Rational expectations and fixed-event forecasts: an application to UK inflation

*Hasan Bakhshi**

and

*George Kapetanios***

and

Anthony Yates†

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* Bank of England.
E-mail: hasan.bakhshi@bankofengland.co.uk

** Bank of England.
E-mail: george.kapetanios@bankofengland.co.uk

† Bank of England.
E-mail: tony.yates@bankofengland.co.uk

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Abstract

This paper tests a version of the rational expectations hypothesis using 'fixed-event' inflation forecasts for the UK. Fixed-event forecasts consist of a panel of forecasts for a set of outturns of a series at varying horizons prior to each outturn. The forecasts are the prediction of fund managers surveyed by Merrill Lynch. Fixed-event forecasts allow tests for whether expectations are unbiased in a similar fashion to the rest of the literature. But they also permit particular tests of forecast efficiency to be conducted - whether the forecasts make best use of available information - that are not possible with rolling event data. The results show evidence of a positive bias in inflation expectations. Evidence for inefficiency is much less clear cut.

Key words: Fixed event forecasts, rational expectations, forecast efficiency.

JEL classification: C12, E37.

Summary

This paper tests a version of the rational expectations hypothesis using 'fixed-event' inflation forecasts. These forecasts can best be explained by describing the data we use. The forecasts are the prediction of fund managers surveyed by Merrill Lynch. Respondents are asked to forecast inflation, say, two years ahead. The following month they are asked for the forecast of inflation for that same date, now one year and eleven months ahead; the next month they are asked for their one year and ten month ahead forecast, and so on. Each month they are asked to forecast the annual inflation rate for the same date. The forecast event is fixed throughout, and the horizon of the forecast shrinks as the time line approaches the event. In the final month, respondents are asked to forecast the annual inflation rate one month ahead. This is what we term a forecast 'event', and we have 7 such events, and typically 23 forecasts, made every month over two years, for each event.

Our fixed-event forecasts allow us to test for whether expectations are unbiased in a similar fashion to the rest of the literature. But they also permit us to conduct particular tests of forecast efficiency - whether the forecasts make best use of available information - that are not possible with rolling event data. We present three efficiency tests. The first test is whether the forecast errors are uncorrelated with past forecast revisions: the intuition here is that under the rational expectations hypothesis (REH) current forecast errors should not be predicted by any past information, which includes past forecast revisions. The second test is whether this period's forecast revision is uncorrelated with last period's. This prediction follows when we note that the current forecast error comprises all future revisions, and combine it with our first test of the REH (that the forecast error is unpredictable). Under the REH, forecast revisions should only reflect news, not past revisions, nor in fact past data on anything at all. This test is particularly interesting since, unlike the first, and unlike tests with rolling event forecasts, it is not complicated by moving average error problems. Third, we test to see if the variance of the forecast errors declines as we get closer to the inflation outturn. Intuitively, it ought to be easier to forecast annual inflation six months ahead, when you already have half the data you need published, than forecasting inflation two years ahead. These tests also follow from our first: the forecasts and forecast errors can be re-written in terms of sums of future forecast revisions, which, if independent of each other, yield expressions for the variance of forecasts and forecast errors in terms of the variance of forecast revisions.

We find evidence of a positive bias in inflation expectations. But the evidence for inefficiency is much less clear cut: in particular, tests on forecast revisions that are robust to the serial correlation structure implied by rational expectations in our dataset do not show significant evidence for inefficiency.

1 Introduction

This paper tests a version of the rational expectations hypothesis (hereafter REH) using 'fixed-event' inflation forecasts. These forecasts can best be explained by describing the data we use. The forecasts are the prediction of fund managers surveyed by Merrill Lynch. Respondents are asked to forecast inflation, say, two years ahead. The following month they are asked for the forecast of inflation for that same date, now one year and eleven months ahead; the next month they are asked for their one year and ten month ahead forecast, and so on. Each month they are asked to forecast the annual inflation rate for the same date. The forecast event is fixed throughout, and the horizon of the forecast shrinks as the time line approaches the event. In the final month, respondents are asked to forecast the annual inflation rate one month ahead. This is what Nordhaus (1987) terms a forecast 'event', and we have 7 such events, and typically 23 forecasts, made every month over two years, for each event.

The literature on testing variants of the REH on survey data is now voluminous. How can we justify adding to it? The reason is that the bulk of this literature (at least the literature on inflation expectations) is based on 'rolling-event' forecasts. The Gallup inflation expectations data studied in Bakhshi and Yates (1998) is an example of a 'rolling-event' study. Each month, Gallup collected forecasts of inflation twelve-months ahead, so that the inflation rate to be forecast (the forecast 'event') 'rolls' forward one month, every month. In a rolling-event time series of forecasts, the event rolls forwards each period, and the horizon is fixed.

Our fixed-event forecasts allow us to test for whether expectations are unbiased in a similar fashion to the rest of the literature. But they also permit us to conduct particular tests of forecast efficiency - whether the forecasts make best use of available information - that are not possible with rolling-event data. We present three efficiency tests. The first test is whether the forecast errors are uncorrelated with past forecast revisions: the intuition here is that under the REH current forecast errors should not be predicted by any past information, which includes past forecast revisions. The second test is whether this period's forecast revision is uncorrelated with last period's. This prediction follows when we note that the current forecast error comprises all future revisions, and combine it with our first test of the REH (that the forecast error is unpredictable). Intuitively, under the REH, forecast revisions should only reflect news, not past revisions, nor in fact past data on anything at all. This test is particularly interesting since, unlike the first, and unlike tests with rolling-event forecasts, it is not complicated by moving average error problems. Third, we test to see if the variance of the forecast errors declines as we get closer to the inflation outturn. Common sense tells us that it ought to be easier to forecast annual inflation six months ahead, when you already have half the data you need published, than forecasting inflation two years ahead. These tests also follow from our first: the forecasts and forecast errors can be re-written in terms of sums of future forecast revisions, which, if independent of each other, yield expressions for the variance of forecasts and forecast errors in terms of the variance of forecast revisions.

