Using Rules to Make Monetary Policy: The Predictive Performance of Taylor Rules Versus Alternatives for the United Kingdom 1992 - 2001

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September 2001

Abstract

We consider an experiment where we use the Taylor rule information set, in°ation and the output gap, to predict the next change in monetary policy for the United Kingdom 1992 - 2000. To do this we use 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. Against this hypothesis we compare a wider information set including more than just in°ation and output gap variables. The in-sample and out-of-sample prediction tests are evaluated using forecast performance tests. Although the Taylor rule is a useful summary for monetary policymakers, the information from in°ation and the output gap is insu±cient to predict the direction of the next change compared to a wider information set, but the usefulness of any rule as an ex ante guide to monetary policymaking is questioned relative to an intelligent committee of policymakers using their own judgment.

1 Introduction

The Taylor rule has emerged as a simple but robust estimate of the relationship between the monetary policy instrument, a short term interest rate, and measures of in°ation and the deviation of output from its trend value. The rule satis¯es all the criteria for a simple rule of thumb. It depends on variables that are easily measured and available in a timely fashion, the rule itself can be readily estimated by econometric methods; it is also capable of explaining the past history of the monetary policy instrument in many of the industrialized countries and o®ers clear and simple guidance to policymakers concerning which of the components of the rule is driving the monetary policy instrument.Taylor (1993) has shown that this rule, with coe±cients of 1.5 on in°ation and 0.5 on the output gap, can explain US monetary policy from 1986 very well. It has been suggested by Ball (1997) and Svensson (1997) that `optimal weights' chosen to minimize the variance of in°ation and output might be higher than these values. Although recent evidence in Taylor (1999, 2000, 2001) suggests that small improvements can be achieved by introducing forward-looking measures of in°ation (Batini et al, 2000), and the exchange rate to re°ect the openness of the economy (Svensson, 2000, 2001), but the gains over the simple Taylor rule are minor.

These results have been examined for a wider set of countries. Clarida et al (1998) estimate 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 aggressively to in°ation, since the estimates of the coe±cients on in°ation are signi¯cantly greater than unity, but mildly towards output gaps. The E3 on the other hand have coe±cient on in°ation estimated below unity or insigni¯cantly di®erent from unity, suggesting that they had policy rules during this period that were dissimilar to those of the G3. E3 countries appeared to be following disin°ation 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).

The Taylor rule provides a good summary of central bank behaviour under the new monetary policy consensus. However, explaining the past is not the same as predicting the future. We might still ask: Does the Taylor rule offer a good guide to future monetary policy? Mervyn King has observed that the Taylor rule embodies common sense and therefore `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]. Although the rule is a good *ex post* summary of successful central bank behavior, we might still ask whether it would be useful as an *ex ante* guide to policymakers.

We begin by re-examining the evidence on Taylor rules. The current evidence is largely based on quarterly data, but monetary policy decisons are made more frequently than once a quarter. The question is whether the evidence, and we will consider the United Kingdom, supports the Taylor rule at the higher frequency required for monthly decision making. We then consider an experiment in which the Taylor rule information set - inflation and the output gap - are used to predict the next change in monetary policy. To do this we use a limited dependent variable approach, where the next rate change could be `upwards', `downwards' or `no change'[1]. 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. Against this hypothesis we compare a wider information set including more than just inflation and output gap variables, and assess the ability of the wider information set to predict against the actual outturn. Finally, we conduct an out-of-sample prediction tests with a test of association in contingency

[1] 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 have been conducted in steps of 25 basis points on a monthly frequency.

tables (Newbold, 1995). If the Taylor rule is a good guide to monetary policymakers the information from inflation and the output gap should be sufficient to predict the direction of the next change, but if a wider information set is superior, the usefulness of the Taylor rule as an ex ante guide to monetary policymaking may be questioned. The paper will determine whether it is possible to do better than a Taylor rule used to predict the next rate change by extending the information set; it is different from the type of analysis proposed by Huang et al (2000) and Orphanides (2000), where the Taylor rule is used to evaluate past decisions on interest rate setting. The analysis is conducted on monthly data for the United Kingdom which has been inflation targeting since 1992. The next section briefly explains the conduct of monetary policy in the United Kingdom over the period 1992-2001 and Section 3 estimates the Taylor rule for this period. Section 4 explains the methodology of the Multinomial Logit model, which is implemented in Section 5, for Taylor rule information and for a wider information set. The out-of-sample performance is assessed in Section 6. Section 7 concludes.

2 The Conduct of UK Monetary Policy

The responsibility for setting interest rates is currently held by the Monetary Policy Committee (MPC) of the Bank of England. The Monetary Policy Committee (MPC) has nine members: the Governor and two Deputy Governors of the Bank of England; two `internal' Executive Directors, responsible for monetary policy analysis and monetary policy operations; and four `external' members appointed by the Chancellor of the Exchequer with `knowledge or experience which is likely to be relevant to the committee's functions'. Its responsibilities, operations and procedures have been detailed by King (1997), Rodgers (1997) and Budd (1998) but we review them briefly here. The objectives of monetary policy are set by the Chancellor of the Exchequer and are detailed in the Bank of England Act 1998 as `(a) to maintain price stability and (b) subject to that, to support the economic policy of Her Majesty's Government, including its objective for growth and employment'. The Bank has an operational target, currently defined as $2\frac{1}{2}$ per cent for the underlying inflation rate (RPI excluding mortgate interest payments), which is reviewed annually by the Chancellor of Exchequer.

The MPC meets at least once a month, and the decision on the official interest rate is typically announced immediately after the meeting, although it may postpone the announcement in order to intervene in the financial markets. Before the decision is made, the MPC meets for a whole day to be briefed by Bank staff on the latest monetary policy developments. In addition, the MPC is provided with a range of the Bank's monetary, economic, statistical and market expertise, supplemented by intelligence from the Bank's network of twelve regional Agencies (Rodgers, 1997). The presentations are given under the following headings: monetary conditions, demand and output, the labour market, prices, and financial markets (Budd, 1998).

After the meeting, in order to promote the openness, the minutes are published on Wednesday of the second week after the MPC's monthly meeting. The minutes contain an account of the discussion of the MPC, the issues that it thought important for its decisions and a record of the voting of each MPC member (King, 1997). However, the minutes do not attribute individual contributions to the discussion, because it is thought that attribution would give a misleading indication of why individual members of the MPC reached their decision, and may lead to prepared statements.

Furthermore, a quarterly Inflation Report is published, which offers information on the prospects for future inflation. Each Report reviews the wide range of economic data needed to assess inflation prospects over the short to medium term, moreover, it also shows the forecast of the inflation with its probability distribution two years ahead, because it is believed that the period of two years allows the monetary policy to have the greatest effect on price level. The inflation projection is published in a fan chart, which requires the MPC to give its judgements not only about the central tendency for inflation but also about the variance and skew of its probability distribution. The Bank publishes seperately the minutes of the three preceding MPC meetings, and the three most recent press notices announcing the MPC's interest rate decisions. This is one of the main instruments for accountability, allow the MPC to be assessed and scrutinized by outside commentators (King, 1997).

