

UK Real-time Macro Data Characteristics*

Anthony Garratt
Birkbeck College

Shaun P Vahey
Reserve Bank of New Zealand

December 21, 2004

Abstract

We characterise the relationships between preliminary and subsequent measurements for 16 commonly-used UK macroeconomic indicators drawn from two existing real-time data sets and a new nominal variable database. Most preliminary measurements are biased predictors of subsequent measurements, with some revision series affected by multiple structural breaks. To illustrate how these findings facilitate real-time forecasting, we use a vector autoregression to generate real-time one-step-ahead probability event forecasts for 1990Q1 to 1999Q2. Ignoring the predictability in initial measurements understates considerably the probability of above trend output growth.

Keywords: real-time data, structural breaks, probability event forecasts

JEL Classification: C22, C82, E00

*We thank Alex Brazier, Dean Croushore, Colin Ellis, George Kapetanios, Simon van Norden, Stephen Machin, Tony Yates and two anonymous referees for helpful comments. We are grateful to seminar participants at the University of Cambridge and the Reserve Bank of New Zealand. Kateryna Rakowsky and Mutita Akusuwan provided excellent research assistance. Financial support from the Department of Applied Economics and from the ESRC (Research Grant No. L38251021) is acknowledged gratefully. Shaun Vahey visited the University of British Columbia during the period in which the first draft was completed. The views expressed in this paper are those of the authors and do not necessarily represent those of the Reserve Bank of New Zealand.

1 Introduction

In this paper, we characterise the revisions to a variety of commonly-used UK macroeconomic indicators. We find that the preliminary measurements of most real-side macro indicators are downwards biased predictors of subsequent measurements (at the sample means). Structural breaks affect the relationships between early and later measurements for many variables.

Previous studies, including (among others) Symons (2001), Castle and Ellis (2002) and Mitchell (2004) have noted the predictability property for the expenditure measure of output and its components. These (combined) studies characterise a subset of the indicators considered in this paper and provide no formal analyses of structural breaks. We use the Bai and Perron (2003a and 2003b) test for multiple breaks of unknown timing to examine the time variation in predictability.

Some of the UK indicators characterised in this study are drawn from two existing real-time data sets, Castle and Ellis (2002) and Egginton, Pick and Vahey (2002). Only Castle and Ellis (2002) characterise the revisions processes in detail (for the expenditure measure of output and its components). In addition, we analyse the real-time quarterly monetary aggregates, nominal GDP and price deflator variables neglected in the existing databases. The preliminary measurements of UK monetary aggregates are largely unbiased. In contrast, initial nominal GDP and GDP price deflator measurements typically understate final measurements. The revisions to these nominal variables rarely exhibit structural breaks. The untypical behaviour of monetary aggregate revisions reflects the very different collection processes for these series.

Macro models often perform better with revised data than with preliminary measurements. Real-time data sets allow researchers to condition their *ex post* model analyses on the information set actually available to forecasters and policymakers in real time. But if researchers ignore the predictability in initial measurements, real-time model performance can be misjudged. We illustrate this with a specific forecasting example. We use a vector autoregression (VAR) in UK real output growth and inflation to forecast the (one-step ahead) probability of above trend growth—sometimes referred to as the likelihood of “positive momentum”. Ignoring the predictability in initial measurements understates the event probability considerably for our 1990Q1 to 1999Q2 evaluation period.

The remainder of the paper is organised as follows. In section 2, we discuss the sources of UK real-time data. We describe our methodology for characterising UK real-time data in section 3 and report the main results in section 4. We analyse our illustrative probability forecasting VAR exercise in section 5. Section 6 concludes.

2 Data sources

Two on-line real-time UK data sources have appeared in the last couple of years: Castle and Ellis (2002) and Egginton, Pick and Vahey (2002).¹ Both studies adopt

¹US data can be downloaded from the Philadelphia Federal Reserve Bank <http://www.phil.frb.org/econ/forecast>. Croushore and Stark (2001) describe data set construction.

the standard terminology used in the more recent literature to describe the data (see, for example, Diebold and Rudebusch (1991)).

Typical macro databases store each time series variable as a column (or row) vector. In the real-time data literature, the remeasurements are recorded as successive column vectors, and the data for each variable are usually stored as a matrix. The “vintage date” refers to the release date of each vector of time series measurements and the “vintage” denotes the column vector of time series data. Real-time data comprises many vintages; each successive column vector represents a vintage containing the data available at that vintage date. The “most recent”, “current” and “final” labels are used interchangeably to denote the column with the latest vintage date. These are not the “true” measurements, however, since these will be revised subsequently too.

Some researchers, including Egginton, Pick and Vahey (2002), use successive vintages (columns) reflecting common practice by applied econometricians in real-time policy and forecasting analyses. Others, including Howrey (1978) and Koenig et al (2003), use measurements that have been revised the same number of times (from the diagonals of the real-time data matrix for a particular variable).

Castle and Ellis (2002) provide the most comprehensive UK real-time data set.² The variables comprise the expenditure components measure of real GDP (known as GDP(E)) in constant prices: private consumption, investment, government consumption, changes in inventories, exports, imports and GDP(E). The quarterly seasonally adjusted variables were published initially by the Office for National Statistics (ONS) in *Economic Trends* and its *Annual Supplement*. An MS-Excel file contains separate sheets for each variable. Following the standard conventions in the literature, the columns reflect the vintages, with time series observations in the rows. The first vintage refers to 1961Q1 and currently the last refers to 2003Q4.³ Since a typical quarter contains multiple vintages, the frequency of the vintage dates exceeds the frequency of the time series observations.

