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DYNAMICS OF THE FEDERAL FUNDS TARGET RATE: A NONSTATIONARY DISCRETE CHOICE APPROACH

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SUMMARY

We apply a discrete choice approach to model the empirical behaviour of the Federal Reserve in changing the federal funds target rate, the benchmark of short-term market interest rates in the US. Our methods allow the explanatory variables to be nonstationary as well as stationary. This feature is particularly useful in the present application as many economic fundamentals that are monitored by the Fed and are believed to affect decisions to adjust interest rate targets display some nonstationarity over time. The chosen model successfully predicts the majority of the target rate changes during the time period considered (1994–2001) and helps to explain strings of similar intervention decisions by the Fed. Based on the model-implied optimal interest rate, our findings suggest that there is a lag in the Fed's reaction to economic shocks during this period.

1. INTRODUCTION

The timing of monetary policy intervention is of widespread general interest in economic affairs, capturing substantial attention in the media as well as academic, commercial and financial circles. In the United States the Federal Reserve Board has a policy-making Federal Open Market Committee (FOMC) that meets regularly eight times a year to discuss open market operations. The FOMC decisions that attract the most attention are the new targets that it may set for the federal funds rate, the benchmark of short-term market interest rates in the US. Similar meetings by monetary authority committees are held in other countries, two notable examples being the Monetary Policy Meetings (MPM) of the Bank of Japan and the meetings of the Monetary Policy Committee (MPC) of the Bank of England.

The present work is concerned with modelling the timing of monetary policy intervention and it reports an empirical analysis of interest rate decision-making dynamics for the US. The method we propose is equally well suited for analysing monetary policy implementation by other central banks and it can also be applied to other forms of market intervention such as exchange rate intervention.

There is a vast literature studying monetary policy, its implementation, interest rate rules and the dynamic behaviour of interest rates. Walsh (1998) provides a recent overview of the extensive theory and empirical evidence relating to the practical operating procedures of monetary policy. It is apparent from this overview and the huge literature that it is impossible to develop a single

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model capable of describing all aspects of monetary policy. The present work, therefore, has a limited perspective that focuses on the issue of the timing of monetary intervention. In doing so, the main characteristics of this study are its implementation of a discrete choice framework for the decision-making intervention and the allowance for potentially nonstationary series that are monitored by the Fed in its decision-making capacity.

Many macroeconomic models specify an 'optimal' interest rate in a continuous way, the most prominent example being the 'Taylor rule' (Taylor, 1993, 1998, 2001; Solow *et al*., 1998; Fair, 2001). The Taylor rule provides a contingency plan for policy and to do so it specifies an optimal interest rate r^* in the form

$$r_t^* = \alpha + \beta(\pi_t - \pi^*) + \gamma(z_t - z_t^*) \tag{1}$$

where π_t and z_t are measures of inflation and output respectively, π^* is the Fed target rate of inflation and z_t^* is a measure of potential output. Fair (2001) proposed including additional regressors like unemployment and the money supply as well as a dummy variable to capture (and test for) potential structural breaks in policy. Another popular approach uses VARs to model the interest rate as a continuous process in studying the actions of the Fed (e.g. Sack, 1998).

In practice, of course, the federal funds target rate is adjusted in a discrete way, both in timing and in magnitude. The timing of Fed decisions is seen by many to be of great importance, is watched by the media and is closely monitored by both government and the private sector. Since 1994, the majority of target rate changes took place on the pre-scheduled meeting days of the FOMC, and the magnitude of the adjustments have been in multiples of 25 basis points (bp). Consequently, if there is a true (unobserved) optimal target rate that varies continuously with other variables, it is unlikely to exactly match the announced target rate.

In estimating a continuous model such as (1), it is generally assumed that the announced target rate equals the actual optimal rate. But this can be misleading because the process of determining the optimal interest rate r_t^* is mixed in with the discrete intervention process of adjusting the federal funds rate. For example, there is frequent discussion of Fed inertia in policy or Fed attempts to smooth policy, although these may not be part of the Fed's real goals in monetary policy. Instead, these features relate more to actual Fed behaviour in adjusting rates and can be distinguished from a rule such as (1) that determines an optimal rate r_t^*, which can be regarded as a contingency plan for Fed policy (Taylor, 1998). It is hard to make this distinction effective in a continuous model. The present paper, therefore, uses a discrete choice model for Fed decision making to treat the dynamic of the decisions and to provide an underlying contingency plan for policy. With this approach, the observed series of announced target rates and an estimated series of optimal interest rates can be used together to capture both the policy plan and the intervention decisions themselves, thereby revealing more detail about the Fed operating procedure.

Following standard procedure in discrete dependent variable models we estimate a linear index (this corresponds here to the contingency plan equation (1) for the optimal interest rate), but we draw information about it from the announced target rate series and its dynamic path as well as the explanatory variables that may figure in Fed policy thinking via a rule such as (1). The discrete rate adjustments are classified into categories by empirically calibrating the index against a set of threshold parameters, according to the extent of the deviation of the estimated optimal rate from the actual lagged target rate. The regression parameters and threshold parameters are estimated jointly by maximum likelihood (ML) using probit and logit regressions.

The simplest classification of the categories is a 'triple choice' approach, which means that we classify rate changes only in terms of decisions to 'decrease', 'increase' or make 'no change'.

More sophisticated alternatives are possible. For instance, we could classify adjustments in terms of the magnitude of the change giving the finer classifications ‘increase 50 bp and more’, ‘increase less than 50 bp’, ‘no change’, ‘decrease less than 50 bp’, ‘decrease 50 bp and more’. In the current work, we describe decisions in terms of the simple triple classification ‘rate cut, rate hike, or no change’. These classifications are sufficient to capture the essence of Fed operating policy and, in addition to these, we use a range of variables characterizing economic fundamentals that potentially influence Fed decisions.

In some related work, Balduzzi *et al*. (1996) investigated the effect of short-term rate targeting by the Fed on the term structure of interest rates and found that expectations of future changes in the target rate is the main driving force of short-term interest rate dynamics. Some recent work on interest rates also addresses the discrete feature of the FOMC practice. Dueker (1999) proposed a probit model approach to estimate the dynamics of federal funds target rate changes. His model assumes stationarity in the data and specifies the optimal interest rate in terms of an autoregressive process. Piazzesi (2001) estimated a model of the yield curve that incorporates a jump effect from FOMC policies and obtained a model-implied policy rule. She found that the Fed reacts mainly to information contained in the yield curve. Hamilton and Jorda (2002) also use a probit approach in modelling the target rates. These authors use the probit model not to predict the timing of interventions, but to predict the size of the rate changes when they occur. For the timing of interventions, they use an autoregressive conditional duration model, and the probit model is used to address the issue that any changes in the target rates are multiples of 25 bp. In both the estimation for the duration model and for the probit model, they include the spread between the six-month treasury bill rate and the lagged target rate as well as macro variables. Their empirical results suggest that when including this spread, which reflects the market expectation of future target rates, the macro variables are not significant. Applying different model specifications, we hope that our work can shed further light on the empirical behaviour of the monetary authority by exploring persistence and possible asymmetry in Fed decision making and by seeing how well macro variables assist in predicting the timing and direction of Fed decisions.