Should the target be missed, the Governor is required to send an open letter to the Chancellor if inflation moves away from the target by more than one percentage point in either direction. The letter will be set out why inflation has moved away from the target by more than one percentage point; the policy action being taken to deal with it; the period within which inflation is expected to return to the target; and how this approach meets the Government's monetary policy objectives.

King (1997) stated that one of the main purposes of the open letters is to explain why, in some circumstances, it would be wrong to try to bring inflation back to target too quickly. In other words, the MPC will be forced to reveal in public its proposed reaction to large shocks. This process involves considerable internal and external expertise, and requires the processing of a wide range of information and, where forecasts and models are required of expected inflation outcomes, good judgment. The Taylor rule, by contrast, is a mechanical rule requiring only two pieces of information, the inflation rate and the output gap. In principle, as McCallum (2000) has noted the monetary policy could be conducted by a `clerk and a calculator', but to date we are not aware of any formal testing of the predictive ability of the Taylor Rule.

3 The Taylor Rule

Taylor (1993) has suggested a simple rule by which the central bank adjusts the nominal short-term interest rate. This 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) as follows:

$$i_t^* = \pi_{t-1} + \beta(\pi_{t-1} - \pi^*) + \gamma(y_{t-1} - y^*) + \bar{r} + \eta_t \quad (1)$$

where π_t is the annual inflation rate (in the case of the United Kingdom the Retail Price Index excluding mortgage interest payments, RPIX)[2], π^* is the inflation target, $\bar{r}$ is the equilibrium real interest rate[3] and $(y_{t-1} - y^*)$ is the output gap, and ε_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. It can be seen from equation (1) that the current value of the nominal interest rate, i_t, depends on the previous value of the output gap and the deviation of the inflation rate from target. The stochastic shock, ε_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 affect the economy with lags of approximately one year to affect output, and two years to affect inflation. 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. In their paper, the modification has been made assuming that within each operating period the central bank has a target for the nominal short-term interest rate, i_t^*, that is based on the state of the economy:

$$i_t^* = \bar{i} + \beta\left(E\left[\pi_{t+n} \mid \Omega_t\right] - \pi^*\right) + \gamma\left(E\left[y_t \mid \Omega_t\right] - y_t^*\right) \qquad (2)$$

where $\bar{i}$ is the long-run equilibrium nominal rate, π_{t+n} is the rate of annualized inflation n periods ahead, E is the mathematical expectation operator and Ω_t is the information available to the central bank at the time it sets the interest rate. Equation (2) can be interpreted as the rule by which central bank sets the target nominal short-term interest rate given its future expectation about inflation and output, based on information available at the time it makes the decision. Rearranging

[2] This series is compiled using a large and representative selection of more than 600 goods and services for which price movements are regularly measured throughout the country. The original source from the Office of National Statistic used 1987 as the base year, however, in this paper the series are re-based using 1995 as the base year.

[3] In the Taylor rule this is a constant, but see Woodford (2001) for the case in favour of a time varying interest rate equivalent to Wicksell's `natural rate'

this equation in order to obtain the feedback rule for the real interest rate, r_t^*, gives:

$$r_t^* = \bar{r} + (\beta - 1)(E[\pi_{t+n} \mid \Omega_t] - \pi^*) + \gamma(E[y_t \mid \Omega_t] - y_t^*) \qquad (3)$$

where $\bar{r}$ is the long-run equilibrium real rate of interest. From equation (3), 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 accomodate changes in inflation. In the latter case, self-fulfilling bursts of inflation and output may be possible.

In reality, the central bank may want to smooth changes in interest rates. Conventional explanations for smoothing interest rate changes include: fear of disrupting capital markets, loss of credibility from sudden large policy reversals, the need for consensus building to support a policy change, etc. (Goodhart, 1996 and Clarida et al, 1998). Thus we can further assume that the actual rate partially adjusts to the target.

$$i_t = (1 - \rho)i_t^* + \rho i_{t-1} + v_t \qquad (4)$$

where v_t is an exogenous random shock to the interest rate and the parameter $\rho \in [0, 1]$ captures the degree of interest rate smoothing. It is also assumed that v_t is i.i.d. Define $\alpha \equiv \bar{r} - \beta\pi^*$ and $\tilde{y}_t \equiv y_t - y_t^*$, we then rewrite equation (2) as

$$i_t^* = \alpha + \beta E[\pi_{t+n} \mid \Omega_t] + \gamma E[\tilde{y}_t \mid \Omega_t] \qquad (5)$$

Combining the target model (5) with the partial adjustment mechanism (4) yields

$$i_t = (1 - \rho)(\alpha + \beta E[\pi_{t+n} \mid \Omega_t] + \gamma E[\tilde{y}_t \mid \Omega_t]) + \rho i_{t-1} + v_t \qquad (6)$$

Finally, to obtain the estimated equation, eliminate the unobserved forecast components from the expression by rearranging the policy rule in terms of realized variables as follows:

$$i_t = (1-\rho)\alpha + (1-\rho)\beta\pi_{t+n} + (1-\rho)\gamma\tilde{y}_t + \rho i_{t-1} + \varepsilon_t \qquad (7)$$

where $\varepsilon_t \equiv -(1-\rho)\{\beta(\pi_{t+n} - E[\pi_{t+n} \mid \Omega_t]) + \gamma(\tilde{y}_t - E[\tilde{y}_t \mid \Omega_t])\} + v_t$ is a linear combination of the forecast errors of inflation and output and the exogenous disturbance v_t.

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 (7) performs well on quarterly data. The equation (7) 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 twelveth difference of the natural logarithm of the RPIX and $\tilde{y}_t$ determined empirically by the residuals from a 1971/01 to 1998/12 regression of the natarul logarithm of the Index of Industrial Production. The estimation method is the Instrumental Variable estimation and the set of instrument variables are $IV \in (1, \pi_{t-1}, ..., \pi_{t-6}, \tilde{y}_{t-1}, ..., \tilde{y}_{t-6}, i_{t-1}, ..., i_{t-6})$. With the value of n = 3, his result is shown in the first row of Table 1. He found that the long-run response coefficient on inflation, $\hat{\beta}$, equals 1.472 (0.424) and on output gap, $\hat{\gamma}$, equals 0.301 (0.068). This result is remarkably close to 1.5 and 0.5 combination as suggestd by Taylor (1993).

Using Nelson's data[4] 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. The results, which take nothing away from Nelson's finding that a Taylor rule can be found for quarterly and monthly data at certain horizons, show that at a monthly frequency - the frequency at which the Bank of England currently sets the policy rate, the estimates are not robust.

Nelson's original model uses the rate from the thinly traded Treasury Bill market as the dependent variable, while the actual policy rate

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

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 period 1970 - 1997, but we consider how the results would change for the last regime if we used the repo rate rather than the Treasury Bill rate. The comparison is found 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. The use of the Gilt repo improves the estimated value of the inflation target[5] from 3.65% to 2.88% when estimated over the sample 1992/10 to 1997/04. The correlation between the Treasury Bill rate and the Gilt repo rate is 0.88, and the estimates are, perhaps unsurprisingly, relatively robust to changes in the dependent variable.

