14	1.07
HPerm(1sdBP)_BIC_roll	.	.	1.22	1.20	1.08	1.08
CFNAI(Dif)_BIC_roll	.	.	.	1.12	1.28	1.10
CFNAI(1sdBP)_BIC_roll	.	.	.	1.14	1.25	1.13
UR_5wk(Level)_BIC_roll	.	1.28	1.07	1.17	1.55	1.22
UR_5wk(Dif)_BIC_roll	.	1.07	1.08	1.14	1.27	1.08
UR_5wk(1sdBP)_BIC_roll	.	1.06	1.09	0.93	1.32	1.11
AHE(Dif)_BIC_roll	.	.	1.07	1.19	1.17	1.10
AHE(1sdBP)_BIC_roll	.	.	1.19	1.32	1.17	1.09
RealAHE(Dif)_BIC_roll	.	.	1.07	1.19	1.17	1.10
RealAHE(1sdBP)_BIC_roll	.	.	1.19	1.32	1.17	1.09
LaborShare(Level)_BIC_roll	.	1.21	1.24	1.22	1.24	1.06
LaborShare(Dif)_BIC_roll	.	1.06	1.32	1.23	1.31	1.16
ULaborShare(1sdBP)_BIC_roll	.	1.17	1.32	1.23	1.29	1.09
CPI_Med(Level)_BIC_roll	.	.	.	1.36	1.34	0.92
CPI_Med(Dif)_BIC_roll	.	.	.	1.13	1.18	1.26
CPI_TrMn(Level)_BIC_roll	.	.	.	1.26	1.14	0.73
CPI_TrMn(Dif)_BIC_roll	.	.	.	1.16	1.16	1.11
ExRate(Dif)_BIC_roll	.	.	.	1.26	1.22	1.16
ExRate(1sdBP)_BIC_roll	.	.	.	1.49	1.20	1.15
tb_spr_BIC_roll	.	1.13	1.50	1.21	1.14	1.17
Triangle model forecasts						
Triangle Constant NAIRU	.	.	1.08	0.78	1.22	1.20
Triangle TV NAIRU	.	.	0.98	0.81	1.07	1.23
Triangle Constant NAIRU (no z)	.	.	1.22	0.95	1.64	1.22
Triangle TV NAIRU (no z)	.	.	1.17	1.21	1.33	1.61
Combination forecasts						
Activity Median Combining	.	0.98	0.99	0.93	1.10	1.09
Activity Mean Combining	.	1.00	0.97	0.91	1.07	1.10
Activity Tr. Mean Combining	.	1.00	0.98	0.93	1.09	1.10
Activity MSE(A) Combining	.	.	0.98	0.91	1.09	1.11
Activity MSE(B) Combining	.	.	0.98	0.91	1.09	1.11
Activity MSE(3 Combining	.	.	0.98	0.91	1.08	1.10
Activity MSE(D) Combining	.	.	0.98	0.89	1.10	1.11
Activity MSE(E) Combining	.	.	0.98	0.89	1.09	1.11
Activity MSE(F) Combining	.	.	0.98	0.89	1.08	1.11
Activity Rec. Best(4q) Combining	.	1.09	1.24	1.02	1.33	1.07
Activity Rec. Best(8q) Combining	.	1.11	1.29	1.02	1.30	1.39
OtherADL Median Combining	.	1.09	1.02	1.06	1.12	1.08
OtherADL Mean Combining	.	1.10	0.99	1.02	1.09	1.07
OtherADL Tr. Mean Combining	.	1.09	0.98	1.05	1.09	1.07
OtherADL MSE(A) Combining	.	.	1.09	1.08	1.10	1.06
OtherADL MSE(B) Combining	.	.	1.07	1.08	1.11	1.06
OtherADL MSE(C) Combining	.	.	1.06	1.08	1.11	1.06
OtherADL MSE(D) Combining	.	.	1.11	1.08	1.10	1.04
OtherADL MSE(E) Combining	.	.	1.09	1.08	1.11	1.04
OtherADL MSE(F) Combining	.	.	1.07	1.08	1.12	1.06
OtherADL Rec. Best(4q) Combining	.	1.07	1.18	1.42	1.12	0.83
OtherADL Rec. Best(8q) Combining	.	1.15	1.32	1.22	1.05	0.91
All Median Combining	.	1.01	0.97	0.98	1.10	1.07
All Mean Combining	.	1.02	0.94	0.94	1.05	1.08
All Tr. Mean Combining	.	1.02	0.94	0.97	1.06	1.07
All MSE(A) Combining	.	.	0.97	0.95	1.07	1.07

All MSE(B) Combining	.	.	0.96	0.95	1.07	1.07
All MSE(C) Combining	.	.	0.96	0.95	1.07	1.07
All MSE(D) Combining	.	.	0.98	0.94	1.09	1.07
All MSE(E) Combining	.	.	0.98	0.93	1.09	1.07
All MSE(F) Combining	.	.	0.97	0.93	1.07	1.07
All Rec. Best(4q) Combining	.	1.07	1.35	1.20	1.32	0.90
All Rec. Best(8q) Combining	.	1.12	1.37	1.03	1.16	1.03
UCSV and Triangle Rec. Best(4q) Combining	.	.	.	0.91	1.14	1.17
UCSV and Triangle Rec. Best(8q) Combining	.	.	.	0.89	1.13	1.21

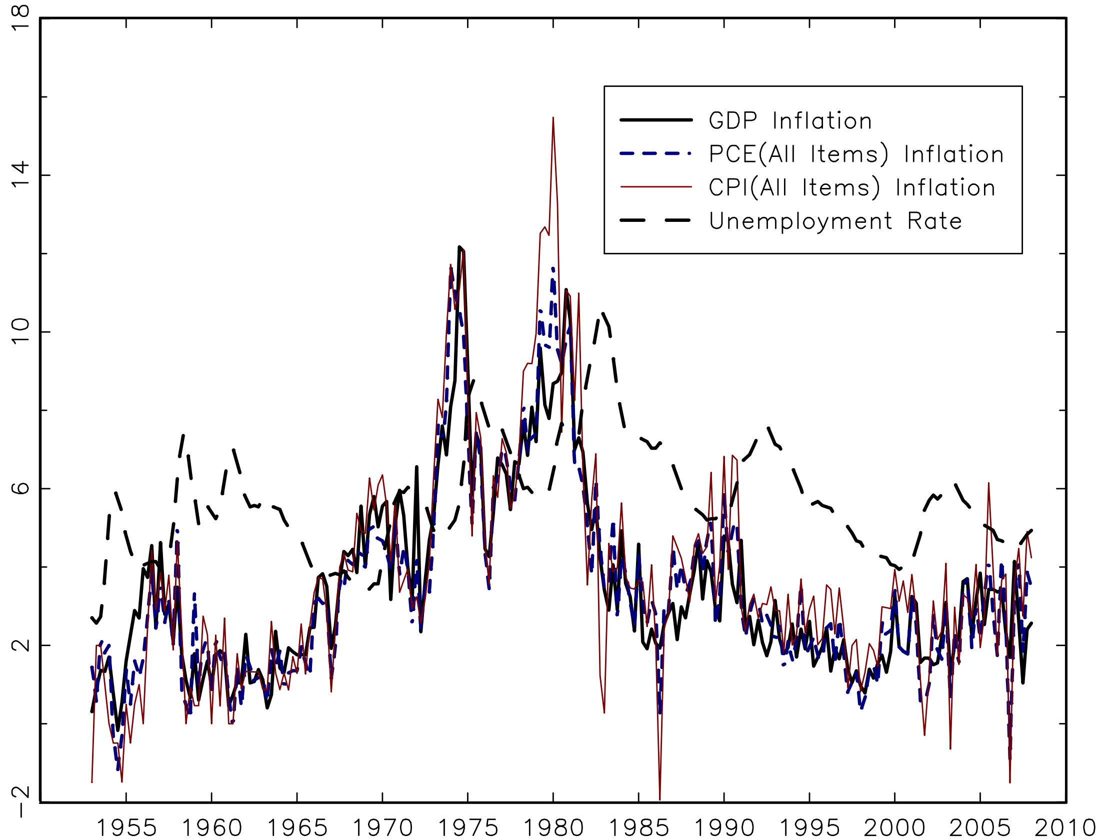


Figure 1. Quarterly rate of U.S. price inflation as measured by the GDP deflator, PCE-all, and CPI-all, and the rate of unemployment.

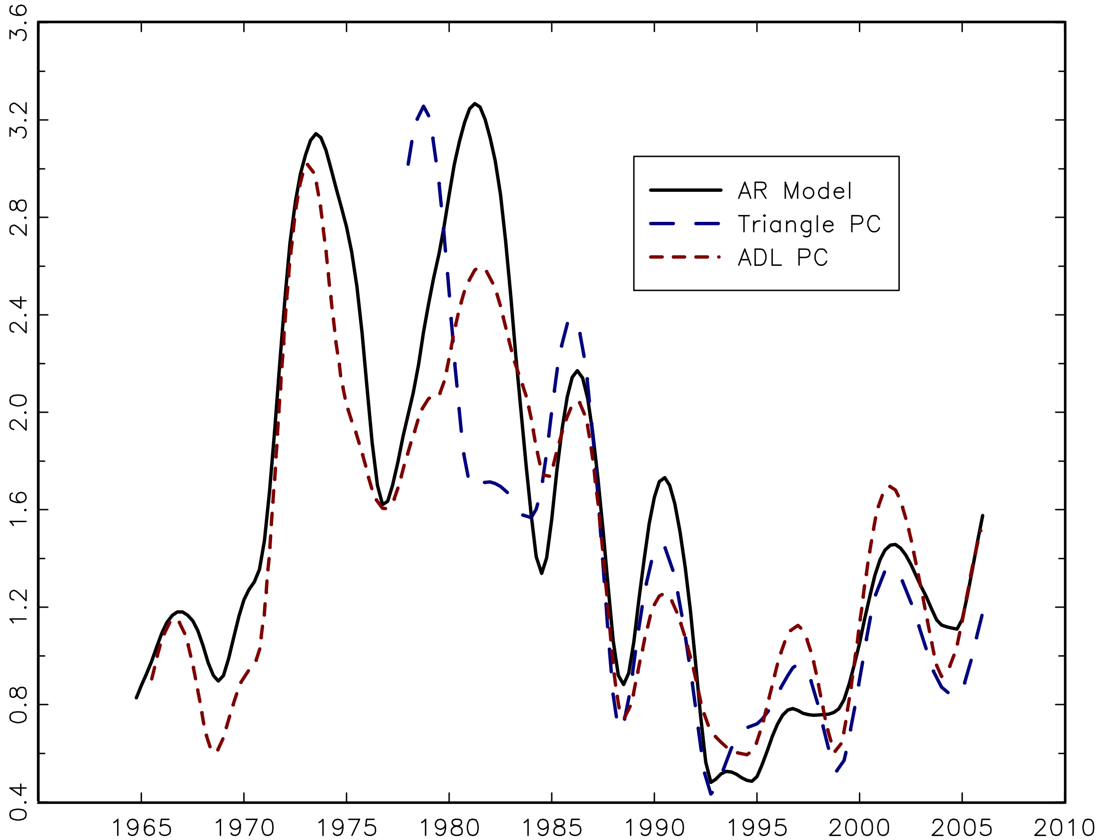
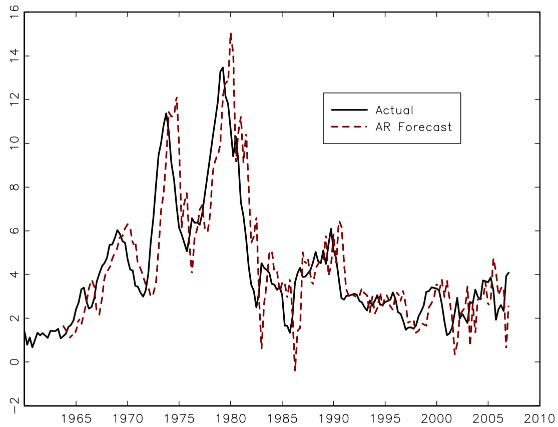
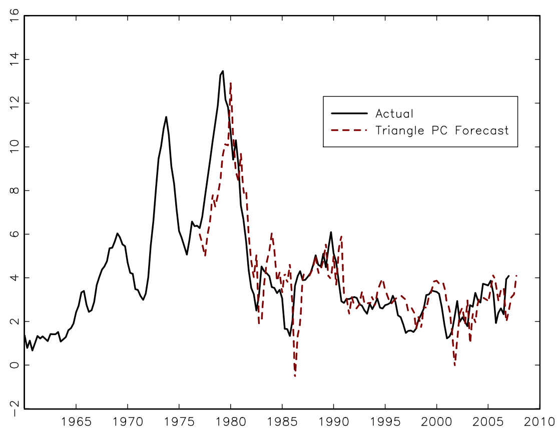