The empirical approach in this paper is partly based on results obtained by Park and Phillips (2000) and further developed by the present authors (2003) for nonstationary choice models. It is very well known that many macroeconomic variables, such as inflation, unemployment, consumer confidence and various leading economic indicators display some characteristics of nonstationarity over time (e.g. random wandering behaviour, the apparent absence of a fixed mean, or even secular growth). When such variables appear in a linear index (such as the right-hand side of (1)) traditional asymptotic theory does not justify probit or logit regressions. In that event, the theory in the authors’ (2003) work is relevant and some important changes occur that affect the pattern of discrete choice decisions. In the present case, these decisions involve market interventions.

Some empirical features of monetary intervention have been documented in the literature. For example, Rudebusch (1995) showed that one target rate change is much more likely to be followed by another change in the same direction, and Goodhart (1996) found similar patterns in other central banks’ behaviour. There is an underlying theory that explains such behaviour.

Park and Phillips (2000) showed that, in a binary (0, 1) choice model with nonstationary covariates, the sample proportion of unit choices converges to a random variable that follows an arc sine law with probability density $1/(\pi\sqrt{y(1-y)})$ on [0, 1]. This result provides some theoretical justification for the empirical phenomenon just mentioned of a string of similar decisions by the monetary authority about intervention. However, the Park–Phillips result is too crude for empirical implementation since the arc sine law (which was originally used to characterize the amount of time spent by a Brownian motion on one side of the origin) often implies an unbroken sequence of consecutive choices that are the same (just as a Brownian motion can stay above the origin for a long time before returning to the origin). In monetary intervention, while it is normal to observe a string of similar decisions by the Fed, it is not usual to observe completely unbroken strings of consecutive decisions that are the same. For example, although there have been 10 decisions to lower the rate target over 2001 : 1–2001 : 12, there have been some months where no change has been made in the rate. Hu and Phillips (2004) extended the Park–Phillips framework to polychotomous choices with parametric thresholds governing the choices. Their framework, which forms the basis of the empirical implementation here, allows for an extended class of arc sine laws in which many different distributional shapes are possible and where strings but not necessarily unbroken strings of similar decisions may occur.

The paper is organized as follows. Section 2 gives a brief introduction of the background of monetary policy intervention in the US. Section 3 describes the model, data and presents econometric findings. Section 4 concludes. The Appendix briefly reviews some relevant theory from Hu and Phillips (2004) on estimation and inference in potentially nonstationary discrete choice models.

2. BACKGROUND ON FOMC AND MONETARY POLICY IN PRACTICE

To achieve its policy goals the Federal Reserve has multiple tools. Perhaps the most powerful of these is its open market operations, for which the relevant authority is the FOMC. The FOMC conducts open market operations 'in a manner designed to foster the long-run objectives of price stability and sustainable economic growth'.[1] The FOMC consists of twelve members and holds eight regularly scheduled meetings each year. Once the FOMC sets the direction of monetary policy, the policy is implemented through open market operations at the trading desk of the Federal Reserve Bank of New York.

By law all depository institutions in the US must keep a percentage of their transaction deposits as reserves. Banks may trade among themselves to satisfy this requirement and the interest rate in this federal funds market is called federal funds market rate. For example, banks in need of funds may borrow overnight loans from banks with excess funds at the market prevailing rate at that time. Large deviations of this market rate from the target rate are transitory due to Fed open market operations. For example, if the Fed wants to lower the federal funds rate, they can purchase US treasury securities and increase supply of reserves. With greater supply of funds in the market, the interest rate will fall. Similarly, the Fed can raise the rate by selling the treasury securities. In this way, the federal funds market rate is kept to be close to the target set by FOMC. For this reason, the Fed's target rate becomes the benchmark for short-term market interest rate and it also has significant effect on other interest rates in the economy (Cook and Hahn, 1989; Rudebusch, 1995).

Shortly after each FOMC meeting, the FOMC issues a statement announcing the main decisions of the meeting together with some brief comments. The minutes of each FOMC meeting are published shortly after the next meeting. In the current paper, instead of relying on any macroeconomic theory, we use those published FOMC statements and minutes as our main reference in specifying the model and collecting the data.

[1] Detailed information about the FOMC can be sourced at http://www.federalreserve.gov/FOMC/

Typically, a statement of the FOMC meeting first highlights the decision on the target rate. Then it gives a short assessment summarizing prevailing economic conditions and the reason for the decision. The minutes include more detail. The main content of the minutes is a discussion of the economic and financial outlook based on the information that is garnered from a broad range of economic indicators. The statistical and anecdotal information considered include various price and inflation measures, data on the labour market such as the unemployment rate and claims for unemployment insurance, industrial production, productivity growth, consumer expenditure, capital spending, contractual activity, inventory and shipment, housing, consumer confidence, business confidence, and many others.

To model Fed decision making on intervention, we distinguish two groups of variables. The first group includes economic fundamentals that are believed to directly influence interest rate targets, such as the inflation rate and unemployment statistics.

The second group of variables include many other indicators of economic and financial conditions. While no macroeconomic theory directly supports these variables as plausible Fed policy targets or as part of a monetary policy rule for determining interest rates, many of these variables serve as leading indicators that the Fed considers in forming its outlook for the economy. For example, consumer and business confidence might be included in this group as useful indicators of future consumer expenditure and business investment. From congressional testimony by the Fed Chairman and FOMC minutes, it is evident that such variables are considered by the Fed in its deliberations.

