Predicting Directional Changes in Interest Rates: Gains from Using Information from Monetary Indicators

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March 2006

Abstract

Predicting the likely change to interest rates is not straightforward. Rates can remain unchanged for long periods, and new information does not necessarily result in immediate changes. This paper offers a method for predicting rates using a limited dependent variable approach to reflect the decision process. We take three recent theoretical models to consider how regular information on inflation and output gaps might be augmented with monetary information. Our results show that prediction of rate changes improves substantially with the use of supplementary monetary indicators.

[1]An earlier version of this paper was prepared for the Bundesbank-IIW workshop on *'What can central banks learn from money and credit aggregates?'*, Eltville, October 27-28. We thank Mike Artis, Katrin Assenmacher-Wesche, Anindya Banerjee, Roel Beetsma, Keith Blackburn, Mick Devereux, Stefan Gerlach, Petra Gerlach-Kristen, Juergen von Hagen, Clemens Kool, Benoit Mojon, Edward Nelson, Manfred Neumann, Denise Osborn, Andreas Schabert, Alan Timmermann, Axel Weber, James Yetman and seminar participants at the Hong Kong Monetary Authority, the Universities of Amsterdam, Manchester and the National University of Singapore for helpful comments.
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1 Introduction

Interest rate setting decisions by central banks are some of the most anticipated and heavily scrutinized events in the economic calendar. Short-term interest rates can exercise considerable leverage over the future path of economic variables (see Goodfriend, 1991). With greater transparency, more information is available on the rate setting process and in this context the actions of monetary policy making committees of central banks can be more readily understood than was previously the case. Committees explain in detail the basis for their actions, giving observers an insight into the reasoning behind their judgments. However, this does not mean that forecasting rate changes is strightforward, and the question of how an outside observer might attempt to predict the direction of future rate changes from current information is still an important issue.

Simple rules that characterize central bank behavior such as the Taylor rule are a useful means of summarizing the relationship between the short-term interest rate and economic data measured by inflation relative to its target and the deviation of output from its trend value, (see Taylor, 1993, 2000, 2001). But while rules offer a useful summary and can be readily estimated by econometric methods (c.f. Judd and Rudebusch, 1998, Clarida *et al.*, 1998, 2000, Gerlach and Smets, 1999, Gerlach and Schnabel, 2000, and Nelson, 2001) they often have unstable coefficients and perform badly in out-of-sample forecasts (see Gerlach, 2005, and Gerlach-Kristen, 2003). Their poor performance is not entirely surprising. Rates are not adjusted continuously but are adjusted when policymakers - who meet at regular but occasional times - decide that the balance of 'new' information suggests a rate change is warranted. The process of confirming signals in economic data or persuading committee members of the case for change can often lead to long periods of 'no change'. As a result the time series of short-term interest rates can appear highly autocorrelated, and under these circumstances the best guide to the level of interest rate can be its previous value. But when new information does emerge, causing rates to change, a predictor that simply takes the previous value as the most likely value for future rates will prove to be inaccurate. This raises two crucial issues for predicting rate changes, namely, the definition of the information set required to make accurate predictions, and the modelling process to account for long pauses in the movement of rates.

The first issue concerns the scope of the information required to make accurate predictions of rate changes. This is ultimately determined empirically but considerable input is derived from theory. Svensson (2003) discusses an optimisation exercise where expected future deviations of inflation from target and output from its potential level are minimized subject to an IS curve and a Phillips curve. The derived optimal behavior implies that inflation and the output gap should be sufficient information to predict rate changes since rates are described by a Taylor rule. In reality, however, central banks refer to a wider variety of information that also includes variables such as input prices, labor market indicators, and exchange rates. We contrast the performance of these information sets versus the performance of three monetary information sets that include indicators proposed in recently published papers by Gerlach and Svensson (2003), Neumann and Greiber (2005) and Nelson (2003). These papers extract information on the deviation of monetary variables from core measures of monetary trends; which have parallels in the relationship between inflation and core inflation in Bryan and Cecchetti (1994).[2]

[2]The relevance of core measures of money for inflation has been supported by a growing literature including Altimari (2001), Trecroci and Vega (2002), Gerlach and Svensson (2003), Assenmache-Wesche and Gerlach (2005), Bruggeman *et al.* (2005) and Neumann and Greiber (2005). Deviations from the core measure indicate inflationary pressures in much the same way that output gaps register pressures on inflation from aggregate demand. The recent evidence that low frequency components of monetary growth helps predict inflation using euro area data in particular is supported by evidence from longer runs of data for more than a century for the US and the UK (c.f. Thoma, 1994,

The second issue concerns the econometric methodology. Our modelling approach involves prediction from a limited dependent variable estimator that predicts the probability of rates being increased, decreased or kept at their current level; it is characterized by a multinomial logit model rather than a directly estimated instrument rule[3]. The different information sets are used to predict the next *most likely* outcome of the committee decision, and by turning the focus away from the *level* of interest rates to the prediction of the *direction* of change in the interest rate, we immediately benefit from a number of advantages. First, we recognize that the interest rate setting process is inherently a set of discrete central bank committee decisions to determine whether rates should change, and if so in which direction. Second, the use of discrete directional change predictions overcomes the problems resulting from the near I(1) behavior in the level of interest rates that plagues equations that seek to predict the level of rates since we no longer use the interest rate itself as the dependent variable.

The paper is organised as follows. Section 2 explains the theoretical framework and derives the optimal rule and the implied information sets including and excluding monetary indicators, it then explains the estimation method. Section 3 describes the data. Section 4 and 5 provide estimates of the direction of change within sample based on over a decade of data from the monthly meetings of the Bank of England monetary policy committee. We consider the ability of the different information sets to predict the direction of change in-sample and out-of-sample[4]. Our results suggest that monetary indicators make accurate and improved predictions, both in-sample and out-of-sample, compared to the preliminary information sets that exclude them. Section 6 concludes showing our results correspond with a growing literature that finds core inflation helps predict inflation, and as a consequence variations of monetary growth around the core help predict directional change in rates.

2 Theoretical Basis for Monetary Indicators

2.1 A Basic Framework

We take the canonical model utilized by among others Bernanke and Woodford (1997), Clarida *et al.* (1998), McCallum and Nelson (1999) and Svensson (2003) as a framework for our theoretical discussion. We make the assumption that the central bank minimizes the discounted sum of future losses

$$W = \frac{1}{2}\sum_{j=0}^{\infty}\delta^{j}[L_{t+j|t}] \tag{1}$$

subject to the backward-looking Phillips and IS curves defined as follows:

$$\pi_{t+j|t} = \pi_{t+j-1|t} + \alpha_y(y_{t+j-1|t} - y^*_{t+j-1|t}) \tag{2}$$

$$y_{t+j|t} = \beta_y y_{t+j-1|t} + \beta_r(r_{t+j-1|t} - \overline{r}) + v_{t+j|t} \tag{3}$$

Haug and Dewald, 2005, Benati 2005). The re-emergence of monetary indicators for informational purposes reverses the previous decline of interest in money noted by King (2001).