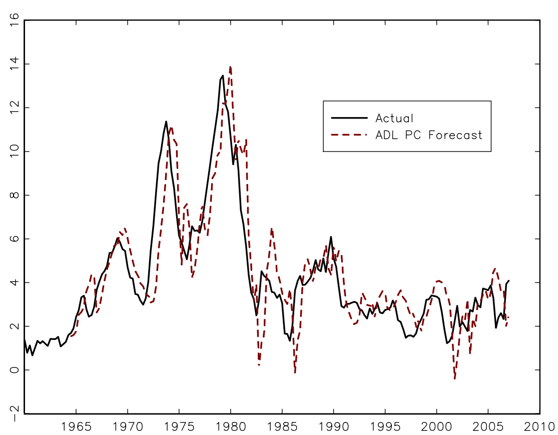
Figure 2. Rolling RMSEs for CPI-all inflation forecasts: AR(AIC), triangle model (constant NAIRU), and ADL-*u* model



(a) AR(AIC)



(b) triangle model



(c) ADL-*u* model

Figure 3. CPI-all inflation and psuedo out-of-sample forecasts.

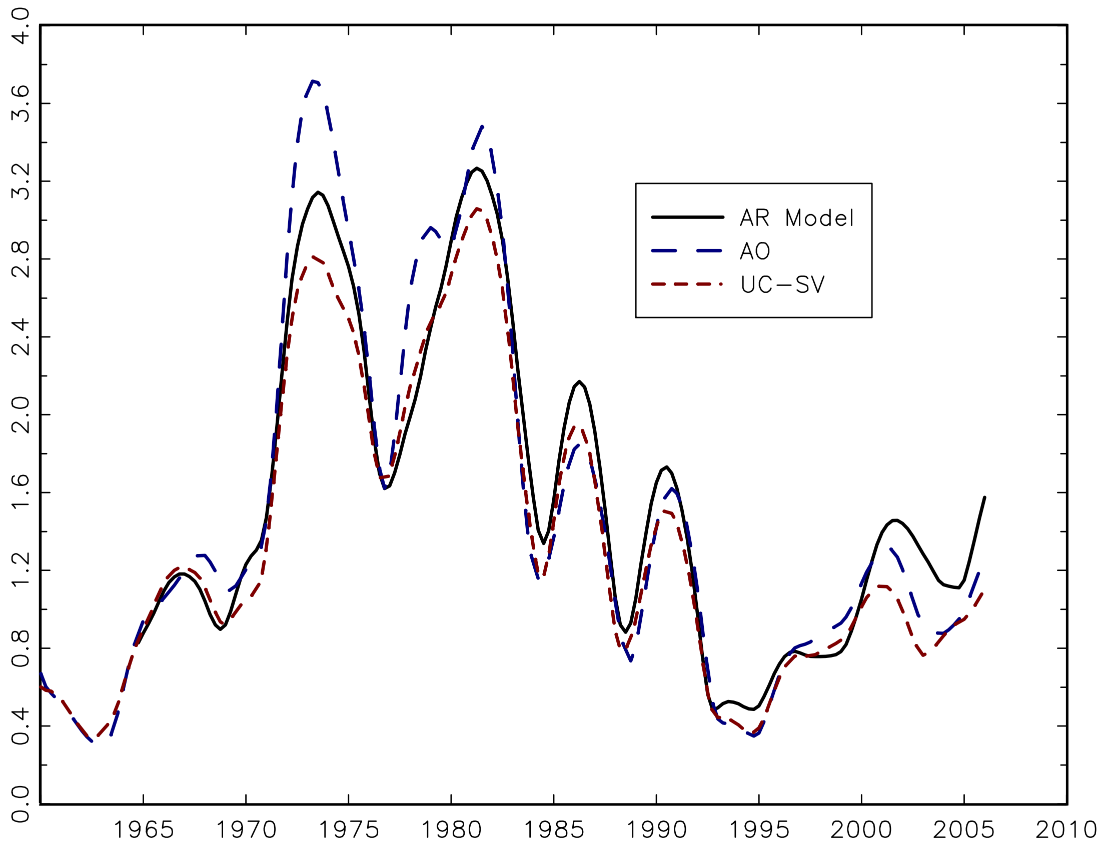


Figure 4. Rolling RMSEs for univariate CPI-all inflation forecasts: AR(AIC), Atkeson-Ohanian (AO), and unobserved components-stochastic volatility (UC-SV) models

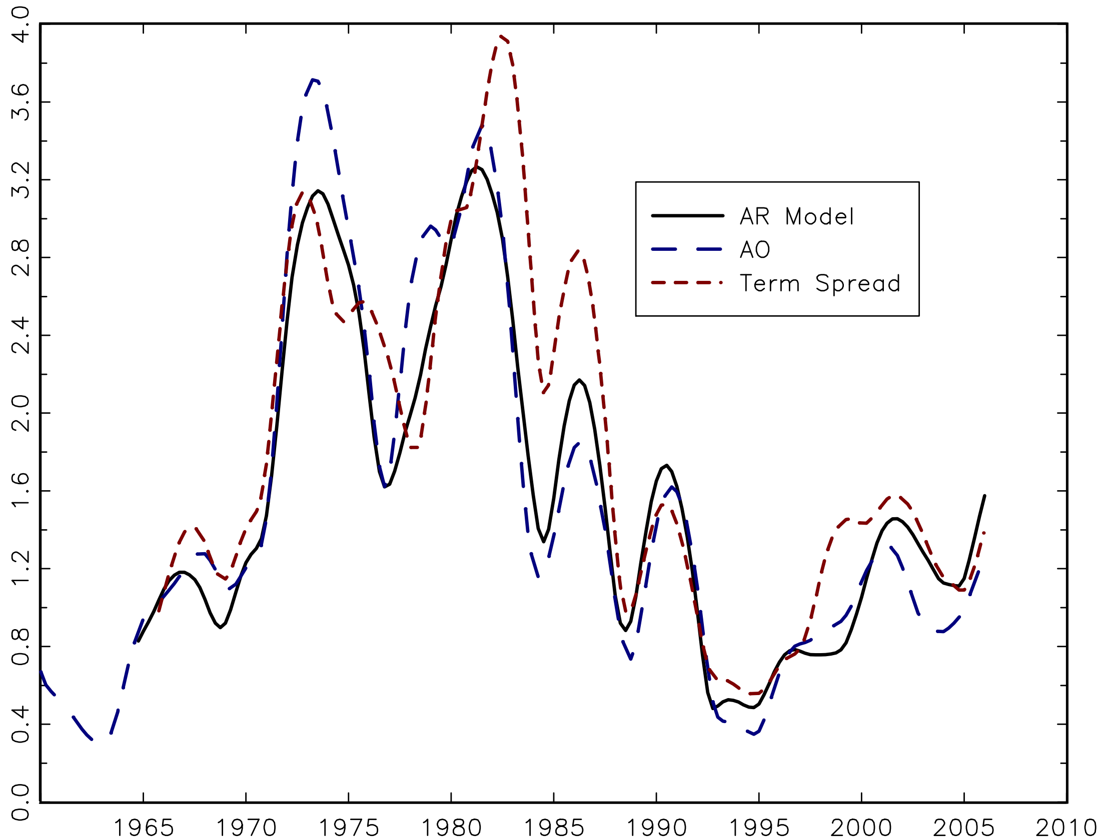


Figure 5. Rolling RMSEs for CPI-all inflation forecasts: AR(AIC), Atkeson-Ohanian (AO), and term spread model

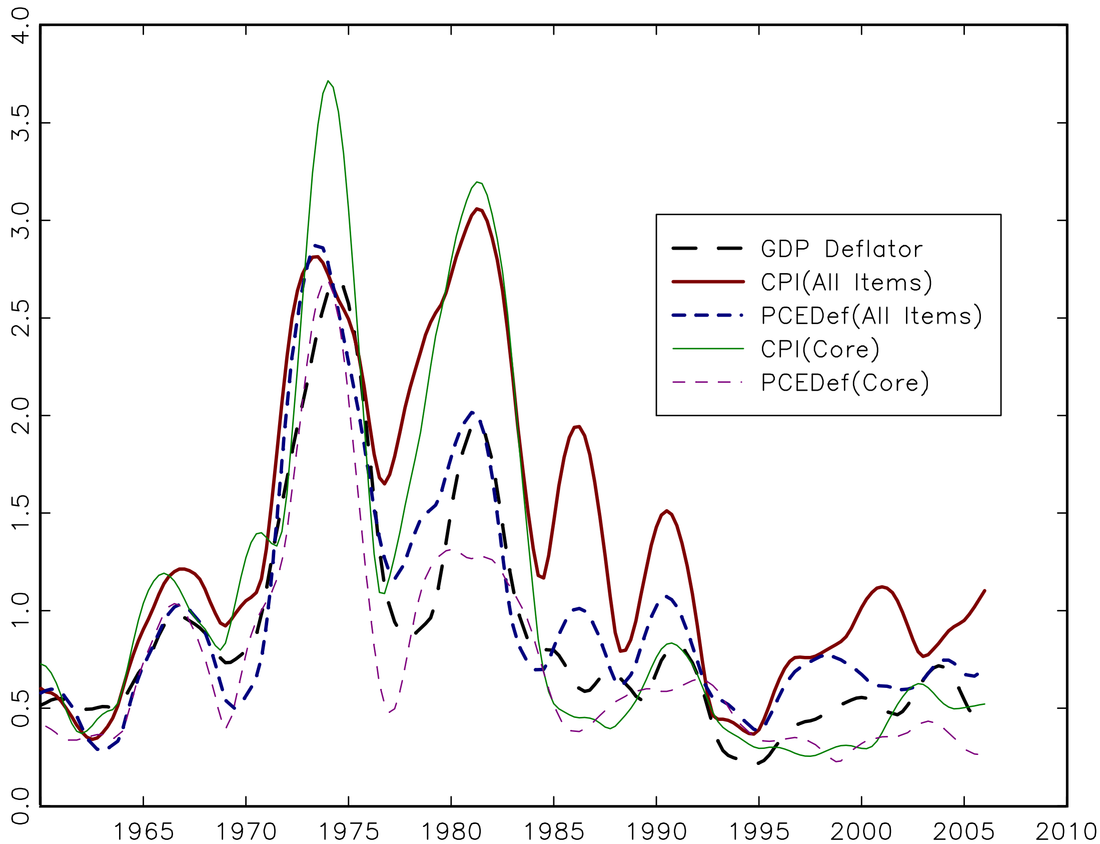


Figure 6. Rolling RMSEs for inflation forecasts, UC-SV model, for all five inflation series

