Predicting Directional Changes in the UK Interest Rate: The Usefulness of Information from the Taylor Rule Versus a Wider Alternative

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April 2004

Abstract

We consider an experiment where we use the Taylor rule information set, inflation and the output gap, to predict the directional change in monetary policy for the United Kingdom 1992 - 2003. To do this we use a multinomial logit limited dependent variable approach, where the next rate change could be 'upwards', 'downwards' or 'no change'. These predictions are compared to the actual outturn, and evaluated against a wider information set, using in-sample and out-of-sample prediction tests. Although the Taylor rule offers a useful summary of *ex post* monetary reactions its information generates poor predictions of the direction of change compared to a wider information set.

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1 Introduction

The Taylor rule has emerged as a simple but robust estimate of the relationship between the short term interest rate and measures of inflation and the deviation of output from its trend value, (see Taylor, 1993, 2000, 2001). The rule satisfies all the criteria for a simple rule of thumb: it depends on variables that are easily measured and available in a reasonably timely fashion. The rule itself can be readily estimated by econometric methods, and it is also capable of explaining the past history of the monetary policy instrument in many of the industrialized countries (c.f. Judd and Rudebusch, 1998, Clarida *et al.*, 1998, 2000, Gerlach and Smets, 1999, Gerlach and Schnabel, 2000, and Nelson, 2000). It should therefore offer a clear and simple guide to policymakers concerning the optimal setting for the monetary policy instrument. In the new monetary policy framework of inflation targeting, it is generally agreed, as Mervyn King has observed, that 'central banks that have been successful appear *ex post* to have been following a Taylor rule even if they had never heard of that concept when they were actually making decisions' *press briefing 10 February 1999* [our emphasis]. But explaining the past is not the same as predicting the future. Even though there is considerable evidence in favour of the Taylor rule using historical time series, there is also evidence that the Taylor rule has unstable coefficients and performs badly in out-of-sample forecasts (see Gerlach, 2003, and Gerlach-Kristen, 2003). Up to this point the literature has not asked the question whether the information that is embodied in the Taylor rule is particularly useful for indicating the *direction* of change in the interest rate at the frequency required for monthly decision making. It is worth asking whether the Taylor rule offers a good guide to *future* monetary policymaking. This is because a good *ex post* summary of successful central bank behaviour may not imply a distinguished performance as an *ex ante* guide for policymaking.

In this paper we consider the usefulness of the Taylor rule for predicting the next rate change. This represents a different approach to previous use of policy rules based on the simulation of Taylor rules (c.f.

Rudebusch and Svensson, 1999), or estimates of the monetary policy rule for different historical episodes (Taylor, 1999). It is also different from the analysis proposed by Huang *et al.* (2000) and Orphanides (2000), where the rule is used to evaluate whether *past* decision making was optimal. Our approach is forward-looking, but again it differs from approaches where the inflation forecast is the intermediate variable (Svensson, 1997) and the performance of the rule is evaluated at various horizons n-steps ahead (see Batini and Haldane, 1999, and Batini and Nelson, 2001). While we agree with the forward-looking approach, these models treat the data as a vector of continuous random variables, but in this paper we evaluate the decisions of the monetary authorities as countable discrete values[1]. In this respect the paper closest to ours is written by Gerlach (2003), which argues in favour of discrete time analysis using probit methods rather than continuous random variable estimation.

Our analysis (and Gerlach's) examines the choice variable as a discrete variable arising from a monthly decision, and conduct an experiment in which the Taylor rule information set - inflation and the output gap - which is used here to predict the next change in monetary policy in the United Kingdom (the euro-area rate in Gerlach (2003)).[2] This approach accurately mimics the decision process that the UK Monetary Policy Committee (MPC) follows on a monthly basis, where the decision is whether to change the interest rate from its current setting on the basis of new information and forecasts of inflation up to two years ahead[3]. The

[1]We examine the evidence on Taylor rules for a sample of monthy data where we treat the data as a vector of continuous random variables to tie our analysis into the previous literature that has followed this methodology. Our findings do not offer much support to this approach, since the coefficients are unstable, and never close the ones indicated by Taylor, despite our attempts to alter the modelling assumptions to achieve the best outcome

[2]By focusing on the next change we are able to model the use of information to forecast changes in the interest rate over very short horizons i.e. one month. Rudebusch (2002) has reinforced the findings of Goodfriend (1991) and Rudebusch (1995) that information is seldom useful to predict changes beyond a few months ahead, and smoothing is a characteristic of the very short term i.e. month-to-month not quarter-to-quarter.

[3]Budd (1998) and King (1997, 2002) offer descriptions of the process by which the

decision is about whether or not to change the rate, and if so, in which direction; thus the outcome can be one of three options - to raise the rate, to leave the rate unchanged, or to lower the rate[4]. To model this choice we utilise a limited dependent variable approach, where the next rate change could be 'upwards', 'downwards' or 'no change'. A multinomial logit model is used to predict the next *most likely* change using monthly data, and these predictions are compared to the actual outturn.

Our results are based on two information sets. The first is the Taylor rule information, which includes inflation and output gap, while the second uses additional data - augmenting the Taylor rule information with monetary, exchange rate, earnings and factor cost data - to assess the ability of the wider information set to predict against the actual outturn. Finally, we conduct out-of-sample prediction tests with a test of association in contingency tables. If the Taylor rule information is a good guide to monetary policymakers then data on inflation and the output gap should be sufficient to predict the direction of the next change accurately, but if a wider information set is superior, the usefulness of the Taylor rule information as an *ex ante* guide to monetary policymaking may be questioned. We emphasise that while having additional variables always produces better in-sample results, it is not necessarily true for out-of-sample results. Out-of-sample predictions are improved only when the added variables possess incremental forecasting power. The paper will determine whether it is possible for the wide information set to do better than the traditional Taylor rule information set in predicting the *next* rate change out-of sample. The analysis is conducted on monthly data for the United Kingdom which has been inflation targeting since 1992[5].

The paper is organised as follows. Section 2 provides some estimates using monthly data for the Taylor rule over the period 1992-2003 to evaluate the performance of the rule at a logistically useful frequency such

MPC makes its decisions.