[3]This approach is very close in method to that of Gali *et al.* (2004) and Gerlach (2005), which use ordered probit estimates. We compared the results from a multinomial logit model with those from an ordered logit model and there was no difference in the ranking of our information sets based on their forecast performance in-sample or out-of-sample.

[4]While additional information always produces better in-sample results, we cannot be sure that the out-of-sample results would be improved unless the additional information contains incremental forecasting power.

where π_t, y_t, r_t and $\overline{r}$ are inflation, output, actual and average real interest rates respectively. Output is subject to a shock, v_t. The parameters $\alpha_y > 0, 0 \leq \delta < 1, \beta_y > 0, \beta_r > 0$ represent the slope of the Phillips curve, the discount rate, the persistence in output, and the intertemporal elasticity of substitution respectively. The nominal interest rate is defined by the Fisher condition as

$$R_{t+j|t} = r_{t+j|t} + \pi_{t+j+1|t}. \tag{4}$$

Defining the loss function as $L_{t+j|t} = (\pi_{t+j|t} - \pi^*)^2 + \lambda(y_{t+j|t} - y^*_{t+j|t})^2$ where the terms π^* and $y^*_{t+j|t}$ are the given inflation target and the expected potential output level; λ is a weight, Svensson (2003) shows that the solution to this loss function in (1) subject to (2) and (3) can be solved using a Langrangian method that yields the first order condition

$$(\pi_{t+j|t} - \pi^*) + \frac{\lambda}{\delta\alpha_y}[(y_{t+j-1|t} - y^*_{t+j-1|t}) - (y_{t+j|t} - y^*_{t+j|t})] = 0. \tag{5}$$

The optimal interest path is then of the form

$$R_t = (\overline{r} + \pi^*) + \left(1 + \frac{1-c}{\alpha_y\beta_r}\right)(\pi_{t+j+1|t} - \pi^*) + \frac{\beta_y}{\beta_r}(y_{t+j|t} - y^*_{t+j|t}) \tag{6}$$

where c is the smallest root of the difference equation in inflation obtained by substituting (2) into (5). This provides the theoretical justification for our preliminary information set based on the Taylor rule. With the addition of other variables of interest in equation (2) the rule would be amended to include these variables in a 'Taylor rule plus' information set with other non-monetary indicators of inflationary pressure.

In the following sections we consider how three theoretical developments introduce money into such a framework. The three approaches we discuss are the P-star based model discussed by Hallman *et al.* (1991), Todter and Reimers (1994), Neumann (1997), Svensson (2000) and Gerlach and Svensson (2003); the core money models discussed by Neumann (2003), Neumann and Greiber (2005) and Assenmacher-Wesche and Gerlach (2005); and the noisy indicator model of Aoki (2003) and Svensson and Woodford (2003) upgraded to include monetary indicators by Nelson (2003).

2.2 P-Star Models

The role for a monetary indicator can be introduced by generating inflation expectations from a P-star based model which relies on the quantity theory defined in logarithms as:

$$m_t + v_t = p_t + y_t \tag{7}$$

We can write the long-run equilibrium, where logarithms of output and velocity equal log potential output, y^*_t, and log equilibrium velocity, v^*_t, to define the long run price level as

$$p^*_t = m_t + v^*_t - y^*_t \tag{8}$$

We take a modified form of the dynamic adjustment process for inflation similar to the P-star literature following Hallman *et al.* (1991) as follows

$$\pi_t = (1 - \alpha_{\Delta p})\pi_{t-1} + \alpha_{\Delta p}\Delta p^*_{t-1} - \alpha_p(p_{t-1} - p^*_{t-1}) + \alpha_y(y_t - y^*_t) + \epsilon_t$$

with $0 \leq \alpha_{\Delta p} < 1; \alpha_p > 0; \alpha_y > 0$. Since from (7) and (8) $p_t - p^*_t = -(\widetilde{m}_t - \widetilde{m}^*_t)$, where $\widetilde{m}_t$ denotes real money balances, we find we have an adjustment equation for inflation given by

$$\pi_t = \pi_{t-1} + \alpha_m(\widetilde{m}_{t-1} - \widetilde{m}^*_{t-1}) - \alpha_{\Delta m}\Delta(\widetilde{m}_t - \widetilde{m}^*_t) + \alpha_y(y_t - y^*_t) + \epsilon_t$$

where $\alpha_p = \alpha_m$ and $\alpha_{\Delta p} = \alpha_{\Delta m}$. Following Svensson (2000, 2003) we use this equation to produce inflation forecasts:

$$\begin{aligned} \pi_{t+j+1|t} &= \pi_{t+j|t} + \alpha_m(\widetilde{m}_{t+j|t} - \widetilde{m}^*_{t+j|t}) - \alpha_{\Delta m}\Delta(\widetilde{m}_{t+j+1|t} - \widetilde{m}^*_{t+j+1|t}) \\ &\quad + \alpha_y(y_{t+j|t} - y^*_{t+j|t}) \end{aligned} \tag{9}$$

This states that inflation forecasts are updated by the information contained in the level and change in the real money gap and the output gap. By re-optimization of the canonical model, with equation (9) replacing equation (2), the optimal rule is

$$\begin{aligned} R_t &= (\overline{r} + \pi^*) + \left(1 + \frac{1-c}{\alpha_m\beta_r}\right)[(\pi_{t+j|t} - \pi^*) + \left(\frac{\beta_x}{\beta_r} + \alpha_m\right)(y_{t+j|t} - y^*_{t+j|t}) \\ &\quad + \alpha_m(\widetilde{m}_{t+j|t} - \widetilde{m}^*_{t+j|t}) - \alpha_{\Delta m}\Delta(\widetilde{m}_{t+j+1|t} - \widetilde{m}^*_{t+j+1|t})]. \end{aligned} \tag{10}$$

Therefore the P-star based model infers that a real money gap and the change in the real money gap should be included in the optimal rule. Variants of this rule include Hallman *et al.* (1991), where $\alpha_{\Delta m} = 0, \alpha_y = 0$; and Todter and Reimers (1994) and Neumann (1997) where $\alpha_{\Delta m} = 1, \alpha_y = 0$. We conclude that while Svensson (2000) shows that this model does not provide a rationale for monetary targeting, it does suggest that there is a role for real money gaps in both the expectational Phillips curve (Gerlach and Svensson, 2003) and in the specific instrument rule.

Thus the Svensson hypothesis (H_S) might imply that the information set for predicting directional change in the interest rate includes $H_S = (1, \pi_t, (y - \overline{y})_t, (\widetilde{m} - \widetilde{m}^*)_t, \Delta(\widetilde{m} - \widetilde{m}^*)_t, controls)'$ adding the level and change in the real money gap as monetary indicators to conventional variables such as inflation, the output gap and other control variables discussed later in the data section.