3. THE MODEL, DATA AND ESTIMATION RESULTS

3.1. The Model

We propose the following model for the FOMC decisions on the target rate

$$r_t^* = \beta' x_t - \varepsilon_t \tag{2}$$

$$y_t^* = r_t^* - r_{t-1} \tag{3}$$

where r_t^* is the *true* but unobservable optimal target rate and x_t is a vector of exogenous explanatory variables, which may be $I(0)$, $I(d)$ or $I(1)$ processes or a mixture of these. The lagged variable r_{t-1} is the target rate that was set in the previous meeting. It is also the rate prevailing up to time t-. The latent variable y_t^* measures the deviations between the underlying optimal target rate r_t^* and r_{t-1}. Like r_t^*, y_t^* is unobservable. We use a triple-choice specification for our discrete choice model in which $y_t = -1$ denotes a decrease in the target rate, $y_t = 0$ denotes no change and $y_t = 1$ denotes an increase. We observe

$$\begin{aligned} y_t &= -1 \quad \text{if} \quad y_t^* < \mu_{n0}^1 \\ y_t &= 0 \quad \text{if} \quad \mu_{n0}^1 \leq y_t^* \leq \mu_{n0}^2 \\ y_t &= 1 \quad \text{if} \quad y_t^* > \mu_{n0}^2 \end{aligned} \tag{4}$$

where μ_{n0}^1 and μ_{n0}^2 are threshold parameters, which may be sample size (n) dependent in case y_t^* is nonstationary (*cf.* (7) in the Appendix). In the present case, this would be appropriate if the unobserved optimal target rate r_t^* wandered randomly about the target rate r_{t-1} set at the previous meeting. The Appendix provides more discussion of this issue and provides empirical evidence of nonstationarity in our application.

The announced target rate at time t is

$$\begin{aligned} r_t &= r_{t-1} - \Delta_t \quad \text{if} \quad y_t = -1 \\ r_t &= r_{t-1} \qquad\quad\ \text{if} \quad y_t = 0 \\ r_t &= r_{t-1} + \Delta_t \quad \text{if} \quad y_t = 1 \end{aligned} \tag{5}$$

No assumption is made about the magnitude of the change (Δ_t) in the target rate at time t. So, we do not require that $\Delta_t = y_t^*$ or that the announced target rate equals the optimal rate.

Equations (2), (3) and (4)–(5) constitute our basic model. The Appendix reviews some estimation and inference procedures from Hu and Phillips (2004) on polychotomous nonstationary choice that are relevant when the indicator variables are nonstationary. In the triple-choice problem of the present application, we have $j = -1, 0, 1$ and the indicator function $\Lambda(t, j)$ defined by (8) in the Appendix is simply

$$\begin{aligned} \Lambda(t, -1) &= \frac{y_t(y_t - 1)}{2} \\ \Lambda(t, 0) &= 1 - y_t^2 \\ \Lambda(t, 1) &= \frac{y_t(y_t + 1)}{2} \end{aligned}$$

The parameters, β and μ, can be estimated by either probit or logit regression. In the present application, we use a probit specification and set $P_j(x_t; \theta)$ in (9) to the cdf of the standard normal distribution. Plugging $P_j(x_t; \theta)$ and $\Lambda(t, j)$ into (9) and maximizing gives the maximum likelihood estimate (MLE).

Besides the use of a discrete choice framework with potentially nonstationary regressors, another characteristic of the model (6) is that we have not assumed an autoregressive process for the optimal target rate r_t^*, which is a common assumption in the literature (for instance, Dueker, 1999). As discussed in the Introduction, in a continuous model framework, the observed target interest rate r_t is commonly taken as the optimal interest rate r_t^*. Since the observed target rate r_t is adjusted in small increments it may be well approximated by a continuous process. An autoregressive representation for r_t (and, by implication, for r_t^*) then seems like a reasonable assumption.

The view taken here is that the optimal interest rate is a tool for the Fed in monitoring the economy and it should be determined by current economic fundamentals and the Fed's outlook for the economy in the near future. This view is also the spirit in Taylor's rule described in (1). In the discrete choice approach taken here, we also let r_t^* be determined in a smooth way by variables that reflect current economic conditions. However, in implementing policy, the Fed should not be obliged to keep the target interest rate 'smooth' and we know that in practice it is adjusted discontinuously. In other words, we consider Fed behaviour in determining the optimal interest rate and its behaviour in actually implementing that policy separately.

3.2. Data

Our sample data includes monthly observations of the target rate and other economic variables from January 1994 till December 2001. Here we are especially interested in Fed decisions at scheduled meetings, giving eight observations each year and 64 observations in total over this period. In each month when there is a scheduled meeting, the target rate in our data set is taken to be the end-of-month observation. During this period, most of the target rate changes took place at scheduled meetings and all target rate changes are multiples of 25 bp. Among the 64 observations, the rate was hiked 12 times and cut 13 times. In Figure 1 the upper graph depicts the federal funds target rate and the lower graph depicts rate adjustments in terms of the three classifications hike/cut/no change.

The consumer confidence index data are from the Conference Board. Other economic data are retrieved from the Federal Statistics webpage[2] and the time series database of the Federal Reserve Bank of St. Louis.[3]

Many economic and business statistics are potential candidates for inclusion in the empirical model. Since we are restricted to monthly data, some series such as GDP are not included. Of the remaining candidate variables, we included the following 11 series in the first estimation stage: annual inflation (computed from the core consumer price index), unemployment rate, initial claims for unemployment insurance, money supply (annual growth of M2), consumer confidence index,