[4]With the exception of a few large reductions in the base rate immediately after the UK exit from the Exchange Rate Mechanism (ERM) all the rate changes in our sample have been conducted in steps of 25 basis points on a monthly frequency.

[5]See the opening remarks in the recent speech by Charles Bean, Chief Economist and MPC member in the *Bank of England Quarterly Bulletin*, Winter 2003 .

as the monthly frequency. The results are not supportive of a continuous random variable approach. Section 3 explains the methodology of the multinomial logit model, which is implemented in Section 4, using both Taylor rule information and the wider information set. The out-of-sample performance is assessed in Section 5. Section 6 concludes.

2 Monthly Estimates of the Taylor Rule

The Taylor Rule suggests that the central bank should adjust the nominal short-term interest rate in response to inflation and the variation of output around trend with response coefficients of 1.5 and 0.5 respectively[6]. A rule of this type has been able to explain US monetary policy from 1986 - 1993 very well. Recent evidence in Taylor (1999) suggests that small improvements can be achieved by introducing forward-looking measures of inflation, and the exchange rate to reflect the openness of the economy (as implemented by Svensson, 2000, 2001 and Batini *et al,* 2003), although Taylor (2000, 2001) argues that the gains over the simple rule are minor. These results have been examined for a wider set of countries. Clarida *et al* (1998) have estimated the forward looking Taylor rule for the G3 (US, Japan, Germany) and the E3 (UK, France and Italy) using the generalized method of moments over a sample beginning in 1979 and ending in the early 1990s for the G3 and prior to the 'hard' ERM for the E3. The results for the G3 imply that all three countries respond aggres-

[6]The rule reflects movements of a real interest rate, according to the deviation of the rate of inflation from the target and the level of output relative to trend (output gap) such that $i_t = \pi_{t-1} + \beta(\pi_{t-1} - \pi^*) + \gamma(y_{t-1} - y^*) + \overline{r} + \eta_t$ where π_t is the annual inflation rate (in the case of the United Kingdom the Retail Price Index excluding mortgage interest payments, RPIX), π^* is the inflation target, $\overline{r}$ is the equilibrium real interest rate and $(y_{t-1} - y^*)$ is the output gap, and η_t is a serially uncorrelated random error. The coefficients β and γ are the weights given to the deviation of the inflation rate from the target and the output gap respectively in the monetary policy rule. The stochastic shock, η_t, is unknown at the time the central bank sets the interest rate: this reflects a realistic assumption about the information available to the central bank at time t. Changes in the policy instrument influence output with a lag of approximately one year and inflation with a lag of two years.

sively to inflation, since the estimates of the coefficients on inflation are significantly greater than unity, but mildly towards output gaps. The E3 on the other hand have coefficient on inflation estimated below unity or insignificantly different from unity, suggesting that their policy rules during this period were dissimilar to those of the G3. E3 countries appeared to be following disinflation strategies which did not approximate to forward-looking Taylor rules. More recent evidence for the UK in Nelson (2000) implies that the response of the UK nominal rate to inflation and output gap are very close to the values of 1.5 and 0.5 proposed by Taylor (1993) for the inflation targeting period 1992-1997 (the range of his sample did not extend beyond 1997).

We follow Clarida *et al* (1998) who allow the central bank to operate a forward-looking monetary policy in response to *expected* inflation and output, rather than lagged actual outcomes. We define the rule for the nominal interest rate as:

$$i_t = (1-\rho)\alpha + (1-\rho)\,\beta\pi_{t+n} + (1-\rho)\,\gamma\widetilde{y}_t + \rho i_{t-1} + \varepsilon_t \qquad (1)$$

where the parameter $\rho \in [0,1]$ captures the degree of interest rate smoothing, the term α can be shown to equal $\bar{i} - \beta\pi^*$, where $\bar{i}$ is the long-run equilibrium nominal rate and π^* is the desired rate of inflation, π_{t+n} is the rate of annualized inflation n periods ahead, and the output gap is $\widetilde{y}_t \equiv y_t - y^*$, for which $y^*$is the level of potential output. The error ε_t has a zero mean and is assumed to be uncorrelated with any variables available at time t. From equation (1), the value of β can be used in evaluating the aggressiveness of central bank monetary policy to inflation. If $\beta > 1$, the target real rate adjusts to stabilize inflation and output (given $\gamma > 0$). With $\beta < 1$, the interest rate is then set to accommodate changes in inflation. In the latter case, self-fulfilling bursts of inflation and output may be possible.

Most of the evidence offering support for the Taylor rule is estimated for quarterly data (c.f. Clarida *et al* (1998), Taylor (1999)), however, Nelson (2000) has reported results for the UK using both quarterly and monthly data. His results confirm that for the inflation targeting period 1992-1997 the equation (1) performs well on quarterly data, and can also reproduce the Taylor result using monthly data from 1992/10 to 1997/04. The data set involves i_t measured by the Treasury Bill rate, π_t measured by the twelfth difference of the natural logarithm of the RPIX and $\widetilde{y}_t$ determined empirically by the residuals from a 1971/01 to 1998/12 regression of the natural logarithm of the index of industrial production based on either the Hodrick-Prescott filter or the quadratic detrending method[7]. The estimation method is the instrumental variable (IV) estimation approach and the set of instrument variables are $IV \in (1, \pi_{t-1}, ..., \pi_{t-6}, \widetilde{y}_{t-1}, ..., \widetilde{y}_{t-6}, i_{t-1}, ..., i_{t-6})$. With the value of n = 3, his results are reproduced in the first row of Table 1. The long-run response coefficient on inflation, $\widehat{\beta}$, equals 1.472 (0.424) and on output gap, $\widehat{\gamma}$, equals 0.301 (0.068), a result that is remarkably close to the 1.5 and 0.5 combination suggested by Taylor (1993).