2.3 Core Money Models

In a framework similar in spirit to the previous section, we can consider an inflation expectations process such as

$$\pi_t = \alpha_\pi \pi_{t-1} + (1 - \alpha_\pi)(\pi_{t-1} - \overline{\pi}_{t-1}) + \alpha_y(y_t - y^*_t) \tag{11}$$

where $\overline{\pi}$ is core inflation, which is determined in the long run in the money market, and $0 \leq \alpha_\pi < 1$ is the weight on past inflation. Neumann (2003) and Neumann and Greiber (2005) use such a model with $\alpha_y = 0$.

Core prices are those prices that result from equating the long-run component of money demand, m^l_t, and real money supply, $\widetilde{m}_t$, equations as given by

$$\begin{aligned} m^l_t &= \gamma_y \overline{y}_t - \gamma_r(\overline{r}^l - \overline{r}^s) \\ \widetilde{m}_t &= m_t - p_t = (\overline{m}_t + s_t) - p_t \end{aligned}$$

where $\overline{y}_t$ is long-run output, $(\overline{r}^l - \overline{r}^s)$ is the permanent long-short differential, s_t is a transitory component to money supply, and γ_y and γ_r are coefficients. Thus the long-run price level is

$$\overline{p}_t = \overline{m}_t - \gamma_y \overline{y}_t + \gamma_r(\overline{r}^l - \overline{r}^s)$$

and core inflation is

$$\overline{\pi}_t = \Delta\overline{m}_t - \gamma_y \Delta\overline{y}_t \tag{12}$$

The similarities with P-star models can be seen since $\overline{p}_t = p_t^* - s_t$. In other words core money is the long-run component of the P-star indicator. Therefore, when we use (11) in (12) to generate inflation and use this to form forecasts of future inflation as before we have

$$\pi_{t+j+1|t} = (1-\alpha_\pi)\pi_{t+j|t} + \alpha_\pi(\Delta\overline{m}_{t+j+1|t} - \gamma_y \Delta\overline{y}_{t+j+1|t}) + \alpha_y(y_{t+j} - y^*_{t+j}) \tag{13}$$

Again when we re-optimize the canonical model, replacing equation (2) with equation (13), the optimal rule is

$$\begin{aligned} R_t &= (\overline{r}+\pi^*) + \left(1 + \frac{1-c}{\alpha_\pi \beta_r}\right)[(\pi_{t+j|t} - \pi^*) + \left(\frac{\beta_x}{\beta_r} + \alpha_\pi\right)(y_{t+j|t} - y^*_{t+j|t}) \\ &\quad + \alpha_\pi(\Delta\overline{m}_{t+j|t} - \pi_{t+j|t} - \gamma_y \Delta\overline{y}_{t+j|t})] \end{aligned}$$

The core model adds a term that is similar to the growth in the real money gap, based on the real core money growth, $(\Delta\overline{m}_{t+j|t} - \pi_{t+j|t})$, minus real core money demand, $\gamma_y \Delta\overline{y}_{t+j|t}$. We could think of this as the gap between growth in real money balances and the growth in the permanent component of money demand. If we label this the Neumann hypothesis (H_N) the information set includes $H_N = (1, \pi_t, (y-\overline{y})_t, (\Delta\overline{m}_t - \pi_t - \Delta\overline{y}_t), controls)'$, which adds the change in long-run trend of nominal money less inflation and long-run trend output, and a long-run nominal money gap.

2.4 Noisy Indicator Models

The noisy indicator framework is used by among others Aoki (2003), Svensson and Woodford (2003) and is discussed further by Nelson (2003) to illustrate the use of information in a 'noisy' environment where current observations of variables such as π_t and y_t are observed with error i.e.

$$\pi_t^o = \pi_t + \varepsilon_{\pi t} \tag{14}$$
$$y_t^o = y_t + \varepsilon_{yt} \tag{15}$$

where π_t^o and y_t^o are the observed data in the current period for inflation and output, contaminated with measurement errors $\varepsilon_{\pi t}$ and ε_{yt}, which are independent, normally distributed mean zero processes. Using a similar framework to that of the previous sections, the interest rate would follow a path similar to (6) under full information. But where data are observed with measurement errors Aoki (2003) shows that the central bank deviates from the optimal interest rate implied by the full information solution, and thus interest rates would deviate from the Wicksellian natural rate, $R^*_{t|t-1}$. In a noisy environment the central bank is unable to perfectly control the interest rate because it cannot observe the true values of inflation and output, resulting in a deviation as it learns about demand and supply shocks. An information asymmetry between central bank, which could only observe true values of variables with a one period lag, and the private sector, which could correctly observe the variables in the current period, would generate a modified optimal rule in which the central bank responds to its best guess of the underlying shocks in period t:

$$R_t = R^*_{t|t-1} + r_\pi(\pi_t^o - \pi^*) + r_y(y_t^o - y^*_{t|t-1}) \tag{16}$$

$$\begin{aligned} &= (\overline{r}+\pi^*) + \left(1 + \frac{(1-c)}{\alpha_x \beta_r}\right)[(\pi_{t+j|t} - \pi^*) \\ &\quad + \left(\frac{\beta_x}{\beta_r} + \alpha_x\right)(y_{t+j|t} - y^*_{t+j|t}) + r_\pi(\pi_t^o - \pi^*) + r_y(y_t^o - y^*_{t|t-1})] \end{aligned} \tag{17}$$

In a modified version of this model, Nelson (2003) adds a further structural equation representing the real money demand function:

$$(m_t - p_t) = \mu_1 E_t(m_{t+1} - p_{t+1}) + \mu_2(m_{t-1} - p_{t-1}) + \mu_y y_t + \mu_R R_t + \eta_t$$

where the forward- and backward-looking terms in the real money variable, $(m_t - p_t)$, are justified by portfolio adjustment costs in an otherwise standard real money demand function and η_t is a demand shock. We characterize the Aoki (2003) reaction function as:

$$R_t = R_{t|t-1} + \gamma(Z_t - Z_{t|t-1}) + \Lambda\phi_{t-1} \tag{18}$$

where $Z_t' = (\pi_t^o, y_t^o)$ is a vector of noisy variables, $\phi_{t-1}$is a term in the Lagrangian multipliers of the first order conditions, and γ and Λ are vectors of coefficients. The optimal rule implies the interest rate should be adjusted to the forecastable part of the natural rate, $R_{t|t-1}$, and the supposed deviations of inflation and output from their predicted values. The modification by Nelson introduces a monetary indicator since the information set, Z_t, is augmented with a noisy *nominal* money growth variable, such that $Z_t' = (\pi_t^o, y_t^o, \Delta m_t^o)$. The modified rule includes information from nominal money growth shocks estimated by the central bank using its best guess of the true money growth rate relative to the observed growth rate, which is distorted by demand shocks. This evidently introduces a role for money as an information variable in the optimal policy rule.

$$\begin{aligned} R_t &= (\bar{r} + \pi^*) + \left(1 + \frac{(1-c)}{\alpha_x \beta_r}\right)[(\pi_{t+j|t} - \pi^*) + r_m(\Delta m_t^o - \Delta m_{t|t-1}) \\ &\quad + \left(\frac{\beta_x}{\beta_r} + \alpha_x\right)(y_{t+j|t} - y_{t+j|t}^*) + r_\pi(\pi_t^o - \pi^*) + r_y(y_t^o - y_{t|t-1}^*)] \end{aligned} \tag{19}$$

The Aoki-Nelson hypothesis (H_{AN}) implies the information set should be: $H_{AN} = (1, \pi_t, (y - \bar{y})_t, (\Delta m_t^o - \Delta m_{t|t-1}), controls)'$, which adds a term in the deviation of the growth of nominal money around its predicted value as a monetary indicator.

