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by

Tae-Hwan Kim, Paul Mizen and Alan Thanaset

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Tae-Hwan Kim, Paul Mizen and Alan Thanaset*

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Abstract

Making accurate forecasts of the future direction of interest rates is a vital element when making economic decisions. The focus on central banks as they make decisions about the future direction of interest rates requires the forecaster to assess the likely outcome of committee decisions based on new information since the previous meeting. We characterize this process as a dynamic ordered probit process that uses information to decide between three possible outcomes for interest rates: an increase, decrease or no-change. When we analyze the predictive ability of two information sets, we find that the approach has predictive ability both in-sample and out-of-sample that helps forecast the direction of future rates.

*Corresponding Author: Paul Mizen, University of Nottingham, University Park, Nottingham, NG7 2RD, UK. email: paul.mizen@nottingham.ac.uk. We are grateful to the Experian Centre of Economic Modelling for funding this research and Tae-Hwan Kim is grateful to the College of Business and Economics for financial support under the project code 2005-1-0244. We thank Mike Artis, Anindya Banerjee, Roel Beetsma, Keith Blackburn, Mick Devereux, Stefan Gerlach, Petra Gerlach-Kristen, Edward Nelson, Denise Osborn, Alan Timmerman, 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.

1 Introduction

Forecasting the direction of future interest rates is essential for economic decision making, since without a clear idea about the direction of interest rates into the future, the consequences of economic choices cannot be properly evaluated. Short term interest rates can exercise considerable leverage over the future path of economic variables (see Goodfriend, 1991), and for this reason the decisions of central bankers are anticipated and heavily scrutinized. Central to the process of determining the future path of interest rates are the actions of central banks that set interest rates, and with greater independence, transparency and accountability the financial markets have more economic information on this process than was previously the case. This information is quickly filtered into forecasts and the movement of yield curves; but despite the ready availability of information, predicting the future direction of rates is by no means easy. Simple rules that characterize central bank behavior such as the Taylor rule appear useful as a 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 the rule offers 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, 2000) it previously has had unstable coefficients and poor out-of-sample forecast performance (see Gerlach, 2005, and Gerlach-Kristen, 2003).

Part of the reason for its poor performance is that the interest rate is highly autocorrelated. This occurs for several reasons inherent in the rate setting process within central banks. First, central banks often set rates by committee - and the need to build an argument to persuade colleagues of the case for change results in periods of no change. Second, central banks are reluctant to reverse changes in rates, which undermines credibility, and therefore appear to smooth rates, leaving interest rates on hold as they assess economic conditions. Rates are also often changed in steps, which results from gradual increases or decreases in rates as committees attempt to gauge the degree of tightening or loosening required in response to economic data. Figures 1 and 2 shows that the interest rate has a step-wise pattern due to the tendency to change rates by a standard amount (25 basis points) and the high frequency of 'no-change' outcomes of central bank committee decisions. The histogram of the frequency of changes illustrates the dominance of the no change option, but the time series graph illustrates the positive autocorrelation in rates, with rate changes in a particular direction being followed by a succession of similarly signed changes.

This means that time series of short-term interest rates under the control of the central bank exhibit high persistence and under these circumstances the best guide to the level of interest rate may be its previous value or its previous direction of change. Occasionally, however, new information emerges to cause rates to change, and a predictor that simply takes the previous value as the most likely value for future rates will prove to be inaccurate. Embedding economic information seen by the policymaking committee is likely to determine when the committee will react to signals to alter the directional change of interest rates. The Taylor rule can be regarded as an effective way of summarizing the behavior of the level of the interest rates using a simple information set comprising the inflation rate and the output gap, but there is no guarantee that this information is sufficient to summarize the policymaker's actions and further information may be more informative when predicting directional change. This paper assesses the predictive power of different information sets for the UK rate setting process using a dynamic probit model to capture the discrete nature of committee decisions (c.f. Eichengreen et al., 1985). Here we determine whether the information accurately predicts the next *most likely* change using monthly data. We base our results on the predictions from several different information sets including a random walk model, a random walk in first differences, the Taylor rule information set and a wider information set augmenting the Taylor rule information with growth rates in monetary, exchange rate, earnings and factor cost variables based on a decade of data from the monthly meetings of the Bank of England monetary policy committee. We make predictions of the direction of change in the interest rate in-sample and out-of-sample using a range of summary statistics to evaluate the proportion of correct predictions from each information set. Our results suggest that additional contemporaneous information makes accurate and improved predictions compared to a Taylor rule baseline out-of-sample.

The paper is organised as follows. Section 2 gives a brief summary of the monetary policy making process in the UK, section 3 discusses the dynamic ordered probit model we use to predict rate changes. Section 4 describes the data, then section 5 provides in-sample estimates of the direction of change using both narrow information and the wider information sets defined below. The out-of-sample performance is assessed in Section 6. Section 7 concludes.

2 Monetary Policymaking in the UK

Summaries of the processes by which monetary policy is conducted are readily accessible in Budd (1998) and in retrospect, King (1997, 2002), therefore this section provides only a brief overview. The responsibility for setting interest rates is currently held by the Monetary Policy Committee (MPC) of the Bank of England. The MPC has nine members including the Governor, two Deputy Governors, and two Executive Directors, responsible for monetary policy analysis and monetary policy operations; the remaining four 'external' members are appointed by the Chancellor of the Exchequer with 'knowledge or experience which is likely to be relevant to the committee's functions'. 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 had an operational target of $2\frac{1}{2}$ per cent in the underlying inflation rate based on RPI excluding mortgage interest payments during the period of our data sample, which was set annually by the Chancellor of Exchequer[1].

The MPC usually meets once a month, and the decision on the official interest rate is typically announced immediately after the meeting at midday on the first Thursday of the month, although it may postpone the announcement in order to intervene in the financial markets. Before the decision is made, the MPC receives a briefing 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. The presentations are given under the following headings: monetary conditions, demand and output, the labor market, prices, and financial markets (Budd, 1998). The MPC then meets in private to discuss the interest rate decision on a Wednesday afternoon and Thursday morning.