Using Nelson's data[8] we examine the robustness of the Taylor rule at the monthly frequency using two different measures of the interest rate, two detrending methods to produce the output gap, and different instruments for the estimation of the coefficients for comparison purposes. Nelson's original model uses the rate from the thinly traded Treasury Bill market as the dependent variable, while the actual policy rate is the rate on Gilt repurchase agreements (the repo rate). There may be some advantages from using the Treasury Bill rate for a comparison of different policy regimes over the longer period, 1970 - 1997, but for our sample (1992-2001) the repo rate is the relevant rate. We consider how the

[7]We could have used real time data on GDP available from the Bank of England's web site in line with Orphanides (2000) and Nelson and Nikolov (2001), but the data is for the expenditure component of GDP, which is updated quarterly. Nelson and Nikolov (2001) show the implications of using real-time data at the quarterly frequency, not the monthly frequency. The real-time component to the data at a monthly frequency is less informative, since observations in between the quarterly figures (given in March, June, September and December, which would be correctly defined as real time data) reflect only the revisions to the *previous* quarterly estimate in subsequent months. The series does not provide a real time measure of output on a monthly frequency, it only provides revisions to the quarterly GDP figures.

[8]We are very grateful to Edward Nelson for supplying us with his data set for results comparison.

results would change for the sample if we used the repo rate rather than the Treasury Bill rate in the two rows of Table 1. Using the Treasury Bill rate the coefficients on inflation and output gap are closer to the Taylor rule coefficients than if the Gilt repo rate is used as the dependent variable, but the use of the Gilt repo improves the estimated value of the inflation target[9] from 3.65% to 2.88% when estimated over the sample 1992/10 to 1997/04.

The purpose of Nelson's work was to assess the extent to which monetary policymakers adhered to a Taylor rule (in the backward looking sense). In this respect his work is an evaluation of Mervyn King's statement, quoted in the introduction, that the central banks were using common sense. He supports the view that the Taylor rule is a good *ex post* summary of central bank behaviour, but we go on to consider whether the rule could be useful for policymaking looking forward. The results in the subsequent Tables show that at a monthly frequency - the frequency at which the Bank of England currently sets the policy rate - Nelson's estimates are not robust, but are plagued by parameter instability in common with estimates of coefficients in Taylor rules for other data (c.f. Gerlach-Kristen, 2003). Table 2 provides estimates of equation (1) using the Hodrick- Prescott filter method of detrending for the output gap. The sample period is 1993/02, which is the first month that the Bank of England was inflation targeting, to 2003/07, giving 126 observations altogether. The variable i_t is the value of the Treasury Bill rate or the Gilt repo rate, announced monthly by the Bank of England. The variable π_{t+n} is the 12-month (annualized) change in the price level , based on the retail price index excluding mortgage interest payments (RPIX), evaluated n months ahead. We consider a range of horizons for monetary policy, ranging from three months (Nelson's horizon) to twenty four months (the upper limit proposed by Batini and Haldane (1999) and Batini *et al* (2001). They suggest a horizon of eighteen to twenty four months ahead. The index of industrial pro-

[9] The desired level of the real interest rate $\overline{r}$ is given by $\overline{r} = \overline{i} - \pi^*$. Using the relationship $\alpha \equiv \overline{i} - \beta\pi^*$ together with $\overline{r} = \overline{i} - \pi^*$, the target inflation rate is obtained through $\pi^* = (\overline{r} - \alpha)/(\beta - 1)$.

duction is used as a proxy for output and the variable $\widetilde{y}_t$, the output gap, is constructed using detrended data for industrial production from 1993/02 to 2003/07. It is possible that the regressors in equation (1) dated later than period t may be correlated to the error term, ε_t, so we use the instrumental variable (IV) estimation method in order to avoid any endogeneity problems. The set of instrument variables are $IV \in (1, \pi_{t-1}, ..., \pi_{t-6}, \pi_{t-9}, \pi_{t-12}, \widetilde{y}_{t-1}, ..., \widetilde{y}_{t-6}, \widetilde{y}_{t-9}, \widetilde{y}_{t-12}, i_{t-1}, ..., i_{t-6}, i_{t-9}, i_{t-12})$. We consider the performance of the equation for both the Treasury Bill rate and the Gilt repo rate.

The results using the Treasury Bill rate as the dependent variable and using the Gilt repo rate as the dependent variable are reported in rows 1-10 and 11-20, respectively, in Table 2 for selected horizons (3, 6, 12, 18, 24), although we estimated the equation for all the horizons from 3 - 24 months. Using the Hodrick-Prescott filter to detrend output we found that, for both the Treasury Bill rate and the Gilt repo rate, the estimate of the inflation target was close to 2.5% for all horizons, but the estimated coefficients on inflation and the output gap varied considerably depending on the dependent variable and the forward-looking horizon. In some cases the coefficients were not significant, in others they were significant but the wrong magnitudes and even negative. The high values of the coefficients in certain cases are due to the fact that the coefficient on the lagged dependent variable is often close to unity, inflating the calculated long-run values of the other coefficients[10].

When re-estimated using quadratic detrending, keeping all other features of the estimation procedure the same, the results were very sim-

[10] A high value of ρ effectively puts great weight on the lagged interest rate, and a low weight on the remaining variables. When equation (1) is estimated, although the parameters on forward-looking inflation and the output gap are quite small, adjustment for the fact that small changes in the instrument persist for a considerable time shows an aggressive response to expected inflation and output gaps. These variables affect future monetary policy as well as the present, so the net response of the interest rate is considerable. Gradualist policies such as these may confirm the observation of Ball (1999), who pointed out that although inflation targeters may want to bring inflation back to target after a shock they may not want to do so *at the maximum speed,* but they imply that the effect of a change in rates is long lasting

ilar. Again the estimated inflation target was close to 2.5 %, but the value of the coefficient on the lagged dependent variable was close to unity, which caused the long-run values of the coefficients to explode. Other changes to our model construction such as reducing the instruments to $IV \in (1, \pi_{t-1}, ..., \pi_{t-6}, \pi_{t-9}, \pi_{t-12}, \widetilde{y}_{t-1}, ..., \widetilde{y}_{t-6}, i_{t-1}, ..., i_{t-6})$, had a minor influence[11].