To anticipate our conclusions, we find evidence of a positive bias in inflation expectations, which recalls some of our earlier work on a different data set (Bakhshi and Yates (1998)). But the evidence for inefficiency is much less clear cut: in particular, tests on forecast revisions that are robust to the serial correlation structure implied by rational expectations in our dataset do not show significant evidence for inefficiency.

The closest antecedents to our work have been on studies looking at the sequence of official estimates of US GNP running up to the final estimate (see Mankiw and Shapiro (1986); Mork (1987); de Leeuw (1990); Neftci and Theodossiou (1991); Joutz and Steckler (1998); on other US GNP forecasts (Nordhaus, (1987); Nordhaus and Durlauf (1984)); on revisions to official estimates of UK GDP components (Patterson and Heravi (1991)); on preliminary money announcements (Mankiw *et al* (1984)); on revisions to earnings expectations (see, for example, Dominitz (1998), but see also a recent survey by Brown (1993)). Batchelor and Dua (1992) report tests on forecasts of a range of varibles by US financial analysts.

The rest of the paper is organised as follows. Section 2 develops the formal tests of REH in the context of fixed-event forecasts. Section 3 describes the Merrill Lynch survey data we use for the tests. Section 4 presents and discusses our results. Section 5 concludes.

2 Tests of rational expectations using fixed-event inflation forecasts

Our first test is a traditional test of unbiasedness, and should need little explanation. Our three tests of efficiency will be less familiar, so we will explain these in more detail. To recap, the tests are: (i) that current forecast errors are uncorrelated with past forecast revisions; (ii) that current forecast revisions are uncorrelated with past forecast revisions; and (iii) that the variance of forecast errors declines the closer is the forecast to the outturn.

Let us begin with some definitions. Let $F_t\pi_T$ be the forecast, conjectured at time t, of inflation at time T. Let $F_t u_T$ be the current forecast error, or the difference between the current forecast of inflation and the eventual outturn at T so that:

$$F_t\pi_T + F_t u_T = \pi_T \qquad \textbf{(1)}$$

Finally, let $FR_{t,T}$ be the revision made between t-1 and t to the forecast of the inflation rate at T, so that:

$$FR_{t,T} = F_t\pi_T - F_{t-1}\pi_T \qquad \textbf{(2)}$$

2.1 Unbiasedness

One characteristic of 'rational' forecasts of inflation is that they are 'unbiased': that is they are equal to the mathematical expectation of inflation plus some random error (which of course has zero expectation). Thus the REH implies, taking expectations of **(1)**, that:

$$E(F_t u_T) = 0 \ \ \forall t, T \qquad \textbf{(3)}$$

and that when we run the regression in **(4)** below:

$$\pi_T = \alpha + \beta F_t\pi_T \qquad \textbf{(4)}$$

the constant, α, is zero and the multiplier, β, is unity. In other words, the expected error within and across forecast events should be zero. Having established the test for unbiasedness, we turn now to explain the tests for efficiency outlined above.

2.2 Efficiency

The first efficiency hypothesis, that current forecast errors should be uncorrelated with past forecast revisions, is obvious from equation **(3)**. Conditional on all past information, including past forecast revisions, the expectation of the current forecast error is zero. We can write this more formally:

$$E(F_t u_T | FR_{t,T}, \ldots, FR_{1,T}) = 0, \quad \forall t \tag{5}$$

To explain the second efficiency hypothesis, that current forecast revisions should be uncorrelated with past forecast revisions, note that the current forecast of inflation will equal the initial forecast of inflation plus all revisions to date, or, formally:

$$F_t \pi_T = F_0 \pi_T + \sum_{s=1}^{t} FR_{s,T} \tag{6}$$

Note also that the current forecast error can be written as the sum of all future revisions to the forecast (since we assume that once the inflation rate to be forecast is published, the data are known, so the forecast converges on the actual inflation rate). Formally:

$$F_t u_T = \sum_{s=t+1}^{T} FR_{s,T} = \pi_T - F_t \pi_T \tag{7}$$

Using the decomposition of the current forecast error in equation **(7)**, which says that the current error is equal to the sum of all future revisions, we can substitute this into equation **(5)** for each value of t to get a series of expectations that we write in equations **(8)** down to **(11)**. The expectation of the forecast revision made between $T-1$ and T, is given by:

$$E(FR_{T,T} | FR_{T-1,T}, FR_{T-2,T}, \ldots, FR_{1,T}) = 0 \tag{8}$$

So, in words **(8)** says that the expected forecast revision at T, (which we know from **(7)** should equal the forecast error at T-1), conditional on all past revisions (right back to the first revision made), should be equal to zero. Moving one period back in time from **(8)** we have a decomposition for the forecast error at $T-2$:

$$E(FR_{T-1,T} + FR_{T,T} | FR_{T-2,T}, FR_{T-3,T}, \ldots, FR_{1,T}) = 0 \tag{9}$$

This says that the expectation of the forecast error at $T-2$, equal to the forecast revision at $T-1$ plus the forecast revision at T, will be zero, conditional on all past forecast revisions (indeed on all past information). Likewise, for the error at $T-3$ we have:

$$E(FR_{T-2,T} + FR_{T-1,T} + FR_{T-1,T} | FR_{T-3,T}, FR_{T-4,T}, \ldots, FR_{1,T}) = 0 \tag{10}$$

and so on to t:

$$E(FR_{t,T} + FR_{t+1,T} + \ldots + FR_{T-1,T} + FR_{T,T} | FR_{t-1,T}, FR_{t-2,T}, \ldots, FR_{1,T}) = 0 \tag{11}$$