Egginton, Pick and Vahey (2002) provide additional real-time data for: GDP(O) (output measure of real GDP), private consumption, retail sales, government surplus, unemployment (total claimant count), M0, M3, M4, industrial production and average earnings.⁴ The first two quarterly series and the remaining monthly variables came from the ONS publications *Economic Trends* and *Financial Statistics*. Variables are downloadable individually in MS-Excel and ASCII text format. With the exception of the monetary aggregates, the sequence of vintages starts in January 1980 and ends in June 1999. For the monetary variables, M0, M3 and M4, the first vintages are June 1981, January 1980 and June 1987 respectively, reflecting availability in the source publications. All variables are seasonally adjusted except the budget surplus. Unfortunately, the Egginton-Pick-Vahey data set contains no “deep history” information. The published versions of the original sources only show a (moving) window of data at any point in time. Empty cells denote data outside of that window—generally in excess of two years before the vintage date.

One concern for researchers interested in UK monetary issues is the absence

²Download from <http://www.bankofengland.co.uk/statistics/gdpdatabase>.

³Annual updates occur in Spring of each year.

⁴Download from <http://www.econ.cam.ac.uk/dae/keepitreal>.

of quarterly monetary aggregates.⁵ To address this omission, we collected real-time data on quarterly seasonally adjusted M0 and M4 from the ONS’ *Economic Trends* for the vintages July 1987 to August 2002. We included (from the same sources) additional real-time information on nominal GDP(E), GDP price deflator, M0 velocity and M4 velocity. The interest in money velocity stems from its pivotal role in the UK’s 1980’s monetary targeting experiments.⁶ For the last four variables, the vintages start in November 1981 and end in 2002. Like the Egginton-Pick-Vahey data set, the absence of deep history results in some empty cells. The Appendix contains more complete data descriptions.⁷

The causes of the UK revisions apparent in all three data sets are discussed in detail by Castle and Ellis (2002) and Mitchell (2004). In brief, revisions occur when the ONS receive new data, change their methodology or re-base variables. The new data category sometimes involves the substitution of delayed survey information for earlier judgement. The changes in methodology, associated with both the major structural reforms, following the *Pickford Report* and the Chancellor’s Initiatives (see Wroe (1993)), and other more minor reforms have unknown implementation dates. In contrast, the re-basing dates are known, and occur approximately every five years. Unlike the other variables in our study, the monetary aggregate data were collected by the Bank of England not the ONS. Topping and Bishop (1989) discuss the definitions, collection of, breaks in and revisions to UK monetary aggregates.

3 Methodology

Our basic model for characterising UK remeasurements:

$$(1) \quad Y_t^k = \alpha + \beta X_t^k + \epsilon_t^k, \quad t = 1, \dots, T$$

where $Y_t^k = X_t^F - X_t^k$ defines the “revisions”, X_t^F denotes the growth rate of the “final” measurement and X_t^k denotes the k^{th} measurement of the growth rate of the macro variable, $k = 1, \dots, K$ where $K < F$. Notice that the preliminary measurement on the right hand side predates the final measurement used to construct the left hand side variable. The model corresponds to the “news” or “rational forecast” specification analysed by (among others) Mankiw, Runkle and Shapiro (1984). The null hypothesis of unbiasedness, $\alpha = 0$ and $\beta = 0$, indicates unpredictable data revisions. The orthogonality error condition of ordinary least squares ensures that revision errors are uncorrelated with preliminary measurements.⁸

Since the index $k = 1, \dots, K$ denotes the successive measurements for each time series observation, the X_t^k variable is formed from many “vintages”: one data point

⁵The monthly seasonally adjusted monetary aggregates contained in Egginton, Pick and Vahey (2002) were seasonally adjusted on a different basis from the quarterly equivalents for some of the period.

⁶See for example Jansen (1998). Although money velocities can be constructed from the component variables, nominal GDP and the relevant monetary aggregates, we report the official measures for completeness.

⁷The data are available in MS-Excel format on request from a.garratt@bbk.ac.uk.

⁸The “noise” model analysed by Mankiw, Runkle and Shapiro (1984) has the “final” measurements as the explanatory variable. In this case, the unbiased revisions are orthogonal to final measurements—the data collection agency remeasures with errors in variables.

is taken from each vintage. In the results that follow, we restrict attention to the $k = 1$ case for brevity. Results for the $k = 2, \dots, K$ case can be obtained from the authors on request.⁹ For the vector of “final” data, X_t^F , we use the vintage available from the ONS’ *Economic Trends*, 6 March 2003 (electronic version). A substantial time interval exists between the respective sample end dates and the final vintage date to allow revisions to occur.¹⁰

Our model could be extended to allow other macro indicators from the same information set as X_t^k as explanatory variables (see, for example, Swanson and van Dijk (2004)). Revisions are “efficient” if, and only if, α , β and the coefficients on the additional explanatory variables are zero. Unfortunately, theory provides no guidance on what other variables might be useful for testing efficiency and unrestricted searches for predictability undoubtedly result in a degree of data snooping. In the absence of a theoretical basis for an examination of the predictability arising from other variables, we prefer to test for bias—a sufficient (but not necessary) condition for inefficiency—and test for multiple structural breaks.

Given the unknown implementation dates of some wide-ranging reforms to the UK data reporting processes (see Wroe (1993)), we adopt the methodology proposed by Bai and Perron (2003a and 2003b) to search for multiple structural breaks of unknown timing.¹¹ We introduce some additional notations to our basic revisions equation (1):

$$(2) \quad Y_t^k = \alpha_j + \beta_j X_t^k + \epsilon_t^k, \quad t = T_{j-1} + 1, \dots, T_j$$

for $j = 1, \dots, m + 1$. The linear regression has m breaks ($m + 1$ regimes) where the indices (T_1, \dots, T_m)—the break points—are unknown, with $T_0 = 0$ and $T_{m+1} = T$. So for the one break point case, $m = 1$ and $j = 1, 2$, and the pair of estimated parameters $[\hat{\alpha}_1, \hat{\beta}_1]$ corresponds to the sample $t = 1, \dots, T_1$ and $[\hat{\alpha}_2, \hat{\beta}_2]$ corresponds to the sample $t = T_1 + 1, \dots, T$. We define a break as a change in at least one of the parameters α and β .