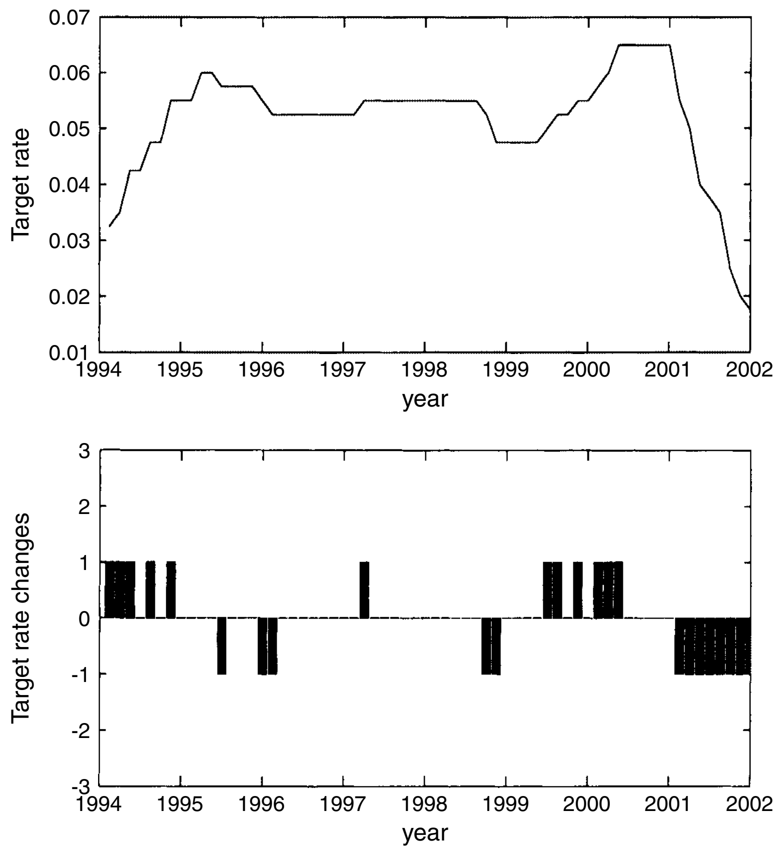

Figure 1. Federal funds target rate and change: 1994–2001

[2] http://www.whitehouse.gov/fsbr/esbr.html
[3] http://www.stls.frb.org/fred/

the annual growth of manufacturers' new orders (nondefence capital goods excluding aircraft), NAPM purchasing index, average weekly working hours, total industry capacity utilization percentage, industrial production index, and lagged target rate changes. The final model retains only those variables whose coefficients are statistically significant and these covariates are M2, initial claims for unemployment insurance, consumer confidence and new orders. Unit root tests were conducted and evidence of nonstationary behaviour was confirmed for each of these four variables.[4]

In matching the Fed decisions on the target rate and prevailing economic variables, we allow a lag of one month to take into account the time lag in the arrival of economic statistics. Thus, for the rate cut decision in June 2001, the monthly economic statistics that were available were for May 2001 and these are the ones included in the regression. In this sense, the model is cast in predictive format.

3.3. Estimation Results

The estimation results are shown in Table I. From the estimates we see that the target rate is lower when unemployment increases, money supply increases, consumer confidence drops and manufacturers' new orders drop. Among the four significant variables, unemployment, M2 and new orders are important economic variables. We note that consumer confidence is also very significant. This is partly explained by statements in the published minutes of the FOMC meetings. For example, in the minutes of the unscheduled conference on January 3, 2001 when the Fed made its first rate cut since November 1998, consumer confidence was mentioned repeatedly. We quote the following comments from the minutes of that meeting.

> In the Committee's discussion of current and prospective economic developments, members commented that recent statistical and anecdotal information provided clear indications of significant slowing in the expansion of business activity and also pointed to appreciable erosion in business and consumer confidence.

The estimated threshold for a rate cut is 94 bp whereas for a rate hike it is 107 bp. These estimates reveal an asymmetry (although not statistically significant) in the threshold with a weaker threshold for rate cuts. Figure 2 displays the model-implied optimal interest rate $\hat{r}_t^*$ (dashed line) and the announced target rate r_t (solid line). Comparing these two series, we can see at least two features.

Table I. Probit regression and threshold parameter estimates

Variable	Estimator	Std.
M2	−0.2738	0.0492
Unemployment claim	−0.0175	0.0033
Consumer confidence	0.0314	0.0074
New orders	0.0392	0.0115
μ_{1n}	−0.0094	0.0021
μ_{2n}	0.0107	0.0021

[4] Z_ρ test statistics were 1.2849 for M2, 0.0734 for unemployment claims, −0.0792 for consumer confidence, and −6.4 for growth in new orders (with a 5% test critical value of −9.9).

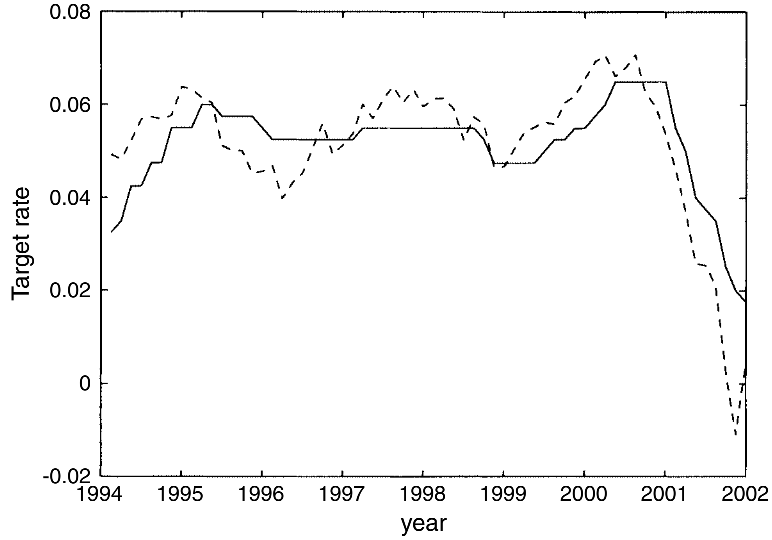

Figure 2. Actual target rate and model implied optimal target rate: 1994–2001

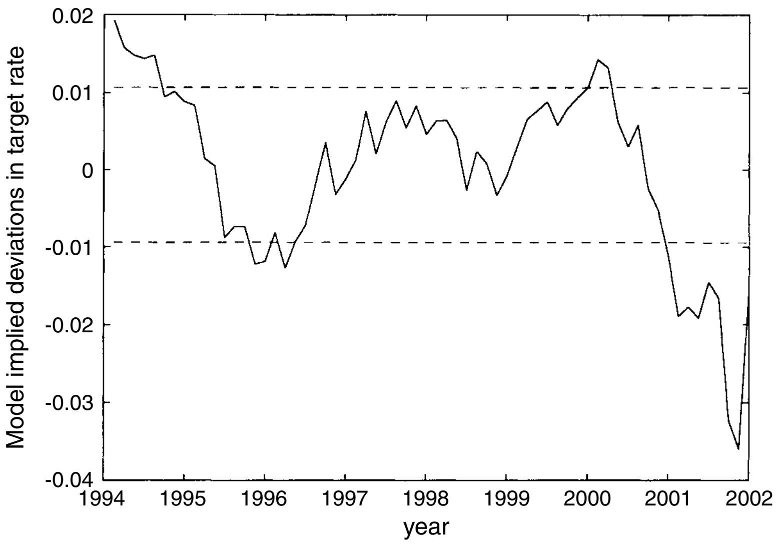

Figure 3. y_t^* and thresholds for adjustment: 1994–2001

First, $\hat{r}_t^*$ is more volatile than r_t. Second, r_t^* seems to lead r_t by about one to three months. This lag in the implementation of monetary policy seems to persist throughout the sample. Balduzzi *et al*. (1996) and Clarida *et al*. (2000) found similar results when they studied target rate changes in earlier periods.