After this meeting, in order to promote the openness, the minutes are published on the 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

[1] The target was revised to 2 per cent of the consumer price index in November 2003 following the decision of the Chancellor to change the measure of inflation and its target.

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 skewness of its probability distribution. The Bank publishes separately 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 of accountability, allowing 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) has 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 must explain 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. In the paper we ask how useful information embodied in a Taylor rule for example might be in terms of its predictive ability over the next interest rate change.

3 Forecasting Interest Rate Changes

3.1 Dynamic Ordered Probit Modelling Framework

In order to forecast the change in interest rates we embed two observations in our forecasting model: interest rate changes are typically discrete and there is considerable persistence in the changes to interest rates. Our preferred framework to explore the properties of this approach is therefore the dynamic probit model, originally proposed by Eichengreen et al. (1985) and was subsequently modified and extended by Dueker (1999, 2000), which we use to investigate forecasts of the *directional change* of the base rate, denoted by Δr_t.

We refer to r_t as the actual interest rate at time t, which is typically changed by discrete amounts of 25 basis points, due to the inherent decisionmaking process of the central bank. But despite the evident discreteness in the *actual* interest rate there is no reason to suppose that the *desired* interest rate, denoted by r_t^*, is discrete. The difference between the two interest rates might be regarded as an indicator of the impetus to change rates. At time t, the central bank decides the appropriate level of the interest rate (r_{t+1}) at time $t+1$. This is determined by considering the gap, $Z_{t+1} = r_{t+1}^* - r_t$, between the desired level (r_{t+1}^*), which is a function of information variables guiding monetary policy, and the current level of the interest rate (r_t). Following this logic, the process of changing the observed interest rate results from Z_{t+1} exceeding certain thresholds in the mind of the policymakers that we will estimate empirically:

$$\begin{aligned}
\Delta r_{t+1} &< 0 \Longleftrightarrow Z_{t+1} < c_0, \\
\Delta r_{t+1} &= 0 \Longleftrightarrow c_0 \leq Z_{t+1} < c_1, \\
\Delta r_{t+1} &> 0 \Longleftrightarrow c_1 \leq Z_{t+1}
\end{aligned}$$

where $\Delta r_{t+1} = r_{t+1} - r_t$ and c_0 and c_1 are the threshold values. We will take the approach that the change in the desired and continuous interest rate (not the observed discrete interest rate) might be determined by information from a $(k+1) \times 1$ vector of relevant variables, X_t, (defined by our different information sets in more detail in the next subsection) as follows:

$$\Delta r_t^* = X_t' \beta^* + \epsilon_t,$$

where $\beta^* = (\beta_0^*, \beta_1^*, ..., \beta_k^*)'$ and it is assumed that the error term ϵ_t is $IIN(0, \sigma^2)$. The width of the information set is an empirical issue that we evaluate by comparing the forecast performance directly, in-sample and out-of-sample.

Following Dueker (2000), we include some additional features in the model. In order to take into account of heteroscedasticty in the error term and any change in the constant term over the sample we assume the variance of the error term and the constant term will be subject to Markov switching as follows:

$$\begin{aligned} \sigma^2 &= \sigma_0^2(1 - S_{1t}) + \sigma_1^2 S_{1t} \\ \beta_0^* &= \beta_{00}^*(1 - S_{2t}) + \beta_{01}^* S_{2t} \end{aligned}$$

where S_{1t} is the binary state variable governing the variance switching and S_{2t} is the binary state variable for the constant switching.

Based on the normality assumption on ϵ_t, the probability of 'down', 'no change' or 'up' is given using the normal cumulative density function Φ:

$$\begin{aligned} P_0 &= \Pr(\Delta r_t < 0) = \Phi(c_0 - X_t'\beta^* - (r_{t-1}^* - r_{t-1})) \qquad (1) \\ P_1 &= \Pr(\Delta r_t = 0) = \Phi(c_1 - X_t'\beta^* - (r_{t-1}^* - r_{t-1})) \\ &\quad -\Phi(c_0 - X_t'\beta^* - (r_{t-1}^* - r_{t-1})) \end{aligned}$$

and $P_2 = \Pr(\Delta r_t > 0) = 1 - \Pr(\Delta r_t < 0) - \Pr(\Delta r_t = 0)$. The maximum-likelihood estimation procedure proposed in Eichengreen et al. (1985) is complicated due to numerical evaluation of the multiple integral in the likelihood function and the Markov switching property of the model. Dueker (1999, 2000) proposed a simpler method of estimating the parameters and their standard errors using a Bayesian method based Gibbs Sampling, which we also employ (details of the proceedure are reported in Casella and George,1992).

Based on the estimates from the model, the predicted probabilities are obtained by plugging those estimates into the equations in (1) and we denote the predicted probabilities $\hat{P}_0, \hat{P}_1$ and $\hat{P}_2$. Our directional prediction $\hat{q}_t$ is then given by

$$\hat{q}_t = m \quad \text{if} \quad \hat{P}_m = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2). \qquad (2)$$

In other words, we predict the next change to be '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 $\hat{P}_2 = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2)$.

3.2 Forecast Evaluations

Since we are interested in the predictability of a given information set, we construct an outcome-based measure of the goodness-of-fit. In order to evaluate the proportion of correct predictions, we cross-tabulate predicted against observed outcomes in a contingency table where we associate the direction of predicted changes against the actual changes of the base rate. The proportion of correct predictions denoted as SC is the sum of all diagonal terms divided by the total number of observations: that is $SC = \frac{1}{T}\sum_{t=1}^{T} \mathbf{1}(\hat{q}_t = q_t)$.