The Bai and Perron (2003a and 2003b) algorithm conducts efficient automated searches for multiple breaks based on a dynamic programming approach. The researcher chooses a maximum number of candidate breaks, N , and a trimming factor, τ . Given these inputs the algorithm splits the sample into feasible sub-samples. The maximised value of the residual sum of squares identifies the candidate breaks for each number of breaks, $n = 1, \dots, N$. The researcher tests the null hypothesis of no structural change against the alternative of many changes by a Sup Wald test. Having identified at least one change, the number of breaks is identified by specifying the null of $n = L$ ($1 \leq L < N$) changes against $L + 1$ changes and conducting a sequence of $SupF(L + 1|L)$ tests.

The Bai-Perron approach is robust to serial correlation and heteroskedasticity. Minor reforms to statistical reporting procedures could induce the latter and slow

⁹Contact a.garratt@bbk.ac.uk. We set $K = 8$ (16) for the quarterly (monthly) variables.

¹⁰We repeated our analysis reported below treating X_t^K as the final measurements. Although this limits the number of revisions allowed in each case the results were qualitatively similar. Again, the tables can be obtained from the authors on request.

¹¹Bai-Perron Gauss code can be downloaded from <http://econ.bu.edu/perron/code.html>. Swanson and van Dijk (2004) consider structural breaks in US revisions but restrict attention to just one break.

adjustment by the agency would cause the former (see Barklem (2000)). Our approach tests the stability of bias allowing for badly-behaved errors.

4 Characterising UK Revisions

4.1 Data

For our characterisations of UK data remeasurements we use sixteen variables in total. The first six variables are from the Castle-Ellis data set and comprise GDP(E), consumption, investment, government expenditure, exports and imports, all for the period 1961Q3-1999Q2; the second six are from the Garratt-Vahey data set and are nominal GDP and the GDP price deflator for 1981Q1-1999Q4, M0 and M4 for 1987Q1-1999Q4, M0 velocity for 1987Q1-1999Q4 and M4 velocity for 1986Q4-1998Q4; the final four are from the Egginton-Pick-Vahey data set and are average earnings for 1979M11-1997M1, industrial production for 1979M11-1997M8, claimant count unemployment for 1979M12-1997M10 and retail sales for 1986M2-1997M12.

Since the indicators vary by source and time series frequency, the sample size, the trimming factor τ (as a proportion of the sample) and the maximum number of breaks, N , vary.¹² We set $N = 5$ and $\tau = 0.15$ for the 150 plus observations for both the quarterly GDP(E) components in the Castle-Ellis data set and the monthly indicators from Egginton-Pick-Vahey.¹³ For the Garratt-Vahey monetary aggregates and velocities, where there are 52 or 53 quarterly observations, we set $N = 1$ and $\tau = 0.25$. For nominal GDP and the price deflator, there are 76 quarterly observations and we set $N = 2$ and $\tau = 0.25$.

We use quarterly or monthly growth rates as appropriate throughout the empirical section.¹⁴ This approach mitigates the level effects that result from base year changes (see Patterson and Hervai (1991)). In general, conventional unit root tests indicate that the variables in equation (2) are stationary, despite the small samples and the likely presence of structural breaks.

Table 1 reports the means and standard deviations of revisions, Y_t^1 . In general, the mean revisions are positive: preliminary measurements understate final measurements but there is considerable variation across variables. Approximately half of the indicators have statistically significant mean revisions at the 5% level (denoted by * in Table 1). Investment has the largest (quarterly) mean revisions: nearly twice as big as GDP(E).¹⁵ The notably small M0 and M4 mean revisions are insignificantly different from zero at the 5% level. The mean absolute error for the monetary aggregates is also notably lower than for the other variables. The preliminary analysis suggest little predictability for monetary aggregate revisions.

To illustrate the scale of revisions, Figure 1 plots GDP(E) from 1961Q3 to 1999Q2 for the first and final measurements. The deviation between the two shows

¹²Bai and Perron (2003b) discuss the appropriate parameter values in small samples.

¹³The Castle-Ellis data set contains (at times) more than one vintage per quarter. We used the vintage available at the start of each quarter and treated the Garratt-Vahey variables analogously.

¹⁴The growth rates for X_t were defined as $100 * (\log_e X_t - \log_e X_{t-1})$.

¹⁵The GDP(E) revisions are comparable in size to those documented by Faust, Rogers and Wright (2004).

the $k = 1$ revision. At times, these are larger in absolute size than the quarterly economic growth rate. Figure 1 also shows that the final measurements are much less volatile post-1989, reflecting the relative stability of the 1990s boom.

Figure 1: GDP(E) Growth, First and Final Measurements

To check for structural change in the mean revision of each variable, we estimated a restricted version of equation (2) with $\beta_j = 0$. We used the Bai-Perron methodology to identify structural breaks of unknown timing in the intercept. There are breaks in the means only for exports (1993Q3) and imports (1992Q1).¹⁶ (The results reported in the next section based on unrestricted estimation of equation (2) suggest that the data reject the $\beta_j = 0$ restriction and that structural breaks are much more prevalent.)

To investigate time variation in the standard deviations for each GDP(E) component, we split the sample into two sub-samples, corresponding approximately to the 1980s and 1990s.¹⁷ The results suggest a fairly consistent pattern: lower standard deviations for the 1990s. For 10 of the 16 variables, the data reject the null hypothesis of equal variances for the two sub-samples at the 5% level using a variance ratio test (denoted by † in Table 1).

We conclude from this preliminary investigation that revisions are often predictable and typically positive, with considerable variation in size across variables and lower 1990s' revision volatility.