Two results seem to stand out as robust. First, the estimate of the target inflation rate seems, with a few exceptions, to be estimated close to the true target value of 2.5%, and very close to its sample mean of 2.57%. Second, the smoothing parameter takes a very high value for each of the horizons, n, which is consistent with the short-term smoothing hypothesis proposed and defended in Goodfriend (1991) and Rudebusch (1995, 2002), since our data refer to a monthly frequency, where smoothing is more realistically expected to be found, in contrast to the quarterly evidence referenced in Goodhart (1996) and Sack (1997). Our smoothing parameter estimates are close to the reported findings of other countries (e.g. Clarida *et al* (1998) report values of ρ equal to 0.91, 0.93, 0.92, 0.95 and 0.95 for Germany, Japan, UK, France and Italy, respectively on monthly data). Furthermore, Bernanke and Mihov (1997) report that the lagged interest rate explains a very high proportion of the forecast variance of the Lombard rate in Germany (96.5% at the one month horizon)[12]. This result confirms that the Bank of England has had a very strong tendency to smooth changes in interest rates month-to-month during this period, so that changes, if they occur, are likely to be in the same direction rather than reversals. It also reflects the fact that in a large number of cases the interest rate did not change from month to month. This is a strong argument in favour of the probit estimation approach (Gerlach, 2003).

The next section considers the predictive performance of the Taylor rule versus other information sets in within-sample and out-of-sample

[11] In the interests of space, we have not reported these results but they are available on request.

[12] It is important to note that all these results are at the monthly frequency. Goodfriend (1991) shows that interest rates are 'essentially unpredictable at forecast horizons longer than a month or two' p.10.

exercises, where, in effect, we ask whether information on inflation and output is sufficient to forecast the directional change in the policy rate. The Taylor rule information set and an alternative information set based on a wider category of variables will be compared as predictors over the same sample period.

3 The Multinomial Logit Model and the Estimation of the Models

The Taylor rule is an effective way of summarizing the behavior of the *level* of interest rates using the simple information set (i.e. inflation rate and output gap) which we refer to as 'Taylor rule information set'. In this section, we use the multinomial logit (ML) model in order to investigate how useful the Taylor rule information would be when forecasting the *directional change* of the base rate. In addition, we select a different information set that includes some macro variables which might be more relevant to the decision making process of the MPC and compare those two information sets in terms of predictability power.

In our model there are three possible directions for the base rate: 'down', 'no change' and 'up'. Accordingly we define a random variable z_t as follows:

$$\begin{aligned} z_t &= 0 \quad \text{if} \quad \Delta i_t < 0, \\ z_t &= 1 \quad \text{if} \quad \Delta i_i = 0, \\ z_t &= 2 \quad \text{if} \quad \Delta i_t > 0, \end{aligned}$$

where $\Delta i_t = i_t - i_{t-1}$. Let X_t represent a $kx1$ vector of explanatory variables available at time t. We always assume that the first element of X_t is one. In the multinomial logit model, the probability of $z_t = 0, 1$ or 2 conditional on X_t is defined using the logit cumulative density function:

$$\begin{aligned} \Pr(z_t &= 1 \mid X_t) = \frac{e^{X_t'\beta_1}}{1 + e^{X_t'\beta_1} + e^{X_t'\beta_2}}, \qquad (2) \\ \Pr(z_t &= 2 \mid X_t) = \frac{e^{X_t'\beta_2}}{1 + e^{X_t'\beta_1} + e^{X_t'\beta_2}}, \end{aligned}$$

and $\Pr(z_t = 0 \mid X_t) = 1 - \Pr(z_t = 1 \mid X_t) - \Pr(z_t = 2 \mid X_t)$ where β_1 and β_2 are unknown $k \times 1$ parameters to be estimated. Then, the log-likelihood function is given by

$$\mathcal{L}(\beta_1, \beta_2) = \sum_{t=1}^{T} \sum_{j=0}^{2} 1[z_j = j] \Pr(z_t = j \mid X_t) \tag{3}$$

where $1[\cdot]$ is the indicator function. The ML estimators $\hat{\beta}_1$ and $\hat{\beta}_2$ are obtained by maximizing the log-likelihood function in (3). We have used LIMDEP to compute the ML estimators $\hat{\beta}_1$ and $\hat{\beta}_2$. Once we have obtained $\hat{\beta}_1$ and $\hat{\beta}_2$, the predicted probabilities are obtained by plugging $\hat{\beta}_1$ and $\hat{\beta}_2$ into the equations in (2) and we denote the predicted probabilities $\hat{P}_0, \hat{P}_1$ and $\hat{P}_2$. Our directional prediction $\hat{z}_t$ is then given by

$$\hat{z}_t = m \quad \text{if} \quad \hat{P}_m = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2). \tag{4}$$

In other words, we predict 'down' if $\hat{P}_0 = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2)$, 'no change' if $\hat{P}_1 = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2)$ and 'up' if $\hat{P}_2 = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2)$. It is worth noting that the statistical significance in the estimated coefficients on the variables in $\hat{\beta}_1$ and $\hat{\beta}_2$ denotes its contribution to predictability. That is to say the more significant the estimated coefficient is, the more important role it plays in calculating the respective probability.

Furthermore, in order to test for the overall significance of the estimation, we utilize the fact that, for any two models where one is the restricted version of the other, the log-likelihood statistic is asymptotically distributed as a chi-squared random variable:

$$LR = -2 \ln \left(\frac{L_R}{L_{UR}} \right) = 2 \left(\ln L_{UR} - \ln L_R \right) \sim \chi^2(q) \tag{5}$$

where q denotes the numbers of restrictions imposed. Thus both restricted and unrestricted models are estimated[13]. In addition, the goodness-of-fit can be measured by adopting the McFadden method, the likelihood ratio index, which analogous to the R^2 in a conventional linear regression model is

[13]The restricted version of the model is obtained by estimating the model with all slope coefficients set to zero.

$$pseudo - R^2 = 1 - \left(\frac{\ln L_{UR}}{\ln L_R} \right). \tag{6}$$

3.1 The Multinomial Logit Model Estimation of the Taylor Rule Information Set

First, we use the Taylor rule information set to predict the direction of change of the base rate. Hence we set $X_t = (1, \pi_{t+12}, \tilde{y}_t, i_{t-1})'$ where π_{t+12} is the 12-month ahead rate of inflation that allows for a reasonable degree of forward-lookingness without limiting the degrees of freedom excessively, $\tilde{y}_t$ is the current value of output gap, and the variable i_{t-1} is the 1-month lagged value of the base rate. The sample period of 1993/03 to 2002/07 gives 113 usable observations.