Figure 3 shows deviations of the optimal rate from the lagged rate. The solid line is $\hat{y}_t^*$, defined in (3), and the dashed lines are the estimated thresholds for inducing rate hike and rate cut

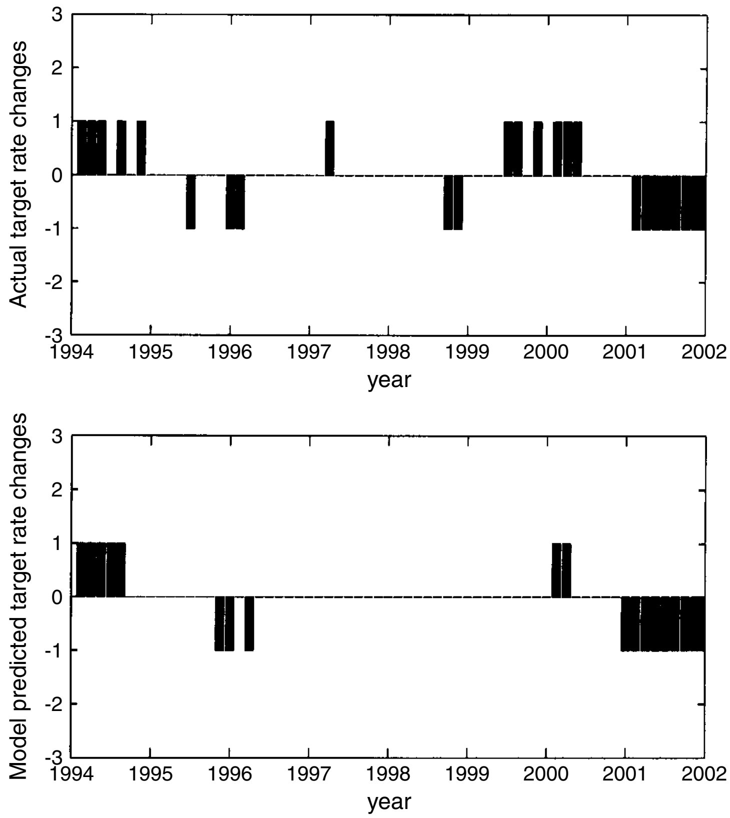

Figure 4. Actual and predicted FOMC decisions: 1994–2001

interventions. In Figure 4, the upper graph plots the actual decision y_t from the data and the lower graph plots the model predicted decision $\hat{y}_t$ inferred from $\hat{y}_t^*$ and $\hat{\mu}_{in}$, $i = 1, 2$.

From these estimation results it is possible to compute the sample proportion of intervention decisions (and predicted decisions) in each category (rate cut, rate hike and no-intervention). As Hu and Phillips (2004) show, these sample proportions have limit distributions that follow an extended class of arc sine laws. For example, if y_t^* is $I(1)$ then the limit laws of the sample proportion of rate cuts ($r_n(-1)$, say), rate hikes ($r_n(1)$, say) and no-intervention ($r_n(0)$, say) are extended arc sine laws with distributions given by the following functionals of standard Brownian motion $W(r)$:

$$r_n(-1) \longrightarrow d \int_0^1 1\left\{W(r) < \frac{\mu_0^1}{\omega_x}\right\} dr$$

$$r_n(1) \longrightarrow d \int_0^1 1\left\{W(r) > \frac{\mu_0^2}{\omega_x}\right\} dr$$

$$r_n(0) \longrightarrow d \int_0^1 1\left\{\frac{\mu_0^1}{\omega_x} < W(r) < \frac{\mu_0^2}{\omega_x}\right\} dr$$

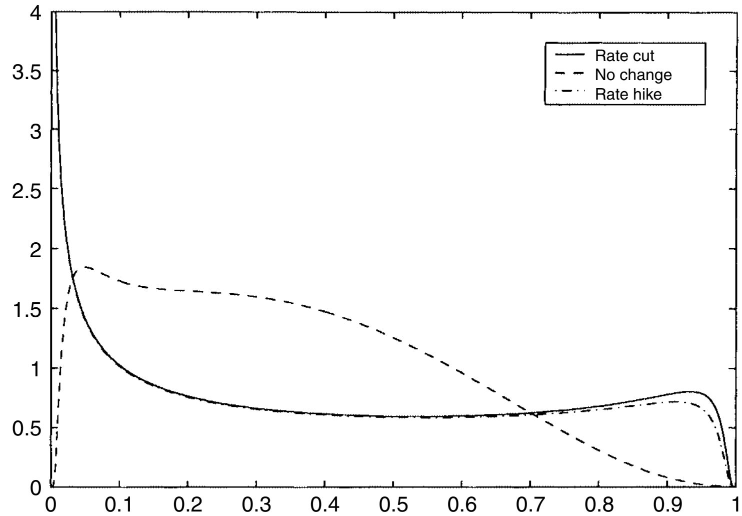

Figure 5. Extended arc sine limit laws for the sample proportions of intervention decisions

where $\mu_0^j = \mu_{n0}^j/\sqrt{n}(j = 1, 2)$ and ω_x^2 is the long-run variance of y_t^*. Using estimated values of μ_0^j and ω_x^2, the limit distributions of $r_n(-1)$, $r_n(1)$ and $r_n(0)$ are shown in Figure 5.

As is apparent from these graphs, the density of $r_n(-1)$ is greatest around the origin, indicating that there is an appreciable chance of getting decisions not to cut rates, but the density also has a peak near unity, showing that there is an appreciable chance of getting a lot of rate cuts. The density of the proportion of rate hikes is also greatest at the origin (again corresponding to the decision not to hike rates) and falls off in a similar fashion to the density of $r_n(-1)$ except that the peak near the unit is lower than that of rate cuts (the probability of getting lots of rate hikes is less than that for rate cuts). This helps to explain strings of similar decisions in Fed policy intervention. The density of the proportion of no-intervention decisions is nearly uniform over the interval (0.1, 0.5) and then falls off to zero at unity. Correspondingly, no-intervention decisions are more evenly distributed through the sample than rate cuts and rate hikes (*cf.* Figure 1).

3.4. Goodness of Fit

The model is estimated with the likelihood computed based on three decisions. The goodness of fit can be summarized by comparing model predicted decisions and actual decisions, as presented in Table II. Out of the 64 meetings we consider in these eight years, we correctly predicted 50 of the decisions, giving an overall correct forecasting percentage of 78%.