2.5 Prediction of Discrete Changes in the Instrument

The instrument rules in the previous sections imply that the central bank will make continual adjustment to the interest rate according to the realised values of the explanatory variables but central banks do not make continual adjustments to their policy instrument for two reasons. First, they hold periodic meetings when they assess the information that has accrued since the previous meeting to make a decision about whether rates should be changed, and second, if a rate change is warranted it is typically administered in terms of 25 or 50 basis points, or larger discrete steps. For this reason we consider the prediction of directional change in interest rates based on the information content from the theory outlined in the previous section.

We use the logit model in order to investigate forecasts of the *directional change* of the base rate, denoted by ΔR_t. In our model there are three possible states for the change in the interest rate: 'downwards', 'no change' and 'upwards'[5]. Accordingly we define a random variable q_t to take

[5] The justification for our choice of three categories comes from the properties of our data, since the majority of changes in rates over the decade 1993-2003 were made in 25 basis point steps (up or down). In only four cases were changes made in 50 basis point steps. While five categories would allow us to take into account the few occasions when rates were cut by 50 basis points, our estimates of the probabilities of a positive or nagative change in rates by 50 basis points would be based on four observations when rates did actually change by this amount.

the values 0, 1 and 2 according to the following relation:

$$\begin{aligned} q_t &= 0 \Longleftrightarrow \Delta R_t < 0, \\ q_t &= 1 \Longleftrightarrow \Delta R_t = 0, \\ q_t &= 2 \Longleftrightarrow \Delta R_t > 0. \end{aligned}$$

Let X_t represent a $k \times 1$ vector of explanatory variables (the relevant information set) available at time t, with the first element of X_t set equal to one. In the logit model, the probability of $q_t = 0, 1$ or 2 conditional on X_t is defined using the logit cumulative density function:

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

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

$$\mathcal{L}(\beta_1, \beta_2) = \sum_{t=1}^{T} \sum_{j=0}^{2} \mathbf{1}[q_j = j] \Pr(q_t = j \mid X_t)$$

where $\mathbf{1}[\cdot]$ is the indicator function. By maximizing the log-likelihood function using LIMDEP to compute the logit estimators $\hat{\beta}_1$ and $\hat{\beta}_2$ and determine the predicted probabilities $\hat{P}_0, \hat{P}_1$ and $\hat{P}_2$, our directional prediction $\widehat{q}_t$ is then given by

$$\widehat{q}_t = m \quad \text{if} \quad \hat{P}_m = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2). \tag{20}$$

We estimate the predictive performance by choosing the most likely direction of change, and having determined the prediction we compare these against the actual outcomes in-sample and out-of-sample.[6] We evaluate the performance of the information set using two criteria. The first is the proportion of correct predictions when we associate the direction of predicted changes against the actual changes of the base rate denoted as $SC = \frac{1}{T}\sum_{t=1}^{T} \mathbf{1}\left(\widehat{q}_t = q_t\right).$

It provides an indication of the proportion of correct predictions in the sample, however it has the disadvantage that a dominant outcome can give the appearance of good predictive performance simply because a poor predictor may permanently select this outcome and would appear to correctly predict whenever the dominant outcome occurs. Like a stopped clock this predictor would be correct some of the time, and with a dominant outcome this might be the majority of the time. To overcome this disadvantage we also report a second measure of performance proposed by Merton (1981) to give a truer indication of predictive ability. Let CP_j be the conditional prediction measure showing the proportion of correct predictions made by $\widehat{q}_t$ when the true state is given by $q_t = j$. From the definition of conditional probability, CP_j is computed by $CP_j = \frac{\frac{1}{T}\sum_{t=1}^{T} \mathbf{1}(\widehat{q}_t = j)\mathbf{1}(q_t = j)}{\frac{1}{T}\sum_{t=1}^{T} \mathbf{1}(q_t = j)}$. Merton's correct measure denoted CP is given by $CP = \frac{1}{J-1}\left[\sum_{j=0}^{J-1} CP_j - 1\right]$ where J is the number of

[6] Under some circumstances this algorithm would give a misleading picture, for example where all three probabilities are close to one third but one outcome marginally dominates. However, these 'two-sided dissents' are very rare: the MPC has had three cases of two-sided dissent since May 1997, but never a close decision where the votes cast for each outcome were more or less equally divided. One-sided dissents and unanimous outcomes are by far the most common result based on the balance of upside and downside risks demonstrated in information variables. In these cases the algorithm should be reliable.

categories. The measure always lies between $-\frac{1}{J-1}$ and 1. For a "stopped-clock" predictor that selected only one outcome that happened to be the dominant outcome where SC would appear to show good predictive ability, but the CP would be close to zero or even negative implying that the predictive ability was poor.

3 Data

Our objective is to predict the direction of change in rates set by the Bank of England over the period 1992 - 2003. This has some distinct advantages since the data are all taken from a period of inflation targeting with no regime change within our sample[7]. Also, with a few exceptions immediately after inflation targeting became the objective of monetary policy, changes in interest rates at a regular monthly frequency have been made in 25 basis point steps. We can readily implement the methodology outlined in the previous section since the decisions of the committee have in practice been whether to change rates upwards, downwards or to leave them at their existing level.

To evaluate the ability of outside observers to predict the direction of change in the interest rate we initially consider predictive information in two information sets that exclude monetary indicators: the first is the information used in a Taylor rule, and the second is a wider information set that includes control variables that central banks routinely use to judge inflationary pressure of which the exchange rate, input prices, and average earnings proved important. These information sets can be written as $H_T = (1, \pi_{t+12}, (y-\overline{y})_t)'$and $H_W = (1, \pi_{t+12}, (y-\overline{y})_t, \Delta R_{t-1}, \Delta^{12} ex_t, \Delta^{12} aei_t, \Delta^{12} inp_t,)'$.

Unless the theoretical model indicates otherwise we always refer to inflation twelve months ahead, π_{t+12}, to allow for a reasonable degree of forward-lookingness without limiting the number of observations available for estimation excessively[8]. This is measured as the annualized change in the retail price index minus mortgage interest payments, RPIX, the stated target for the Bank of England during our sample period. In addition we include the output gap, $(y$-$\overline{y})_t$, with the natural rate y^* proxied by a long-run trend, $\overline{y}$. The long-run trend is derived using either a Hodrick-Prescott filter or a linear-quadratic trend following Clarida *et al.* (1998), which allows us to evaluate whether our findings are influenced by the filtering process. One concern in particular is that the Hodrick Prescott (HP) filter is two-sided, using future as well as past and contemporary data and therefore is not strictly consistent with real-time policymaking decisions, although forward-looking policymakers might make use forecasts of output to determine the long-run trend in output. Our results reported later illustrate that the use of a linear-quadratic (LQ) trend to filter the data provide identicial predictive performance based on long-run trend output that is not reliant on future data. The correlation between the two proxies for the long-run trend is 0.72. The output data used in this paper is monthly GDP reported by the *National Institute for Economic and Social Research* and described in detail in Mitchell *et al.* (2005); this is a more representative indicator of aggregate demand pressures than the index of industrial production often used in empirical studies of policy rules, is 'real-time' and is not revised[9]. We also add the variable ΔR_{t-1}, which is the 1-month

[7] Budd (1998) and King (1997, 2002) offer descriptions of the process by which the MPC makes its decisions.