The logit estimation result is shown in Table 3. Inflation and the output gap appear to have significant roles to play in predicting the directional change in the interest rate, although the one month lagged value of base rate does not help. The $p-$value for the goodness-of-fit χ^2-test is 0.202, so we do not reject the null hypothesis that all coefficients except the constant are jointly zero at the 5% significance level, which contradicts the individual t-test results.

Since we are interested in the predictability of a given information set, we can construct an outcome-based measure of the goodness-of-fit. In order to evaluate the proportion of correct predictions, one can construct a cross-tabulation of predicted against observed outcomes (contingency table) where we associate the direction of predicted changes decided by (4) against the actual changes of the base rate. Table 4 shows the contingency table for the Taylor rule information set. The proportion of correct predictions denoted as SC is just sum of all diagonal terms divided by the total number of observations: that is

$$SC = \frac{1}{T} \sum_{t=1}^{T} \mathbf{1} \left(\widehat{z}_t = z_t \right). \tag{7}$$

Based on our sample period, the prediction using the Taylor rule information set is always "no change" in the interest rate in 113 cases without exception. In practice, there are 79 occasions when this is the correct prediction, hence we find that the $SC = \frac{79}{113}$, which suggests that we have approximately 70 per cent correct predictions. Since the value of z_t equals 1 most of the time a dominant outcome drives this result. The proportion of correct predictions when there was no change was 100 per cent, but by contrast, there were no correct predictions for the state of the rising interest rate and for the state of falling interest rate. Thus the overall proportion of the correct prediction against actual outcomes stems from the state where there was no change in the interest rate. Therefore, although the dominance of correct predictions is encouraging, this in turn is due to the fact that "no change" is the most common outcome. Bodie *et al* (1996) indicate that a high success rate generated by a "stopped-clock" strategy is not good evidence of predictability. The measure SC in (7) cannot distinguish between seemingly successful predictability of a "stopped-clock" and true predictability, however, a technique proposed by Merton (1981) can be straightforwardly applied to give a truer indication of predictive ability. Let CP_j be the proportion of the correct predictions made by $\widehat{z}_t$ when the true state is given by $z_t = j$. In other words, let us define our measure as the conditional probability of correct predictions. From the definition of conditional probability, CP_j is computed by

$$CP_j = \frac{\frac{1}{T}\sum_{t=1}^{T} \mathbf{1}\left(\widehat{z}_t = j\right) \mathbf{1}\left(z_t = j\right)}{\frac{1}{T}\sum_{t=1}^{T} \mathbf{1}\left(z_t = j\right)}.$$

and then Merton's correct measure denoted CP is given by

$$CP = \frac{1}{J-1}\left[\sum_{j=0}^{J-1} CP_j - 1\right] \tag{8}$$

where J is the number of categories. The measure always lies between $-\frac{1}{2}$ and 1. For example, for a "stopped-clock" strategy, where only one of CP_i's is equal to one and the other two CP_j's are zero, the CP is zero implying that there is no predictability in that stategy. Any forecasting model generating a negative value of CP can be regarded as being inferior to the stopped clock strategy. On the other hand, for a perfect forecasting model, all CP_j's equal unity, which implies that CP also equals unity.

For the Taylor rule information set we find that $CP_0 = \frac{0}{20}, CP_1 = \frac{79}{79}$ and $CP_2 = \frac{0}{14}$ from Table 4, indicating zero predictability when the base rate is falling and rising. Unsurprisingly, the $CP = 0$, indicating no predictive ability for the direction change of rates using the Taylor rule information.

3.2 The Multinomial Logit Model Estimation of the Wide Information Set

We define a new independent variable vector for an alternative information set, which will be referred to as the wide information set. The interest rate setting process involves a great deal more information than the Taylor rule variables. Each month the monetary policy committee receives a briefing from the staff of the Bank of England that gives attention to information arising from a range of other sources. The contents of these meetings are summarized in the *Minutes of the MPC Committee, and* the quarterly *Inflation Report*, which contains chapters on money and financial markets; demand and outputs; the labour market; costs and prices; monetary policy since the previous report; and the prospects for inflation. The variables in the wide information set were chosen to reflect the extra information given through these sources[14]. In

[14]We should note that we have chosen the extra variables to indicate the relative performance of the two information sets, and to determine whether the Taylor rule information is sufficient to predict the next change. We do not intend to argue that an alternative rule based on these variables would be the optimal strategy nor that our information set is the "correct" set. Our results are illustrative and no particular significance should be attached to the variables we have chosen as representatives of wider data except for the purpose of ranking performance in predictive ability on the basis of more information that the Taylor rule provides.

A related but different approach is discussed in Bernanke and Boivin (2001), where the usefulness of large amounts of information is assessed using the factor model approach of Stock and Watson (1999a, b). In that paper, the question is how the Fed might make decisions in a 'data rich' environment. The focus is upon the use of large data sets to improve forecast accuracy rather than the evaluation of monetary policy decision rules in a discrete variable context. We refer readers that are interested in the optimal construction and use of large data sets in that direction.

each case we had to use our judgement select a representative variable to capture a range of information. Our selection includes data on growth rates in: the M4 money stock as an indicator of the inflationary pressure arising from monetary sources, $\Delta M4_t$; the sterling exchange rate index to capture the effects of imported inflation (effectively the component of RPIX arising from sources other than domestic conditions), ΔEX_t; the average earnings index represents the gauge of the labour market as earnings put pressure on prices, ΔAEI_t; and finally, the input price index to capture rising costs from other sources, ΔINP_t[15]. In addition we include (lagged) inflation, π_{t-1}, the output gap, $\widetilde{y}_t$, and i_{t-1},the 1-month lagged value of base rate[16]. The wide information set is: $X_t = (1, \Delta M4_t, \Delta EX_t, \Delta AEI_t, \Delta INP_t, \pi_{t-1}, \widetilde{y}_t, i_{t-1})'$. The sample period is from 1993/03 to 2002/07, giving 113 observations altogether.

[15] The M4 is the broad definition of the money stock, which comprises holdings by the M4 private sector (i.e. private sector other than monetary financial institutions) of notes and coin, together with their sterling deposits at monetary financial institutions in the UK (including certificates of deposit and other paper issued by monetary financial institutions of not more than 5 years original maturity).