Table II. Policy intervention predictions

	Cut at time t	No change at time t	Hike at time t
Cut was predicted	9	3	0
No change was predicted	4	35	6
Hike was predicted	0	1	6

Piazzesi (2001) derives a model-implied FOMC policy rule and she found that the Fed reacts mainly to information contained in the yield curve. In Table 6 in Piazzesi (2001), which reports the forecasting evaluation a of model-implied target model, the model that performs best is the unconditional full model. This model predicts 30 out of the 40 FOMC meetings from 1994 to 1998 correctly, giving a 75% overall correct forecasting percentage. On this count, our model performs slightly better. If we are especially interested in predicting rate changes, the unconditional full model in Piazzesi (2001) predicts four out of six rate hikes and zero out of five rate cuts. So our model also performs better in predicting rate changes.

In analysing the results of a forecasting exercise relating to a future event or action, Kaminsky *et al*. (1998) use a statistic called the 'adjusted noise to signal ratio'.[5] This ratio in our model is 8.5% for rate cuts and 3.8% for rate hikes, while the ratio in Piazzesi's full model is 10.61% for rate hikes and is undefined for rate cuts. The comparison with Piazzesi (2001) can also be interpreted as a comparison with market expectations, since the inferences about FOMC decisions in Piazzesi (2001) are drawn from the yield curve, which reflects market expectations of future FOMC decisions.

Furthermore, in Table II, the phrase 'at time t' in the header emphasizes the timing of the action. This is important because, as is apparent from Figure 2, there is evidence of a lag between the model-implied target rate and the actual target rate. Table II records as successful predictions only those cases where the actions occurred exactly in the months where they were predicted to take place.

In reporting within-sample forecasting performance of the model in Table II, we use point estimates (not confidence interval limits) of the thresholds in making decisions on rate cuts and rate hikes. When we report a predicted change, we use a simple rule for ease of reporting—decision

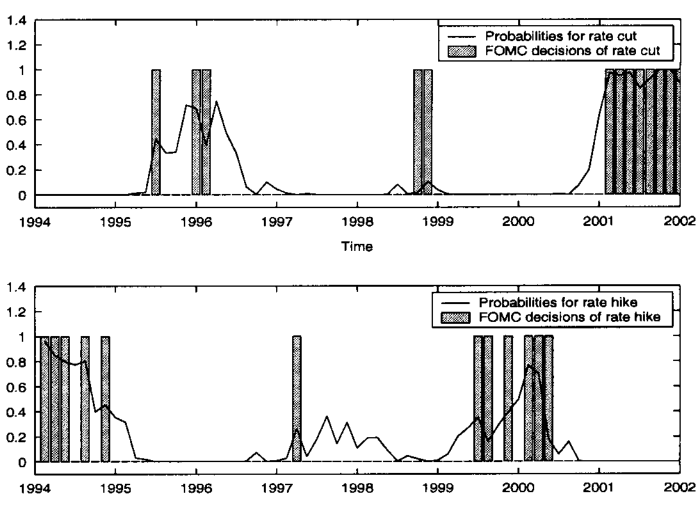

Figure 6. Estimated probabilities of rate cuts and rate hikes

[5] Let A denote the event that an action is predicted and happened; let B denote the event that an action is predicted but did not happen; let C denote the event that an action is not predicted but happened; and, last, let D denote the event that an action is not predicted and did not happen. Outcomes are preferred when entries A and D are large while entries B and C are small. The 'adjusted noise to signal ratio' is defined to be $[B/(B+D)]/[A/(A+C)]$.

j is made because it has the largest probability as a possible outcome. So in Table II we do not distinguish, for instance, between cases where the estimated probability of the action, $P_j(x_t;\hat{\theta})$, is 0.51 or 0.99. In the practical use of our model in forecasting Fed intervention, it may also be useful to report the probits or predicted probabilities of the various forms of intervention directly. These calculations are given in Figure 6 where the estimated probabilities of (rate cut and rate hike) interventions are shown against the background of the actual Fed decision.

3.5. Some Spatial Density and Hazard Rate Calculations

For describing nonstationary time series data, Phillips (1998) introduced the idea of using a spatial density estimate, which measures the amount of time a series spends in the vicinity of each spatial point. The methods can be applied to nonstationary data as well as stationary data, where upon rescaling they correspond to time-invariant probability density estimates. Some empirical illustrations of the technique, including hazard function estimates as well as spatial densities, were given in Phillips (2001) to which the reader is referred for background discussion. The methods were applied here to provide some additional perspective on the results of our probit analysis of Fed intervention and the behaviour of federal funds rate targets. Specifically, we construct spatial density estimates for the fitted optimal interest rate r_t^* and its various components and hazard functions for rate cuts and rate hikes.

Figure 7 shows the estimated spatial density of the model-implied optimal interest rate r_t^*, showing that r_t^* spends most of the time between 4% and 7%. Using the same methods, Figure 8 shows the estimated density of $\hat{y}_t^*$. Using the estimated density for $\hat{y}_t^*$ we calculate hazard functions for rate cuts and rate hikes and show the results in Figures 9 and 10. Both hazard functions display several small peaks, but the overall shapes indicate that the higher is $\hat{y}_t^*$ the greater the chance of a hike (up to 150 bp above r_{t-1}), and that the lower is $\hat{y}_t^*$ the greater the chance of a cut (to around 190 bp below r_{t-1}).