The next step we take is to estimate the equation (7) using two different methods of detrending for the output gap. The sample period in our estimation is between 1993/02, which is the starting month when the Bank of England using the inflation targeting, to 2000/12, giving 95 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 is the 12-month (annualized) change in the price level, using Retail Price Index excluding Mortgage Interest Payment (RPIX). The Index of Industrial Production is used as a proxy for output and the variable $\tilde{y}_t$, the output gap, is measured empirically by passing the value of Index of Industrial Production from 1993/02 to 2000/12 through the Hodrick-Prescott filter. Because it is possible that the regressors in equation (7) dated later than period t may be correlated to the error term, ε_t, so we use the method Instrumental Variable estimation in order to avoid any endogeneity problems. The set of instrument variables are $IV \in (1; \pi_{t-1}; \ldots; \pi_{t-6}; \pi_{t-9}; \pi_{t-12}; \tilde{y}_{t-1}; \ldots; \tilde{y}_{t-6}; \tilde{y}_{t-9}; \tilde{y}_{t-12}; i_{t-1}; \ldots; i_{t-6}; i_{t-9}; i_{t-12})$.

[5] The relationship $\alpha \equiv \bar{i} - \beta\pi^*$ and $\bar{i} = \bar{r} + \pi^*$; $\alpha \equiv \bar{r} + (1-\beta)\pi^*$ allow us to construct the estimate of the inflation target, π^*, where

$$\pi^* = (\bar{r} - \alpha)/(\beta - 1) \quad (8)$$

We also consider a range of horizons for monetary policy, ranging from three months (Nelson's horizon) to twenty four month (Batini and Haldane (1999) and Batini et al (2001) note that if monetary policy is forward looking in°ation should be replaced by expected in°ation. They suggest a horizon of eighteen to twenty four months ahead). 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 ¯lter to detrend output we found that, for both the Treasury Bill rate and the Gilt repo rate, the estimate of the in°ation target was close to 2.5% for all horizons, but the estimated coe±cients on in°ation and the output gap varied considerably depending on the dependent variable and the forward-looking horizon. In some cases the coe±cients were not signi¯cant, in others they were signi¯cant but the wrong magnitudes and even negative. The high values of the coe±cients in certain cases are due to the fact that the coe±cient on the lagged dependent variable is often close to unity, in°ating the calculated long-run values of the other coe±cients[6].

We re-estimated the equation using a di®erent detrending method, keeping all other features of the estimation procedure the same, the results using the Treasury Bill rate as the dependent variable and using the Gilt repo rate as the dependent variable are reported in row 1-10

[6] It can be seen from equation (6) that a high value of ½ e®ectively puts great weight on the lagged interest rate, and a low weight on the remaining variables. When equation (7) is estimated, although the parameters on forward-looking in°ation 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 in°ation and output gaps. These variables a®ect future monetary policy as well as the present, so the net response of the interest rate is considerable. Gradualist policies such as these may con¯rm the observation of Ball (1999), who pointed out that although in°ation targeters may want to bring in°ation back to target after a shock they may not want to do so at the maximum speed, but they imply that the e®ect of a change in rates is long lasting

and 11-20, respectively, in Table 3. The Index of Industrial Production is used as a proxy for output and the output gap, $\tilde{y}_t$, is measured empirically by the residuals from a 1993/02 to 2000/12 regression of the Index of Industrial Production on a quadratic trend (following Clarida et al (1998) and Nelson (2000)). The results are dramatically different from the previous results. With a quadratic trend, the coefficient on inflation rate is wrongly signed for value of $n = 3$; the coefficient values are considerably different from the Taylor rule values and are not always significantly different from zero. The estimated inflation target is close to 2.5 % when we use the Treasury Bill rate as the dependent variable, but is not consistently estimated at values remotely close to 2.5% when we use the Gilt repo rate. Again the coefficient on the lagged dependent variable is close to unity.

Finally, we altered the construction of the instrument set, reducing the instruments to $IV \in (1; \pi_{t-1}; \ldots; \pi_{t-6}; \pi_{t-9}; \pi_{t-12}; \tilde{y}_{t-1}; \ldots; \tilde{y}_{t-6}; i_{t-1}; \ldots; i_{t-6})$; the effect on the estimated inflation target and the lagged dependent variable is minor, but the estimated coefficients on inflation and the output gap were highly variable and far from the Taylor rule predictions.

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%, very close to its mean of 2.57% over the sample. The second is the finding that the smoothing parameter takes a very high value for each of the horizons, n, which is consistent with the smoothing hypothesis proposed by Goodhart (1996) and Sack (1997). The estimated parameters reflect the 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). This result confirms that the Bank of England has had a very strong tendency to smooth change in interest rates during this period, so that changes, if they occur, are likely to be in the same direction rather than reversals.

Nevertheless, it is obvious that the estimation results can vary considerably according to the dependent variable, the detrending method used for constructing the output gap, the forward-looking horizon, and the instrument set. Only for the choice of detrending method, the forward-looking horizon, and the instrument set used by Nelson (2000) do we obtain the classical Taylor rule. Although we consider this to be a special case, we use the Taylor rule for our subsequent tests of predictive performance versus other information sets in within-sample and out-of-sample exercises. In effect we ask whether inflation and output are suffice to forecast the next change in the policy rate. In the next section, the Taylor rule information set and an alternative information set based on a wider category of information referred to in Section 2 will be compared as predictors of the probability of the next change in the base rate.

4 The Multinomial Logit Model and the Estimation of the Models

In many cases, especially when making a policy decision, analysts are interested in predicting not only the level of interest rates, but also the directional change of interest rates. The Taylor rule is an effective way of summarising 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 model in order to investigate how useful the Taylor rule information set is in 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.

There are only three possible directions or categories that the base rate can take: `down', `no change' and `up'. Accordingly we define a random variable z_t as follows:

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

$$z_t = 2 \quad \text{if} \quad \Delta i_t > 0$$

where $\Delta i_t = i_t - i_{t-1}$. Let X_t represent an information set with k variables. 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 a given information set X_t is defined using the logit cumulative density function:

$$\Pr(z_t = 1 \mid X_t) = \frac{e^{X_t'\beta_1}}{1 + e^{X_t'\beta_1} + e^{X_t'\beta_2}}; \tag{9}$$
$$\Pr(z_t = 2 \mid X_t) = \frac{e^{X_t'\beta_2}}{1 + e^{X_t'\beta_1} + e^{X_t'\beta_2}};$$

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

$$L(\beta_1, \beta_2) = \sum_{t=1}^{T} \sum_{i=0}^{2} 1[z_i = i] \Pr(z_t = i \mid X_t) \tag{10}$$

where $1[\cdot]$ is the indicator function. The ML estimators $\hat{\beta}_1$ and $\hat{\beta}_2$ are obtained by maximising the log-likelihood function in (10). 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 (9) 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

$$\hat{z}_t = m \quad \text{if} \quad \hat{P}_m = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2). \tag{11}$$