4.2 Testing for Bias

Tables 2, 3 and 4 summarise the results from our regressions based on equation (2) using 16 macro indicators for the first measurements ($k = 1$).¹⁸ In each case, we report the p-value for the Wald test of the null hypothesis for unbiasedness, $\alpha = \beta = 0$, Newey-West heteroskedasticity and serial correlation consistent standard errors and an LM-test statistic for serial correlation.¹⁹ The tables show the bias for each parameter-stable segment; if there are no structural breaks, we report the results for the full sample. The break points are also shown on a time line in Figure 2.

4.2.1 Castle-Ellis Variables

Table 2 reports the results for GDP(E) and its components. Most of these variables have breaks that pre-date the late 1980s' and early 1990s' structural reforms to ONS practices. The exports break in 1993Q3 coincides with the rebasing of national

¹⁶The pre and post-break means were 0.23 (Newey-West coefficient standard error 0.091) and 0.81 (0.204) for exports and 0.02 (0.176) and 0.73 (0.219) for imports.

¹⁷The sample mid-points defined the break dates for the Garratt-Vahey and Egginton-Pick-Vahey variables.

¹⁸Tables for subsequent measurements (up to two years after the initial measurement) can be obtained from the authors on request. Except for the monetary aggregates, the data reject the null hypothesis of unbiasedness for all k at the 1% level. However, the degree but not the direction of bias varies considerably with k .

¹⁹The Newey-West truncation factor was 4; and the serial correlation test was for up to 4th (12th) order for the quarterly (monthly) data.

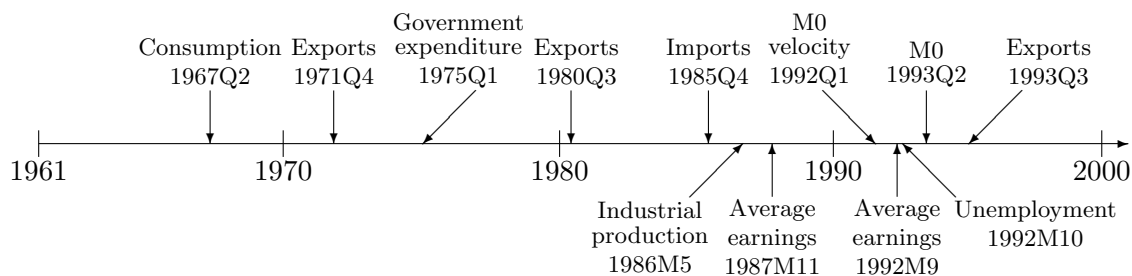


Figure 2: Break Points

accounts. In general, the null hypothesis of $\alpha = \beta = 0$ can be rejected at the 1% level, with variation in the size of the bias across variables. Initial measurements are unfailingly revised upwards (at the sample means). For example, the estimated α and β values for GDP(E) (investment) are in the region of 0.4 (0.6) and -0.6 (-0.3) respectively. This implies preliminary GDP(E) (investment) measurements around the sample mean (quarterly) output growth of 0.4% (0.5%) would be revised to nearly 0.6% (0.9%). Nearly all variables subject to structural breaks display bias before and after the breaks; the absolute values of the coefficients are sometimes larger post-break. The null hypothesis of unbiased revisions can only be rejected in one sub-sample: for imports before the mid-1980s' break.

4.2.2 Garratt-Vahey Variables

Table 3 reports the results for the six Garratt-Vahey nominal variables. With the exception of the early 1990s' breaks for M0 and its velocity, these variables show stability over the period. Although nominal GDP revisions and the GDP price deflator both exhibit significant bias at the 1% level, the monetary aggregates do not, with p-values above 10% and smaller coefficients (in absolute value). The narrower measure, M0, displays bias before the early 1990s' break. In general, the revisions to the money velocities are biased at the 1% level—reflecting the predictability of nominal GDP revisions—with an early 1990s' break for the narrower measure.

4.2.3 Egginton-Pick-Vahey Variables

Table 4 reports the results for the remaining four variables, all taken from the Egginton-Pick-Vahey data set. Both unemployment and industrial production have one break (in the early 1990s and mid-1980s, respectively); average earnings has two breaks (one in the late 1980s, the other in the early 1990s). In contrast, retail sales exhibits no breaks. In general, the preliminary measurements are downwards biased predictors of subsequent measurements at their sample means—matching the pattern observed for real-side quarterly indicators. The exceptions are unemployment, average earnings and industrial production before their respective first breaks. These

sub-samples display unbiasedness at the 15% level and above. All three indicators exhibit bias at the 1% level for subsequent sub-samples, consistent with statistical quality degradation.

4.2.4 Discussion

The predictability of revisions indicates the potential for improvements in UK statistical quality. An agency aiming to minimise revisions could exploit revision predictability. However, filtering prior to data release can create difficulties for monetary and fiscal control. In the absence of transparency, transformed preliminary measurements severely complicate inferences about the data generating process (Sargent (1989)).²⁰

A statistical agency may prefer a less direct route to efficient revisions based on gradual reforms to the quality of surveys and in-house estimates. The UK's well-known statistical reforms, associated with the *Pickford Report* and the subsequent Chancellor's Initiatives (see Wroe (1993)), had minor impacts on predictability. As shown in Figure 2, only five structural breaks occurred in the 1989-1995 period. For unemployment, predictability increased post-break. The monetary aggregates produced by the Bank of England were unaffected by the reforms to ONS procedures. Both exports and average earnings exhibit statistically significant predictability after their early 1990s' breaks.

Our preliminary analysis indicated that there was, however, some evidence that the volatility of revisions fell after the *Pickford Report*. To check the robustness of this characterisation in the presence of structural breaks, we tested for constant variances across each break identified by the Bai-Perron approach. Using a variance ratio test, the null of no difference in the variance can be rejected at the 5%, with revisions volatility lower post-break for most cases. The exceptions are unemployment and average earnings (second break).