The sterling exchange rate index is the sterling exchange rate against a basket of twenty currencies, monthly business-day averages of the mid-points between the spot buying and selling rates for each currency as recorded by the Bank of England at 16.00 hours each day. They are not official rates, but representative rates observed in the London interbank market by the Bank's foreign exchange dealers. Each of the currencies' countries is given a competitiveness weight which reflects that currency's relative importance to UK trade in manufacturing based in 1989-1991 average aggregate trade flows. The original source from the Bank of England used 1990 as the base year, however, in this paper the series are re-based using 1995 as the base year.

Average earnings are obtained by dividing the total paid by the total number of employees paid, including those on strike. This series is of the whole economy, seasonally adjusted, and use 1995 as the base year (1995=100).

The input price index is the indices of input prices (material and fuel purchased) for all manufacturing industry. This series are seasonally adjusted, and use 1995 as the base year (1995=100).

[16] Here, we use the lagged value of the inflation rate rather than the forward-looking value because the out-of-sample prediction using the wide information set (assessed in the next section) requires the use of lagged values for its execution. The sample period is identical to the one used for the evaluation of predictive ability with the Taylor rule information set allowing direct comparisons over performance in predictive ability.

The estimation result is shown in Table 5. The results indicate that all the variables have a statistically significant impact in determining the probabilities of a directional change in the interest rate. The goodness-of-fit χ^2-statistic is 53.50 and hence we can reject the null hypothesis that all coefficients are zero in the test for overall significance of the model at 5% significant level. The R^2 for this wide information set approximately equals 0.29.

Table 6 shows the contingency table of predicted against observed outcomes for this wide information set. The proportion of the correct prediction against the actual outcomes is $SC = \frac{89}{113}$, indicating approximately 79% of predictions are correct. There are far more variations in the prediction around the 'no change' dominant outcome, which is an encouraging signal that the data set is richer than the Taylor rule information set. We also note that there are no counter predictions (as indicated by the zeros in the top right and bottom left corners of the contingency tables), so the interest rate is never predicted to fall when it rises or vice versa. The number of correct predictions against the actual outcomes for each state ('down', 'no change' and 'up' respectively) are $CP_0 = \frac{10}{20}, CP_1 = \frac{74}{79}$ and $CP_2 = \frac{5}{14}$. These figures result in a better correct predictions measure for the wide information set ($CP = 40$ per cent), which indicates that the inclusion of additional information beyond that of the Taylor rule information set improves the prediction of the directional change.

On the surface of things the predictions of directional change from the Taylor Rule information set are reasonably good because the predictions are correct 70% of the time. The wide information set improves marginally on this with correct predictions 79% of the time. However, when we take into account the stopped clock aspect of the problem, we find that the Taylor rule information set acts exactly like a stopped clock, since its correct predictions indicator is zero, but for the wide information set the correct predictions are higher at 40%.

These findings focus on the within sample performance of the information sets, but in-sample estimation is likely to lead to over-fitting and, as a result, tends to overestimate true predictability. In the next section, we will carry out an *out–of-sample* forecast exercise in order to assess the true predictive ability of these information sets.

4 The Out-of-Sample Prediction of the Change in the Interest Rate: Taylor Rule Information Set versus Wide Information Set

This section makes one-step ahead predictions of the directional change of the base rate, that is $\hat{z}_{t+1}$, using the past and current information available only up to time t. We adopt an expanding window method, which allows the successive observations to be included in the initialisation sample prior to the forecast of the next one-step ahead prediction of the direction of change while keeping the start date of the sample fixed[17]. By this method we forecast $\hat{z}_{t+1}$, $\hat{z}_{t+2}$, etc., but importantly, in order to make a true out-of-sample prediction, only known values of the variables in each information sets can be used as predictors (not forward-looking values that are generated using forecasting methods). The initial estimation window is 1993/03 to the observation 1998/12 with 70 observations. The first prediction date is 1999/01 and we make 55 out-of-sample predictions.

4.1 Forecasting the Change in the Interest Rate: The Taylor Rule Information Set

Table 7 shows the cross-tabulations of the predicted against observed outcomes using the Taylor rule information only. As with the in-sample predictions we find that although the actual interest rate varies over the prediction period, the Taylor rule information set predicts no change in the interest rate in the majority of cases. In all but four cases out of

[17] We also examined the forecasting performance out-of-sample using a rolling window method but the results were unchanged and therefore we do not report the results.

fifty-five out-of-sample predictions the prediction is for no change, and of these four predictions only one case was a correct prediction of a cut in the interest rate. For the remaining 51 observations, the Taylor rule information set correctly predicts 'no change' in the interest rate in 35 cases, therefore, the proportion of correct predictions against the actual outcomes equals SC $=\left(\frac{36}{55}\right)$ which is a 65 per cent prediction rate. Since this result stems from the dominant 'no change' outcome during the period of the out-of-sample test, we expect to find that the Merton test of correct predictions is much less impressive. The correct predictions measure based on the Taylor rule information set has a negative value (CP = -0.10) which implies the predictive performance of the Taylor rule information set is very poor out of sample (and worse than a stopped clock strategy).

4.2 Forecasting the Change in the Interest Rate: The Wide Information Set

Table 8 illustrates the contingency table of the predicted against actual outcomes out-of-sample results for the wide information set. This model can predict by drawing on a greater range of information besides the Taylor rule information which is nested in the data. The wide information set predicts changes in the interest rate more often than the Taylor Rule information set and has a superior percentage of correct predictions against the actual outcomes based on the $SC = \frac{41}{55} = 75$ per cent. Importantly, we find that the higher value of the proportion of the correct prediction against the actual outcomes does not result from a dominant outcome. The evidence shows that the wide information predicts exactly the same number of 'no changes' in the repo rate as the Taylor rule (thirty-five in all), but it is more capable of predicting positive and negative changes to interest rates. When we calculated the Merton's measures we found that Merton's correct predictions measure from the out-of-sample exercise is $CP = 36$ per cent. This provides strong evidence of better predictive performance over the Taylor rule information set since the wide information set is not only correct more often, but also has the capability to accurately predict the direction of change in the interest rate.