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 statistic

$$-2\ln\left(\frac{L_R}{L_{UR}}\right) = 2(\ln L_{UR} - \ln L_R) \sim \chi^2_{q;\alpha} \tag{12}$$

where q and α denotes the numbers of restrictions imposed and the significance level, respectively. Thus both restricted and unrestricted model are estimated[7]. Twice the difference between the log-likelihood function of the two models has the Chi-squared distribution with q degrees of freedom, and can be compared with the Chi-squared critical value. The hypotheses for the test are

$$\begin{aligned} H_0 &: \theta_j = 0 \text{ for } j = 2, \ldots, q+1 \\ H_1 &: \text{at least one } \theta_j \neq 0, \text{ for } j = 2, \ldots, q+1 \end{aligned}$$

where θ_j is the j^{th} parameter for the variable in the independent variable vector, x_t. 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

$$\text{pseudo} - R^2 = 1 - \left(\frac{\ln L_{UR}}{\ln L_R}\right). \tag{13}$$

4.1 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 leaded rate of inflation which 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 is from 1993/03 to 1999/12. The total number of observations is 82.

[7] Restricted version of the model can be obtained by estimating the model with all slope coefficients set to zero.

The logit estimation result is shown in Table 5. It is interesting to find that, contrary to the level regression, only the output gap appears statistically significant which implies its ability to play a roll in the probabilities prediction. The 1-month lagged value of base rate do not help in predicting the directional change in the base rate. The $p-$value for the goodness-of-fit χ^2-test is 0.091, so we barely reject the null hypothesis that all coefficients except the constant are jointly zero at the 10% significance level. The R^2 is also very small, 0.07. Nonetheless, as pointed out by Greene (1993), the coefficients obtained from the Multinomial Logit model are difficult to interprete. It is also important to note that the parameters estimated are not the marginal effects, like those of any nonlinear regression model. In order to understand some economic intuitions from the estimation, we will investigate the marginal effects of the attributes on the probabilities which can be calculated by the following:

$$\delta_m = \frac{\partial \hat{P}_m}{\partial X_t} = \hat{P}_m \left(\hat{\beta}_m - \sum_{i=0} \hat{P}_i \hat{\beta}_i \right) = \hat{P}_m \left(\hat{\beta}_m - \bar{\beta} \right) \tag{14}$$

It is apparent that these marginal effects for each of the outcomes will vary with the values of X_t. Therefore, it will be useful and convenient to calculate their values at the means of the independent variables. Table 6 illustrates the marginal effect of the characteristics on each probabilities. It can be seen, for example, that at the mean values of the inflation rate and output gap, an increase in the value of both variables will result in an increase in the probability that the base rate will rise in the next period, $\hat{P}_2$, but will lead to a decrease in the probability of a falling interest rate, $\hat{P}_0$. To be more precise, holding constant other variables, a 1% increasing in the expected inflation will increase the $\hat{P}_1$ by 0.22% and decrease the $\hat{P}_0$ and $\hat{P}_2$ by 0.17% and 0.04%, respectively. Furthermore, holding constant other variables, a 1% increasing in the output gap will raise $\hat{P}_2$ by 0.67% and lower $\hat{P}_0$ and $\hat{P}_1$ by approximately 0.007% and 0.06%, respectively. Since $\hat{P}_2$ increases by more than the other probabilities, $\hat{P}_0$ and $\hat{P}_1$, these will result in the tendency of the interest rate to be raised in the subsequent period. These marginal effects are calculated at the mean value of X_t and will be different if calculated at other values of X_t.

Since we are interested in the predictability of a given information set, we can also 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 or a contingency table where we associate the direction of predicted changes decided by (11) and the actual changes of the base rate. Table 7 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

$$SC = \frac{1}{T} \sum_{t=1}^{T} 1(\hat{z}_t = z_t): \quad (15)$$

The prediction using the Taylor rule information set always predicts no change in the interest rate, except for one observation, where a falling interest rate is correctly predicted. We found $SC = \frac{56}{82}$, which suggests that we have approximately 68% correct predictions. A close look at the data allows us to see that the value of z_t equals 1 most of the time, which means that the dominant outcome is where there was no change in the interest rate (the proportion is $\frac{56}{57} = 98\%$). While in the state of the rising interest rate and in the state of falling interest rate, there are no correct predictions at all. Thus the overall proportion of the correct prediction against actual outcomes mainly 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. However, as pointed out correctly by Bodie et al (1996), a high success rate generated by a "stopped-clock" strategy is not good evidence of predictability. For example, if you always predict 'no rain' in San Diego, you may be right 95% of the time. The measure SC in (15) cannot distinguish between seemingly successful predictability of a "stopped-clock" and true predictability. The technique proposed by Merton (1981) can be straightforwardly applied to this situation. Let CP_i be the proportion of the correct predictions when $z_t = i$. As we discussed earlier, we find that $CP_0 = \frac{0}{13}; CP_1 = \frac{56}{57}$ and $CP_1 = \frac{0}{12}$

from Table 7; virtually no predictability when the base rate is falling and rising. Then, Merton's correct measure denoted CP is given by

$$CP = \frac{1}{2}[CP_0 + CP_1 + CP_2 - 1]$$

which is always between 0 and 1. For example, for a "stopped-clock" strategy, only one of CP_i's is equal to 0.98 and the other two CP_i's are zero. Hence, the correct measure CP is approximately zero indicating that there is no predictability. On the other hand, for a perfect forecaster, all CP_i's are equal to one and hence the correct measure CP is one, revealing the correct status of perfect predictability. For the Taylor rule information set, we find CP even becomes negative which overules the apparent success rate of $SC = 68\%$ implying that the true predictability of the Taylor rule information set can be very small.

4.2 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 refered to as the wide information set onward. It is apparent from Section 2 that 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 Bank staff that gives attention to information arising from a range of other sources. The contents of these meetings are summarised in the Bank of England's publication, Minutes of the MPC Committee. In addition to these, the Bank produces a 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. In each case we had to use our judgement select a representative variable to capture a range of information. Our selection included: the M4 money stock as an indicator of the inflationary pressure arising from monetary sources; the Sterling Exchange Rate

Index to capture the e®ects of imported in°ation (e®ectively the component of RPIX arising from sources other than domestic conditions); the Average Earning Index represents the gauge of the labour market as earnings put pressure on prices; and ¯nally, the Input Price Index[8] to capture rising costs from other sources. These are in addition to RPIX, our measure of in°ation, which we assume is still a central part of the Bank of England's judgment, through the forecasting exercises conducted internally. The wide information set is now a collection of these new variables in addition to lagged RPIX, output gap and base rate: $X_t = (1; M4_{t-1}; EX_{t-1}; AEI_{t-1}; INP_{t-1}; RPIX_{t-1}; \tilde{y}_t; i_{t-1})'$: The variable $M4_{t-1}$ is the 1-month lagged value of the natural logarithm of M4 money stock, EX_{t-1} is the 1-month lagged value of the natural logarithm of Sterling Exchange Rate Index, AEI_{t-1} is the 1-month lagged value of the natural logarithm of Average Earnings Index, INP_{t-1} is the 1-month lagged value of the natural logarithm of Input Price Index, $RPIX_{t-1}$ is the 1-month lagged value of the natural logarithm of RPIX[9],

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

TheSterling 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 o±cial 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 re°ects that currency's relative importance to UK trade in manufacturing based in 1989-1991 average aggregate trade °ows. 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).