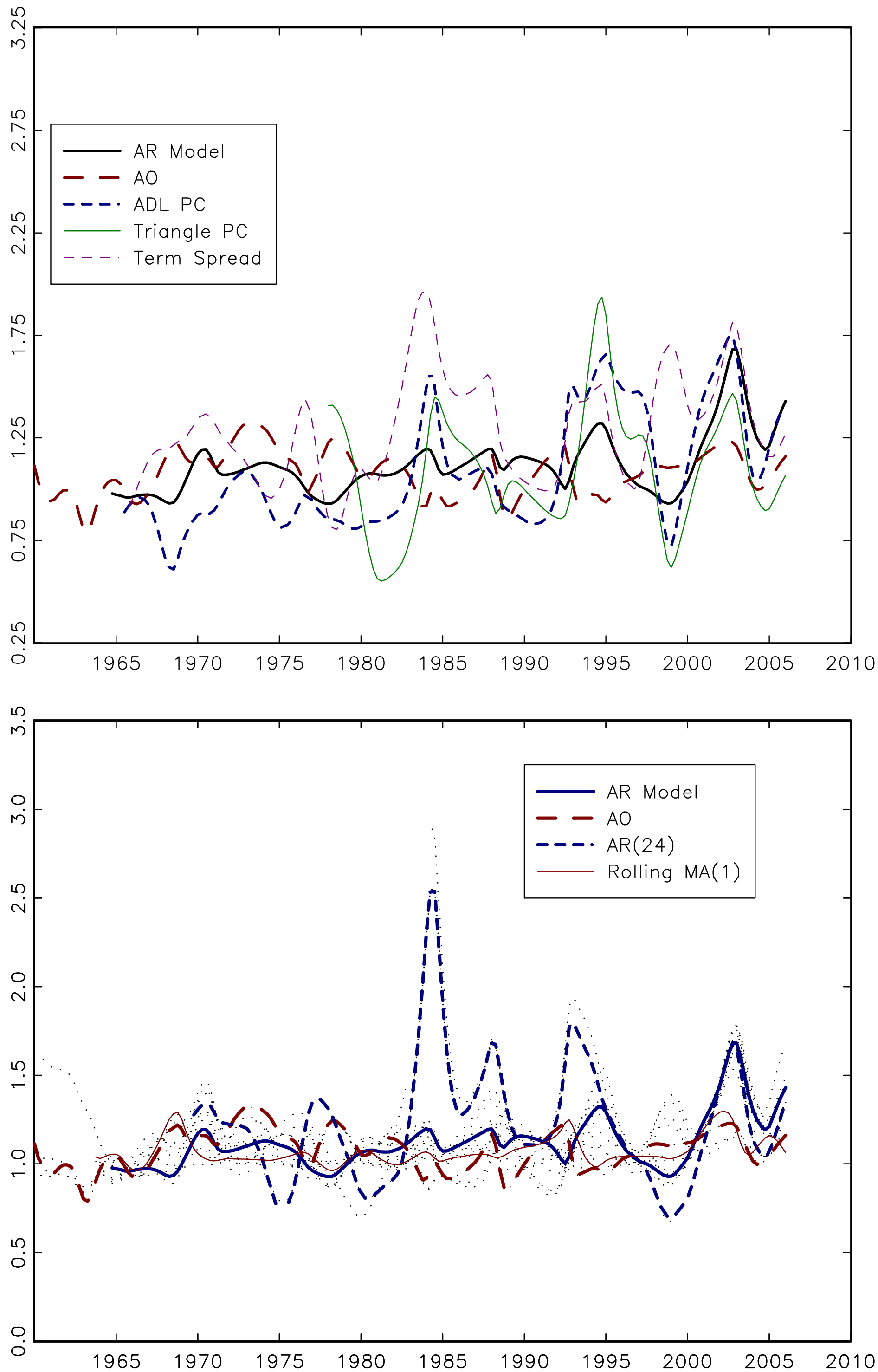
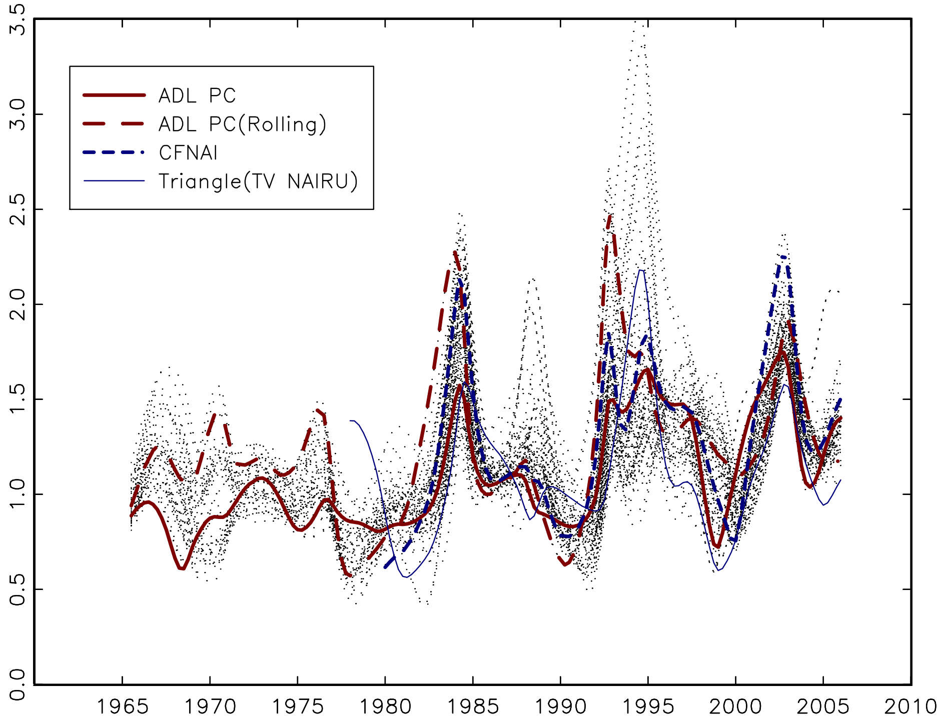


Figure 7
(a) Relative rolling RMSE of prototype models: CPI-all
(b) Relative rolling RMSE of univariate models: CPI-all



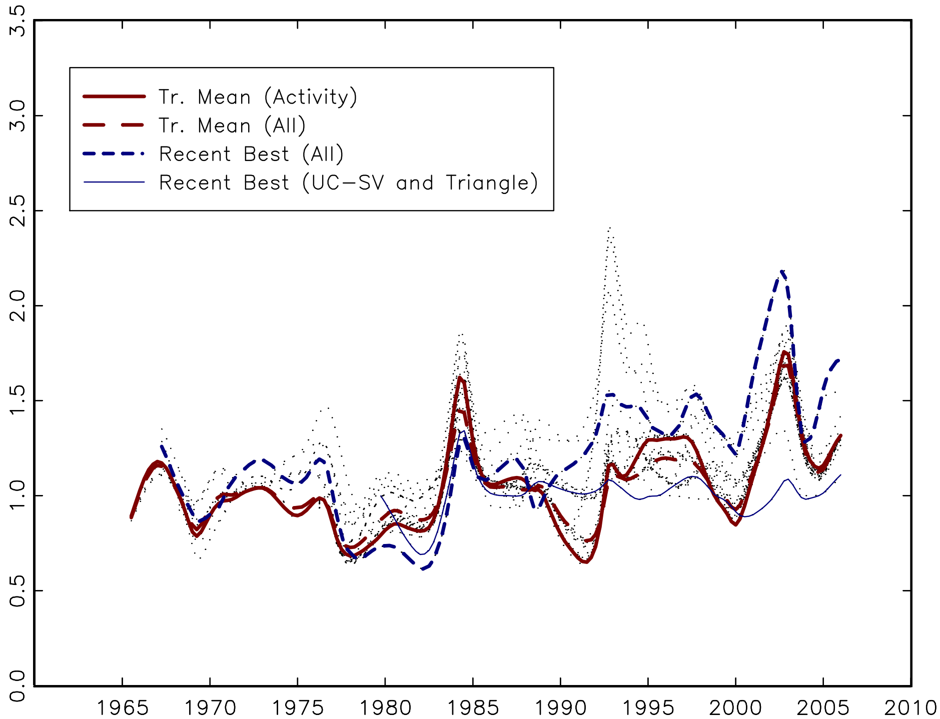


Figure 7
(c) Relative rolling RMSE of Phillips curve forecasts: CPI-all
(d) Relative rolling RMSE of combination forecasts: CPI-all