We can now use **(8)** to eliminate the term in $FR_{T,T}$ from **(9)** to get **(12)**:

$$E(FR_{T-1,T} | FR_{T-2,T}, FR_{T-3,T}, \ldots, FR_{1,T}) = 0 \tag{12}$$

and then use **(9)** to eliminate the terms in $FR_{T,T}$ and $FR_{T-1,T}$ from **(10)** to get **(13)**:

$$E(FR_{T-2,T}|FR_{T-3,T}, FR_{T-4,T}, \ldots, FR_{1,T}) = 0 \quad \textbf{(13)}$$

We can continue in this fashion, eliminating terms in future revisions, on to the forecast revision at t :

$$E(FR_{t,T}|FR_{t-1,T}, FR_{t-2,T}, \ldots, FR_{1,T}) = 0 \quad \textbf{(14)}$$

so that we have a series of expressions that tell us that the expected value of each forecast revision is independent of all previous forecast revisions. These expressions are **(8)** and **(12)** to **(14)**.

We have now established two tests of efficiency using fixed-event forecasts, and can formulate these econometrically.

$$F_t u_T = \alpha + \sum_{s=t-a}^{t-b} \beta_s FR_{s,T}, \;\; a > b \geq 1 \quad REH \Rightarrow H_0 : \alpha, \beta_s = 0, \;\; \forall s \quad \textbf{(15)}$$

This is a regression of forecast errors on past revisions and a test for a zero constant and multipliers. We can also run a regression of current forecast revisions on past revisions, and a test of zero constant and multipliers:

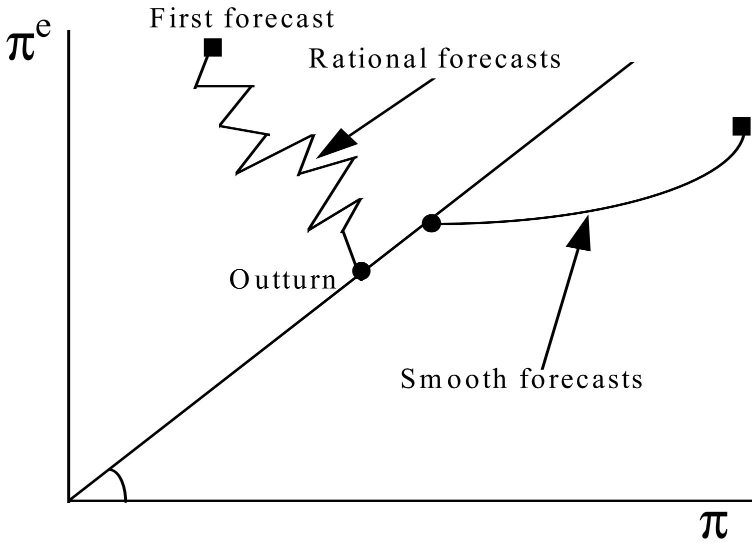
$$FR_{t,T} = \alpha + \sum_{s=t-a}^{t-b} \beta_s FR_{s,T}, \;\; a > b \geq 1 \quad REH \Rightarrow H_0 : \alpha, \beta_s = 0, \;\; \forall s \quad \textbf{(16)}$$

Note that efficiency implies that forecast revisions should look like a martingale: they should be ‘spiky’ rather than ‘smooth’ as we show in Figure 1. Since the expected value of each revision is zero, the expected value of each forecast is last period’s forecast. Formally:

$$E(FR_{t,T}) = 0, \forall t \Leftrightarrow E(F_t \pi_T) = F_{t-1} \pi_T \quad \textbf{(17)}$$

Strictly, equations **(3)** and **(7)** - from which regressions **(15)** and **(16)** derive - tell us that the current forecast error should not be predictable from any past information, which includes past forecast revisions, but will also include any other information to which agents will have access. Abel and Mishkin (1983) show that the validity of the tests like those in **(15)** and **(16)** is not affected by excluding from the RHS all other possible variables that agents might have in their information sets. Furthermore, given that we would want a parsimonious approximation to the information set forecasters use (to economise on degrees of freedom), the one we have is probably the best parsimonious representation of the information set possible, since the least costly information for forecasters to acquire, and therefore the information they are most likely to have at their disposal, is information on their own past forecast revisions.

Chart 1: Fixed event forecasts



It is easy to see from regression **(16)** the advantages of using fixed-event forecast data. First, past forecast revisions, which are clearly in agents' information sets, are not available in rolling-event data. Second, in most rolling-event forecasts, the forecasting horizon exceeds the forecasting frequency. The Gallup data are a case in point: these are twelve-month ahead forecasts for inflation, sampled every month. As a result, the forecast errors across forecasts are not uncorrelated even if REH holds. In particular this overlap induces an MA structure in the forecast errors. It is difficult in practice to distinguish between serially correlated forecast errors due to the overlapping nature of the data and that due to the failure of efficiency. Of course we can (and we do) take account of a serial correlation structure that is allowed by REH. But imposing a complicated serial correlation structure in small samples can still lead to biased inferences. Using regressions based on forecast revisions, such as **(16)** where the error structure implied by REH is much simpler can make our inference more reliable.

Chart 1 plots what we might expect our fixed-event forecasts to look like under rational expectations. In inflation/expected inflation space, forecasts should average around the line where $\pi = \pi^e$ (expectations are unbiased) and approach the inflation outturn along a spiky path.

In the chart we can see how one forecast approaches the inflation outturn along a spiky, and therefore rational path; along another we have the forecast approaching the outturn along a smooth path. On this path we would find that forecast revisions were positively correlated with past forecast revisions.