5 Forecasting Case Study

Strong revisions predictability gives scope for improving real-time forecast performance. To illustrate this, we consider a probability event forecasting exercise.

We compute one step ahead out-of-sample forecasts for the evaluation period 1990Q1-1999Q2 using the unrestricted VAR estimated recursively:²¹

$$(3) \quad \mathbf{X}_t^m = \delta^m + \sum_{i=1}^4 \Gamma_i^m \mathbf{X}_{t-i}^m + \varepsilon_t^m$$

where $\mathbf{X}_t^m = (y_t^m, p_t^m)'$, $m = 1, F$ and B . The variables y and p denote quarterly output growth and inflation (defined using the GDP price deflator). The superscript

²⁰Sargent (1989) considers an agency that filters preliminary measurements of investment based on a predictable relationship with output. The efficiently transformed data exhibit an apparent investment accelerator even if the economic relationships do not.

²¹The sample start date reflects the availability of real-time GDP price deflator data.

$m = 1, F$ and B denotes the set of first, final and bias-adjusted measurements respectively. We define the bias-adjusted measurements, X_t^B , as:

$$(4) \quad X_t^B = \alpha + (1 + \beta)X_t^1$$

where X_t^1 denotes the first measurement. We assume that the forecaster knows the true values of α and β and that they are equal to the respective sample coefficients from equation (2).²²

To arrive at our preferred specification for the forecasting VAR, we first tested for stationarity and then selected the lag order. We could not reject the null of a unit root in the levels data but could reject the null in first differences at the 5% level using augmented Dickey-Fuller tests (for both first and final measurement data). We selected the lag order by estimating a sequence of unrestricted VAR(p), $p = 0, 1, 2, \dots, 6$ models. For the first measurement data, $m = 1$, the optimal Akaike Information Criteria selected lag length was zero; but for final data, $m = F$, the lag order equalled four. Bearing in mind that unnecessary lags causes inefficiency but not bias in the OLS estimators, we standardised the lag length at four for first, final and the bias-adjusted data.

For model evaluation, we consider an economic agent monitoring business cycle turning points by calculating the probability of above trend output growth. This is sometimes referred to as “positive momentum” or “above speed limit” growth in the monetary policy literature (Walsh (2003)). We take the (final data) average economic growth rate for the evaluation period, 0.52%, as the “trend”, the agent calculates the probability $\Pr[y_t^m > 0.52|\Omega_{t-1}]$, for $m = 1, F$ and B where Ω_{t-1} denotes the information set dated $t - 1$. Confidence intervals are of limited help to our agent because the concern with turning points implies little interest in whether any particular forecast confidence interval encompass a specific value for output. Garratt et al (2003a) and Clements (2004) discuss in detail the appropriateness of probability forecasts and their relationships to standard forecast confidence intervals.

We compute the probability forecasts by stochastic simulation by the methods described by Garratt et al (2003b, appendix).²³ Figure 3 plots the probabilities of the event for the three data types. For most of the evaluation period, final data results in a higher probability of above mean output growth than with first measurement data. The average difference in probabilities is 11.6 percentage points (with a standard deviation of 22.4%). Using bias-corrected measurements rather than first-measurement data reduces considerably the mean (absolute) difference in

²²Real-time ($m = 1$) GDP growth and GDP price deflator inflation exhibit no breaks (see section 4). The values for $\hat{\alpha}$ and $\hat{\beta}$ for GDP growth are 0.444 and -0.573 and for GDP price deflator inflation are 0.696 and -0.595 respectively.

²³To obtain probability forecasts by stochastic simulation we simulate values of

$$\mathbf{x}_{T+1}^{m(s)} = \hat{\delta}^{m(s)} + \sum_{i=1}^4 \hat{\Gamma}_i^m \mathbf{x}_{t-i}^{m(s)} + \varepsilon_{T+1}^{m(s)}$$

where T runs from 1989Q4 to 1999Q1, the parameter estimates vary with each recursion, the superscript ‘(s)’ refers to the s^{th} replication of the simulation algorithm ($s = 1, 2, \dots, 1000$) and the $\varepsilon_{T+1}^{m(s)}$ ’s are drawn using a nonparametric method with replacement. Garratt et al (2003b) label this type of uncertainty as the effects of unobserved future shocks.

forecast probabilities to 4.8 percentage points (with a standard deviation of 21.7%), although substantial differences on Figure 3. One Step Ahead Probability of Above-trend Output Growth. Figure

For more formal forecasts evaluation, Table 5 reports the proportion of correctly forecast events, P , the Kuipers score statistic, KS , and the Pesaran-Timmermann (1992) directional market timing statistics, PT .

Table 5: Evaluation of probability event forecasts

Measurements	P	KS	PT
First	55.3%	0.047	0.270
Final	73.7%	0.514	2.865
Bias adjusted	63.2%	0.368	1.428

We consider 38 events in total; one event (above trend growth) for each time period in the 1990Q1 to 1999Q2 evaluation period. We assume that an event can be correctly forecast if the associated probability forecast exceeds 50 percent. Although over 70% of events can be correctly forecast using final data, using first measurements and bias-adjusted measurements reduces the success rate by approximately 19 and 10 percentage points respectively.

The Kuipers scores also suggest that bias adjustment improves forecast performance. This statistic measures the proportion of above mean growth rates that were correctly forecast minus the proportion of below mean growth rates that were incorrectly forecast. The test provides a measure of the accuracy of directional forecasts, with high positive numbers indicating high predictive accuracy. Using first measurements gives a KS of approximately 0.05; bias-adjustment betters this score by 0.32 — considerably closer to the final data score of 0.51.