Interest rate changes in our sample have a dominant outcome (no change) and therefore we need to modify the SC measure to allow for the observation of Bodie et al. (1996) who indicate that a high success rate generated by a "stopped-clock" strategy is not good evidence of predictability. The measure SC cannot distinguish between seemingly successful predictability of a "stopped-clock" and true predictability, however, a technique proposed by Merton (1981) can be straightforwardly applied to give a truer indication of predictive ability. Let CP_j be the proportion of the correct predictions made by $\hat{q}_t$ when the true state is given by $q_t = j$. In other words, let us define our measure as the conditional probability of correct predictions. From the definition of conditional probability, CP_j is computed by $CP_j = \frac{\frac{1}{T}\sum_{t=1}^{T}\mathbf{1}(\hat{q}_t=j)\mathbf{1}(q_t=j)}{\frac{1}{T}\sum_{t=1}^{T}\mathbf{1}(q_t=j)}$ and then Merton's correct measure denoted CP is given by $CP = \frac{1}{J-1}\left[\sum_{j=0}^{J-1} CP_j - 1\right]$, where J is the number of categories. The measure always lies between $-\frac{1}{J-1}$ and 1. For a "stopped-clock" strategy, where only one of CP_i's is equal to one and the other CP_j's are zero, the CP is zero implying that there is no predictability in that strategy. Any forecasting model generating a negative value of CP can be regarded as being inferior to the stopped clock strategy. On the other hand, for a perfect forecasting model, all CP_j's equal unity, which implies that CP also equals unity.

4 Data

We use monthly data from the Bank of England's Monetary Policy Committee (MPC) for the sample period of 1993/2 through 2003/7. This has some distinct advantages. First, the data are all taken from a period of inflation targeting when decisions were taken to change interest rates on a monthly frequency[2]. This means that the monetary policy regime has been consistent for the entire sample and could not be responsible for changes in the behavior of the relationship. Second, with a few exceptions immediately after inflation targeting became the objective of monetary policy, changes in interest rates at a monthly frequency have been made in 25 basis point steps. Therefore we can readily implement the dynamic probit methodology using three categories since the decision of the MPC has been in practice been whether to change the rate upwards, downwards or make no change in 25 basis point steps (up or down). In only four cases were changes made in larger steps of 50 basis point steps[3]. Figure 1 shows the stepwise nature of the interest rate decision since 1993. The pertinent characteristics that require a dynamic ordered probit methodology to model the interest rate are the tendency for rates to be altered in 25 basis point steps, for these changes to be occasional with long periods of 'no change', and the highly persistent nature of the series. The characteristics of the data are similar to the US Federal Fund rate time series studied by Hamilton and Jorda (2002) that is modeled using an autoregressive conditional hazard model. The institutional details differ between the US and the UK, but in the UK the MPC operates much like the FOMC in setting the short term interest rate consistent with its objectives, and in Table 1 we record the decisions to change rates.

To evaluate the ability of outside observers to predict the direction of change in the interest rate we consider two information sets and compare their performance against naive forecasts using random walk, AR(1), random walk in first difference and two linear Taylor rule models, the first of which uses the Taylor rule information set to predict the direction of change of the base rate. It is now generally accepted that central banks that target inflation use future (expected) values

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

[3] 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 negative change in rates by 50 basis points would be based on a very small number of observations when rates did actually change by this amount.

of inflation as their intermediate variable (see Svensson, 1997, Batini and Haldane, 1999, Batini and Nelson, 2001) therefore we use the 12-month ahead rate of inflation, π_{t+12}, that allows for a reasonable degree of forward-lookingness without limiting the degrees of freedom in estimation excessively. The Bank of England recognises that the changes to rates today will likely affect output with a lag of some twelve months and inflation with a lag of 18-24 months. It therefore looks ahead between one year and two years to judge where inflation will be at that horizon to judge whether rate changes are required now to ensure that inflation is close to target in 12-24 months time. In Svensson's terminology it performs *inflation forecast targeting*, and publishes its own forecasts of inflation up to two years ahead. Why then do we not use the Bank's own forecast 24 months ahead? First, the forecast is given as a fan chart with shaded red areas to indicate the probability of inflation lying within a range - the numbers of the forecasts are not published and could only be imprecisely inferred from the fan charts. Second, the forecasts 24 months ahead lie close to target - so the forecast would correspond closely to the target value. The Bank may believe that its own actions will result in a target level of inflation two years ahead, but this is not very informative for our purposes since we want to judge the signal from inflation relative to the target. For these reasons we construct our own forecast 12 months ahead to reflect the forward-looking nature of monetary policy without restricting our sample unduly. Inflation 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, $\tilde{y}_t = y_t - \overline{y}$, with the natural rate y^* proxied by the long-run trend, $\overline{y}$, derived using a Hodrick-Prescott filter; we also add the variable Δr_{t-1}, which is the 1-month lagged change in the Treasury Bill rate, and control variables for other influences on the decision to change rates. The output data 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[4]. 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. Although this modification departs from the original Taylor rule, it corresponds to the adjusted Taylor rule used by among others Clarida et al. (1998), and allows for an important feature of the data namely persistence. Therefore we define $X_t = (1, \pi_{t+12}, \tilde{y}_t, \Delta r_{t-1})'$. The sample period of 1993/02 to 2003/07 gives 126 usable in-sample observations.

Second we consider a wide information set including additional variables beyond those in the Taylor rule information set. The Taylor rule information is supposed to provide a summary of economic conditions with respect to inflation and pressure on inflation from aggregate demand, but in practice pressures to raise interest rates can come from many other sources. Each month the Monetary Policy Committee receives a briefing from the staff of the Bank of England that gives attention to information arising from a range of other sources. The contents of these meetings are summarized in the *Minutes of the MPC Committee,* and the quarterly *Inflation Report*, which contains chapters on money and financial markets; demand and outputs; the labour market; costs and prices; monetary policy since the previous report; and the prospects for inflation. The variables

[4]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 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.

in the wide information set were chosen to reflect the extra information given through these sources[5]. In each case we had to use our judgement to select a representative variable to capture a range of information. Our selection includes data on growth rates in: the M4 money stock as an indicator of the inflationary pressure arising from monetary sources, $\Delta M4_t$; the sterling exchange rate index to capture the effects of imported inflation (effectively the component of RPIX arising from sources other than domestic conditions), ΔEX_t; the average earnings index to represent the extent to which labour market earnings put pressure on prices, ΔAEI_t; and finally, the input price index to capture rising costs from other sources, ΔINP_t[6]. In addition we include π_{t+12},the 12-month ahead rate of inflation, the output gap, $\tilde{y}_t$, and r_{t-1},the lagged value of the base rate. The wide information set is: $X_t = (1, \pi_{t+12}, \tilde{y}_t, \Delta r_{t-1}, \Delta M4_t, \Delta EX_t, \Delta AEI_t, \Delta INP_t)'$.