[8] The Bank of England has no official horizon for inflation, although it typically projects inflation over a two year horizon. Its own projections are reported in a fan chart, but rarely deviate from the target value at 24 months ahead, making their own forecasts relatively uninformative for our purpose. Preliminary estimates were conducted on inflation horizons ranging from t-1 to t+24 and these results are available from the authors on request.

[9] The monthly GDP series are constructed with a short lag of about five weeks and are publicly available from the National Institute. This data would have been available as recorded to the monetary policy committee in the later part of the sample. However, the MPC could not have seen the data for the earlier part of the sample since the series was constructed in the early 2000s and was backcast to form a time series from that point using the component

lagged change in the Treasury Bill rate, and control variables for other influences on the decision to change rates. The change in the Treasury Bill rate captures a smoothing effect (see Goodhart, 1996, Sack, 1998, and Rudebusch, 2002), and the anticipations in short-term market rates of a change in the official rate. The remaining control variables are measured by the annualized changes in the sterling effective exchange rate index, $\Delta^{12}ex_t$,the average earnings index, $\Delta^{12}aei_t$, and the input price index, $\Delta^{12}inp_t$ to allow for the significant influence of other inflationary pressures discussed in the Bank of England's Inflation Report that might also affect the directional change of interest rates.

We include monetary indicators using three different measures that correspond to the P-star models, the core money models and the noisy indicator models referred to previously. In all cases the monetary measure is based on the monthly amounts outstanding of monetary financial institutions' sterling M4 liabilities to the private sector (in sterling millions) seasonally adjusted. The P-star models use real money balances, constructed by subtracting the retail price index from the nominal amounts, and subtracting from these the desired holdings of sterling M4 to derive the so-called real money gap. Desired real money balances are determined from a long-run trend in real money balances extracted using either the Hodrick-Prescott filter or the linear-quadratic trend, making the real money gap a similar concept to the output gap. The real money gap and the change in the real money gap are added to the twelve-period ahead inflation rate and the output gap plus controls to form a new information set, $H_S = (1, \pi_{t+12}, (y - \overline{y})_t, (\widetilde{m} - \widetilde{m}^*)_t, \Delta(\widetilde{m} - \widetilde{m}^*)_t, \Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1})'$.

The core money model focuses on the long-run nominal money growth in relation to long-run output growth and inflation. The monetary measure used to supplement the twelve-period ahead inflation rate and the output gap is the long-run trend growth of nominal money balances (the Hodrick Prescott filter of the change in the logarithm of M4 balances) minus inflation and the long-run trend growth of output (either the Hodrick-Prescott filter or the linear-quadratic trend of the change in the logarithm of monthly GDP), $H_N = (1, \pi_{t+12}, (y - \overline{y})_t, (\Delta\overline{m}_{t+12} - \pi_{t+12} - \Delta\overline{y}_{t+12}), \Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1})'$

The noisy indicator models include a measure of the nominal money gap, constructed in the same way as the output gap by subtracting either the Hodrick-Prescott filter or the linear-quadratic trend of the change in the logarithm of M4 balances from actual values. This measure provides a guide to the unpredictable growth of M4 balances which is used to supplement the forward-looking inflation and output gap information. Since this model uses the central bank's own best guess of the interest rate, we include the lagged short term interest rate as a further information variable. The information set is $H_{AN} = (1, \pi_{t+12}, (y - \overline{y})_t, (\Delta m_t^o - \Delta m_{t|t-1}), \Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1})'$. The sample period of 1993/03 to 2003/06 gives 125 observations for predicting the directional change in the interest rate.

4 In-Sample Predictions

The logit estimation results are given in Table 1. The table provides a summary of the predictive performance of different information sets based on the 'stopped clock' (SC) and correct predictions (CP) methods of determining predictive ability. These are evaluated twice, once for data that is detrended using the HP filter and again for the data detrended using the LQ trend method. A comparison of the SC and CP scores in each case reveals that the predictive ability in each case

series. They would certainly have seen the major component series comprising the index of industrial production, construction and private services (extracted from retail sales, productive activity and monthly trade data) in real time.

is virtually identical. It appears that the two-sided nature of the HP filter does not distort the results in comparison to an alternative filter than makes no use of future dated information. Also, the relative improvement in the predictive performance with the addition of information, and in particular monetary information, is very similar. The conclusions drawn from an LQ detrended dataset would not differ from those drawn from an HP detrended dataset. We now evaluate the results in more detail[10].

4.1 Preliminary Information Sets

In Table 1 the Taylor rule information set appears to predict well, since seventy percent of the time the predictions are correct: the model correctly identifies 78 occasions when the 'no change' outcome occurs. However, it does so because it always predicts 'no change', and it never correctly predicts an upward or downward change in rates. This is a classic 'stopped clock' prediction problem, identified by Bodie *et al* (1996), and can be illustrated from a cross-tabulation of predicted against observed outcomes in a contingency table. When we associate the direction of predicted changes against the actual changes of the base rate, Table 2 shows the proportion of correct predictions SC for the Taylor rule information set, which always predicts 'no change' in the interest rate in all 112 cases without a single exception. The appearance of high predictive ability stems from the fact that the no change state occurs the majority of the time, and in these 78 cases the prediction coincides with the actual outcome. Our conditional prediction indicator shows $CP_0 = \frac{0}{20}, CP_1 = \frac{78}{78}$ and $CP_2 = \frac{0}{14}$ and $CP = 0.00$, suggesting a very poor predictive performance.

When we widen the information set to include other variables that the Bank of England routinely considers in judging whether a change in the interest rate is required, based on the information provided in the quarterly *Inflation Report* we find some improvement on the basic Taylor rule information set. We use representative control variables such as annualized changes in the exchange rate, input prices, and average earnings to indicate inflationary pressures, but exclude monetary indicators at this stage. The SC and CP indicators of predictive ability improve. The proportion of correct predictions is given by $SC = 0.79$. A larger number of correct predictions when the interest rate increased or decreased means that the $CP = 0.42$ improves markedly, hence the true predictive ability is improved. This result is not due to the fact that we have increased the number of explanatory variables included in our information set. Some of our control variables are insignificant despite the fact that they are included in the equations to predict directional change. In the next section we consider whether monetary indicators might further improve the in-sample predictive ability.