[9] Here, we use the lagged value of the RPIX rather than the leaded value because the out-of-sample prediction using the wide information set will be assessed in the

$\tilde{y}_t$ is our measure of output gap and i_{t-1} is the 1-month lagged value of base rate. We also re-scales some of the variables by multiplying the variables $M4_{t-1}; EX_{t-1}; AEI_{t-1}; INP_{t-1}$ and $RPIX_{t-1}$ by 100 in order to get sensibles estimated coefficients. The sample period is from 1993/03 to 1999/12, giving 82 observations altogether.

The estimation result is shown in Table 8. The result indicates that the coefficients for Sterling Exchange Rate Index and Input Price Index are significantly different from zero at least with 10% significant level. These variables contribute in explaining the direction of change in the base rate. Although the coefficient of the 1-month lagged base rate in the set of parameters $\hat{\beta}_1$ is not statistically significant, it is so in the set of parameters $\hat{\beta}_2$ (see equation (9)). This means the lagged value of base rate plays a part in predicting the state of rising interest rate but not the state of a falling interest rate. The goodness-of-fit χ^2-statistic is 44.80 and hence we can reject the null hypothesis of the test for overall significance of the model at 5% significant level which implies that at least one variable in the model can explain the probabilities of the change in the repo rate. The R^2 for this wide information set approximately equals 0.37. This result indicates that there is a considerable improvement in the goodness-of-fit in this model from the previous model where the Taylor rule information set is used in the estimation.

The marginal effects of the characteristics on each probabilities are represented in the Table 9. Table 10 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 $SC = \frac{62}{82}$. Hence, approximately 76% of predictions are correct, with far more variations in the prediction. The number of correct predictions against the actual outcomes in the state of 'down', 'no change' and 'up' are $CP_0 = \frac{6}{13}; CP_1 = \frac{52}{57}$ and $CP_2 = \frac{4}{12}$, respectively. Therefore, the correct measure for this wide information set is $CP = 35\%$, which is substantially higher than the previous case where the Taylor rule information set is used in the estimation. Another important consideration is that there are

next section. It is a essential criterion to use only lagged values in the out-of-sample prediction.

no counter predictions, so the interest rate is never predicted to fall when it rises or vice versa. These results indicate a substantial improvement in the ability to predict the change in the interest rate from the model where the Taylor rule information set is used as independent variables.

All the empirical results we have found so far strongly suggests that the wide information set that is more relevant to the decision making process of the MPC than the Taylor rule information set when used to predict the directional change of the base rate. However, the empirical fact that we can correctly predict the directional change of the base rate 76% of the time and the correct measure CP is 35% is rather surprising. Note that the actual outcomes are dominated by the state of `no change' in the interest rate. Therefore, if one always predicts that the interest rate will not change during his period of interest, his prediction is likely to be impressively correct almost all of the times. However, the other two states of outcomes, `falling' and `rising' that are less likely to occur, ought to be taken into account in order to obtain the correct measure of the prediction power. Here, in this case, the wide information set when used to predict the direction of change in the base rate, taken into account issue of the dominant state of `no change' outcome, it can correctly predict 35% of the time. Of course, one can ask whether or not these numbers can measure the true predictability of the wide information set. This question should be answered because these numbers have been obtained from in-sample estimation in that we have in fact used future information when making predictions. Usually any in-sample estimation is likely to lead to over-¯tting 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 answer the question.

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

The objective of this section is then to make 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. Once we have obtained $\hat{z}_{t+1}$, then we move the current time to $t + 1$ and make one-step-ahead predictions of $\hat{z}_{t+2}$ using the information available only up to time $t + 1$. This process will be repeated until the last observation in the sample is predicted. The initial estimation window is 1993/03 to the observation 1997/12 with 58 observations. The first prediction target date is 1998/1. Given the small number of observations, we use an expanding window method; that is, the first observation is fixed at 1993/03 while the estimation window is expanding by one observation each time. Importantly, in order to make this a true out-of-sample prediction, only lagged values of the variables in each information sets will be used as predictors. We will use the lagged value of inflation rate (π_{t-1}), output gap ($\tilde{y}_{t-1}$) and base rate (i_{t-1}) in the out-of-sample prediction for the Taylor rule information set and the lagged value of M4 money stock ($M4_{t-1}$), Sterling Exchange Rate Index ($EXCH_{t-1}$), Average Earnings Index (AEI_{t-1}), Input Price Index (INP_{t-1}) and Retail Price Index excluding mortgage interest payments ($RPIX_{t-1}$) for the wide information set.

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

From the second column Table 11, we found that although the actual outcome varied, the Taylor rule information set predicts no change in the interest rate in almost all out-of-sample observations. Table 12 shows the cross-tabulations of the predicted against observed outcomes. From total 36 predictions test, there are only two observations, 1999/03 and 2000/03, where the Taylor Rule information set predicts fallings in the interest rate. Both predictions are incorrect, because the actual outcomes were `no change'. For all remaining 34 observations, the Taylor rule information set predicts `no change' in the interest rate. Out of these 34 predictions, 22 are correct and 12 are incorrect. Therefore, the proportion of correct prediction against the actual outcomes equals $\frac{22}{36}$ which is 61 per cent. The evidence suggests that this ratio mainly stems from the dominated `no change' outcome during the period of the out-of-sample test. The Merton's measures for this out-of-sample exercise using Taylor rule information set has a negative value which implies the poor performance in predictability of the Taylor rule information set.

However, we note that we have used information in the detrenging process that would not have been available to the central bank. To correct for this we detrend industrial production using the period from the beginning of the sample to the last observation before the date we wish to forecast the change in the interest rate. The result of the predictions out-of-sample improves somewhat. There are now 23 out of 36 predictions that are correct and these continue to fall within the `no change' category. The proportion of correct prediction against the actual outcomes equals $\frac{23}{36}$ which is 64 per cent up from 61 per cent previously.