2.3 Variance bound tests

In this section we provide simple temporal inequalities for the variance of forecasts and forecast errors. By simple conditioning arguments we can prove that:

$$var(F_t\pi_T) \leq var(F_{t+1}\pi_T), \forall t \tag{18}$$

To prove this note that under rational expectations $F_t\pi_T$ is simply the expectation of π_T conditional on the information set at time t. Note also that the information set at time t is part of the information set at time $t+1$. By using the conditional Jensen's inequality we can show that the variance of an expectation conditional on a set A is smaller than the variance of an expectation conditional on a set B if A is part of B. Thus **(18)** holds.

We also have a variance bound for the forecast error. Recall from equation **(7)** that the current forecast error can be written as the sum of all future revisions to the forecast. Comparing any two forecast errors at t and $t+1$ we have that:

$$var(F_t u_T) = var(FR_{t+1,T}) + var(FR_{t+2,T}) + \ldots + var(FR_{T,T}) \tag{19}$$

The above says that the variance of the forecast error is simply the sum of the variances of all future forecast revisions (since there is no covariance between the forecast revisions for a given forecast event). Similarly,

$$var(F_{t+1}u_T) = var(FR_{t+2,T}) + var(FR_{t+3,T}) + \ldots + var(FR_{T,T}) \tag{20}$$

which implies:

$$var(F_{t+1}u_T) = var(F_t u_T) - var(FR_{t+1,T}) \tag{21}$$

In general, we have that:

$$var(F_{t+1}u_T) \leq var(F_t u_T) \tag{22}$$

Or, in words, we have a prediction that the variance of forecast errors should decline as we approach the inflation outturn. This is intuitive: the variance of the forecast errors should fall as there is a progressively shorter time period over which shocks can occur.

We have now provided a theoretical grounding for the unbiasedness and efficiency tests. We turn now to describe our forecast data in section 3, and present the results of the tests in section 4.

3 Data

We use data on expectations of inflation compiled by Merrill Lynch, from a survey of around 70 fund managers. We have forecasts of seven inflation 'events': forecasts of the annual increase in the UK Retail Price Index at December 1994, 95, 96 and 97 and forecasts of the annual increase in the UK RPIX index[(1)] at December 1998, 99 and 2000. We do not include the 2001 forecast event as the survey was discontinued at the beginning of 2001 in its present form. Chart 2 plots the data. The dots on the figure indicate inflation outturns. The lines plot the evolution of the inflation forecasts as they approach the inflation outturns. Note that the lines plot the average inflation forecast across fund managers surveyed by Merrill Lynch.

There are several interesting points to note. In all but one of the 7 events the forecasts lie systematically above the outturn. However, for each given event, a systematic overprediction does not signal rejection of the rational expectations hypothesis as the hypothesis refers to averages *across events*. Second, forecasts approach the outturn along a fairly spiky path, and this we interpret as casual evidence that they are efficient, as defined in section 2.

4 Results

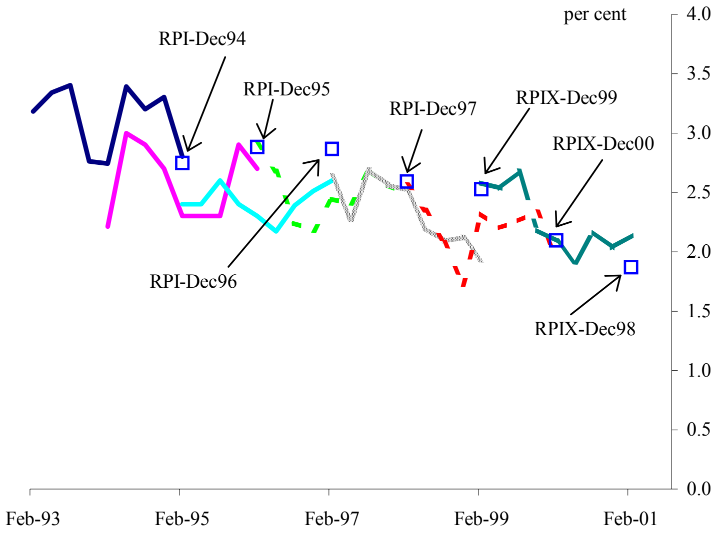
We begin by testing whether forecast errors are unbiased and uncorrelated with past revisions; then move on to test whether forecast revisions are uncorrelated with past forecast revisions; and finally turn to variance bounds tests.

4.1 Efficiency and unbiasedness tests with forecast error as LHS variable

Tables A-C below report the results of our regressions of forecast errors on past revisions. We can use this to test our efficiency hypothesis in equation **(15)** but also to test for unbiasedness. In Table A, FE94 is the forecast error for the inflation event of December 1994; C denotes a constant. Two

(1) The question posed to fund managers changed in the middle of 1998. Up to 1997 the question concerned RPI inflation. From 1998 onwards the focus changed to RPIX inflation.

Chart 2: The data: forecasts and outturns



lags of forecast revisions are used in the regressions. A joint test of unbiasedness and efficiency (ie rational expectations) is given by the F-test of $\alpha = \beta_s = 0$ in regression **(15)**.

Table A presents results for regressions run for each forecast event separately. It shows that in each year we reject the hypothesis that forecast error is mean zero at the 5% level of significance. But in each year bar 1998 and 2000 we can accept the hypothesis that the forecast errors are uncorrelated with past revisions. Notice how the average forecast error (given by the constant in Table D) has changed over the years: in 1994 inflation forecasts were significantly above the outturn. By 1997 this bias had changed sign and forecasts were significantly below the outturn. The bias becomes positive but smaller for subsequent events. Note that in all these regressions in Table A (and those in Table D) we report standard errors calculated using Newey-West (1987) standard errors. This is to allow for the errors in the regressions in Table A to be (a) autocorrelated because of the moving average forecast error induced by the overlapping observation nature of the data and (b) heteroskedastic because the variance of the forecast error falls as the event date is approached. As we have mentioned before a constant that is significantly different from zero in a single event regression provides no evidence of failure of REH. One can imagine a situation where a single shock just before the realisation of the outturn can lead to all forecasts within a given event being biased in one direction. However, we get a consistent pattern of significant positive biases across events. In that sense, we consider the above results as informative.