4.2 Monetary Indicators

The estimation result based on the three monetary indicators is shown in Table 1. In each panel we add monetary indicators to the information set including just the basic Taylor rule information; we then add successive control variables. Given the improvement in the directional change predictions in the previous section when control variables are added it is unsurprising to find that SC and CP predictions for the monetary aggregates in isolation improve further when we also add control variables. Our findings show that all three monetary indicators have a statistically significant impact in determining the probabilities of a directional change in the interest rate: in all but one case the monetary variables are statistically significant in the predictive equations, and the SC and CP indicators are always higher than information sets that exclude monetary information.

[10] Contingency tables and forecast performance indicators are derived from HP filtered data but the same information has been generated for LQ detrended data and the results are available from the authors on request.

In order to compare the performance of information sets including monetary indicators with the preliminary non-monetary information sets we include all the control variables in the information set to ensure that the latter is a nested model. The models including the control varaibles uniformly gave the maximum CP score for all types of monetary indicator. We focus our attention on the predictive ability of the information sets with the maximum CP score in each case[11].

Table 2 shows the contingency table of predicted against observed outcomes for each monetary indicator based on the maximum CP criterion. All three peform well in-sample and there is little to choose between them. For the real money indicator the proportion of the correct prediction against the actual outcomes is $SC = 0.79$[12]. There is far more variation in the predictions, and the 'no change' is still the dominant outcome in accordance with the pattern of decisions in the data, but it is not exclusive of other outcomes. The fact that these other outcomes are occasionally predicted implies that the information sets including monetary data set are richer than the preliminary information sets. 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 $CP_0 = \frac{11}{20}, CP_1 = \frac{71}{78}$ and $CP_2 = \frac{7}{14}$. These figures result in a better correct predictions measure for the preliminary information sets ($CP = 48$ per cent), which indicates that a real money indicator improves the prediction of the directional change.

Similar results are found with the core money indicator and the nominal money indicator. For the core money indicator the proportion of the correct prediction against the actual outcomes is $SC = 0.80$, with no counter predictions, and the number of correct predictions against the actual outcomes for each state ('down', 'no change' and 'up' respectively) are $CP_0 = \frac{9}{20}, CP_1 = \frac{73}{78}$ and $CP_2 = \frac{8}{14}$, giving $CP = 48$ per cent. For the nominal money indicator $SC = 0.79$, with no counter predictions, and the Merton correct predictions statistics are $CP_0 = \frac{11}{20}, CP_1 = \frac{71}{78}$ and $CP_2 = \frac{7}{14}$, giving $CP = 48$ per cent.

These findings focus on the in-sample performance of the monetary indicators, and show strong evidence of additional predictive ability when monetary information is included in the information set. To be sure that our results are empirically useful we seek to confirm these results in out-of-sample forecasts of direction of change.

5 Out-of-Sample Predictions

To produce out-of-sample predictions of the directional change we make one-step ahead predictions of the interest rate, that is $\widehat{q}_{t+1}$, 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 initialization 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[13]. 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 (that is, the forward-looking inflation rate is now replaced by its first-lagged value). The initial estimation window is 1993/03 to the

[11] In fact the predictive ability with lower CP scores is still impressive and in all cases predicts better than the Taylor rule information set.

[12] In all cases we report the predictions from multinomial logit estimates but a similar level of prediction is achieved with ordered probit estimates (results available from authors on request).

[13] We also examined the forecasting performance out-of-sample using a rolling window method but the results were unchanged.

observation 1998/12 with 70 observations. The first prediction date is 1998/01 and we make 66 out-of-sample predictions.

5.1 Forecasting using Preliminary Information Sets

Table 3 shows the cross-tabulations of the predicted against observed outcomes using the Taylor rule information only and the information set that also includes the control variables. 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 none of the sixty-six out-of-sample predictions does the prediction deviate from 'no change'. The dominant 'no change' outcome leads us to expect the Merton test of correct predictions will be unimpressive, and $CP = 0.00$ as before, which implies the Taylor rule information set has no predictive performance out-of-sample. Attempts to predict the direction of change using this information set would only be right when no change was made, and would always fail to predict any actual change in rates. For the information supplemented with control variables the predictions are much improved. The $SC = 73$ per cent and the Merton correct prediction measure indicates $CP = 43$ per cent. The deviation from a single prediction of no-change is marked, and yet there are no predictions of an increase when a decrease occurs and vice versa.

5.2 Forecasting using Monetary Indicators

Table 3 also illustrates the contingency table of the predicted against actual outcomes out-of-sample results for the monetary indicators. This model can predict by drawing on a greater range of information besides the preliminary information sets which are nested in the model. The real money indicator has a superior percentage of correct predictions against the actual outcomes based on the $SC = 79$ per cent against these information sets and the higher proportion of the correct predictions against the actual outcomes does not result from a dominant outcome. The evidence shows that real money indicators predict much better based on Merton's correct predictions measure from the out-of-sample exercise with a figure of $CP = 60$. Other indicators show similar levels of performance relative to the preliminary information sets. The core money indicator has $SC = 77$ per cent and a $CP = 52$ per cent, while the nominal money indicator has a $SC = 76$ per cent $CP = 49$ per cent. On out-of-sample forecasts using the maximum CP criterion as the discriminator the real money gap information set offers better predictive ability than the other monetary indicators, providing strong evidence of better predictive performance over all other information sets with the capability to accurately predict the direction of change in the interest rate.

5.3 Diagnostic Performance

None of the models used to predict the directional change was able to reject the hypothesis that the variables used to make the prediction were jointly insignificant on the basis of a Chi-squared (χ^2) test. The McFadden psuedo-R^2 (goodness-of-fit) measure improved with the addition of monetary information.

A further test of the superior out-of-sample performance when using monetary indicators can be provided by calculating the mean squared prediction errors out-of-sample. Let R_t be the actual base rate at time t over the out-of-sample period (where $t = 1998/01, ..., 2003/06$ and the total number of observations is 66). We define $R^I_{t|t-1}$ be the predicted base rate for time t based on an information set I available up to time $t-1$ where the information set I corresponds to the five different information sets discussed in the previous section. 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, given by:

$$MSPE = \frac{1}{66}\sum_{t=1}^{66}(R_t - R^I_{t|t-1})^2$$

Table 4 reports the results indicating that prediction errors are much reduced by using additional information from monetary indicators compared to the information from a Taylor rule. The mean squared prediction errors are 86%, 64% and 55% of those for the Taylor rule.

Although we found that the monetary indicators have greater ability to predict the direction of change in the interest rate with more accuracy than other information sets, 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 is significantly different from zero in each case. This can be tested by the χ^2-independence test as used 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 T_i be the total for the i^{th} row and C_j be the total for the j^{th}column in the contigency table, then, the expected number of observations in each entry, denote by $\widehat{E}_{ij}$, is defined as $\widehat{E}_{ij} = \frac{T_i C_j}{N}$ where N is the total number of observations. 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 contingency 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). For the monetary indicators the statistics reported in Table 4 are compared to the 5 per cent critical value of 9.49 and clearly reject the null of no association, which implies that there *are* associations between the predicted and the actual outcomes when using the monetary indicators. We can conclude that the ability to predict the direction of change in the interest rate using these indicators does not arise by chance.