5 In-Sample Predictions

We begin in-sample evaluations with the dynamic ordered probit model using the Taylor rule information and the wider information set including other explanatory variables. We begin by comparing results based on the Taylor rule information set shown in Table 2. First, we notice that although the model allows for Markov switching to capture heterogeneity in variance and a shifting constant, the estimated drift coefficients, (β_0^*) are not significantly different from zero (since the 90% confidence intervals for drifts embrace zero). Second, the estimated coefficients for inflation, output gap and lagged interest rate $(\beta_1^*, \beta_2^*, \beta_3^*)$ indicate that inflation and the lagged level of interest rates are significant while the output gap is not significant as a predictor of the change in rates. Finally, our estimation shows that the cut-off coefficients (c_0, c_1) indicating the estimated thresholds where the impetus would cause rates to be changed downwards or upwards are -0.46 and +0.81, which are significantly different from zero, but include +25 bp and -25bp values within the confidence intervals around the estimated thresholds.

Based on our sample period, the Taylor rule information set predicts 'no change' in the interest rate 71 times, an upward change 9 times and a downward change 33 times. Of these there are 93 occasions when the correct prediction is made, hence we find that the $SC = \frac{93}{113}$, which suggests

[5] No particular significance should be attached to the variables we have chosen as representatives of wider data except for the purpose of ranking performance in predictive ability on the basis of more information that the Taylor rule provides. A related but different approach is discussed in Bernanke and Boivin (2001), where the usefulness of large amounts of information is assessed using the factor model approach of Stock and Watson (1999a, b). In that paper, the question is how the Fed might make decisions in a 'data rich' environment. The focus is upon the use of large data sets to improve forecast accuracy rather than the evaluation of monetary policy decision rules in a discrete variable context. We refer readers that are interested in the optimal construction and use of large data sets in that direction.

[6] The M4 is the broad definition of the money stock, which comprises holdings by the M4 private sector (i.e. private sector other than monetary financial institutions) of notes and coin, together with their sterling deposits at monetary financial institutions in the UK (including certificates of deposit and other paper issued by monetary financial institutions of not more than 5 years original maturity). The sterling exchange rate index is the sterling exchange rate against a basket of twenty currencies, monthly business-day averages of the mid-points between the spot buying and selling rates for each currency as recorded by the Bank of England at 16.00 hours (GMT) each day. They are not official rates, but representative rates observed in the London interbank market by the Bank's foreign exchange dealers. Each of the currencies' countries is given a competitiveness weight which reflects that currency's relative importance to UK trade in manufacturing based in 1989-1991 average aggregate trade flows. The original source from the Bank of England used 1990 as the base year, however, in this paper the series are re-based using 1995 as the base year. Average earnings are obtained by dividing the total paid by the total number of employees paid, including those on strike. This series is of the whole economy, seasonally adjusted, and use 1995 as the base year (1995=100). The input price index is the indices of input prices (material and fuel purchased) for all manufacturing industry. This series are seasonally adjusted, and use 1995 as the base year (1995=100).

that we have approximately 82 per cent correct predictions. Since the value of q_t equals 1 (that is no change) about 63% of the time, it is not clear whether the dominant outcome of 'no change' drives the result. To allow for the dominant outcome we report the Merton correct prediction statistic, which calculates correct predictions using the proportion of correct predictions as q_t takes each of its three values: hence $CP_0 = \frac{20}{20}, CP_1 = \frac{65}{79}$ and $CP_2 = \frac{8}{14}$ from Table 3, implying that $CP = 0.7$, i.e. there is substantial predictive ability for the direction change of rates using the Taylor rule information set.

The estimation result based on the wide information set is shown in Table 4. Once again the Markov switching drift parameters are insignificant. A wider set of variables is included in the information set comprising inflation, output gap, lagged level of interest rates, and changes in money stock, the exchange rate, the average earnings index and input prices, but among the coefficients for these variables $(\beta_1^*, ..., \beta_7^*)$ only those referring to inflation, lagged interest rate and changes in the exchange rate are significant. The estimated cut-off coefficients (c_0, c_1) show that the impetus would result in a change of actual rates if it exceeded -0.32 or 1.07, which are both significantly different from zero, but the upward changes does not include +25bp in the 90% confidence interval.

Table 5 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 $SC = \frac{90}{113}$, indicating approximately 80% of predictions are correct. Comparing this statistic with the Merton correct prediction we find $CP_0 = \frac{20}{20}, CP_1 = \frac{64}{79}$ and $CP_2 = \frac{6}{14}$, hence $CP = 62$ per cent, which is marginally lower than the Taylor rule information set, resulting from a slightly worse record of predicting upward changes in rates despite a better record of predicting no change.

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

6 Out-of-Sample Predictions

This section makes one-step ahead predictions of the directional change of the base rate, that is $\hat{q}_{T+1}$, 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 initialisation sample prior to the forecast of the next one-step ahead prediction of the direction of change while keeping the start date of the sample fixed. By this method we forecast $\hat{q}_{T+1}$, $\hat{q}_{T+2}$, etc., but importantly, in order to make a true out-of-sample prediction, only known values of the variables in each of the information sets can be used as predictors. For this, (i) the forward-looking inflation rate is now replaced by its first-lagged value; i.e. when we produce $\hat{q}_{T+1}(1, 2,\text{or } 3)$ for the next period $(T + 1)$ standing at time T, the information set we use is $X_T = (1, \pi_T, \tilde{y}_T, r_T, \Delta M4_T, \Delta EX_T, \Delta AEI_T, \Delta INP_T)$, and (ii) the output gap measure (the level of output minus it HP trend) is recalculated each time; i.e. the HP trend is re-estimated only using the observations up to time T. We start with $T =$ December 1998 (70th observation) and increase T by one each time until T reaches the second-last observation (June 2003, the 125th observation); $T = 70, 71, ..., 125$. Hence, the first prediction date is January 1999 and the last prediction date will be July 2004, which will produce 56 out-of-sample predictions.