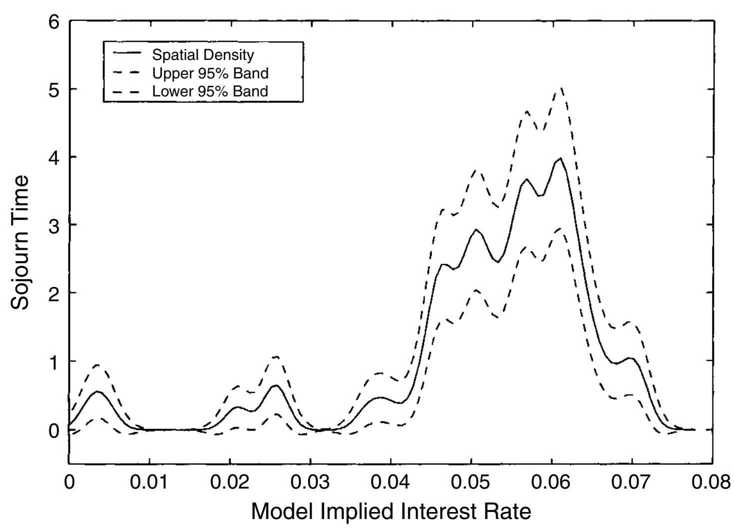

Figure 7. The spatial density of $\hat{r}_t^*$

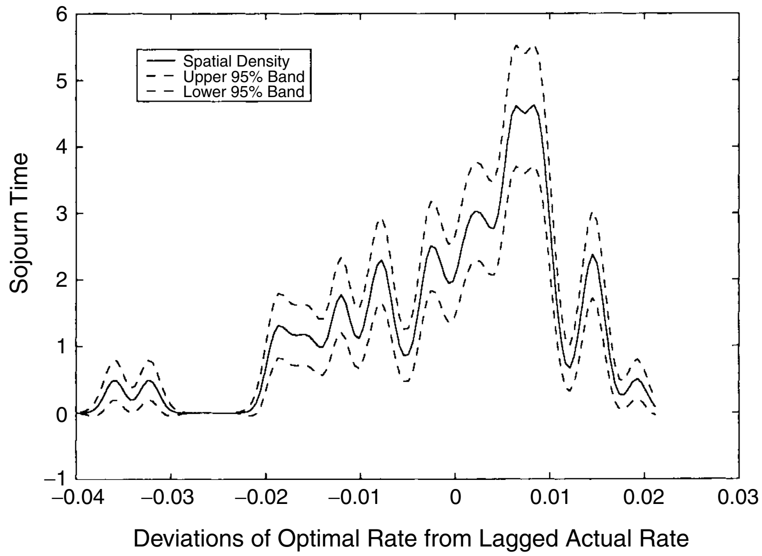

Figure 8. The spatial density of $\hat{y}_t^*$

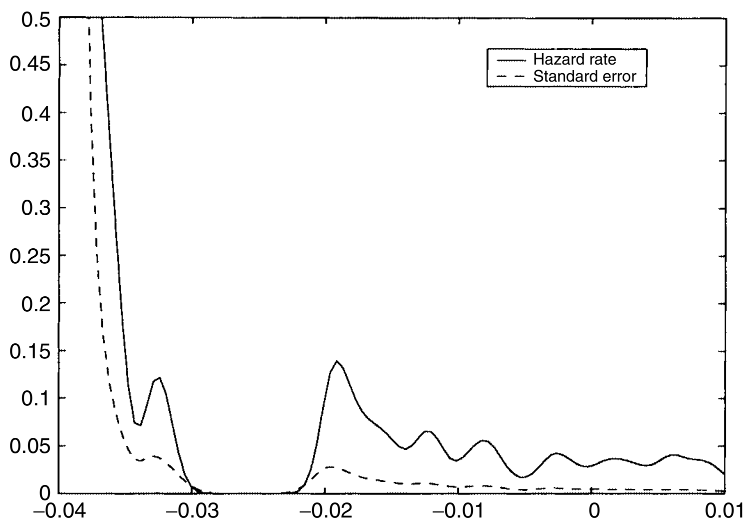

Figure 9. Hazards for target rate cut

4. CONCLUSION

This paper proposes a discrete choice approach to model the dynamics of federal funds target rates and our methods permit the regressors to be nonstationary as well as stationary variables. It is usually hard to predict policy movements accurately with a single econometric model. This seems especially so in the case of monetary policy, where the Fed admits its decisions are based on a broad range of statistical indicators and even anecdotal information. However, the results

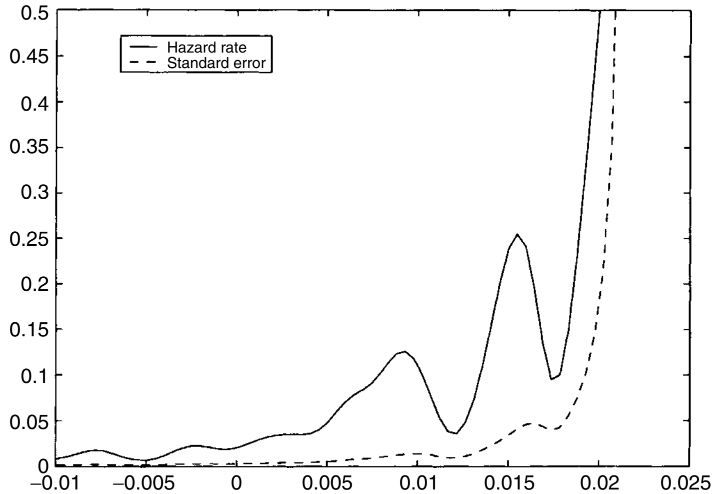

Figure 10. Hazards for target rate hike

indicate that the empirical model approximates the market intervention decisions fairly well using a small number of economic variables. For some periods like that of the year from January 2001 to December 2001, we predicted all FOMC decisions correctly.

Several aspects of our work suggest further research. First, this work is mostly concerned with the 'qualitative' side of Fed intervention, focusing on whether there is a change in the target rate and the direction and timing of that change. The model as it presently stands does not distinguish 25 bp and 50 bp changes. The main reason for not using finer classifications of rate adjustments at the moment is to avoid small sample bias and imprecision. Finer classifications mean much smaller sample sizes for each group. In our present data set, for example, there are only four hikes of magnitude 50 bp or higher, compared with 64 observations in total. It would also be interesting to consider FOMC decisions outside of scheduled meetings, which might well be classified into a different category representing greater urgency in which large thresholds are needed to precipitate action. Again, the small number of observations (one unscheduled hike and three to four cuts) over the sample period make it very difficult to estimate such thresholds.

Second, the discrete choice approach to market intervention and its allowance for potential nonstationarity in the data is well suited to the analysis of other problems. For instance, the approach can be applied to study policy intervention in the foreign exchange market. In these and other situations, it is often useful to have a model that explains and predicts the decision to intervene so that answers can be given to questions like when a change is going to occur, what are the critical factors in precipitating a change and what is the probability of a change occurring.