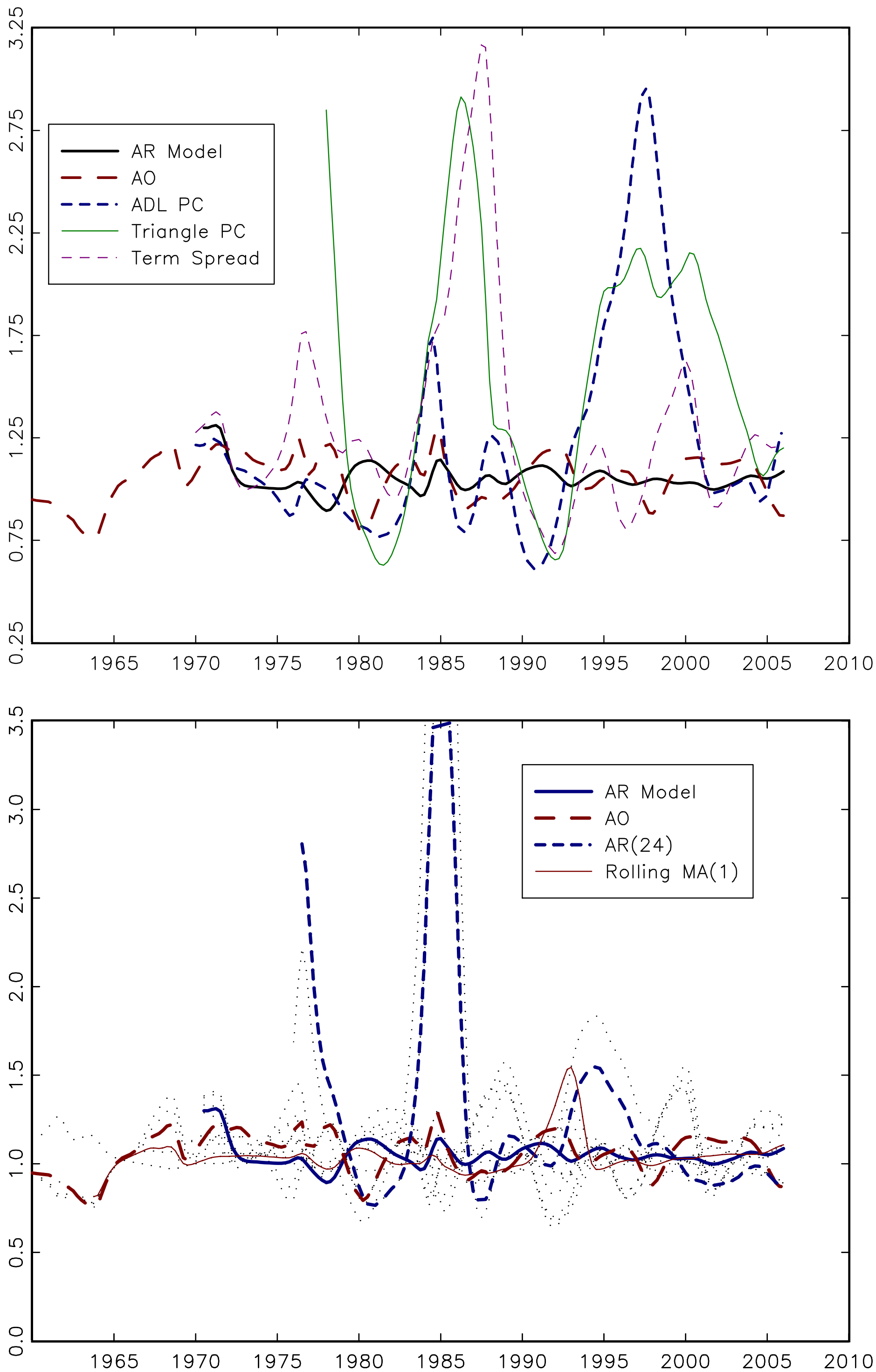


Figure 8
(a) Relative rolling RMSE of prototype models: CPI-core
(b) Relative rolling RMSE of univariate models: CPI-core

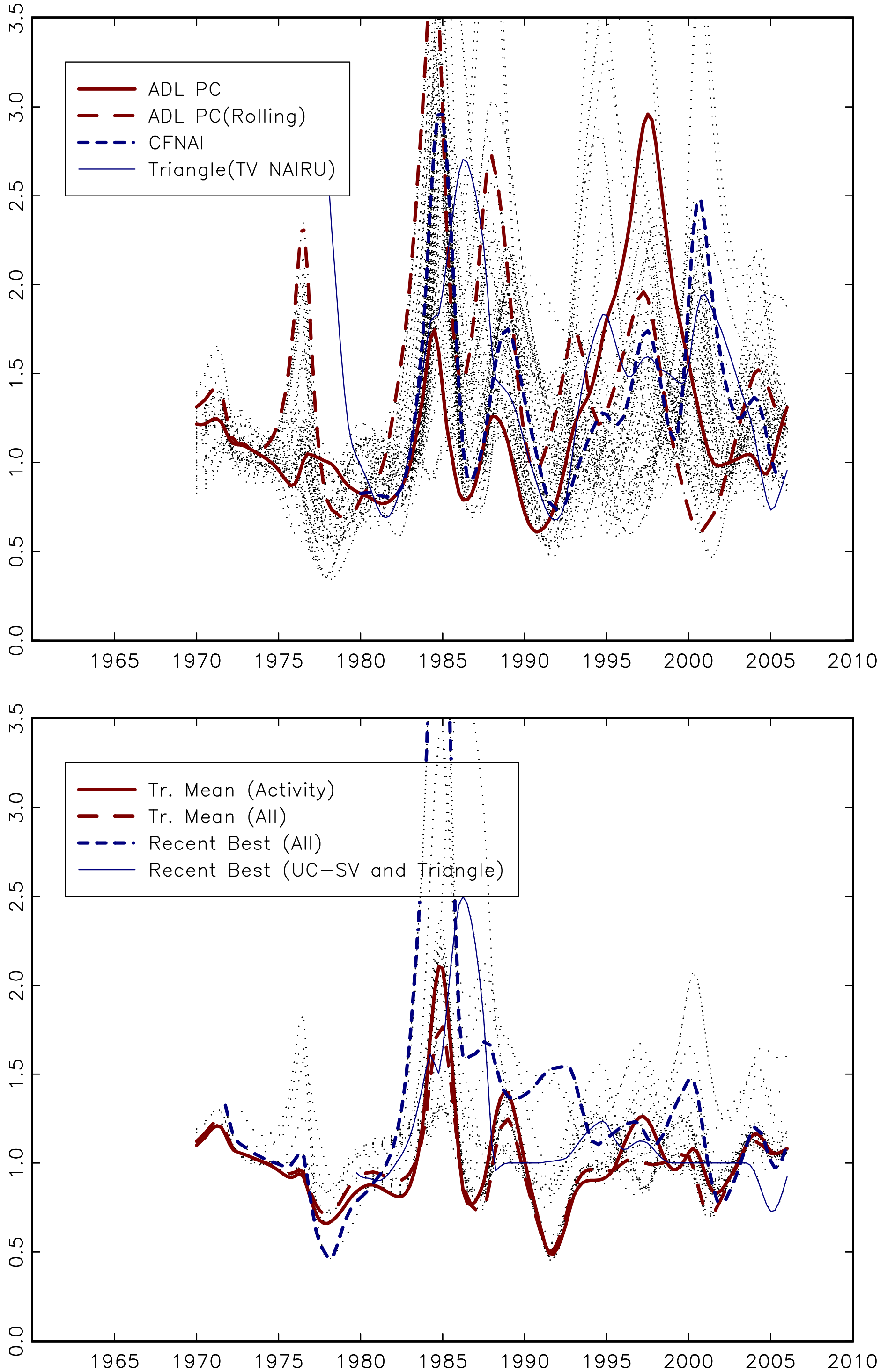


Figure 8
(c) Relative rolling RMSE of Phillips curve forecasts: CPI-core
(d) Relative rolling RMSE of combination forecasts: CPI-core

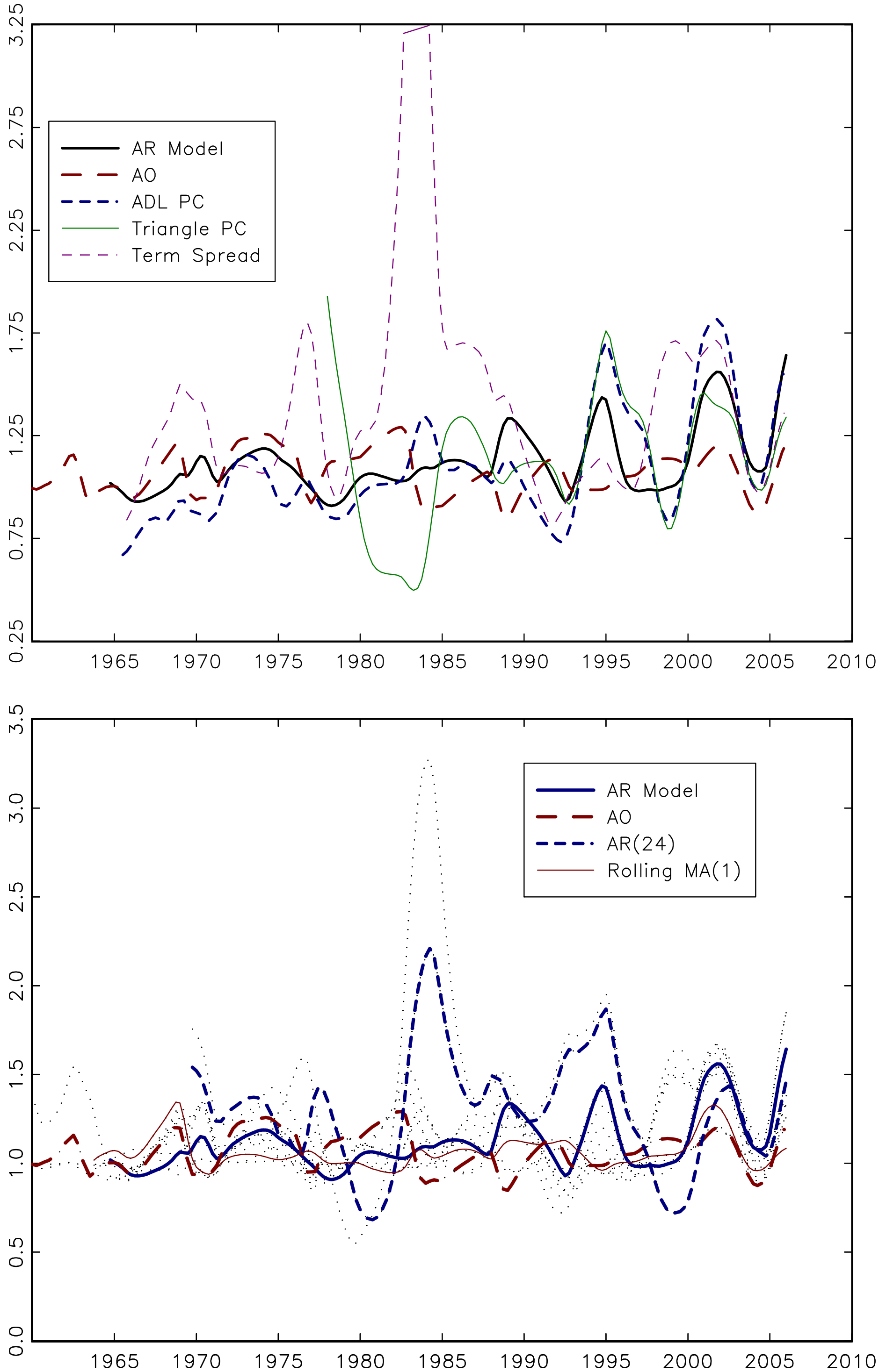


Figure 9
(a) Relative rolling RMSE of prototype models: PCE-all
(b) Relative rolling RMSE of univariate models: PCE-all