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

In forecasting the out-of-sample results for the wide information set we included the new data to allow the model to predict by drawing on a greater range of information. This has the advantage that the information set nests the Taylor rule information, but in practice, we found that better results were produced by excluding the output series than including it. The third column of Table 11 shows the out-of-sample prediction using the wide information set and Table 13 illustrates the contingency table of the predicted against actual outcomes. The result is di®erent from the previous case where the Taylor rule information set is used. The wide information set predicts changes in the interest rate more often than the Taylor Rule information set. The proportion of the correct prediction against the actual outcomes is $SC = \frac{24}{36} = 67\%$. We found that the higher value of the proportion of the correct prediction against the actual outcomes does not result from the case where there was no change in the interest rate which is the dominated state of outcome. The evidence shows that the wide information predicts approximately the same number of changes in the repo rate as the Taylor rule, but that it is more capable of predicting positive and negative changes, especially during the successive cut in rates from 1998/10-1999/4. When we calculated the Merton's measures we found : $CP_0 = \frac{5}{7}; CP_1 = \frac{17}{24}$ and $CP_2 = \frac{2}{5}$ which implies that the correct measure from the out-of-sample exercise is $CP = 41\%$: This confirms a strong evidence for predictability. The wide information set has the capability to predict the direction of change in the interest rate. 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. Figure 1 illustrates the interest rate paths comparing the actual outcomes with the pridicted outcomes using Taylor's rule information set and wide information set. We assume here that if a change is predicted, the magnitude of the predicted change is set to equal the actual size of change in that period. For example, in 1998/10, the wide information set predicted a falling in the interest rate, since there were actually a 50 basis points cut in the repo rate, we then set the size of predicted cut to 50 basis points too. It can be seen from Figure 1 that the interest rate path predicted by the wide information set closely resembles the actual interest rate path, especially during 1998/09 to 2000/02. Finally, whether $CP = 41\%$ is significantly different from zero or not can be tested by the χ^2 – independence test used in Schnader and Stekler (1990) and Kolb and Stekler (1996), which will be illustrated in the next section.

6 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, we may wonder whether the results found arose by the actual ability to predict or simply just by chance. In this section, we perform the so-called Test of Association in Contingency Tables[10]. We want to test the following hypotheses.

H_0 : No association between the predicted and the actual outcomes

H_1 : There are associations between the predicted and the actual outcomes

Let R_i be the total for the i^{th} row and C_j be the total for the j^{th}column in Table 13. Then, the expected number of observations in each entry, denote by $\hat{E}_{ij}$, is defined as $\hat{E}_{ij} = \frac{R_i C_j}{N}$ where and N is the total number of observations in the table. The χ^2-test statistic is then given by

$$\sum_{i=1}\sum_{j=1}\frac{(N_{ij}-\hat{E}_{ij})^2}{\hat{E}_{ij}}$$

where N_{ij} is the frequency in the $(i,j)^{th}$ cell in the table. This statistic is approximately 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 (results in zero denominator), but for the wide information set the calculated statistic value equals 19.61, while the statistic $\chi^2_{4,0.05}$ equals 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

[10] See Newbold (1995), p. 415-419

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.

7 Conclusion

A great deal of consensus has emerged in monetary policy making in the 1990s. The trinity of flexible exchange rates, inflation targeting and the empirical support for a Taylor rule have been central to this consensus. This paper has sought to step back from the evidence in favour of the Taylor rule as an ex post summary of sensible central bank behaviour 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.

Using monthly data from the United Kingdom for the period of inflation targeting we find that the 'Taylor rule' specification receives less support than for quarterly data, a result consistent with monthly evidence provided by Clarida et al (1998). In tests of Taylor rule information as a predictor of base rate change appears to predict well in sample and out-of-sample, but on closer inspection we find that in both cases, the 'no change' outcome dominates. We find that a wider set, that includes monetary, exchange rate, labour market, and factor cost information 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 than if a wider set of information were used to form a 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 behaviour. Parallel results, detailing the shortcomings of the Taylor rule and variant of it for the ECB rate setting process, draw similar conclusions (see Alesina et al (2001)). 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. This exercise shows that good performance as an ex post summary of events does not imply good performance as an ex ante predictor. The Monetary Policy Committee can sleep easy in their beds, there is a role for policymakers who can form judgments about monetary conditions and make changes accordingly. The rule may o®er some useful guidance, but it will not replace them.

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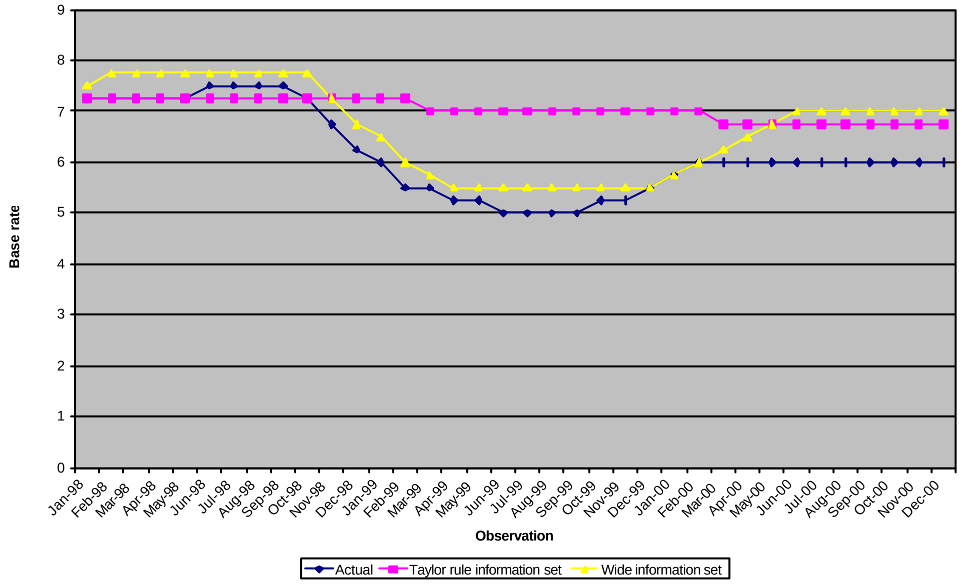

Figure 1: Comparison of the repo rate paths

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

n	$\hat{\rho}$	$(1-\hat{\rho})\alpha$	$(1-\hat{\rho})\beta$	$\hat{\beta}$	$(1-\hat{\rho})\gamma$	$\hat{\gamma}$	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	$\hat{\rho}$	$\widehat{(1-\rho)\alpha}$	$\widehat{(1-\rho)\beta}$	$\hat{\beta}$	$\widehat{(1-\rho)\gamma}$	$\hat{\gamma}$	π^*
3	0.904	0.241	0.129	1.356	0.168	1.761	2.08%
	(0.048)	(0.281)	(0.136)	(1.138)	(0.070)	(1.009)	
6	0.898	0.203	0.163	1.593	0.148	1.444	2.18%
	(0.045)	(0.271)	(0.118)	(0.967)	(0.067)	(0.884)	
12	0.926	-0.014	0.125	2.424	0.094	1.725	2.43%
	(0.030)	(0.320)	(0.065)	(1.743)	(0.035)	(1.280)	
18	0.979	-0.435	0.220	10.405	0.074	3.479	2.53%
	(0.046)	(0.473)	(0.107)	(25.433)	(0.073)	(7.298)	
24	0.970	-0.210	0.162	5.328	0.031	1.038	2.35%
	(0077)	(0.855)	(0.170)	(18.349)	(0.086)	(4.104)	
3	0.949	-0.003	0.124	2.422	0.189	3.703	2.54%
	(0.036)	(0.217)	(0.100)	(1.665)	(0.055)	(2.826)	
6	0.943	-0.093	0.175	3.080	0.186	3.283	2.50%
	(0.033)	(0.218)	(0.087)	(1.707)	(0.056)	(2.237)	
12	0.982	-0.357	0.179	9.961	0.177	9.857	2.612
	(0.028)	(0.250)	(0.073)	(16.023)	(0.054)	(16.401)	
18	1.030	-0.851	0.255	-8.357	0.149	-4.879	2.60%
	(0.038)	(0.407)	(0.091)	(9.320)	(0.062)	(6.701)	
24	0.995	-0.174	0.083	15.497	0.120	22.336	2.48%
	(0.055)	(0.604)	(0.116)	(174.849)	(0.071)	(230.305)	