In Tables B and C below we present the results of pooled regressions, beginning with models with common constants across years, and in Table C with fixed effects, or variable constants. The pooled results allow us to impose common coefficients (common αs and βs) in equation **(15)** and exploit the extra degrees of freedom that the cross-event data brings. But there is a trade-off. Our efficiency test here is whether we can accept the hypothesis that all the events are efficiently forecasted or not. If we reject this test, it is still possible that some of the events were indeed forecast efficiently: in other words that the common coefficients assumption that pooling the data involves does not hold.

For each set of pooled regressions in Tables B and C (and later on in Tables E and F) we present results using a standard ordinary least squares estimator and a generalised least squares (GLS) estimator. The OLS results rely on the classical assumption that all errors, regardless of which forecast event generated them, are identically and independently distributed. The GLS results allow for cross-sectional (ie across forecast event) heteroskedasticity. The assumption of no serial correlation underlying the OLS estimator is problematic. Given that we investigate multistep forecasts the errors of the estimated regressions are likely to be serially correlated even under the null hypothesis of rational expectations. This will not affect the consistency of the parameter estimates but standard OLS errors will not be valid. We therefore use a Newey-West correction to address this issue.

However, it turns out that we can use the rational expectations hypothesis itself to model the serial correlation structure of the errors in our pooled regression explicitly, and we digress at this point to explain what we will call a 'rational expectations serial correlation correction' to the standard errors used to conduct the efficiency and unbiasedness tests.

Suppose that a forecaster is asked today for a forecast of inflation one and two years ahead. Suppose that tomorrow, some news arrives, like a fall in the exchange rate. The day after tomorrow, the forecaster is asked for forecasts of those same inflation rates, and revises them up, knowing that, for a while at least, a fall in the exchange rate, other things equal, tends to increase inflation. Two things are clear. First, the error that the forecaster makes on today's forecast of the one and two year ahead forecast will be correlated, even if the forecasts are rational. Both will have missed the exchange rate fall that occurs tomorrow. Second, the forecast revisions for the one and two year ahead forecast made between today and the day after tomorrow will also be correlated.

We can explain this error correlation structure more formally. The sequence of errors in the pooled regression for the forecast errors, for T forecast events and a maximum horizon of H, under the null hypothesis, is given by:

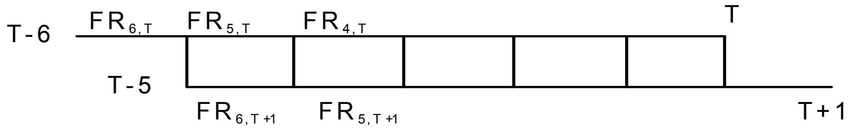
$$F_{-H+1}u_1, F_{-H+2}u_1, \ldots, F_0 u_1, F_{-H+2}u_2, F_{-H+3}u_2, \ldots, F_1 u_2, \ldots, F_{-H+T}u_T, F_{-H+T+1}u_T, \ldots, F_{T-1}u_T.$$

As we have seen earlier we can decompose the errors (equivalent to the forecast errors) into forecast revisions. We assume that:

1. $E(FR_{h,t}^2) = \sigma_1^2$
2. $Cov(FR_{h_1,t}, FR_{h_2,s}) = \sigma_2$ if $t - h_1 = s - h_2$
3. $Cov(FR_{h_1,t}, FR_{h_2,s}) = 0$ otherwise

The first assumption gives the variance of the forecast revisions. This assumption may be generalised to $E(FR_{h,t}^2) = \sigma_{h,1}^2$, to allow the variance to depend on the forecast horizon. The second assumption says the forecast revisions for different forecast events which occur in the same period have a non-zero covariance. The third assumption states that otherwise the forecast revisions are uncorrelated. To appreciate these assumptions further we provide an illustration in Chart 3. There, we present two lines indicating two forecast events ending at time T and $T+1$ respectively. At all points where vertical lines meet with the forecast event lines new forecasts for T and $T+1$ are produced. The intervals between the new forecasts represent forecast revisions. Our assumptions for the covariances between forecast revisions are illustrated by noting that the forecast revisions $FR_{5,T}$ and $FR_{6,T+1}$ resulting from the forecasts made at time $T-5$ will be correlated. The same will hold for any pair of forecast revisions resulting from forecasts produced at the same point in time such as the forecast revisions $FR_{4,T}$ and $FR_{5,T+1}$ resulting from the forecasts made at time $T-4$. Any other pairs of forecast revisions such as, eg $FR_{5,T}$ and $FR_{5,T+1}$ will not be correlated under rational expectations.

Chart 3: Forecast revisions



These assumptions lead to the following covariance specification for the errors.

1.
$$E(F_h u_t^2) = h\sigma_1^2 \quad \textbf{(23)}$$

2.
$$Cov(F_{h_1}u_t, F_{h_2}u_t) = min(h_1, h_2)\sigma_1^2, \ \ h_1 \neq h_2 \quad \textbf{(24)}$$

3.
$$Cov(F_{h_1}u_t, F_{h_2}u_{t+s}) = max(min(h_2 - s, h_1), 0)\sigma_2, \ \ s > 0 \quad \textbf{(25)}$$

This covariance specification may seem hard to grasp but follows from the covariance specification of the forecast revisions once we take into account that forecast errors are simply sums of forecast revisions. Estimation of the pooled regression enables estimation of the parameters in the covariance matrix which is then used to construct the standard errors for the OLS parameter estimates. The regression using forecast revisions as LHS variables has a similar, but simpler covariance matrix specification.