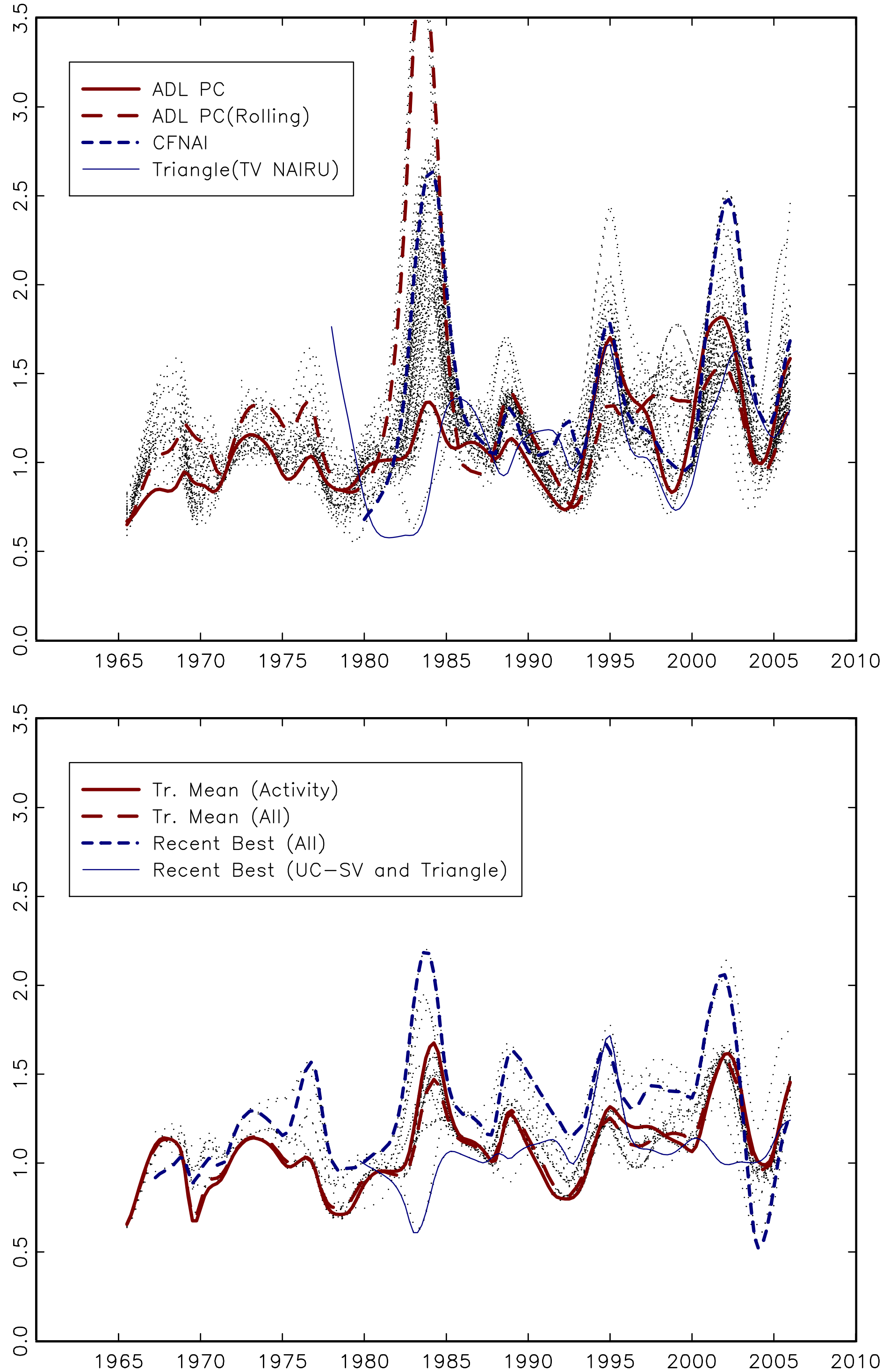
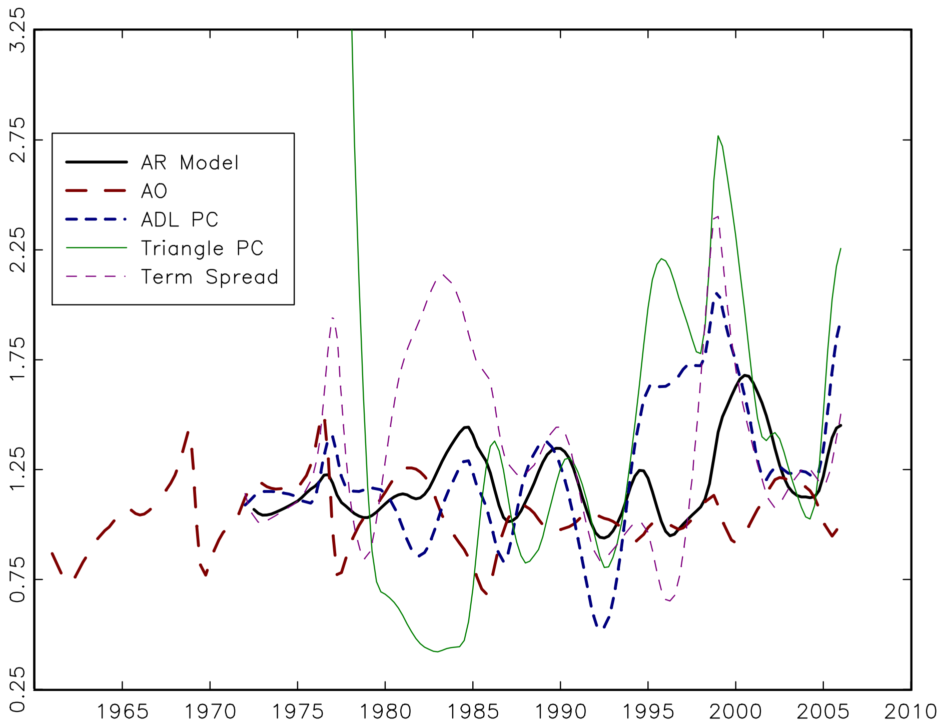


Figure 9
(c) Relative rolling RMSE of Phillips curve forecasts: PCE-all
(d) Relative rolling RMSE of combination forecasts: PCE-all



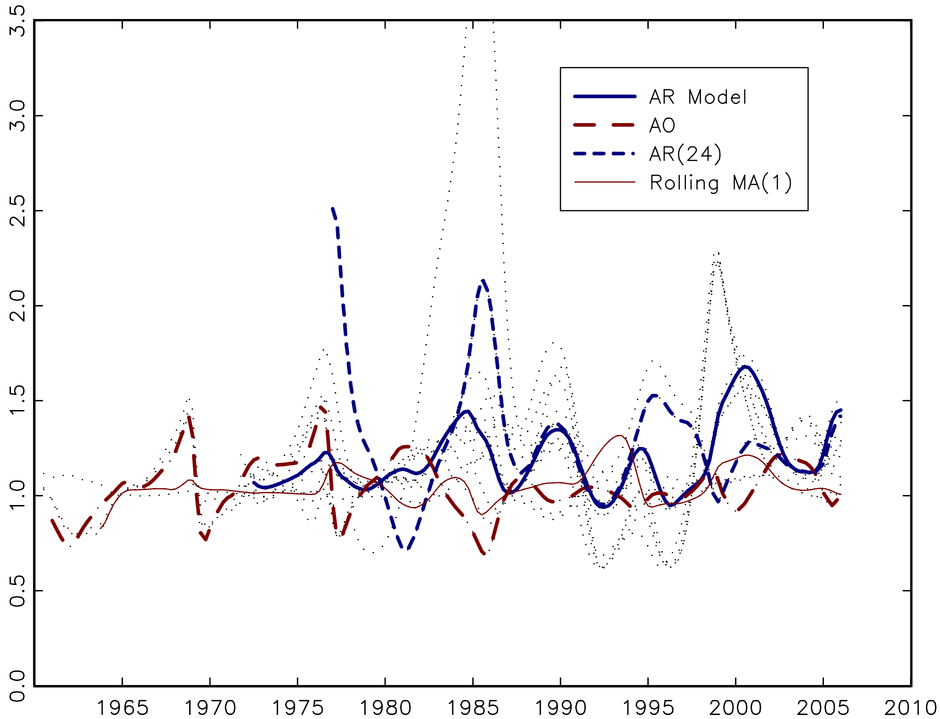


Figure 10
(a) Relative rolling RMSE of prototype models: PCE-core
(b) Relative rolling RMSE of univariate models: PCE-core

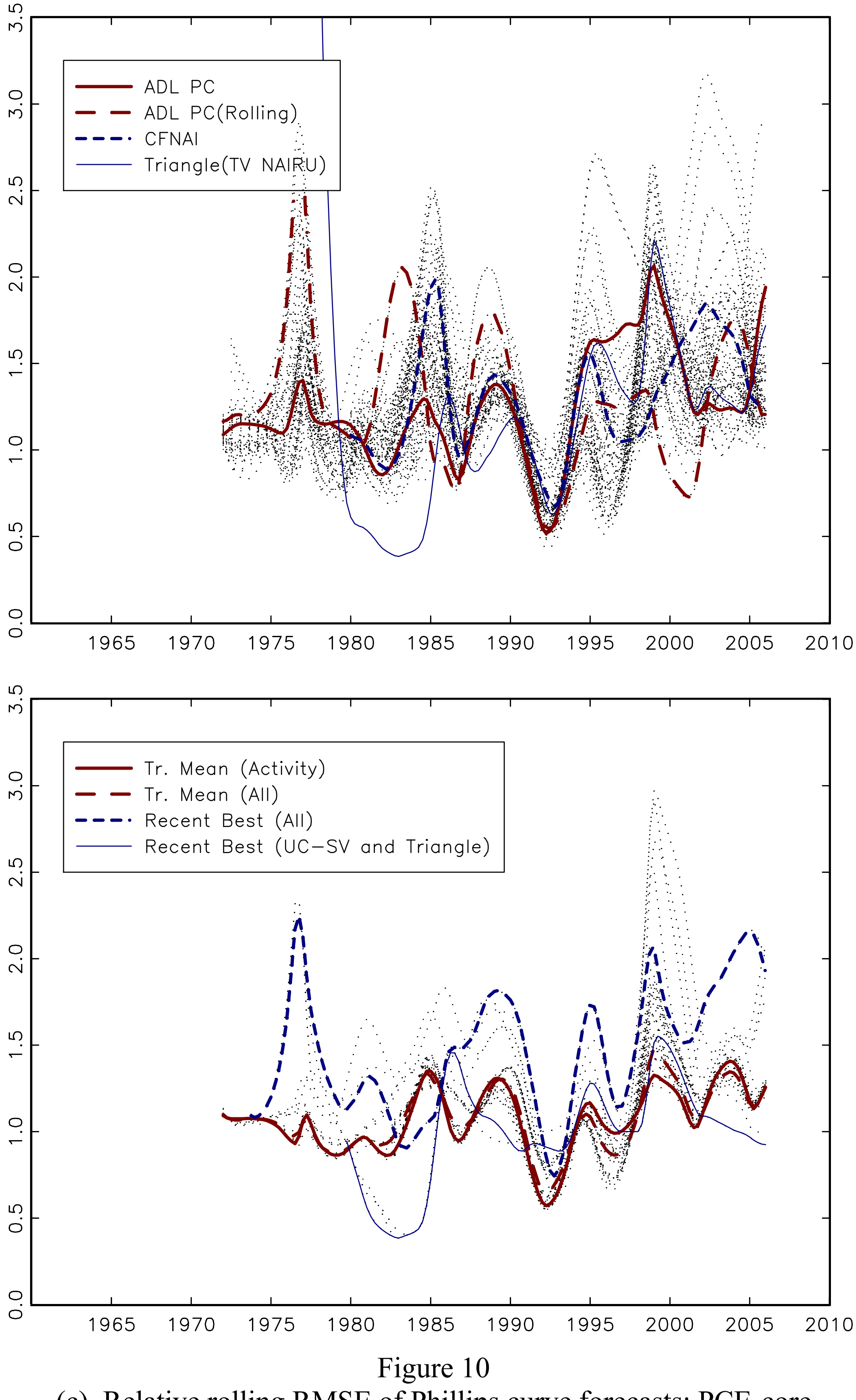


Figure 10
(c) Relative rolling RMSE of Phillips curve forecasts: PCE-core
(d) Relative rolling RMSE of combination forecasts: PCE-core