Using the dynamic ordered probit model, the probabilities are calculated through:

$$\begin{aligned}\hat{P}_0 &= \Pr(\Delta r_{T+1} < 0) = \Phi(c_0 - X_T'\beta^* - (r_T^* - r_T)) \\ \hat{P}_1 &= \Pr(\Delta r_{T+1} = 0) = \Phi(c_1 - X_T'\beta^* - (r_T^* - r_T)) \\ &\quad -\Phi(c_0 - X_T'\beta^* - (r_T^* - r_T))\end{aligned}$$

and $\hat{P}_2 = \Pr(\Delta r_{T+1} > 0) = 1 - \Pr(\Delta r_{T+1} < 0) - \Pr(\Delta r_{T+1} = 0)$. The prediction $\hat{q}_{T+1}$ is then given by

$$\hat{q}_{T+1} = m \quad if \quad \hat{P}_m = \max(\hat{P}_0, \hat{P}_1, \hat{P}_2).$$

6.1 Alternative Information Sets and Forecast Methods

In order to evaluate our forecasts we make use of several alternative forecasts in which the level of the base late for the next period is predicted based on the current and past information. The level of the base late for the next period is denoted by $\hat{r}_{T+1}$. Our directional predictions are derived by comparing this level prediction with the current level of the base rate (r_T), taking into account the threshold values discussed in the previous section. For example, if the predicted base rate for the next month ($\hat{r}_{T+1}$) is larger than the current level (r_T) by c_1, then our directional prediction is 'up' implying that $\hat{q}_{T+1} = 2$. Hence, the prediction $\hat{q}_{T+1}$ is then given by

$$\begin{aligned}\hat{q}_{T+1} &= 0 \quad \text{if} \quad \hat{r}_{T+1} - r_T < c_0 \\ \hat{q}_{T+1} &= 1 \quad \text{if} \quad c_0 \leq \hat{r}_{T+1} - r_T < c_1 \\ \hat{q}_{T+1} &= 2 \quad \text{if} \quad c_1 \leq \hat{r}_{T+1} - r_T\end{aligned}$$

6.1.1 Naive Forecasts

Our first set of alternatives is based on naive forecasts using simple formulae to generate predictions for rate changes. We consider the random walk model, $r_t = r_{t-1} + \epsilon_t$ where the level prediction for the next period is given by the current level of the base rate; i.e. $\hat{r}_{T+1} = r_T$; an AR(1) model, $r_t = \alpha + \beta r_{t-1} + \epsilon_t$ that drops the unit coefficient on the lagged dependent variable, with a level prediction for the next period is given by $\hat{r}_{T+1} = \hat{\alpha} + \hat{\beta} r_T$ based on OLS estimates; and the random walk in the first differences, $\Delta r_t = \Delta r_{t-1} + \epsilon_t$, which we will call "no-change forecast model" since this model tends to produce the same predictions, repeating the last outcome. That is, if the last month was a no change, then this model predicts no change, and keep producing the same prediction until a change occurs. The model can be rewritten so that the level prediction for the next period is given by $\hat{r}_{T+1} = 2r_T - r_{T-1}$. These models are naive but not totally unrealistic since changes to rates by central banks are strongly autocorrelated, and past information on interest rates may be sufficient to provide accurate predictions of future levels or changes.

6.1.2 Linear Taylor Rules

A second set of forecasts is generated by the linear Taylor rule. Here we have two models, the first is, $r_t = \alpha + \beta\pi_{t-1} + \delta\tilde{y}_{t-1} + \gamma r_{t-1} + \epsilon_t$ where the level prediction for the next period is given by $\hat{r}_{T+1} = \hat{\alpha} + \hat{\beta}\pi_T + \hat{\delta}\tilde{y}_T + \hat{\gamma} r_T$ with $\hat{\alpha}, \hat{\beta}, \hat{\delta}, \hat{\gamma}$ given by OLS estimates. This model is generated using the inflation deviation from target and the output gap (i.e. a narrowly defined information set). A second linear Taylor rule model is augmented with a wider information and modelled as $r_t = X_{t-1}'\beta + \epsilon_t$ with $X_{t-1} = (1, \pi_{t-1}, \tilde{y}_{t-1}, r_{t-1}, \Delta M4_{t-1}, \Delta EX_{t-1}, \Delta AEI_{t-1}, \Delta INP_{t-1})$. Hence, the level prediction for the next period is given by $\hat{r}_{T+1} = X_T'\hat{\beta}$ where $\hat{\beta}$ are OLS estimates.

6.2 Forecasting using the DOP model

Table 6 shows the cross-tabulations of the predicted against observed outcomes using the Taylor rule information only. The Taylor rule information set tends to predict 'down' in the interest rate in the majority of cases. In all but 19 cases out of 56 out-of-sample predictions the prediction is for 'down', and there are counter-predictions (downward change when a upward change occurred and vice versa). The predictive ability based on the proportion of correct predictions against the actual outcomes equals $SC = \frac{22}{55}$ which is a 39 per cent prediction rate, while the Merton statistic of correct predictions is $CP = 10$ per cent.

Table 7 illustrates the contingency table of the predicted against actual outcomes out-of-sample results for the Taylor rule with a wide information set. This model can predict by drawing on a greater range of information besides the Taylor rule information which is nested in the data. It also predicts 'down' the majority of the time and has one counter-prediction, but the total number of correct predictions against the actual outcomes based on the $SC = \frac{29}{56} = 52$ per cent is better than the previous information set. Importantly, we find that the higher value of the proportion of the correct predictions against the actual outcomes does not result from a dominant outcome. The evidence shows that the wide information predicts more 'no changes' in the repo rate compared to the Taylor rule but it is more capable of predicting negative changes to interest rates. When we calculated the Merton's measures we find that Merton's correct predictions measure from the out-of-sample exercise is $CP = 24$ per cent, larger than twice the CP figure for the narrower information set. This provides strong evidence of better predictive performance over the Taylor rule information set since the wide information set is not only correct more often, but also has the capability to accurately predict the direction of change in the interest rate when there is a non-zero change.