The results using these assumptions are labelled OLS^e in Table B. Note that we also present standard errors that allow for cross-event heteroskedasticity in the data. This correction would be useful if we believed, for example, that the variance of shocks affecting inflation, and perhaps therefore the accuracy of forecasts, was shrinking over time. These results are denoted '$\text{OLS}^{f\prime}$ ' in the tables.

In Table B we see once again that we reject the hypothesis that forecast errors are unbiased. The t-tests of zero constants report a rejection, for all of the methods we use to calculate our standard errors. The results on efficiency are more mixed. Results using common constants (in Table B) suggest efficiency. We can see this from looking at the standard errors on the coefficients on the lags of forecast revisions in Table B. But results with fixed effects (in Table C) suggest that forecast errors are correlated with past revisions. T-tests reject the hypothesis of zero coefficients on the forecast revision lags (once again, across all methods for calculating the standard errors). It is unlikely that the constants are equal across events (and even with 'rational' forecasters we might observe changing constants, as perhaps, forecasters learn about a new inflation regime), so we view the fixed-effect results as likely to be more informative. Note that so far, our inference about rational expectations has been robust across all the different methods we use to compute the standard errors of parameters.

We turn next to conduct the efficiency tests using forecast revisions as the LHS variable: this is the test that is only possible, of course, with the fixed-event data that we have here. There may be an additional advantage of the forecast revisions tests: as we have clearly indicated in section 2, the serial correlation structure of the forecast errors implied by REH is complex and may not be easily captured even using the error specification in **(23)-(25)** above. Regressions using forecast revisions have a much simpler serial correlation structure under REH.

4.2 Efficiency and unbiasedness tests with forecast revision as LHS variable

Recall that REH predicts that forecast revisions should not be autocorrelated (see equation **(16)**). We test for this, beginning with tests for each event separately, (Table D) and then moving to panel tests (Tables E and F).

Table D presents results when we conduct this regression separately for each forecast event. We have between 17-23 observations for these regressions, so they are really suggestive rather than conclusive. In the table, FR94 denotes the forecast revision for the inflation event of December 1994 and so on; C denotes the constant.

For each inflation event (1994-2000) we run regressions of the revision on two lags and a constant. Table D suggests that the evidence for efficient inflation forecasts from these tests is mixed. In some of the forecast events (94,96) the revisions show signs of autocorrelation: in others they do not.

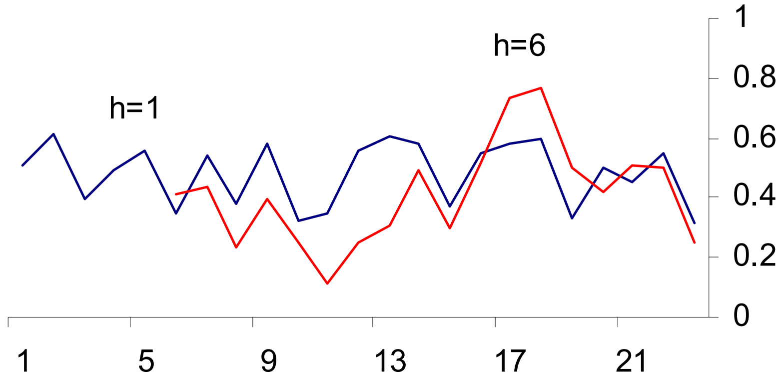
Tables E and F present pooled results analogous to those in Tables B and C. We follow the same strategy as before, presenting results assuming common coefficients (Table E) and then fixed effects (Table F). In each case we present OLS (uncorrected and corrected in two ways for serial correlation), and heteroscedastic GLS estimates. There is clear evidence of bias in forecast revisions. There is more mixed evidence of inefficiency. It is interesting to note that the null hypothesis of rational expectations is rejected in all cases apart from the case where we use the OLS standard errors corrected for the serial correlation error structure implied by the presence of rational expectations,(2) denoted OLS^e . Unlike the case of forecast error regressions the evidence for inefficiency is not conclusive. This is the main difference between the two sets of results. As we have discussed before, the simpler structure of the covariance of the forecast revisions under REH, compared to forecast errors, leads us to view this result as more reliable that that obtained in the previous subsection. In other words, in our forecast revisions regressions we put more weight on our OLS^e results than we do in our forecast errors regressions.

4.3 Variance bounds tests

We turn now to examine the second moment properties of the forecasts and the forecast errors. From equation **(21)**, we would expect the variance of the forecast errors to decline as we get closer to the inflation outturn.(3) A casual way of investigating this is to run a regression of the absolute value of forecast errors on a variable akin to a time-trend that measures the number of months remaining before the inflation outturn. When we do this, and pool together all the forecast observations across forecast events, we obtain the following regression (Newey-West standard

(2) Serial correlation in pooled results for forecast revisions simply reflects the fact that there are nonzero covariances between forecast revisions for forecasts made at the same point in time for different forecast events.
(3) There are two conceptually distinct reasons for this. Firstly, annual RPIX inflation is a function of two observations of the RPIX index at two distinct points in time separated by a year and therefore forecasts of inflation produced less than a year before the final outturn use part of the actual data underlying the inflation outturn. Secondly, the closer the forecasts to the outturn the fewer the shocks that can cause forecast errors actually occur on average.