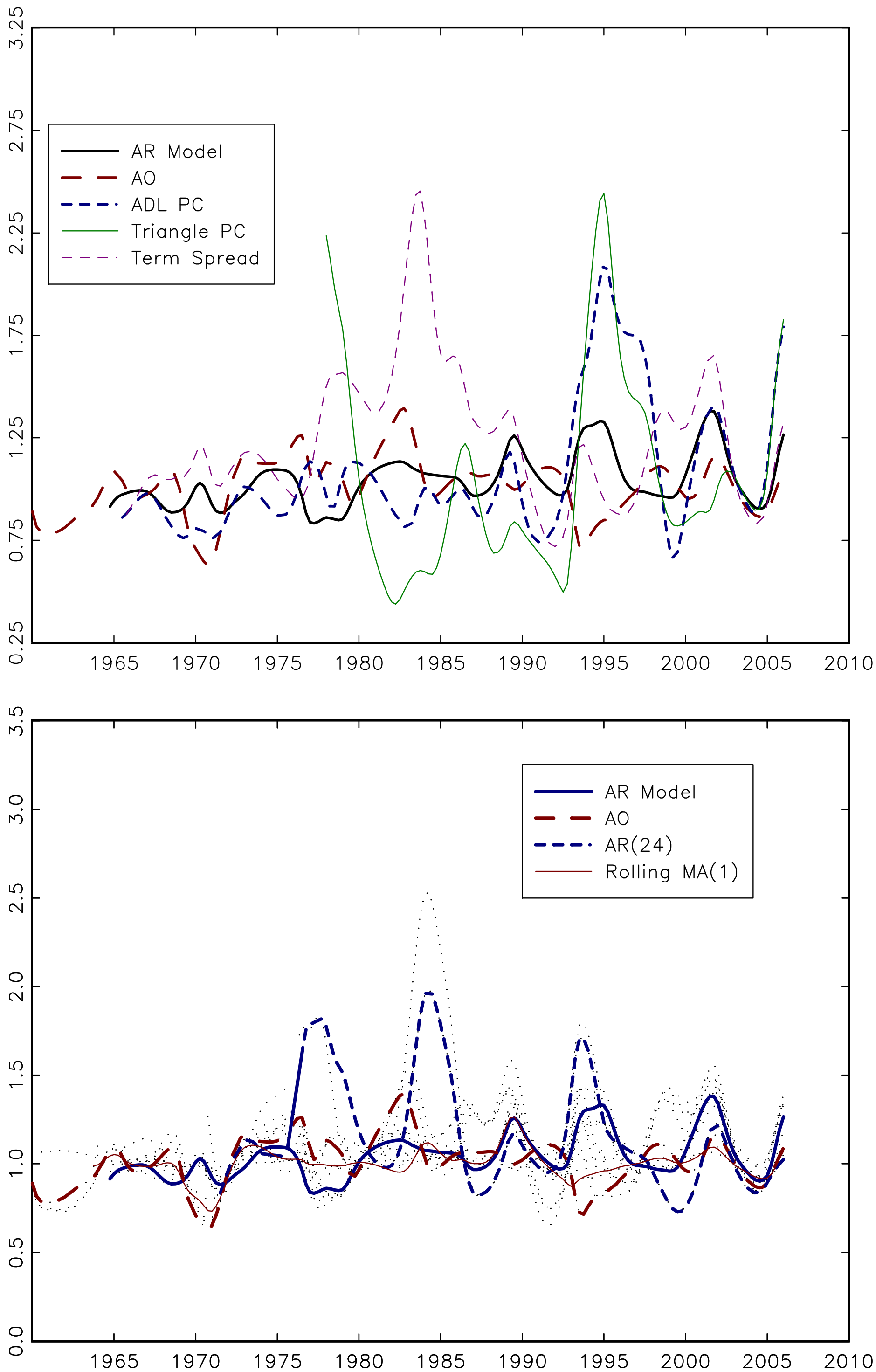


Figure 11
(a) Relative rolling RMSE of Phillips curve forecasts: GDP deflator
(b) Relative rolling RMSE of combination forecasts: GDP deflator

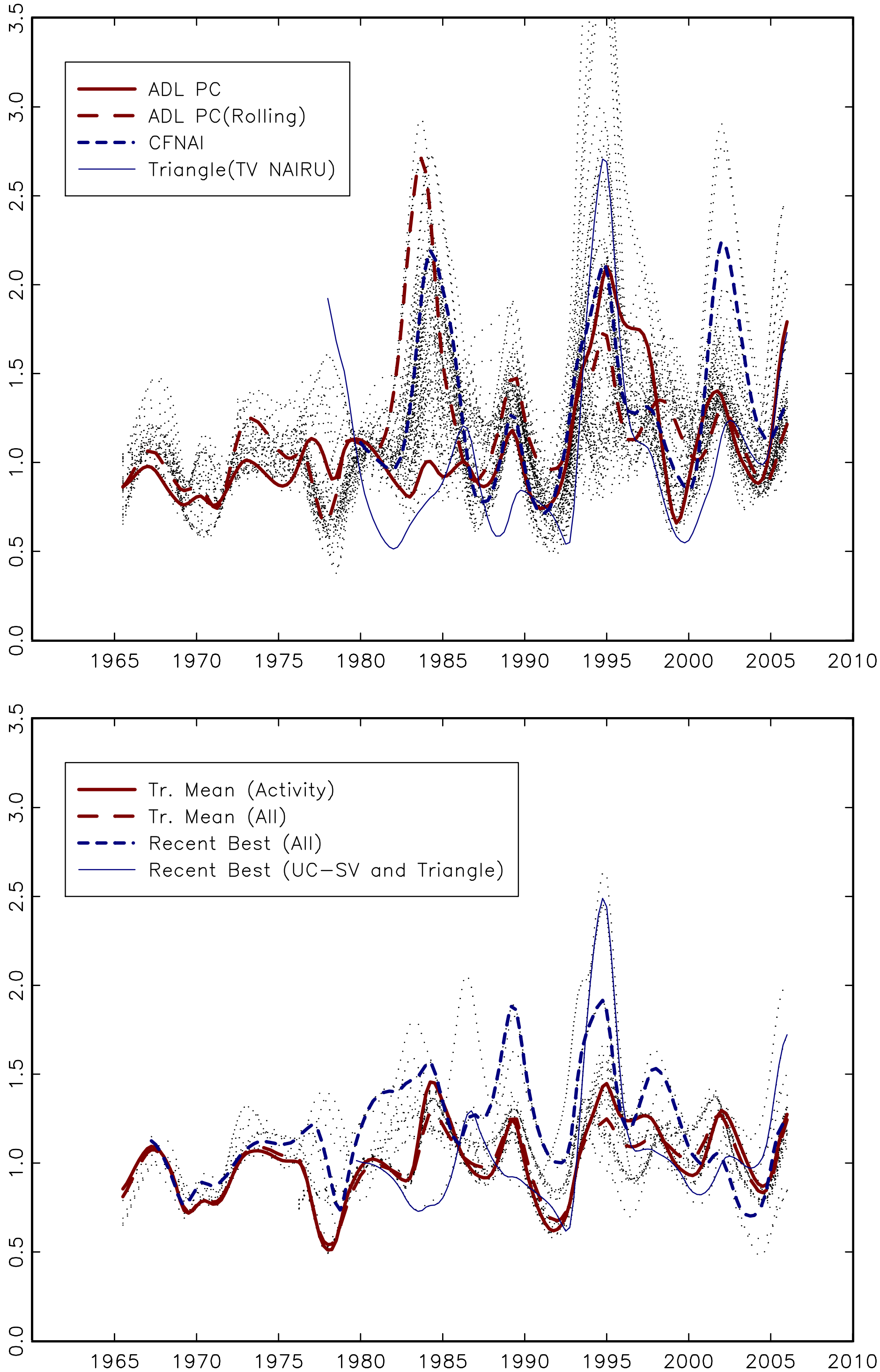


Figure 11
(c) Relative rolling RMSE of prototype models: GDP deflator
(d) Relative rolling RMSE of univariate models: GDP deflator

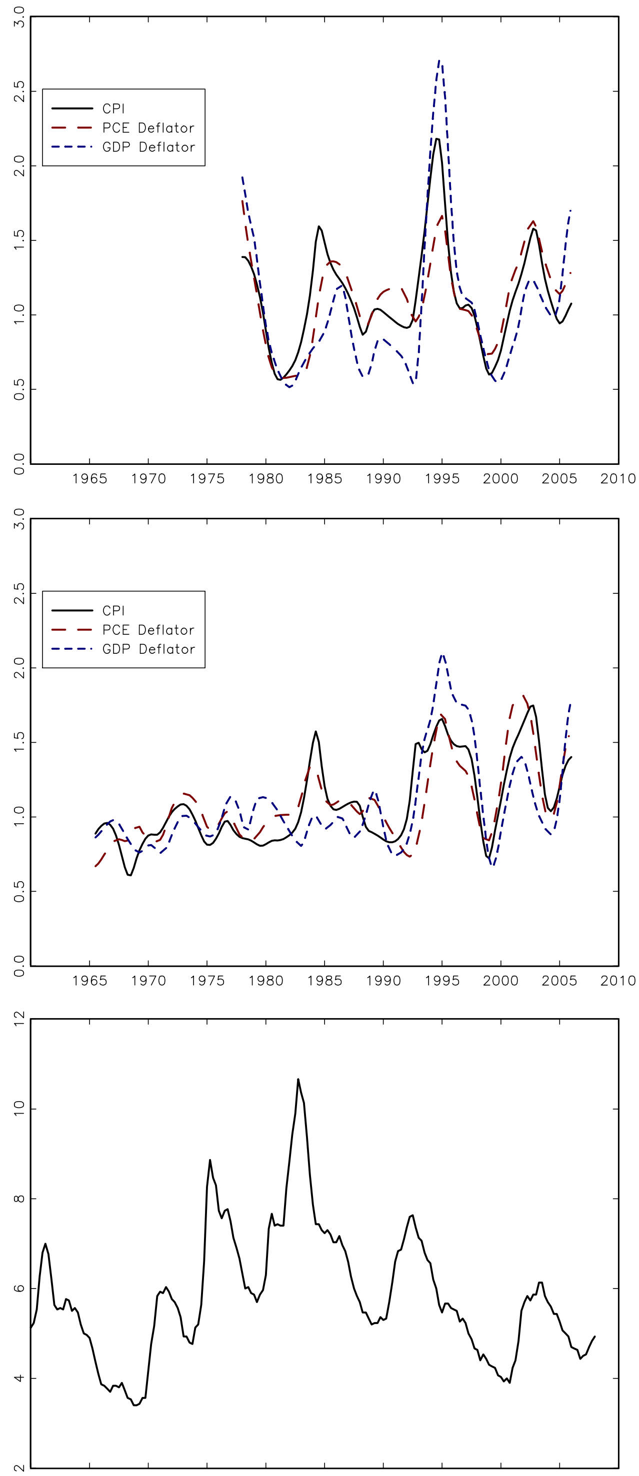


Figure 12. RMSEs of headline inflation forecasts, relative to UC-SV, for (a) triangle model and (b) ADL-*u* model. The unemployment rate is plotted in (c).