To evaluate the relative performance of the association between the predictor and the actual series in our many contingency tables we can use the Cramer's V-statistic. This is a scaled measure of the Chi-square (χ^2) test which can be used to directly compare the degree of association in one contingency table to another. Since the Cramer's V always lies between 0 and 1, where 0 indicates no association between the actual and predicted outcomes and 1 indicates perfect association between the two categories, we can evaluate the strength of the association between the predictor and the actual outcome. Comparing our information sets out-of-sample we find the V-statistics are 0.47, 0.58, 0.49, 0.52 for the information sets based on the 'Taylor rule plus', the real money indicator, the core money indicator and the nominal money indicator. This suggests that the real money indicator has the strongest association with the actual path of interest rates, but the nominal indicator also has quite strong association. The V-statistic of strength in association is almost identical to the CP indicator of conditional prediction in terms of scale

5.4 Predicted Interest Rate Paths

The final test of the performance of our information sets is to consider the predicted paths that interest rates would have followed if the predictions from each information set had been followed.

We compare these paths with the actual path in Figure 1. The Taylor rule information set performs badly since it predicts no change and rates stay constant at 7.25 percent, but other indicators have sufficient variation to follow the actual path of interest rates much better. The first reduction in rates from July 1998 to December 1999 is identified by all information sets, although the monetary indicators follow the actual path most closely. The subsequent levelling off of rates and the following increase is also captured by these indicators, but they continue to predict rate increases beyond the point that actual rates increase. This overprediction of the number of increases distorts the picture of subsequent predictions, which are largely correct in determining the timing of changes, but incorrect on the magnitude of the level of rates, which are between 75-125 basis points above the level of actual rates. All the indicators pick up the downturn in rates in 2001 and the real money indicator and the core money indicators pick up a further reduction in 2003.

6 Discussion and Conclusions

This paper has used a canonical theoretical framework to consider relevant information sets for the prediction of direction change in interest rates. We formulate monetary policymaking in terms of a derived rule for interest rates and model the decision process using a discrete limited dependent variable that uses information to decide between three possible outcomes for interest rates: an increase, decrease or no-change. This represents a step forward in the literature that has almost exclusively focused on modeling the operational interest rate as a continuously adjusting variable (the level of interest rates) as a function of a small set of variables, typically just inflation and the output gap. Using monthly data from the United Kingdom we find that this information set as a predictor of interest rate change has some superficial success. It appears to perform well, both in-sample and out-of-sample, but closer inspection shows that this is largely because the 'no change' outcome dominates in the inflation targeting regime of recent years. When genuine predictive ability is evaluated allowing for the 'stopped clock' phenomenon, it is a poor predictor. We find that a predictor based on monetary indicators improves predictions substantially both in-sample and out-of-sample.

This result adds to a growing literature that shows a role for monetary indicators. Various approaches that extract the core monetary trend using time series filtering techniques find the core measure as a monetary indicator predicts inflation even allowing for the impact of other explanatory variables (see Altimari, 2001, Trecroci and Vega, 2002, Gerlach and Svensson, 2003, Gali *et al.*, 2004, Assenmacher-Wesche and Gerlach, 2005, Benati, 2005, Bruggemann *et al.*, 2005, Neumann and Greiber, 2005). The relevance of the core measures to inflation indicates that deviations of monetary growth from the core measure ought to be an indicator of the need to change rates and this is what we find in this paper. Our results quantify the extent of the improvement in predictive ability when monetary information is added to conventional information sets and the gains are substantial.

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Table 1: Predictive Performance In Sample

Information set	Significant variables	HP SC	HP CP	LQ SC	LQ CP
Preliminary Information Sets					
$\pi_{t+12}, (y-y^*)_t$	$\pi_{t+12}, (y-y^*)_t$	0.70	0.00	0.70	0.00
$\pi_{t+12}, (y-y^*)_t, \Delta^{12}ex_t, \Delta^{12}aei_t,$	$\pi_{t+12}, \Delta^{12}ex_t, \Delta^{12}inp_t, \Delta R_{t-1}$	0.79	0.42	0.80	0.48
$\Delta^{12}inp_t, \Delta R_{t-1}$					
Real Money Indicators					
$\pi_{t+12}, (y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t,$	$(y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t, \Delta R_{t-1}$	0.71	0.19	0.73	0.26
$\Delta(\widetilde{m}-\widetilde{m}^*)_t, \Delta R_{t-1}$					
$\pi_{t+12}, (y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t,$ $\Delta(\widetilde{m}-\widetilde{m}^*)_t, \Delta^{12}ex_t, \Delta R_{t-1}$	$(y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t, \Delta^{12}ex_t,$ ΔR_{t-1}	0.79	0.43	0.79	0.45
$\pi_{t+12}, (y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t,$ $\Delta(\widetilde{m}-\widetilde{m}^*)_t, \Delta^{12}ex_t, \Delta^{12}aei_t, \Delta R_{t-1}$	$(y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t, \Delta^{12}ex_t,$ ΔR_{t-1}	0.80	0.48	0.79	0.48
$\pi_{t+12}, (y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t, \Delta(\widetilde{m}-\widetilde{m}^*)_t,$	$\pi_{t+12}, (y-y^*)_t, (\widetilde{m}-\widetilde{m}^*)_t,$	0.79	0.48	0.79	0.48
$\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1}$	$\Delta^{12}ex_t, \Delta R_{t-1}$				
Core Money Indicators					
$\pi_{t+12}, (y-y^*)_t, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12}$ $, \Delta R_{t-1}$	$(y-y^*)_t, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ ΔR_{t-1}	0.71	0.19	0.72	0.20
$\pi_{t+12}, (y-y^*)_t, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ $\Delta^{12}ex_t, \Delta R_{t-1}$	$\pi_{t+12}, \Delta^{12}ex_t, \Delta R_{t-1}$	0.76	0.35	0.77	0.35
$\pi_{t+12}, (y-y^*)_t, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ $\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta R_{t-1}$	$\pi_{t+12}, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ $\Delta^{12}ex_t, \Delta R_{t-1}$	0.76	0.36	0.79	0.40
$\pi_{t+12}, (y-y^*)_t, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ $\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1}$	$\pi_{t+12}, (\Delta\overline{m}-\pi-\Delta\overline{y})_{t+12},$ $\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1}$	0.80	0.48	0.80	0.50
Nominal Money Indicators					
$\pi_{t+12}, (y-y^*)_t, (m-m^*)_t, \Delta(m-m^*)_t,$	$(m-m^*)_t, \Delta R_{t-1}$	0.72	0.27	0.70	0.18
ΔR_{t-1}					
$\pi_{t+12}, (y-y^*)_t, (m-m^*)_t, \Delta(m-m^*)_t,$ $\Delta^{12}ex_t, \Delta R_{t-1}$	$(m-m^*)_t, \Delta(m-m^*)_t,$ $\Delta^{12}ex_t, \Delta R_{t-1}$	0.80	0.45	0.76	0.37
$\pi_{t+12}, (y-y^*)_t, (m-m^*)_t, \Delta(m-m^*)_t,$ $\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta R_{t-1}$	$(m-m^*)_t, \Delta^{12}ex_t, \Delta R_{t-1}$	0.80	0.48	0.78	0.40
$\pi_{t+12}, (y-y^*)_t, (m-m^*)_t, \Delta(m-m^*)_t,$ $\Delta^{12}ex_t, \Delta^{12}aei_t, \Delta^{12}inp_t, \Delta R_{t-1}$	$\pi_{t+12}, (m-m^*)_t, \Delta^{12}ex_t,$ ΔR_{t-1}	0.79	0.48	0.79	0.41