Chart 4: Variance tests



errors in parentheses):

$$|F_t u_T| = 0.19_{(0.04)} + 0.030_{(0.004)}(T - t) \quad \textbf{(26)}$$

Another regression on the squares of the forecast errors verifies our conclusions

$$F_t u_T^2 = -0.04_{(0.06)} + 0.04_{(0.007)}(T - t) \quad \textbf{(27)}$$

The coefficient on the variable measuring the number of months remaining before the inflation outturn is positive and significant (with a t-statistic of 7.72 and 6.49 in the two equations respectively). This suggests that the absolute size and variance of the forecast error falls as the outturn is approached. This is consistent with, although not proof of, the prediction of the variance bound test in equation **(21)** above.

Applying our variance bounds test more formally, we can test the null hypotheses that $Var(F_{t+h}u_T) = Var(F_t u_T)$ against the alternative hypotheses that $Var(F_{t+h}u_T) < Var(F_t u_T)$ for $t = T - 24, \ldots, T - 1 - h$. Chart 4 presents the probability values of these tests for $h = 1$ and $h = 6$. Clearly the null hypotheses are never rejected. In other words, we cannot, from the data, reject the hypothesis that the variance of forecast errors made close to the outturn are just as large as those associated with forecasts made further away from the outturn. But the power of the test here is very low, since we have only a very small sample size across events to calculate the variances at particular horizons.

5 Conclusions

We presented tests of unbiasedness and efficiency in fixed-event inflation forecasts collected by Merrill Lynch. These forecasts give us time series of forecasts of one particular inflation outturn (a 'forecast event'), in contrast to the rolling-event data employed by most other studies of survey inflation expectations.

Looking at seven such events - forecasts of inflation at December 1994-2000 - we find that these forecasts are biased, although the positive bias is smaller for later forecast events. It is important to stress that the evidence of bias, such as it is, is not itself indicative of 'irrationality'. A private sector that took time to learn - in a sense that we could usefully describe as 'rational' - about the change in the inflation regime that occurred following the ERM exit, for example, may well have recorded 'biases' in regression tests like those we have presented.

Rather, we intend that the reader focuses on the tests here that are only possible with fixed-event data; those that involve forecast revisions data. We investigated forecast efficiency in three ways. First, we tested that forecast errors were not correlated with past revisions, and found that there was indeed some evidence of inefficiency defined in this way. Secondly, we tested that forecast revisions are not autocorrelated. Importantly, this test, unlike the first, (and unlike tests of the REH using rolling-event surveys), is not subject to the inference problems associated with overlapping forecast errors. Evidence from this second test was less supportive of inefficiency. The third test - that the variance of the forecasts and forecast errors declines the closer is the forecast to the inflation outturn - also seems reasonably congruent with the forecasts being efficient, but our sample size is far too small to be sure. We note that, in some cases, taking explicit account of the cross-event correlation structure in forecast errors and forecast revisions that we would expect under REH affects our inference. A very important caveat to the validity of all the results above is the very small sample size of forecast events we have. It is conceivable that these results are simply an artefact of the particular data we have chosen to examine. But if they are not, then they could be useful for conjectures about how the economy responds to changes in the inflation regime, or to other shocks that affect inflation, since we know that models of the economy with 'rational expectations' behave very differently from those where expectations evolve differently.

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Appendix: Tables

Table A: Are forecast errors unbiased, or correlated with past revisions? Regressions for each forecast event separately [(a)]

LHS	RHS	Coef	Std-Error	F-stat (p-values)
FE94	C	0.54	0.16**	0.01**
	FR94(-1)	0.30	0.52	
	FR94(-2)	0.24	0.48	
FE95	C	1.23	0.08**	0.00**
	FR95(-1)	0.74	0.40*	
	FR95(-2)	0.51	0.38	
FE96	C	0.70	0.18**	0.00**
	FR96(-1)	0.28	0.65	
	FR96(-2)	0.29	0.53	
FE97	C	-0.28	0.05**	0.00**
	FR97(-1)	0.38	0.24	
	FR97(-2)	0.30	0.27	
FE98	C	0.59	0.08**	0.00**
	FR98(-1)	0.66	0.21**	
	FR98(-2)	0.78	0.26**	
FE99	C	0.25	0.09**	0.02**
	FR99(-1)	0.29	0.50	
	FR99(-2)	0.04	0.46	
FE00	C	0.27	0.03**	0.00**
	FR00(-1)	0.68	0.19**	
	FR00(-2)	0.32	0.21	

(a) Starred F-stat and standard errors indicate significance of F-tests and t-tests at the 5% significance level. Double stars indicate significance at the 10% significance level.

Table B: Are forecast errors unbiased, or correlated with past revisions? Pooled Results [(a)]

Estimator	RHS Vars	Coef	Std-Error	F-stat (p-values)
OLS [(b)]	C	0.46	0.04**	0.00**
	FR(-1)	0.16	0.35	
	FR(-2)	0.20	0.35	
OLS [(c)]	C	0.46	0.08**	0.00**
	FR(-1)	0.16	0.34	
	FR(-2)	0.20	0.35	
OLS [(d)]	C	0.46	0.07**	0.00**
	FR(-1)	0.16	0.31	
	FR(-2)	0.20	0.34	
GLS [(e)]	C	0.46	0.05**	0.00**
	FR(-1)	0.17	0.36	
	FR(-2)	0.21	0.36	

(a) Starred F-stats and standard errors indicate significance of F-tests and t-tests at the 5% significance level. Double stars indicate significance at the 10% significance level.
(b) No serial correlation correction for standard errors.
(c) Newey-West serial correlation correction for standard errors.
(d) Rational Expectations serial correlation correction for standard errors.
(e) Across event heteroscedasticity assumption for coefficient estimates and standard errors.