6.3 Forecasting using the Alternative Models

Our results indicate that on out-of-sample evidence the Taylor rule information set augmented with additional variables such as money supply growth, change in the exchange rate, input prices and average earnings outperforms the narrowly defined Taylor rule information set. This section provides a basis for comparison with alternative forecasting models that predict the level of the interest rate on the basis of a random walk, AR(1), random walk in first differences and linear predictions using the Taylor rule and augmented Taylor rule. These levels predictions are converted into directional predictions using the deviation of the prediction minus the current level versus different threshold values including the estimated threshold values from the dynamic ordered probit analysis, and thresholds of +25,-25 basis points, +10, -10, basis points and 0,0 basis points. As the thresholds tend towards zero, smaller deviations from the current interest rate are sufficient to generate a prediction of a rate change. Although the thresholds are arbitrary they give an indication of the improvement or deterioration in the directional predictions over a range of threshold values.

For the random walk model, as can be seen in Table 8, the level prediction is always equal to the current level, which implies only 'no change' predictions occurs irrespective of the threshold values. Hence we find that there are 56 predictions of 'no change' irrespective of the actual outcome and hence the SC $= \frac{38}{56} = 68$ per cent, but the CP $= 0$. Hence our information sets using the dynamic ordered probit model outperform a simple random walk on the CP criterion, which allows for the stopped clock phenomenon where the random walk model *appears* to predict well on the SC criterion.

Other naive models perform as badly as the random walk model when the threshold values are set to equal the estimated values from the dynamic ordered probit model: here SC values are identical to the random walk at 68 per cent, the CP values are zero. The naive models do better than the random walk model as the threshold tends to zero, but this reflects the fact that for the AR(1) model (see Table 9) as the thresholds tend to zero the number of predictions of upward and downward changes increase while the 'no change' predictions decrease. This reduces the SC score but improves the CP value, but the improvements in the CP are never superior to CP values compared to the predictions out-of-sample for the dynamic ordered probit model except for the random walk in first differences where the improvement in SC and CP is greater as the thresholds approach zero (see Table 10). This model exploits the autocorrelation in the changes to rates and uses this information to predict levels, and hence predicted changes in rates, quite well. Given that (i) there are 38 no changes during the out-of-sample period and (ii) such cases tend to form a cluster, it can be certainly expected that this no-change forecast model will perform well.

The results from the linear predictions of the Taylor rule have similar properties to the naive AR(1) model. When the threshold values are set to equal the estimated values from the dynamic ordered probit model the SC values are identical to the random walk at 68 per cent and the CP values are zero, but as the thresholds tend to zero the predictions of upward and downward changes increase while the 'no change' predictions decrease, and this reduces the SC value but improves the CP value. There is no combination of threshold values which provides an outcome better than the DOP model in terms of both SC and CP.

Our results imply that there is some gain from forecasts of directional change out-of-sample using dynamic ordered probit models over naive forecasts of the level of interest rates, such as random walk and AR(1) models, and linear Taylor rule forecasts when comparing predictions using the same estimated threshold values. Here Merton's correct prediction test indicates a superior performance using more than a decade of UK data, and use of a wider information set improves the predictive ability compared to a narrowly defined data set such as the 'Taylor rule' information set. Surprisingly, our results show that one naive predictor is able to offer good out-of-sample forecasts using the assumption of 'no change' to the change in rates i.e. a first-difference random walk model provided the thresholds for the impetus to change are narrowly defined. It does so because it can exploit the autocorrelation in the change to interest rates when rates are adjusted and the tendency for rates to remain unchanged for long periods (when a period of 'no changes' begins it makes one forecast error before reverting to a 'no change' prediction which is correct for the remainder of the period rates are unchanged). Other linear models can predict well for other threshold values, but we are unable to compare their performance directly with the dynamic ordered probit model because the thresholds are different.

7 Conclusion

Accurate prediction of the future direction of interest rates is a vital element when making economic decisions. The focus on central banks as they make decisions about the future direction of interest rates requires an assessment of the likely outcome of committee decisions based on new information since the previous meeting. We formulate monetary policy making in terms of a specific instrument rule 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 as a function of a small set of variables, typically just inflation and the output gap.

Our results using monthly data from the United Kingdom offer some interesting results. First, the use of broader information sets improves in-sample and out-of-sample predictions relative to the 'Taylor rule' information set when based on the dynamic ordered probit model, which reflects the highly persistent and step-wise nature of the interest rate series. Second, most naive models predict badly when compared with dynamic ordered probit models using similar threshold values, and these include a random walk, an AR(1) model, and two linear forecasts based on the same Taylor rule and wider information sets used in the dynamic ordered probit models. Third, a simple first-difference random walk model predicts well out-of-sample, offering superior performance in some instances when the thresholds are narrowly defined compared to the dynamic ordered probit model. The ability of this model to exploit the autocorrelation in the change to interest rates when rates are adjusted, while at the same time capturing the tendency for rates to remain unchanged for long periods, gives a simple but effective forecast for the change in UK interest rates. Linear models also sometimes offer good predictions, but we cannot make direct comparisons with the dynamic ordered probit predictions because the threshold values differ.