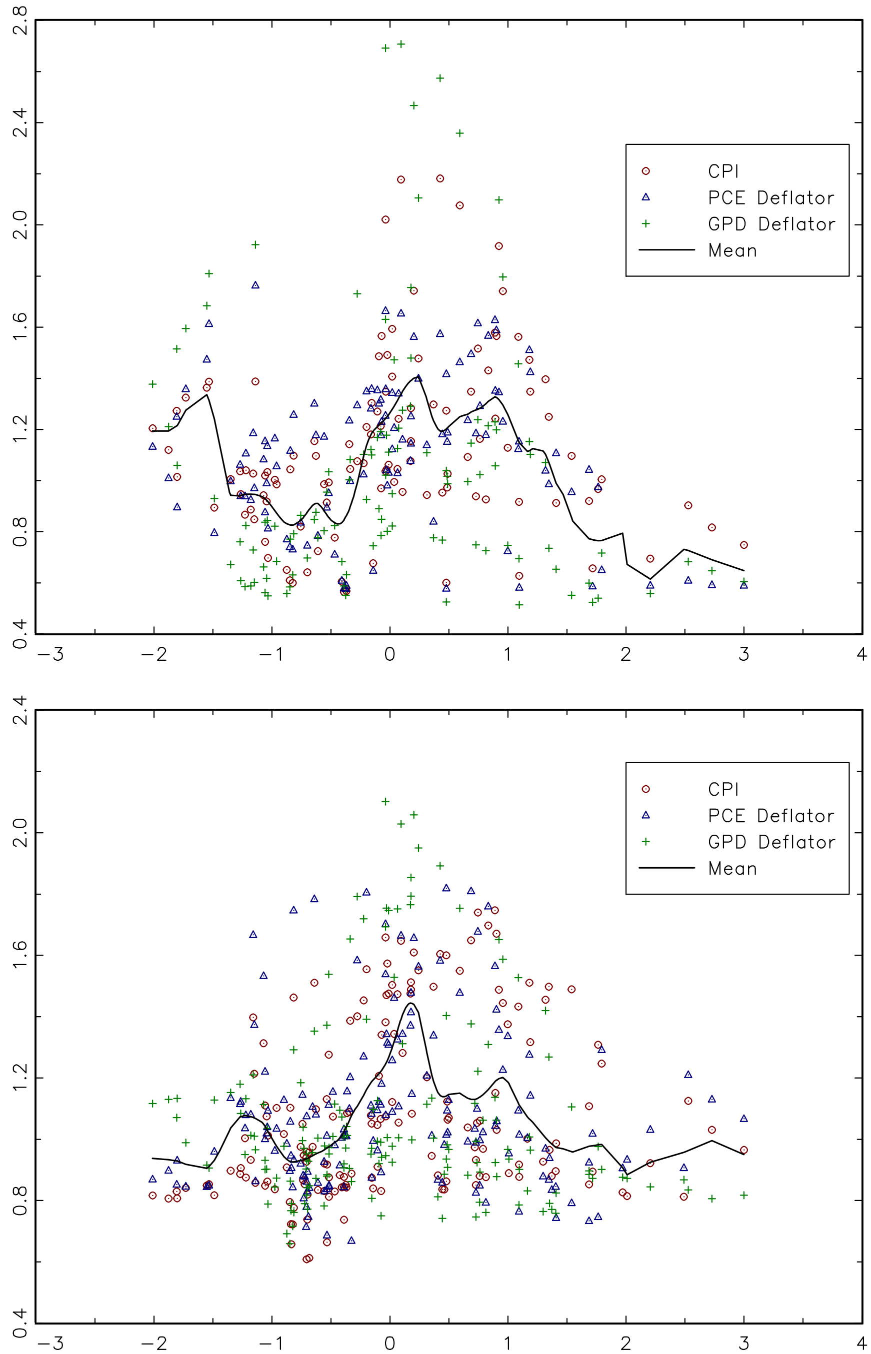


Figure 13
Scatterplot of RMSE of headline inflation forecasts, relative to UC-SV, vs. the unemployment gap (two-sided bandpass); mean is kernel regression estimate using data for all three series. Each point represents a quarter.
(a) triangle model; (b) ADL-*u* model

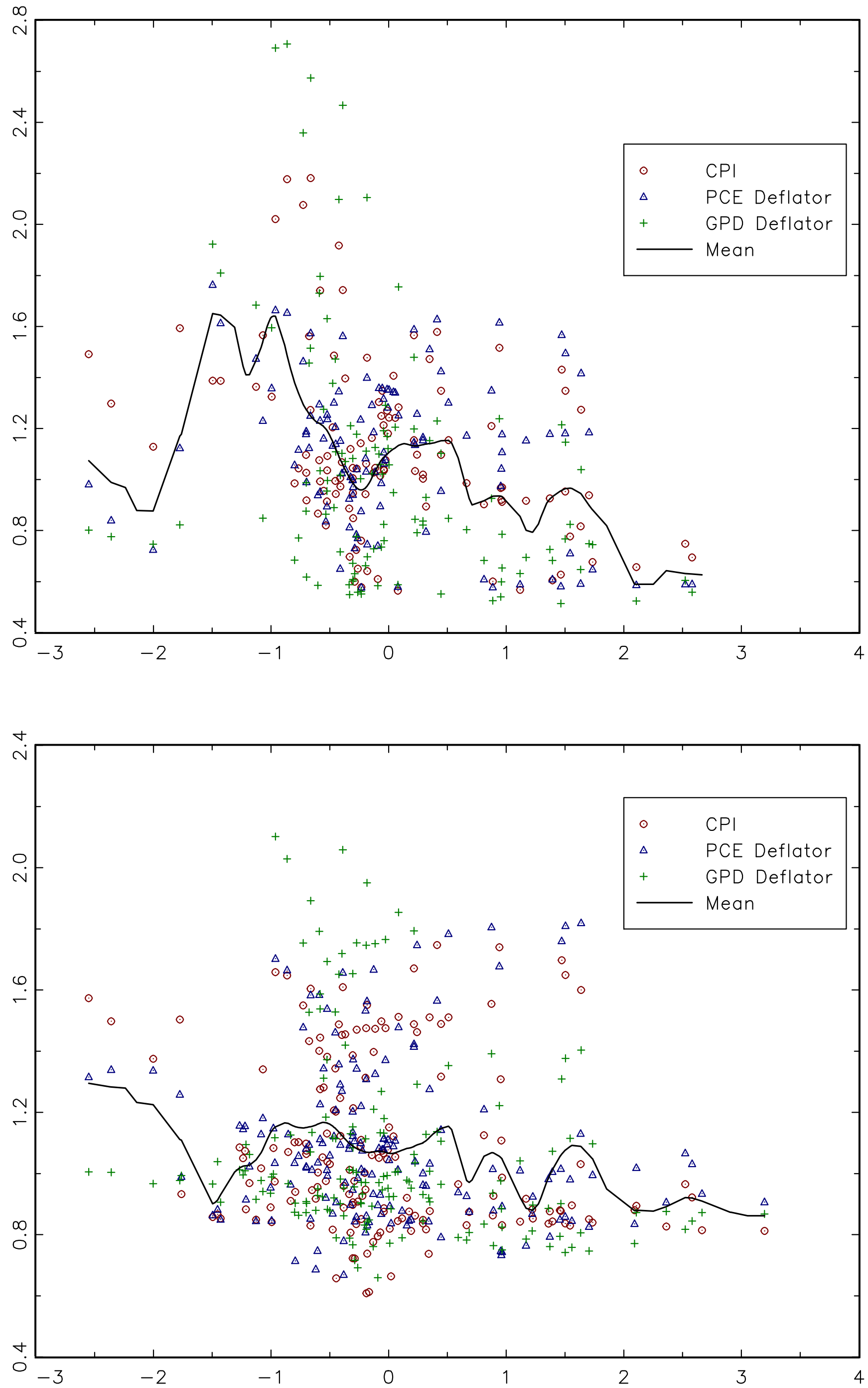


Figure 14
Scatterplot of RMSE of headline inflation forecasts, relative to UC-SV, vs. the four-quarter change in the unemployment gap (two-sided bandpass); mean is kernel regression estimate using data for all three series. Each point represents a quarter.
(a) triangle model; (b) ADL-*u* model