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 80 (from 1994/02 to 2000/09)

For $n = 6$; the number of observations used in the estimation is 77 (from 1994/02 to 2000/06)

For $n = 12$; the number of observations used in the estimation is 71 (from 1994/02 to 1999/12)

For $n = 18$; the number of observations used in the estimation is 65 (from 1994/02 to 1999/06)

For $n = 24$; the number of observations used in the estimation is 59 (from 1994/02 to 1998/12)

Table 3: Monthly estimates for the Taylor rule coefficients detrending using a quadratic trend

n	ρ	$(1-\rho)\alpha$	$(1-\rho)\beta$	β	$(1-\rho)\gamma$	γ	π^*
3	0.900	1.165	-0.257	-2.573	0.131	1.313	2.35%
	(0.042)	(0.396)	(0.159)	(2.132)	(0.047)	(0.685)	
6	0.887	0.596	0.017	0.148	0.062	0.555	2.37%
	(0.041)	(0.441)	(0.172)	(1.523)	(0.055)	(0.498)	
12	0.884	0.511	0.048	0.419	0.075	0.651	1.98%
	(0.046)	(0.471)	(0.130)	(1.199)	(0.051)	(0.348)	
18	0.940	-0.040	0.138	2.300	0.053	0.879	7.66%
	(0.063)	(0.632)	(0.134)	(4.306)	(0.051)	(0.646)	
24	0.967	-0.318	0.193	5.907	0.040	1.227	2.65%
	(0.083)	(0.883)	(0.175)	(19.548)	(0.051)	(2.875)	
3	0.954	0.923	-0.288	-6.342	0.137	3.010	2.27%
	(0.033)	(0.303)	(0.141)	(6.642)	(0.039)	(2.506)	
6	0.923	0.376	0.024	0.311	0.066	0.857	1.88%
	(0.031)	(0.332)	(0.134)	(1.716)	(0.043)	(0.638)	
12	0.926	0.331	0.018	0.241	0.094	1.277	1.21%
	(0.031)	(0.331)	(0.095)	(1.325)	(0.035)	(0.521)	
18	0.969	-0.163	0.106	3.442	0.084	2.718	3.61%
	(0.042)	(0.442)	(0.096)	(7.053)	(0.032)	(3.203)	
24	0.956	0.082	0.042	0.975	0.089	2.035	-66.26%
	(0.051)	(0.566)	(0.111)	(3.513)	(0.034)	(2.397)	

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 80 (from 1994/02 to 2000/09)

For $n = 6$, the number of observations used in the estimation is 77 (from 1994/02 to 2000/06)

For $n = 12$, the number of observations used in the estimation is 71 (from 1994/02 to 1999/12)

For $n = 18$, the number of observations used in the estimation is 65 (from 1994/02 to 1999/06)

For $n = 24$, the number of observations used in the estimation is 59 (from 1994/02 to 1998/12)

Table 4: Monthly estimates for the Taylor rule coefficients using a different instrument set

n	$\hat{\rho}$	$(1-\hat{\rho})\alpha$	$(1-\hat{\rho})\beta$	$\hat{\beta}$	$(1-\hat{\rho})\gamma$	$\hat{\gamma}$	π^*
3	1.006	0.008	-0.328	53.336	0.035	-5.72	2.65%
	(0.046)	(0.003)	(0.165)	(379.050)	(0.015)	(41.370)	
6	0.967	0.005	-0.114	-3.476	0.022	0.662	2.72%
	(0.052)	(0.004)	(0.208)	(11.249)	(0.020)	(1.540)	
12	0.961	0.008	-0.211	-5.418	0.042	1.082	2.64%
	(0.040)	(0.006)	(0.267)	(10.596)	(0.032)	(1.652)	
18	0.956	0.008	-0.207	-4.719	0.056	1.289	2.58%
	(0.051)	(0.011)	(0.354)	(5.814)	(0.045)	(1.183)	
24	1.007	-0.004	0.153	-19.297	0.012	-1.573	2.54%
	(0.081)	(0.012)	(0.312)	(167.831)	(0.037)	(18.951)	

The dependent variable is the Treasury Bill rate.

For $n = 3$; the number of observations used in the estimation is 86 (from 1993/08 to 2000/09)

For $n = 6$; the number of observations used in the estimation is 83 (from 1993/08 to 2000/06)

For $n = 12$; the number of observations used in the estimation is 77 (from 1993/08 to 1999/12)

For $n = 18$; the number of observations used in the estimation is 71 (from 1993/08 to 1999/06)

For $n = 24$; the number of observations used in the estimation is 65 (from 1993/08 to 1998/12)

Table 5: The multinomial logit model estimation for Taylor rule information set

Variable	Coefficient	Standard Error	b/S.E.	$Pr(\|Z\| < z)$
Set of parameters β_1				
Constant	-0.8874	3.8618	-0.230	0.8183
π_{t+12}	1.4592	1.0566	1.381	0.1673
$\tilde{y}_t$	-0.0034	0.1777	-0.193	0.8466
i_{t-1}	-0.1975	0.4306	-0.459	0.6465
Set of parameters β_2				
Constant	2.0821	5.1798	0.402	0.6877
π_{t+12}	0.7939	1.4368	0.553	0.5806
$\tilde{y}_t$	0.6907	0.4085	1.691	0.0909
i_{t-1}	-0.7502	0.6047	-1.241	0.2147

Dependent variable: z_t; R^2 : 0.07

Log likelihood function: -63.16523, Restricted log likelihood function: -67.73383

Chi-squared: 9.137206, Degrees of freedom: 6, Significance level: 0.1660075

Table 6: The marginal effects of the characateristics vector for Taylor rule information set