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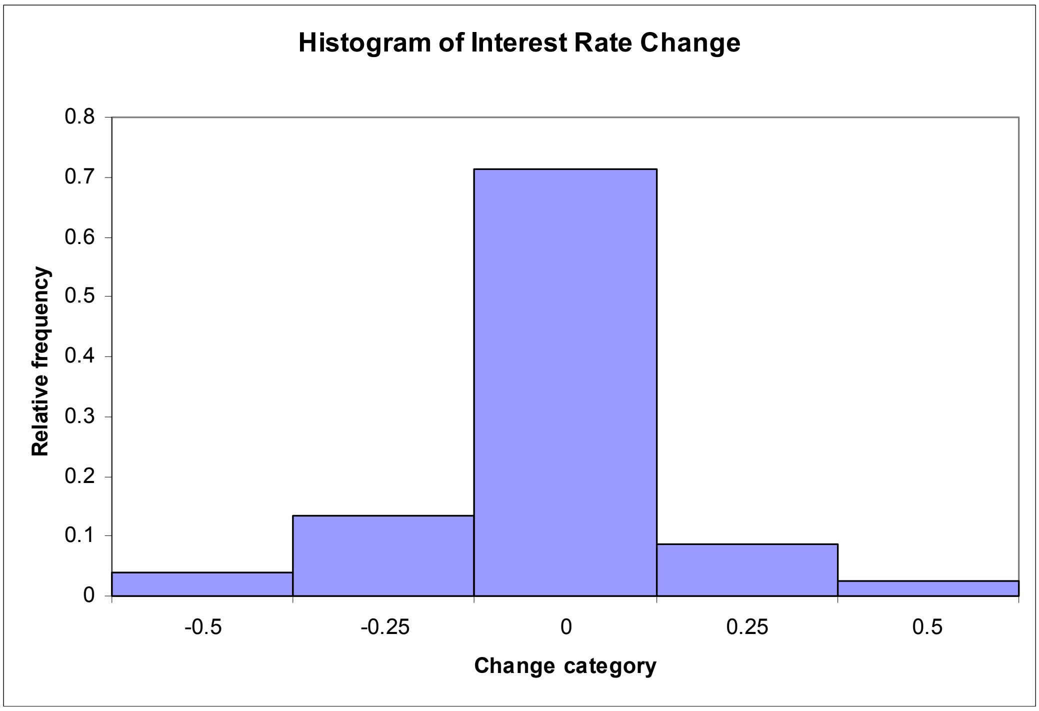

Figure 1: Histogram of Interest Rate Change

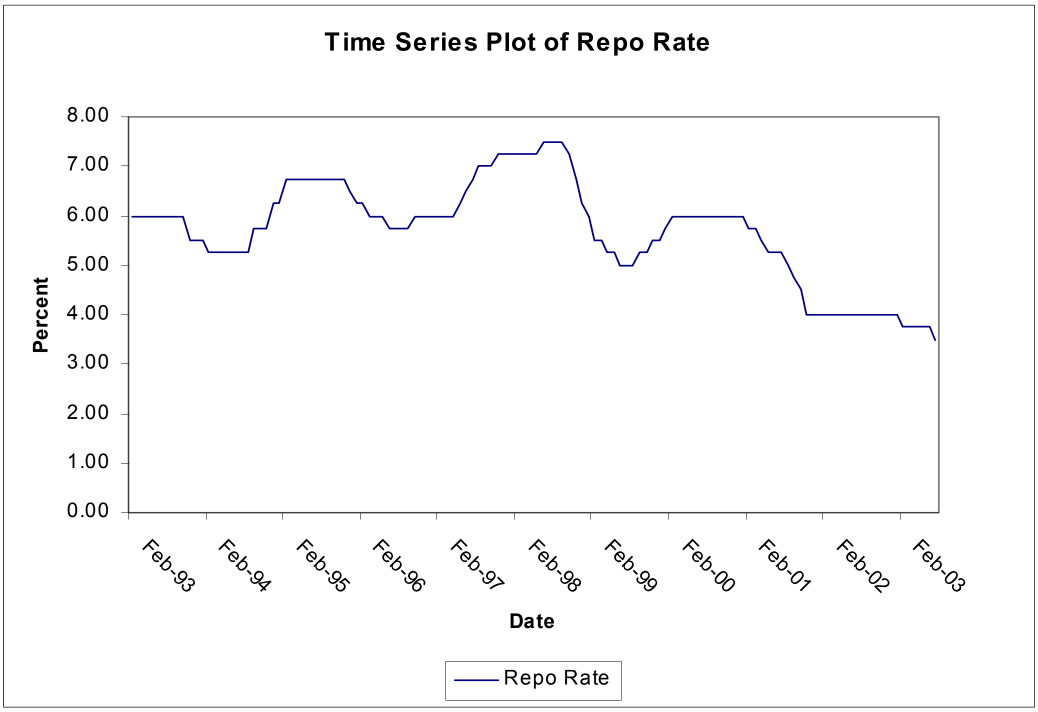

Figure 2: Time Series Plot of Repo Rate

Table 1: Calendar of Changes in the Repo Rate

Date of Change	Rate Level	Rate Change	Duration in Days	Day of the Week
23 November 1993	5.50	-0.50	N/A	Tuesday
8 February 1994	5.25	-0.25	77	Tuesday
12 September 1994	5.75	+0.50	216	Monday
7 December 1994	6.25	+0.50	86	Wednesday
2 February 1995	6.75	+0.50	57	Thursday
13 December 1995	6.50	-0.25	314	Wednesday
18 January 1996	6.25	-0.25	36	Thursday
8 March 1996	6.00	-0.25	50	Friday
6 June 1996	5.75	-0.25	90	Thursday
30 October 1996	6.00	+0.25	146	Wednesday
6 May 1997	6.25	+0.25	188	Tuesday
6 June 1997	6.50	+0.25	31	Friday
10 July 1997	6.75	+0.25	34	Thursday
7 August 1997	7.00	+0.25	28	Thursday
6 November 1997	7.25	+0.25	91	Thursday
4 June 1998	7.50	+0.25	210	Thursday
8 October 1998	7.25	-0.25	126	Thursday
5 November 1998	6.75	-0.50	28	Thursday
10 December 1998	6.25	-0.50	35	Thursday
7 January 1999	6.00	-0.25	28	Thursday
4 February 1999	5.50	-0.50	28	Thursday
8 April 1999	5.25	-0.25	63	Thursday
10 June 1999	5.00	-0.25	63	Thursday
8 September 1999	5.25	+0.25	90	Wednesday
4 November 1999	5.50	+0.25	57	Thursday
13 January 2000	5.75	+0.25	70	Thursday
10 February 2000	6.00	+0.25	28	Thursday
8 February 2001	5.75	-0.25	364	Thursday
5 April 2001	5.50	-0.25	56	Thursday
10 May 2001	5.25	-0.25	35	Thursday
2 August 2001	5.00	-0.25	84	Thursday
18 September 2001	4.75	-0.25	47	Tuesday
4 October 2001	4.50	-0.25	16	Thursday
8 November 2001	4.00	-0.50	35	Thursday
6 February 2003	3.75	-0.25	455	Thursday
10 July 2003	3.50	-0.25	154	Thursday