APPENDIX: NONSTATIONARY DISCRETE CHOICE

This section briefly reviews some recent results from Hu and Phillips (2004)—hereafter HP—on estimation and inference in potentially nonstationary discrete choice models. The model considered in that work has the form

$$y_t^* = x_t'\beta_0 - \varepsilon_t \quad \text{for} \quad t = 1, \ldots, n \tag{6}$$

where x_t is an $(m \times 1)$ vector of explanatory variables and ε_t is an error taken to be *iid* with distribution function F. The dependent variable y_t^* is assumed to be unobserved and what we do observe is the indicator y_t and

$$\begin{aligned} y_t &= 0 \quad \text{if} \quad y_t^* \in (-\infty, \sqrt{n}\mu_0^1) \\ &= 1 \quad \text{if} \quad y_t^* \in (\sqrt{n}\mu_0^1, \sqrt{n}\mu_0^2) \\ &\vdots \\ &= J-1 \quad \text{if} \quad y_t^* \in (\sqrt{n}\mu_0^{J-1}, \sqrt{n}\mu_0^J) \\ &= J \qquad \text{if} \quad y_t^* \in (\sqrt{n}\mu_0^J, \infty) \end{aligned} \tag{7}$$

We assume that x_t is predetermined and is an integrated time series: $x_t = x_{t-1} + v_t$ with $x_0 = O_p(1)$ and

$$v_t = \Pi(L)e_t = \sum_{i=1}^{\infty} \Pi_i e_{t-i}$$

where the coefficients Π_i, the *iid* innovations e_t and F satisfy certain regularity conditions laid out in HP. In (7) the threshold parameters are $\mu_{n0}^j = \sqrt{n}\mu_0^j$, which accords with the stochastic order of the indicator y_t^* for sample size $t = O(n)$.

In the general discrete choice model, the probability distribution of y_t, written as $P(y_t = j) = P_j(x_t; \theta_0)$, has the explicit form

$$\begin{aligned} P_0(x_t; \theta_0) &= 1 - F(x_t'\beta_0 - \sqrt{n}\mu_0^1) \\ P_j(x_t, \theta_0) &= F(x_t'\beta_0 - \sqrt{n}\mu_0^j) - F(x_t'\beta_0 - \sqrt{n}\mu_0^{j+1}) \quad \text{for} \quad j = 1, \ldots, J-1 \\ P_J(x_t; \theta_0) &= F(x_t'\beta_0 - \sqrt{n}\mu_0^J) \end{aligned}$$

Let

$$\Lambda(t, j) = \frac{\Pi_{i=0,\ldots,J \& i \neq j}(y_t - i)}{\Pi_{i=0,\ldots,J \& i \neq j}(j - i)} \tag{8}$$

and it is easy to verify that $\Lambda(t, j) = 1\{y_t = j\}$, the indicator function for $y_t = j$. The log likelihood function can then be written as

$$\log L_n(\theta) = \sum_{t=1}^{n} \sum_{j=0}^{J} \Lambda(t, j) \log P_j(x_t; \theta) \tag{9}$$

As is apparent from the definition, $P_j(x_t; \theta_0)$ involves the nonlinear function $F(x_t'\beta_0 - \sqrt{n}\mu_0^j)$ of the $I(1)$ process x_t. This complication produces an interesting feature in the asymptotics that ML estimates $(\hat{\beta}_n, \hat{\mu}_n)$ of the parameters (β_0, μ_0) converge at the rate $n^{3/4}$ and have a mixed normal limit distribution as $n \to \infty$, whose conditional covariance matrix depends on the local times (at the thresholds) of a Brownian motion arising from the limit process of a standardized version of the index $x_t'\beta_0$. Standard methods of statistical inference turn out to be justified asymptotically in this case. Details are provided in Phillips *et al*. (2003), which provides a corrigenda to the asymptotics in Hu and Phillips (2004).

The particular application of these methods in the present paper involves a decision rule that is based on the deviation, $y_t^* = r_t^* - r_{t-1}$, between the optimal rate and the lagged target rate. The nature of the asymptotics then depends on the stochastic order of y_t^*. The Z_ρ statistic for the series y_t^* is -7.06, which is larger than the 5% level critical value of -9.9. So the null hypothesis that y_t^* is unit root nonstationary is accepted.

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REFERENCES

Balduzzi P, Bertola G, Foresi S. 1996. A model of target changes and the term structure of interest rates. *Journal of Monetary Economics* **39**: 223–249.

Clarida R, Gali J, Gertler M. 2000. Monetary policy rules and macroeconomic stability: evidence and some theory. *Quarterly Journal of Economics* **115**(1): 147–180.

Cook T, Hahn T. 1989. The effects of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics* **24**: 331–352.

Dueker M. 1999. Measuring monetary policy inertia in target fed funds rate changes. *Federal Reserve Bank of St. Louis Review* **81**(5): 3–9.

Fair R. 2001. Actual federal reserve policy behavior and interest rate rules. *FRBNY Economic Policy Review* **March**: 61–72.

Goodhart CA. 1996. Why do the monetary authorities smooth interest rates? Special Paper No. 81, LSE Financial Markets Group.

Hamilton JD, Jorda O. 2002. A model for the federal funds rate target. *Journal of Political Economy* **110**: 1135–1167.

Hu L, Phillips PCB. 2004. Nonstationary discrete choice. *Journal of Econometrics* **120**: 103–138.

Kaminsky G, Lizondo S, Reinhart C. 1998. Leading indicators of currency crises. International Monetary Fund Staff Paper 45.

Park JY, Phillips PCB. 2000. Nonstationary binary choice. *Econometrica* **68**: 1249–1280.

Phillips PCB. 1998. Econometric analysis of Fisher's equation. Cowles Foundation Discussion Paper No. 1180. Presented at the Irving Fisher Conference, Yale University, 1998.

Phillips PCB. 2001. Descriptive econometrics for nonstationary time series with empirical illustrations. *Journal of Applied Econometrics* **16**: 389–413.

Phillips PCB, Jin S, Hu L. 2003. Nonstationary discrete choice: a corrigenda. Yale University, working paper.

Piazzesi M. 2001. An econometric model of the yield curve with macroeconomic jump effect. NBER Working Paper No. 8246.

Rudebusch GD. 1995. Federal reserve interest rate targeting, rational expectations and the term structure. *Journal of Monetary Economics* **35**: 245–274.

Sack B. 1998. Does the Fed act gradually? A VAR analysis. Board of Governors of the Federal Research System, April 1998.

Solow RM, Taylor JB, Friedman BM. 1998. *Inflation, Unemployment, and Monetary Policy*. MIT Press: Cambridge, MA.

Taylor JB. 1993. Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy* **39**: 195–214.

Taylor JB. 1998. Monetary policy guidelines for employment and inflation stability. In *Inflation, Unemployment, and Monetary Policy*, Solow RM, Taylor JB, Friedman BM (eds). MIT Press: Cambridge, MA.

Taylor JB (ed.). 2001. *Monetary Policy Rules*. Studies in Business Cycles, No. 31. National Bureau of Economic Research: Cambridge, MA.

Walsh CE. 1998. *Monetary Theory and Policy*. MIT Press: Cambridge, MA.