Variable	Coefficient	Standard Error	b/S.E.	Pr(|Z| < z)
Marginal Effect on $Pr(z_t = 0)$				
Constant	0.0684	0.4964	0.138	0.8904
π_{t+12}	-0.1799	0.1630	-1.103	0.2700
$\tilde{y}_t$	-0.0071	0.0232	-0.305	0.7600
i_{t-1}	0.0346	0.0579	0.598	0.5496
Marginal Effect on $Pr(z_t = 1)$				
Constant	-0.3298	0.5991	-0.550	0.5820
π_{t+12}	0.2183	0.1612	1.354	0.1757
$\tilde{y}_t$	-0.0596	0.0324	-1.839	0.0659
i_{t-1}	0.0198	0.0671	0.296	0.7676
Marginal Effect on $Pr(z_t = 2)$				
Constant	0.2614	0.4285	0.610	0.5419
π_{t+12}	-0.0384	0.1098	-0.350	0.7265
$\tilde{y}_t$	0.0667	0.0609	1.095	0.2736
i_{t-1}	-0.0544	0.0589	-0.924	0.3557

Mean of $\pi_{t+12} = 2.5242$; $\tilde{y}_t = -0.2074$ and $i_{t-1} = 6.1707$

Table 7: The cross-tabulations of predicted against observed outcomes

	Predicted			
Actual	0	1	2	Total
0	0	13	0	13
1	0	56	1	57
2	0	12	0	12
Total	1	81	0	82

Result from the estimation of Taylor rule information set in the Multinomial Logit model

Table 8: The multinomial logit model estimation for wide information set

Variable	Coefficient	Standard Error	b/S.E.	$\Pr(\lvert Z\rvert < z)$
Set of parameters β_1				
Constant	-592.9578	298.0226	-1.990	0.0466
$M4_{t-1}$	0.0249	0.4211	0.059	0.9529
EX_{t-1}	0.8985	0.3291	2.730	0.0063
AEI_{t-1}	0.0633	0.7495	0.084	0.9327
INP_{t-1}	0.8277	0.3093	2.676	0.0075
$RPIX_{t-1}$	-0.5552	1.1625	-0.478	0.6329
$\tilde{y}_t$	-0.3500	0.3684	-0.950	0.3421
i_{t-1}	-0.8386	0.7066	-1.187	0.2353
Set of parameters β_2				
Constant	-932.3616	341.9809	-2.726	0.0064
$M4_{t-1}$	-0.6217	0.5465	-1.138	0.2553
EX_{t-1}	1.5301	0.4188	3.653	0.0003
AEI_{t-1}	-0.4588	0.8794	-0.522	0.6019
INP_{t-1}	1.2221	0.3703	3.300	0.0010
$RPIX_{t-1}$	1.5611	1.7765	0.879	0.3795
$\tilde{y}_t$	0.8940	0.7766	1.151	0.2497
i_{t-1}	-2.7337	1.0796	-2.532	0.0113

Dependent variable: z_t; R^2 : 0.33

Log likelihood function: -42.40160, Restricted log likelihood function: -67.73383

Chi-squared: 50.66447, Degrees of freedom: 12, Significance level: 0.000005

Table 9: The marginal effects of the characateristics vector for the wide information set

Variable	Coefficient	Standard Error	b/S.E.	$Pr(\|Z\| < z)$
Marginal Effect on $Pr(z_t = 0)$				
Constant	25.8819	32.1760	0.804	0.4212
$M4_{t-1}$	-0.0004	0.0183	-0.023	0.9820
EX_{t-1}	-0.0393	0.0453	-0.868	0.3854
AEI_{t-1}	-0.0022	0.0321	-0.068	0.9456
INP_{t-1}	-0.0360	0.0412	-0.876	0.3811
$RPIX_{t-1}$	0.0218	0.0595	0.365	0.7149
Δy_t	0.0138	0.0211	0.654	0.5134
i_{t-1}	0.0380	0.0513	0.741	0.4586
Marginal Effect on $Pr(z_t = 1)$				
Constant	-17.7782	15.4042	-1.154	0.2485
$M4_{t-1}$	0.0147	0.0207	0.708	0.4793
EX_{t-1}	0.0245	0.0235	1.042	0.2974
AEI_{t-1}	0.0137	0.0352	0.0389	0.6975
INP_{t-1}	0.0265	0.0215	1.231	0.2185
$RPIX_{t-1}$	-0.0679	0.0618	-1.099	0.2716
Δy_t	-0.0409	0.0277	-1.479	0.1391
i_{t-1}	0.0047	0.0491	0.095	0.9240
Marginal Effect on $Pr(z_t = 2)$				
Constant	-8.1037	11.8410	-0.684	0.4937
$M4_{t-1}$	-0.0143	0.0226	-0.631	0.5282
EX_{t-1}	0.0149	0.0213	0.698	0.4854
AEI_{t-1}	-0.0115	0.0195	-0.589	0.5560
INP_{t-1}	0.0096	0.0140	0.682	0.4952
$RPIX_{t-1}$	0.0462	0.0749	0.617	0.5372
Δy_t	0.0271	0.0437	0.621	0.5343
i_{t-1}	-0.0427	0.0621	-0.688	0.4912

Mean of $M4_{t-1} = 1338.52$, $EX_{t-1} = 470.26$, $AEI_{t-1} = 465.01$, $INP_{t-1} = 450.91$, $RPIX_{t-1} = 463.29$, $\Delta y_t = 0.2074$ and $i_{t-1} = 6.1707$

Table 10: The cross-tabulations of predicted against observed outcomes

	Predicted			
Actual	0	1	2	Total
0	6	7	0	13
1	2	52	3	57
2	0	8	4	12
Total	8	67	7	82

Result from the estimation of wide information set in the Multinomial Logit model

Table 11: The out-of-sample prediction result

Observation	Actual	T	W	Observation	Actual	T	W
1998/01	1	1	2	1999/07	1	1	1
1998/02	1	1	2	1999/08	1	1	1
1998/03	1	1	1	1999/09	1	1	1
1998/04	1	1	1	1999/10	2	1	1
1998/05	1	1	1	1999/11	1	1	1
1998/06	2	1	1	1999/12	2	1	1
1998/07	1	1	1	2000/01	2	1	2
1998/08	1	1	1	2000/02	2	1	2
1998/09	1	1	1	2000/03	1	0	2
1998/10	0	1	1	2000/04	1	1	2
1998/11	0	1	0	2000/05	1	1	2
1998/12	0	1	0	2000/06	1	1	2
1999/01	0	1	0	2000/07	1	1	1
1999/02	0	1	0	2000/08	1	1	1
1999/03	1	0	0	2000/09	1	1	1
1999/04	0	1	0	2000/10	1	1	1
1999/05	1	1	1	2000/11	1	1	1
1999/06	0	1	1	2000/12	1	1	1

T: using the Taylor rule infomration set as predictors

W: using the wide information set as predictors

Table 12: The cross-tabulations of predicted against observed outcomes

	Predicted			
Actual	0	1	2	Total
0	0	7	0	7
1	2	22	0	24
2	0	5	0	5
Total	2	34	0	36

Result from the out-of-sample prediction of the Taylor rule information set

Table 13: The cross-tabulations of predicted against observed outcomes

	Predicted			
Actual	0	1	2	Total
0	5	2	0	7
1	1	17	6	24
2	0	3	2	5
Total	6	22	8	36

Result from the out-of-sample prediction of the wide information set