HP: Hodrick-Prescott filter

LQ: Linear-quadratic trend

SC: "Stopped-clock" measure of predictability

CP: "True" measure of predictability

Table 2: Contingency Tables - In Sample (Maximum CP criterion)

(A)			SC=0.70	CP=0.00
		Predicted		
Actual	0	1	2	Total
0	0	20	0	20
1	0	78	0	78
2	0	14	0	14
Total	0	112	0	112
(B)			SC=0.79	CP=0.42
		Predicted		
Actual	0	1	2	Total
0	8	12	0	20
1	2	74	2	78
2	0	7	7	14
Total	10	93	9	112
(C)			SC=0.79	CP=0.48
		Predicted		
Actual	0	1	2	Total
0	11	9	0	20
1	5	71	2	78
2	0	7	7	14
Total	16	87	9	112
(D)			SC=0.80	CP=0.48
		Predicted		
Actual	0	1	2	Total
0	9	11	0	20
1	4	73	1	78
2	0	6	8	14
Total	13	90	9	112
(E)		Predicted	SC=0.79	CP=0.48
Actual	0	1	2	Total
0	11	9	0	20
1	3	71	4	78
2	0	7	7	14
Total	14	87	11	112

(A) Taylor rule information set

(B) Taylor rule information set plus control variables

(C) Real monetary indicator

(D) Core monetary indicator

(E) Nominal monetary indicator

Table 3: Contingency Tables - Out-ot-Sample (Maximum CP criterion)

(A)			SC=0.70	CP=0.00
		Predicted		
Actual	0	1	2	Total
0	0	15	0	15
1	0	46	0	46
2	0	5	0	5
Total	0	66	0	66
(B)			SC=0.73	CP=0.43
		Predicted		
Actual	0	1	2	Total
0	7	8	0	15
1	6	38	2	46
2	0	2	3	5
Total	13	48	5	66
(C)			SC=0.79	CP=0.60
		Predicted		
Actual	0	1	2	Total
0	8	7	0	15
1	2	40	4	46
2	0	1	4	5
Total	10	48	8	66
(D)			SC=0.77	CP=0.52
		Predicted		
Actual	0	1	2	Total
0	9	6	0	15
1	4	39	3	46
2	0	2	3	5
Total	13	47	6	66
(E)		Predicted	SC=0.76	CP=0.49
Actual	0	1	2	Total
0	8	7	0	15
1	3	39	4	46
2	0	2	3	5
Total	11	48	7	66

(A) Taylor rule information set

(B) Taylor rule information set plus control variables

(C) Real monetary indicator

(D) Core monetary indicator

(E) Nominal monetary indicator

Table 4: Diagnostic Statistics

Information set	(I) Pseudo-R^2	(II) χ^2 exclusion test	(III) MSPEs	(IV) χ^2 test of association
Taylor rule	0.25	45.82 (0.00)	4.97	N/A
Taylor rule plus control variables	0.38	69.73 (0.00)	3.06	29.60 (0.00)
Real money indicator	0.44	80.56 (0.00)	4.28	44.60 (0.00)
Core money indicator	0.45	81.90 (0.00)	3.19	32.08 (0.00)
Nominal money indicator	0.40	72.86 (0.00)	2.77	36.06 (0.00)

(I) Goodness-of-Fit (In-sample)

(II) Overall significance of regressors (In-sample)

(III) Mean square prediction errors (Out-of-sample)

(IV) Test of association between actual and predicted outcomes in contingency tables (Out-of-sample)

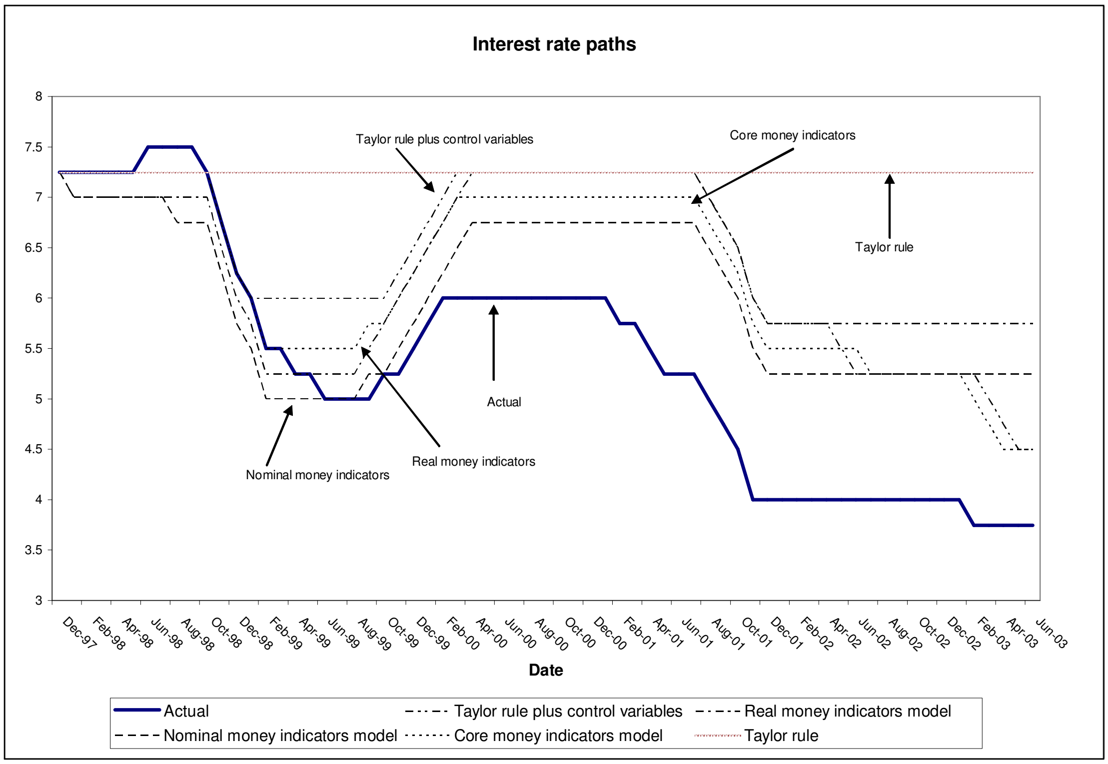

Figure 1: Interest rate paths