Table 2: Dynamic Ordered Probit Results for the Taylor Rule Information Set

Coefficient	Posterior Mean	90% Confidence Lower	Interval Upper
Intercept (β_0^*)			
β_{00}^*	0.1091	-0.3927	0.6035
β_{01}^*	0.2364	-0.2498	0.7440
Slope			
β_1^*	0.1424	0.0193	0.2649
β_2^*	-0.0235	-0.1411	0.0947
β_3^*	-0.2645	-0.4197	-0.0875
Cut-off			
c_0	-0.4649	-1.0434	-0.0485
c_1	0.8110	0.3246	1.1409

Table 3: In-Sample Contingency Table for the Taylor Rule Information Set

	Predicted			
Actual	0	1	2	Total
0	20	0	0	20
1	13	65	1	79
2	0	6	8	14
Total	33	71	9	113

$SC = 0.8230, CP = 0.6971$

Table 4: Dynamic Ordered Probit Results for the Wide Information Set

Coefficient	Posterior Mean	90% Confidence Lower	Interval Upper
Intercept (β_0^*)			
β_{00}^*	0.0398	−0.5262	0.5704
β_{01}^*	0.2101	−0.3043	0.7467
Slope			
β_1^*	0.1485	0.0125	0.2886
β_2^*	−0.0035	−0.1414	0.1247
β_3^*	−0.2210	−0.3826	−0.0439
β_4^*	0.1474	−1.1686	1.6034
β_5^*	0.2542	0.0014	0.5239
β_6^*	−0.0528	−1.2301	1.0807
β_7^*	0.3110	−0.2420	0.8676
Cut-off			
c_0	−0.3150	−0.6740	−0.0224
c_1	1.0740	0.7553	1.5421

Table 5: In-Sample Contingency Table for the Wide Information Set

Predicted

Actual	0	1	2	Total
0	20	0	0	20
1	14	64	1	79
2	0	8	6	14
Total	34	72	7	113

$SC = 0.7965, CP = 0.6193$

Table 6: Out-of-Sample Contingency Table for the Dynamic Ordered Probit Model with the Taylor rule information set

Predicted

Actual	0	1	2	Total
0	9	5	0	14
1	26	12	0	38
2	2	1	1	4
Total	37	18	1	56

$SC = 0.3929, CP = 0.1043, \chi^2 = 13.3177$

Table 7: Out-of-Sample Contingency Table for the Dynamic Ordered Probit Model with the Wide Information Set

Predicted

Actual	0	1	2	Total
0	11	3	0	14
1	18	17	3	38
2	1	2	1	4
Total	30	22	4	56

$SC = 0.5179, CP = 0.2415, \chi^2 = 6.8722$

Table 8: Out-of-Sample Contingency Table for the Random Walk Model

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

Table 9: Out-of-Sample Contingency Table for the AR(1) Model

$c_0 = -0.4770$ and $c_1 = 0.6747$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.25$ and $c_1 = 0.25$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.10$ and $c_1 = 0.10$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = c_1 = 0.00$

Predicted

Actual	0	1	2	Total
0	3	0	11	14
1	18	0	20	38
2	0	0	4	4
Total	21	0	35	56

$SC = 0.1250, CP = 0.1071$

Table 10: Out-of-Sample Contingency Table for the Random Walk in First Difference Model

$c_0 = -0.4770$ and $c_1 = 0.6747$

Predicted

Actual	0	1	2	Total
0	2	12	0	14
1	2	36	0	38
2	0	4	0	4
Total	4	52	0	56

$SC = 0.6786, CP = 0.0451$

$c_0 = -0.25$ and $c_1 = 0.25$

Predicted

Actual	0	1	2	Total
0	2	12	0	14
1	2	36	0	38
2	0	4	0	4
Total	4	52	0	56

$SC = 0.6786, CP = 0.0451$

$c_0 = -0.10$ and $c_1 = 0.10$

Predicted

Actual	0	1	2	Total
0	7	7	0	14
1	7	29	2	38
2	0	2	2	4
Total	14	38	4	56

$SC = 0.6786, CP = 0.3816$

$c_0 = c_1 = 0.00$

Predicted

Actual	0	1	2	Total
0	7	7	0	14
1	7	29	2	38
2	0	2	2	4
Total	14	38	4	56

$SC = 0.1250, CP = 0.3816$

Table 11: Out-of-Sample Contingency Table for the Linear Model with the Taylor Rule Information Set

$c_0 = -0.4649$ and $c_1 = 0.8110$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.25$ and $c_1 = 0.25$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	1	55	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.10$ and $c_1 = 0.10$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	2	36	0	38
2	0	4	0	4
Total	2	54	0	56

$SC = 0.6429, CP = -0.0263$

$c_0 = c_1 = 0.00$

Predicted

Actual	0	1	2	Total
0	8	0	6	14
1	17	0	21	38
2	0	0	4	4
Total	35	0	21	56

$SC = 0.2143, CP = 0.2857$

Table 12: Out-of-Sample Contingency Tables for the Linear Model with the Wide Information Set

$c_0 = -0.3150$ and $c_1 = 1.0740$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.25$ and $c_1 = 0.25$

Predicted

Actual	0	1	2	Total
0	0	14	0	14
1	0	38	0	38
2	0	4	0	4
Total	0	56	0	56

$SC = 0.6786, CP = 0.0000$

$c_0 = -0.10$ and $c_1 = 0.10$

Predicted

Actual	0	1	2	Total
0	1	13	0	14
1	6	28	4	38
2	0	2	2	4
Total	7	43	6	56

$SC = 0.5536, CP = 0.1541, \chi^2 = 9.3058$

$c_0 = c_1 = 0.00$

Predicted

Actual	0	1	2	Total
0	9	0	5	14
1	23	0	15	38
2	0	0	4	4
Total	32	0	24	56

$SC = 0.2143, CP = 0.3214$