Table C: Are forecast errors unbiased, or correlated with past revisions? Pooled Results with across-event fixed effects [(a)]

Estimator	RHS Vars	Coef	Std-Error	F-stat (p-values)
OLS [(b)]	C-94	0.56		0.00**
	C-95	1.22		
	C-96	0.72		
	C-97	-0.28		
	C-98	0.57		
	C-99	0.27		
	C-00	0.27		
	FR(-1)	0.48	0.20**	
	FR(-2)	0.38	0.20*	
OLS [(c)]	C-94	0.56		0.00**
	C-95	1.22		
	C-96	0.72		
	C-97	-0.28		
	C-98	0.57		
	C-99	0.27		
	C-00	0.27		
	FR(-1)	0.48	0.18**	
	FR(-2)	0.38	0.16**	
OLS [(d)]	C-94	0.55		0.00**
	C-95	1.22		
	C-96	0.71		
	C-97	-0.28		
	C-98	0.57		
	C-99	0.27		
	C-00	0.27		
	FR(-1)	0.48	0.13**	
	FR(-2)	0.38	0.13**	
GLS [(e)]	C-94	0.55		0.00**
	C-95	1.22		
	C-96	0.71		
	C-97	-0.28		
	C-98	0.57		
	C-99	0.27		
	C-00	0.27		
	FR(-1)	0.48	0.20**	
	FR(-2)	0.37	0.20*	

(a) Starred F-stats and standard errors indicate significance of F-tests and t-tests at the 5% significance level. Double stars indicate significance at the 10% significance level.
(b) No serial correlation correction for standard errors.
(c) Newey West serial correlation correction for standard errors.
(d) Rational Expectations serial correlation correction for standard errors.
(e) Across event heteroscedasticity assumption for coefficient estimates and standard errors.

Table D: Are forecast revisions unbiased, or correlated with past revisions? Regressions for each forecast event separately [(a)]

LHS	RHS	Coef	Std-Error	F-stat (p-values)
FR94	C	-0.10	0.04**	0.06*
	FR94(-1)	-0.16	0.19	
	FR94(-2)	-0.40	0.17**	
FR95	C	-0.06	0.04	0.39
	FR95(-1)	0.15	0.43	
	FR95(-2)	0.16	0.17	
FR96	C	-0.10	0.03**	0.00**
	FR96(-1)	-0.51	0.17**	
	FR96(-2)	-0.40	0.12**	
FR97	C	0.01	0.03	0.89
	FR97(-1)	-0.01	0.19	
	FR97(-2)	-0.06	0.16	
FR98	C	-0.05	0.02**	0.05**
	FR98(-1)	0.02	0.14	
	FR98(-2)	-0.41	0.25	
FR99	C	-0.25	0.02**	0.34
	FR99(-1)	-0.01	0.11	
	FR99(-2)	0.10	0.20	
FR00	C	-0.01	0.02	0.47
	FR00(-1)	-0.27	0.17	
	FR00(-2)	-0.02	0.18	

(a) Starred F-tests indicate significance at the 5% significance level. Double stars indicate significance at the 10% significance level.

Table E: Are forecast revisions unbiased, or correlated with past revisions? Pooled Results [a]

Estimator	RHS Vars	Coef	Std-Error	F-stat (p-values)
OLS [b]	C	-0.04	0.01**	0.00**
	FR(-1)	-0.06	0.09	
	FR(-2)	-0.13	0.09	
OLS [c]	C	-0.04	0.01**	0.01**
	FR(-1)	-0.06	0.09	
	FR(-2)	-0.13	0.08	
OLS [d]	C	-0.04	0.02**	0.17
	FR(-1)	-0.06	0.13	
	FR(-2)	-0.13	0.13	
GLS [e]	C	-0.05	0.01**	0.00**
	FR(-1)	-0.12	0.08	
	FR(-2)	-0.18	0.08**	

(a) Starred F-tests indicate significance at the 5% significance level. Double stars indicate significance at the 10% significance level.
(b) No serial correlation correction for standard errors.
(c) Newey-West serial correlation correction for standard errors.
(d) Rational Expectations serial correlation correction for standard errors.
(e) Across event heteroscedasticity assumption for coefficient estimates and standard errors.

Table F: Are forecast revisions unbiased, or correlated with past revisions? Pooled Results with across-event fixed effects [(a)]

Estimator	RHS Vars	Coef	Std-Error	F-stat (p-values)
OLS [(b)]	C-94	-0.08		0.01**
	C-95	-0.07		
	C-96	-0.08		
	C-97	0.01		
	C-98	-0.05		
	C-99	-0.04		
	C-00	-0.01		
	FR(-1)	-0.10	0.09	
	FR(-2)	-0.17	0.09*	
OLS [(c)]	C-94	-0.08		0.00**
	C-95	-0.07		
	C-96	-0.08		
	C-97	0.01		
	C-98	-0.05		
	C-99	-0.04		
	C-00	-0.01		
	FR(-1)	-0.10	0.09	
	FR(-2)	-0.17	0.09**	
OLS [(d)]	C-94	-0.08		0.35
	C-95	-0.07		
	C-96	-0.08		
	C-97	0.01		
	C-98	-0.05		
	C-99	-0.04		
	C-00	-0.01		
	FR(-1)	-0.10	0.13	
	FR(-2)	-0.17	0.13	
GLS [(e)]	C-94	-0.09		0.00**
	C-95	-0.08		
	C-96	-0.08		
	C-97	0.01		
	C-98	-0.06		
	C-99	-0.04		
	C-00	-0.01		
	FR(-1)	-0.19	0.08**	
	FR(-2)	-0.23	0.08**	

(a) Starred F-tests indicate significance at the 5% significance level. Double stars indicate significance at the 10% significance level.
(b) No serial correlation correction for standard errors.
(c) Newey West serial correlation correction for standard errors.
(d) Rational Expectations serial correlation correction for standard errors.
(e) Across event heteroscedasticity assumption for coefficient estimates and standard errors.