The PT statistic allows a formal hypothesis of directional forecasting performance. As shown in Granger and Pesaran (2000), this hypothesis test uses the same information as the Kuipers score. Under the null hypothesis that the forecasts and realisations are independently distributed the PT statistic has a standard normal distribution. The first measurement data reject the null of no ability to forecast observed changes with a probability value of 0.78. Bias-adjustment reduces the probability value to 0.15 — indicating rejection at the 15% level. Final data give clear rejection at the 1% level. We conclude that bias adjustment improves probability forecasting performance for this particular forecasting example.²⁴

²⁴We also used the “probability integral transform” (PIT) method, due to Rosenblatt (1952) and discussed in detail by Clements (2004). The two events considered were above-trend output growth and above-trend inflation, giving 76 probability forecasts and their associated realisations for the 38 quarters from 1990Q1 to 1999Q2. We calculated the probability of observing values no greater than the actual (final data) values. Under the null hypothesis that the set of density forecasts match the actual data generating density, the PITs are uniformly distributed $U[0,1]$. The Kolmogorov-Smirnov statistics indicate marginal rejection for final data but clear rejection with first measurements at the 5% significance level. The bias-adjusted measurements indicated marginal rejection at the same significance level.

Although this analysis indicates the scope for exploiting revision predictability, we emphasise that the variation in predictability across variables and through time ensures that performance improvement is case specific. Furthermore, the parameters of equation (2) were assumed to be known by the agent (and identified as the population coefficients). In the presence of structural breaks, parameter learning may limit the scope for increasing forecast accuracy. Modelling the impacts of bounded rationality on real-time forecast and policy model performance is an interesting area for subsequent research.

6 Conclusions

By utilising both existing and new sources of real-time data, this paper has characterised the revision processes for 16 UK macro indicators. The main finding—that the preliminary measurements of UK macro variables are generally biased—confirms a widely-held suspicion that UK macro measurements are inefficient. Where present, the bias causes preliminary measurements to understate later measurements (at the sample means) and structural breaks result in some variation in revisions predictability. Monetary aggregates, M0 and M4, are typically unbiased (at least, post-break). Using a forecasting probability example, we have demonstrated the potential to improve real-time model performance by utilising bias-adjusted data.

References

- [1] Bai, J., and P. Perron (1998) “Estimating and Testing Linear Models with Multiple Structural Changes”, *Econometrica*, 66, 47-78.
- [2] Bai, J., and P. Perron (2003a) “Computation and Analysis of Multiple Structural Change Models”, *Journal of Applied Econometrics*, 18, 1-22.
- [3] Bai, J., and P. Perron (2003b) “Critical Values for Multiple Structural Change Tests”, *Econometrics Journal*, 6, 72-78.
- [4] Barklem, A. (2000) “Revisions Analysis of Initial Estimates of Key Economic Indicators and GDP Components”, *Economic Trends*, 556, 31-52.
- [5] Castle, J. and C. Ellis (2002) “Building a Real-time Database for GDP(E)”, *Bank of England Quarterly Bulletin*, February, 42-49.
- [6] Clements, M.P. (2004) “Evaluating the Bank Of England Density Forecasts of Inflation”, *Economic Journal*, 114, 844-866.
- [7] Croushore, D. and T. Stark (2001) “A Real-time Data Set for Macroeconomists” *Journal of Econometrics*, 105, 111-130.
- [8] Diebold, F. X., and G. D. Rudebusch (1991) “Forecasting Output with the Composite Leading Index: A Real-Time Analysis”, *Journal of the American Statistical Association*, 86, 603-610.
- [9] Egginton, D.M., A. Pick and S.P. Vahey (2002) “ ‘Keep It Real!’ A Real-time UK Macro Data Set”, *Economics Letters*, 77, 15-20.
- [10] Faust, J., J.H. Rogers and J.H. Wright (2004) “News and Noise in G7 GDP Announcements”, *Journal of Money, Credit and Banking*, forthcoming.
- [11] Garratt, A., K. Lee, M.H. Pesaran, and Y. Shin, Y. (2003a) “Forecast Uncertainties in Macroeconometric Modelling: An Application to the UK Economy”, *Cambridge University Discussion Paper*, available at <http://www.econ.cam.ac.uk/faculty/pesaran>.
- [12] Garratt, A., K. Lee, M.H. Pesaran, and Y. Shin, Y. (2003b) “Forecast Uncertainties in Macroeconometric Modelling: An Application to the UK Economy”, *Journal of American Statistical Association, Applications and Case Studies*, 98, 464, 829-838.
- [13] Granger, C.W.J. and M.H. Pesaran (2000), “Economic and Statistical Measures of Forecast Accuracy,” *Journal of Forecasting*, 19, 537-560.
- [14] Howrey, E.P. (1978) “The Use of Preliminary Data in Econometric Forecasting”, *Review of Economics and Statistics*, 60, 193-200.
- [15] Jansen, N. (1998), “The Demand for M0 in the United Kingdom Reconsidered: Some Specification Issues”, *Bank of England Working Paper 83*.