A further test of the superior out-of-sample performance can be provided by calculating the mean squared prediction errors. Let i_t be the actual base rate at time t over the out-of-sample period (where $t =$ 1999/01, ..., 2003/07 and the total number of observations is 55). We define $\hat{i}_t^T$ be the predicted base rate for time t based on the Taylor information set available up to time $t-1$, and $\hat{i}_t^W$ be the predicted base rate for time t based on the wide information set available up to time $t-1$ (here both $\hat{i}_t^T$ and $\hat{i}_t^W$ are obtained through the rule (4)). Then the mean squared prediction errors (MSPE) for each information set provides an indication of the performance of the directional change predictor in following the decisions made in real time by the Monetary Policy Committee. The prediction errors are:

$$\begin{aligned} MSPE(\hat{i}_t^T) &= \frac{1}{55}\sum_{t=1}^{55}(i_t - \hat{i}_t^T)^2 = 1.06, \\ MSPE(\hat{i}_t^W) &= \frac{1}{55}\sum_{t=1}^{55}(i_t - \hat{i}_t^W)^2 = 0.69. \end{aligned}$$

The evidence shows that the prediction errors are 54 per cent greater under the Taylor rule information set than under the wider information set, or in other words, the gain from the additional information is a reduction in prediction errors to 65 per cent of the errors made under the Taylor rule information set. This result suggests that the wide information set has a better record than the Taylor rule information because it can predict when a non-zero change should occur. A monetary policy maker reliant on a Taylor rule would make a fewer changes to rates than one that considered a wider information set. A simple test of the mean squared prediction errors under each information set illustrates that the wide information set reduces the errors a policymaker would make if they were to consider a wider information set.

5 Test of Association in Contingency Tables

Although we found that the wide information set has greater ability to predict the direction of change in the interest rate with more accuracy than the Taylor rule information set, these results may have been generated by sampling errors i.e., the difference in the actual ability to predict could have arisen by chance. We need to assess whether the Merton's correct prediction $CP = 36$ per cent is significantly different from zero. This can be tested by the χ^2-independence test proposed in Schnader and Stekler (1990) and Kolb and Stekler (1996).The null hypothesis is that there is no association between the predicted and actual outcomes, and the alternative is that they are associated.

Let R_i be the total for the i^{th} row and C_j be the total for the j^{th}column in Table 8. Then, the expected number of observations in each entry, denote by $\widehat{E}_{ij}$, is defined as $\widehat{E}_{ij} = \frac{R_i C_j}{N}$ where N is the total number of observations in the table. The χ^2-test statistic is then given by:

$$\sum_{i=1}^{3}\sum_{j=1}^{3}\frac{(O_{ij}-\widehat{E}_{ij})^2}{\widehat{E}_{ij}}$$

where O_{ij} is the frequency in the $(i,j)^{th}$ cell in the table. This statistic is asymptotically distributed as χ^2 random variable with 4 degrees of freedom.

In the out-of-sample prediction for the Taylor rule information set, the test cannot be performed, as there is no variation in the predictions (which results in a zero in the denominator), but for the wide information set the statistic is 31.22, while the 5 per cent critical value is 9.49. Clearly, we can reject the null of no association, which implies that there *are* associations between the predicted and the actual outcomes for the wider information set. We can conclude that the ability to predict the direction of change in the interest rate by the wide information set does not arise by chance. The wide information set has the capability to predict the direction of change in the interest rate.

6 Conclusion

A consensus has provided support for the Taylor rule as a description of the monetary policymaking process. We do not undermine the usefulness of the Taylor rule as a description of common sense central banking. What this paper does do is to step back from the time series evidence in order to ask whether the Taylor rule could be usefully used by a central bank to predict the next change in interest rates. In other words, we have asked whether the Taylor rule works as an *ex ante* monetary policy making rule. To do this we have developed a complementary methodology to evaluate the predictions of directional change in the interest rate.

Using monthly data from the United Kingdom for the period of inflation targeting we find that a continuous random variable estimate of the Taylor rule specification receives little support largely because of the common occurrence of the decision not to change the level of the interest rate. A discrete limited dependent variable approach is required. This provides evidence that the Taylor rule information as a predictor of base rate change appears to perform well, both in sample and out-of-sample, but again because the 'no change' outcome dominates, on closer inspection we find poor genuine predictive ability. We find that a predictor based on information that includes the growth rate of money, changes in the exchange rate, labour market pressure on wages, and changes to other inputs, as representatives of a wider set of data available to decision makers, does better, in sample and out of sample. The Taylor predicts that no change should take place far more often than the wider information set, and a monetary policy maker relying on Taylor rule information set would do far less to alter interest rates than if a wider set of information were used to inform a policy judgment.

Our conclusion is that the Taylor rule is less successful as an *ex ante* predictor of monetary policy actions than it is as an *ex post* summary of central bank behavior. Parallel results, detailing the shortcomings of the Taylor rule and its variants for the ECB rate setting process, draw similar conclusions (see Alesina *et al (*2001), Gerlach (2003), Gali *et al.* (2004)). We agree with McCallum (2000) and Svensson (2001) that it is not possible to delegate monetary policymaking to a 'clerk with a calculator', no matter how wide the information set, and add that good performance as an *ex post descriptor* does not imply good performance as an *ex ante predictor*. In this respect we underscore the testimony of ECB President Trichet who stated in his confirmation hearings that 'in reality central banks never allow themselves to adopt a totally mechanical approach and they know very well that the extraordinarily complexity of reality cannot be reduced to an equation' (cited in Gali et al 2004, p. 6.). Information from rules offers useful guidance to policymakers, but it cannot replace them. In this paper we show that even a limited amount of additional information can provide better guidance.