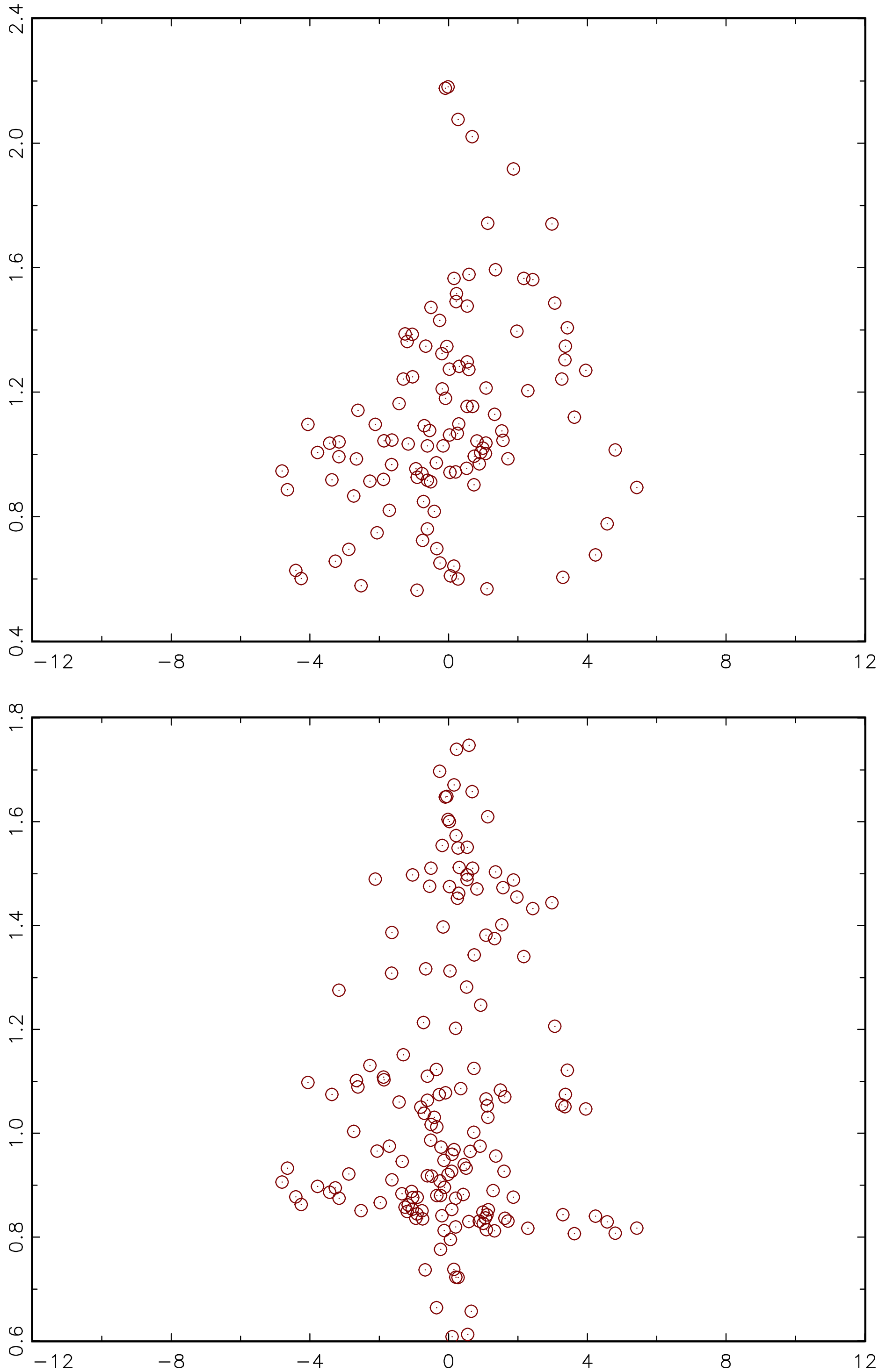


Figure 15
Scatterplot of RMSEs of CPI-all inflation forecasts from (a) triangle model and (b) ADL-*u* model, relative to UC-SV, vs. the four-quarter change in four-quarter inflation. Each point represents a quarter.

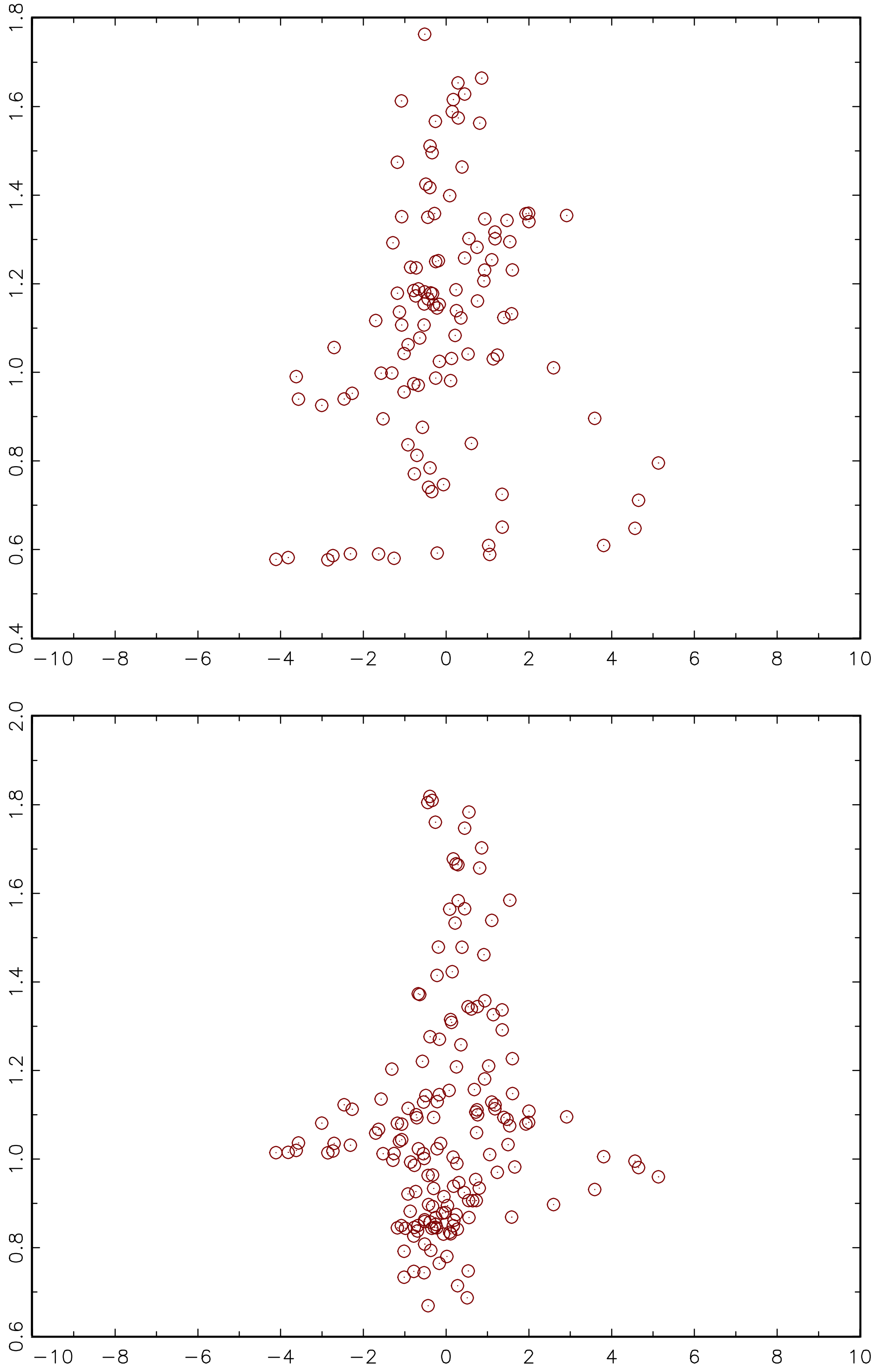


Figure 16
Scatterplot of RMSEs of PCE-all inflation forecasts from (a) triangle model and (b) ADL-*u* model, relative to UC-SV, vs. the four-quarter change in four-quarter inflation. Each point represents a quarter.

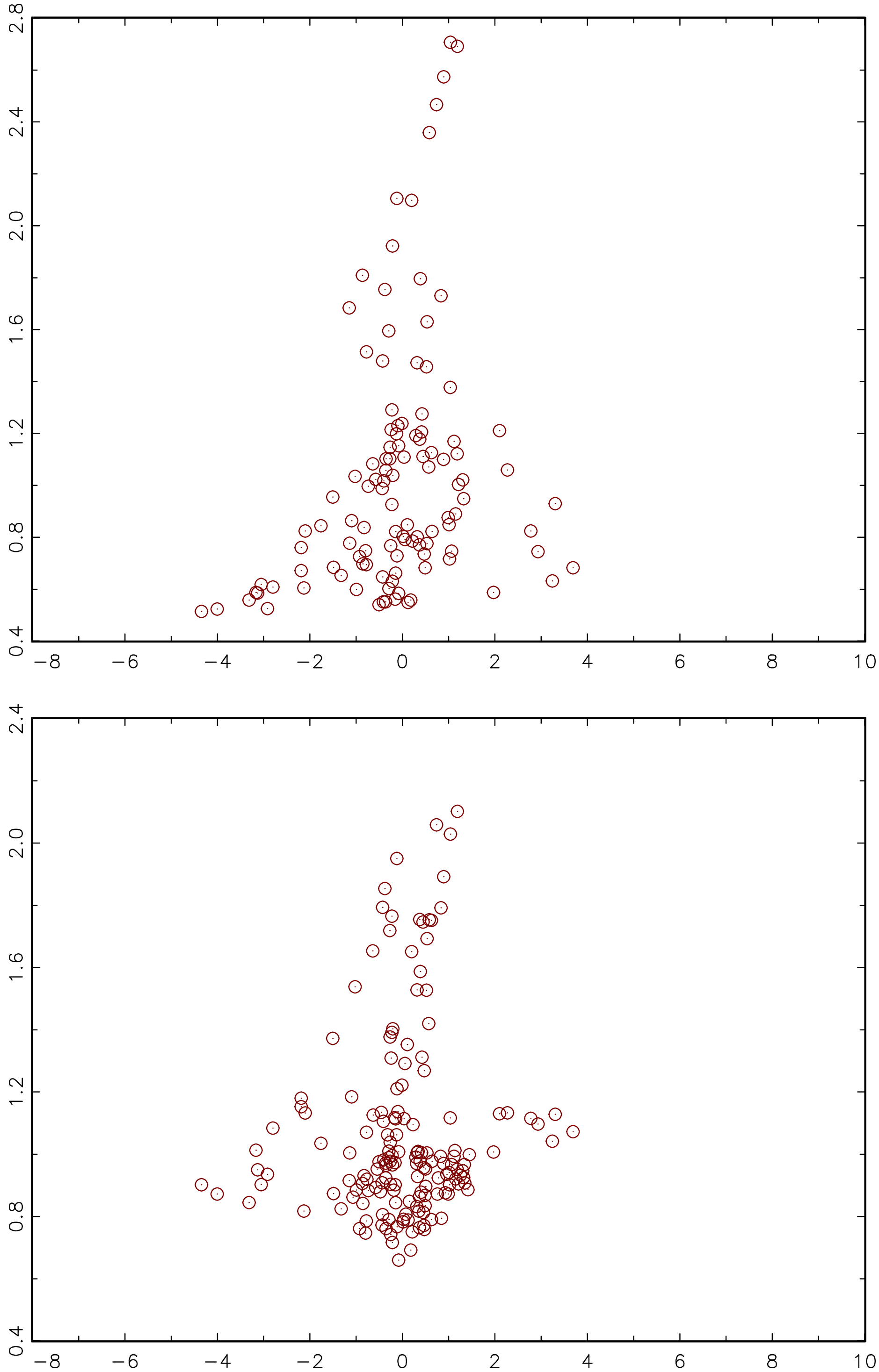


Figure 17
Scatterplot of RMSEs of GDP inflation forecasts from (a) triangle model and (b) ADL-*u* model, relative to UC-SV, vs. the four-quarter change in four-quarter inflation. Each point represents a quarter.