- [16] Koenig, E., S. Dolmas and J. Piger (2003) “The Use and Abuse of ‘Real-time’ Data in Economic Forecasting”, *Review of Economics and Statistics*, 85, 618-628.
- [17] Mankiw, N.G., Runkle, D.E and M.D. Shapiro (1984) “Are Preliminary Announcements of the Money Stock Rational Forecasts”, *Journal of Monetary Economics*, 14, 15-27.
- [18] Mitchell, J. (2004) *Revisions to Economic Statistics*, National Institute of Economic and Social Research, April.
- [19] Newey, W.K. and K.D. West (1987) “A Simple Positive Semidefinite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”, *Econometrica*, 55, 703-708.
- [20] Patterson, K. D., and S. M. Heravi (1991) “Data Revisions and the Expenditure Components of GDP” *Economic Journal*, 101, 887-901.
- [21] Pesaran, M.H. and A. Timmermann (1992), “A Simple Nonparametric Test of Predictive Performance,” *Journal of Business and Economic Statistics*, 10, 461-465.
- [22] Pickford S. (1989) *Government Economic Statistics: A Scrutiny Report*, Cabinet Office, HMSO.
- [23] Rosenblatt, M. (1952) “Remarks on a Multivariate Transformation”, *Annals of Mathematical Statistics*, 23, 470-472.
- [24] Sargent, T., (1989) “Two Models of Measurements and the Investment Accelerator”, *Journal of Political Economy*, 97, 251-287.
- [25] Swanson, N.R. and D. Van Dijk (2004) “Are Statistical Reporting Agencies Getting It Right? Data Rationality and Business Cycle Asymmetry”, *Econometric Institute Report EI 2001-28*, revised 2004.
- [26] Symons, P. (2001) “Revisions Analysis of Initial Estimates of Annual Constant Price GDP and Its Components”, *Economic Trends*, 568, 48-65.
- [27] Topping, S.L. and S. L. Bishop (1989), “Breaks in Monetary Series” Bank of England Discussion Paper, Technical Series, No. 23.
- [28] Walsh, (2003) “Speed Limit Policies: the Output Gap and Optimal Monetary Policy”, *American Economic Review*, 93, 265-278.
- [29] Wroe, D. (1993) “Improving Macro-economic Statistics”, *Economic Trends*, 471, 191-199.

7 Appendix: Summary of Garratt-Vahey real-time data

In this appendix, we describe the real-time data collected specifically for this study (referred to as the Garratt-Vahey data set in the main text). The data consist of monthly vintages of nominal macroeconomic variables. Each variable has many different vintages—reflecting the revisions and updates that occur over time. In the MS-Excel files, the data are stored as a matrix for each variable. Successive column vectors of the matrix represent different (more recent) vintages of data; each contains the most recent measurements available at that vintage date. The data were collected by examining various issues of *Economic Trends*, which is published by the ONS (formally the Central Statistical Office).

The figures reported were in the public domain at the end of the month in question. For each vintage, the observations are identical to those in the relevant published source. The window length reported by the source publications is affected by page layout considerations—it varies by variable and by vintage date. Missing data are recorded as empty cells. The two excel files containing the data described below, *nomY&Pdef.xls* and *money.xls*, are available from the authors on request.

In the following section, the definition, source, code, period and relevant notes are described for each variable.

1. Nominal GDP (*Excel file: nomY&Pdef.xls, Spreadsheet: nominal_mktp(sa)*).
Definition:- Gross domestic product at market prices, current price £ Million, seasonally adjusted.
Source:- ONS *Economic Trends*.
Code:- FNAME (from Nov 1981 to Sept 1985), CAOB (from Oct 1985 to Sept 1998) and YBHA (from Oct 1998 onwards).
Period:- Monthly vintages from Nov 1981 to August 2002, on quarterly observations 1976Q1 to 2002Q1.
2. GDP price deflator (*Excel file: nomY&Pdef.xls, Spreadsheet: deflator_mktp*).
Definition:- Implied market price deflator (average estimate).
Source:- ONS *Economic Trends*.
Code:- DJDT (from Nov 1981 to Oct 1998) and YBGB (from Oct 1998 onwards).
Period:- Monthly vintages from Nov 1981 to August 2002, on quarterly observations 1976Q1 to 2001Q4.
3. M0 money (*Excel file: money.xls, spreadsheet: M0_sa*).
Definition:- M0, £ Million, Amount outstanding, seasonally adjusted.
Source:- ONS *Economic Trends*.
Code:- AVAE.
Period:- Monthly vintages from July 1987 to August 2002, on quarterly observations 1983Q1 to 2002Q1.

4. M4 money (*Excel file: money.xls, spreadsheet: M4_sa*).
Definition:- M4, £ Million, Amount outstanding, seasonally adjusted.
Source:- ONS *Economic Trends*.
Code:- AUYN.
Period:- Monthly vintages from July 1987 to August 2002, on quarterly observations 1983Q1 to 2002Q1.
5. VM0 money (*Excel file: money.xls, spreadsheet: V(M0)*).
Definition:- Velocity of circulation.
Source:- ONS *Economic Trends*.
Code:- AVAM.
Period:- Monthly vintages from July 1987 to August 2002, on quarterly observations 1983Q1 to 2002Q1.
6. VM4 money (*Excel file: money.xls, spreadsheet: V(M4)*).
Definition:- Velocity of circulation.
Source:- ONS *Economic Trends*.
Code:- AUYU.
Period:- Monthly vintages from July 1987 to August 2002, on quarterly observations 1983Q1 to 2002Q1.

Table 1: Summary Statistics for Revisions, Y_t^1

	Sample	Mean	MAE	SD	SD 1990s
GDP(E):	1961Q3 1999Q2	0.24*	0.88	1.20 [†]	0.31
Consumption:	1961Q3 1999Q2	0.10*	0.72	0.95 [†]	0.48
Investment:	1961Q3 1999Q2	0.49*	1.87	2.40 [†]	1.71
Government expenditure:	1961Q3 1999Q2	-0.07	0.96	1.32	1.07
Exports:	1961Q3 1999Q2	0.32*	1.45	1.80 [†]	1.52
Imports:	1961Q3 1999Q2	0.16	1.44	1.84 [†]	1.33
Nominal GDP:	1981Q1 1999Q4	0.29*	0.56	0.70	0.64
GDP deflator:	1981Q1 1999Q4	0.07	0.62	0.79 [†]	0.64
M0:	1987Q1 1999Q4	0.05	0.36	0.52 [†]	0.29
M4:	1987Q1 1999Q4	-0.01	0.26	0.35	0.31
M0 velocity:	1987Q1 1999Q4	0.25*	0.61	0.71 [†]	0.40
M4 velocity:	1986Q4 1999Q4	0.39*	0.54	0.68	0.67
Average earnings:	1979M11 1997M1	0.03	0.49	0.68	0.77
Industrial production:	1979M11 1997M8	0.05	0.68	0.93 [†]	0.72
Unemployment:	1979M12 1997M10	0.02	0.41	0.61	0.72
Retail sales:	1986M2 1997M12	0.04	0.56	0.73 [†]	0.60