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Table 1: Taylor rule estimation results for Treasury Bill rate and Gilt repo rate)

n	$\widehat{\rho}$	$\widehat{(1-\rho)\alpha}$	$\widehat{(1-\rho)\beta}$	$\widehat{\beta}$	$\widehat{(1-\rho)\gamma}$	$\widehat{\gamma}$	π^*
3	0.579	0.007	0.620	1.472	0.127	0.301	3.65%
	(0.091)	(0.004)	(0.263)	(0.424)	(0.031)	(0.068)	
3	0.609	0.005	0.655	1.675	0.083	0.213	2.88%
	(0.076)	(0.004)	(0.230)	(0.375)	(0.021)	(0.063)	

Table 2: Monthly estimates of the Taylor rule coefficients using the Hodrick-Prescott filter

n	$\widehat{\rho}$	$\widehat{(1-\rho)\alpha}$	$\widehat{(1-\rho)\beta}$	$\widehat{\beta}$	$\widehat{(1-\rho)\gamma}$	$\widehat{\gamma}$	π^*
3	0.967	-0.119	0.116	3.527	0.142	4.334	2.70%
	(.025)	(0.199)	(0.090)	(2.773)	(0.061)	(3.060)	
6	0.951	-0.285	0.222	4.501	0.117	2.366	2.56%
	(.026)	(0.213)	(0.091)	(2.310)	(0.057)	(1.404)	
12	0.977	-0.264	0.153	6.753	0.090	3.981	2.58%
	(0.025)	(0.228)	(0.071)	(8.153)	(0.054)	(4.429)	
18	0.986	-0.239	0.123	8.832	0.116	8.323	2.60%
	(0.030)	(0.270)	(0.070)	(20.738)	(0.056)	(17.821)	
24	0.966	-0.012	0.085	2.501	0.074	2.161	2.36%
	(0.036)	(0.352)	(0.083)	(4.307)	(0.592)	(2.891)	
3	0.965	-0.198	0.155	4.395	0.238	6.743	2.59%
	(0.022)	(0.180)	(0.081)	(2.620)	(0.059)	(3.975)	
6	0.958	-0.329	0.227	5.344	0.200	4.706	2.52%
	(0.021)	(0.178)	(0.073)	(2.577)	(0.052)	(2.305)	
12	0.987	-0.320	0.153	11.402	0.174	12.955	2.59%
	(0.021)	(0.203)	(0.062)	(18.626)	(0.048)	(19.859)	
18	1.016	-0.527	0.165	-10.319	0.154	-9.637	2.63%
	(0.025)	(0.242)	(0.062)	(15.493)	(0.047)	(15.339)	
24	0.996	-0.185	0.081	19.451	0.105	25.149	2.57%
	(0.029)	(0.288)	(0.068)	(141.907)	(0.049)	(176.158)	

The dependent variable is the Treasury Bill rate in the first ten rows and the Gilt repo rate in the next ten rows.

For $n = 3$, the number of observations used in the estimation is 111 (from 1994/02 to 2003/04)

For $n = 6$, the number of observations used in the estimation is 108 (from 1994/02 to 2003/01)

For $n = 12$, the number of observations used in the estimation is 102 (from 1994/02 to 2002/07)

For $n = 18$, the number of observations used in the estimation is 96 (from 1994/02 to 2002/01)

For $n = 24$, the number of observations used in the estimation is 90 (from 1994/02 to 2001/07)

Table 3: The multinomial logit model estimation for Taylor rule information set

Variable	Coefficient	S.E.	b/S.E.	$\Pr(\lvert Z\rvert < z)$
Set of parameters $\widehat{\beta}_1$				
Constant	-1.2086	2.4917	-0.485	0.6276
π_{t+12}	1.3884	0.7113	1.952	0.0509
$\widetilde{y}_t$	0.6929	0.4179	1.658	0.0973
i_{t-1}	-0.1117	0.3097	-0.361	0.7183
Set of parameters $\widehat{\beta}_2$				
Constant	-4.0078	3.5618	-1.125	0.2605
π_{t+12}	1.3868	0.9870	1.405	0.1600
$\widetilde{y}_t$	1.1150	0.5696	1.958	0.0503
i_{t-1}	0.0613	0.4369	0.140	0.8883

Dependent variable: z_t, pseudo-R^2 = 0.05, LR = 8.531057, p-value = 0.20

Table 4: In-sample contingency table for Taylor rule information set

Predicted

Actual	0	1	2	Total
0	0	20	0	20
1	0	79	0	79
2	0	14	0	14
Total	0	113	0	113

$SC = 0.7$

$CP = 0$

Table 5: The multinomial logit model estimation for wide information set

Variable	Coefficient	S.E.	b/S.E.	$\Pr(\|Z\| < z)$
Set of parameters $\widehat{\beta}_1$				
Constant	-9.7614	3.9078	2.498	0.0125
$\Delta M4_t$	-0.5888	0.1885	-3.124	0.0018
ΔEX_t	0.2216	0.0786	2.819	0.0048
ΔAEI_t	-1.2165	0.5297	-2.297	0.0216
ΔINP_t	0.0312	0.2360	0.132	0.8949
π_{t-1}	-0.5413	1.0605	-0.510	0.6097
$\widetilde{y}_t$	0.7203	0.5311	1.356	0.1750
i_{t-1}	0.3631	0.5634	0.644	0.5193
Set of parameters $\widehat{\beta}_2$				
Constant	0.7884	7.2794	0.108	0.9138
$\Delta M4_t$	-0.4975	0.2825	-1.761	0.0782
ΔEX_t	0.3737	0.1084	3.447	0.0006
ΔAEI_t	0.0911	0.8142	0.011	0.9911
ΔINP_t	0.7780	0.4270	1.822	0.0685
π_{t-1}	-0.4609	1.6291	-0.283	0.7772
$\widetilde{y}_t$	0.1032	0.9428	0.110	0.9128
i_{t-1}	0.2034	0.8181	0.249	0.8037

Dependent variable: z_t, pseudo-$R^2 = 0.29$, LR = 53.49, p-value = 0.00

Table 6: In-sample contingency table for the wide information set

Predicted

Actual	0	1	2	Total
0	10	10	0	20
1	3	74	2	79
2	0	9	5	14
Total	13	93	7	113

$SC = 0.79$

$CP = 0.40$

Table 7: Out-of-sample contingency table for Taylor rule information set

Predicted

Actual	0	1	2	Total
0	1	12	0	13
1	3	35	0	38
2	0	4	0	4
Total	4	51	0	55

$SC = 0.65$

$CP = -0.10$

Table 8: Out-of-sample contingency table for wide information set

Predicted

Actual	0	1	2	Total
0	4	9	0	13
1	3	35	0	38
2	0	2	2	4
Total	7	46	2	55

$SC = 0.75$

$CP = 0.36$