Notes: The revisions, Y_t^1 , are defined as the final measurement, X_t^F , minus the first measurement, X_t^1 . Each measurement, X_t , refers to the quarter-on-quarter (first 12 variables) or month-on-month (last 4 variables) growth rate in percent. MAE is the mean absolute error; SD refers to standard deviation and SD 1990s refers to the standard deviation for the 1990s. The symbol * denotes statistical significance at the 5% level using a Newey-West corrected t-statistic based on a regression of the revision on a constant. Significantly lower variance for the 1990s at the 5% level using a variance ratio test is denoted by [†] (for exact break dates see main text).

Table 2: Revisions regressions, Castle-Ellis

	Sample	α	β	\bar{R}^2	Wald-test	LM-test
GDP(E):	1961Q3 1999Q2	0.444 (0.065)	-0.573 (0.050)	0.58	0.00	0.30
Consumption:	1961Q3 1967Q2	0.478 (0.120)	-0.682 (0.087)	0.64	0.00	0.86
	1967Q3 1999Q2	0.252 (0.072)	-0.288 (0.051)	0.20	0.00	0.00
Investment:	1961Q3 1999Q2	0.563 (0.147)	-0.320 (0.074)	0.17	0.00	0.01
Government expenditure:	1961Q3 1975Q1	0.421 (0.185)	-0.591 (0.182)	0.24	0.01	0.17
	1975Q2 1999Q2	0.181 (0.083)	-0.816 (0.128)	0.33	0.00	0.01
Exports:	1961Q3 1971Q4	0.630 (0.117)	-0.237 (0.032)	0.43	0.00	0.13
	1972Q1 1980Q3	0.219 (0.156)	-0.068 (0.077)	0.01	0.34	0.03
	1980Q4 1993Q3	0.495 (0.139)	-0.525 (0.063)	0.45	0.00	0.00
	1993Q4 1999Q2	1.274 (0.290)	-0.458 (0.159)	0.25	0.00	0.43
Imports:	1961Q3 1985Q4	0.156 (0.130)	-0.120 (0.043)	0.05	0.03	0.00
	1986Q1 1999Q2	0.920 (0.290)	-0.473 (0.082)	0.42	0.00	0.67

Notes: Revisions regression, Equation (2), $Y_t^1 = \alpha_j + \beta_j X_t^1 + \epsilon_t^1$. Newey-West standard errors (truncation factor equals 4) are in parentheses. We report p-values of the Wald-test for $\alpha = \beta = 0$ and the LM-test statistic for up to 4th-order serial correlation.

Table 3: Revisions regressions, Garratt-Vahey

	Sample	α	β	\bar{R}^2	Wald-test	LM-test
Nominal GDP:	1981Q1 1999Q4	0.929 (0.141)	-0.431 (0.097)	0.27	0.00	0.22
GDP deflator:	1981Q1 1999Q4	0.696 (0.135)	-0.595 (0.078)	0.30	0.00	0.16
M0:	1987Q1 1993Q2	0.555 (0.131)	-0.494 (0.078)	0.50	0.00	0.09
	1993Q3 1999Q4	0.114 (0.077)	-0.035 (0.041)	-0.03	0.46	0.08
M4:	1987Q1 1999Q4	-0.020 (0.081)	0.006 (0.030)	-0.02	0.97	0.16
M0 velocity:	1987Q1 1992Q1	0.937 (0.049)	-1.040 (0.190)	0.72	0.00	0.97
	1992Q2 1999Q4	0.025 (0.074)	-0.538 (0.114)	0.48	0.00	0.26
M4 velocity:	1986Q4 1999Q4	0.254 (0.111)	-0.141 (0.80)	0.04	0.00	0.91

Notes: Revisions regression, Equation (2), $Y_t^1 = \alpha_j + \beta_j X_t^1 + \epsilon_t^1$. Newey-West standard errors (truncation factor equals 4) are in parentheses. We report p-values of the Wald-test for $\alpha = \beta = 0$ and the LM-test statistic for up to 4th-order serial correlation.

Table 4: Revisions regressions, Egginton-Pick-Vahey

	Sample	α	β	\bar{R}^2	Wald-test	LM-test
Average earnings:	1979M11 1987M11	0.108 (0.072)	-0.138 (0.079)	0.05	0.23	0.00
	1987M12 1992M9	0.464 (0.091)	-0.688 (0.129)	0.45	0.00	0.01
	1992M10 1997M1	0.257 (0.028)	-0.907 (0.045)	0.87	0.00	0.19
Industrial production:	1979M11 1986M5	0.050 (0.081)	-0.033 (0.076)	-0.01	0.80	0.06
	1986M6 1997M8	0.103 (0.047)	-0.508 (0.092)	0.29	0.00	0.00
Unemployment:	1979M12 1992M10	0.063 (0.056)	-0.026 (0.30)	0.00	0.42	0.00
	1992M11 1997M10	-0.428 (0.154)	-0.328 (0.101)	0.25	0.01	0.13
Retail sales:	1986M2 1997M12	0.120 (0.029)	-0.390 (0.042)	0.41	0.00	0.00

Notes: Revisions regression, Equation (2), $Y_t^1 = \alpha_j + \beta_j X_t^1 + \epsilon_t^1$. Newey-West standard errors (truncation factor equals 4) are in parentheses. We report p-values of the Wald-test for $\alpha = \beta = 0$ and the LM-test statistic for up to 12th-order serial correlation.