Dynamics of the Federal Funds Target Rate: A Nonstationary Discrete Choice Approach*

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Abstract

We apply a discrete choice approach to model the empirical behavior 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 empirical model is determined using the PIC criterion (Phillips and Ploberger, 1996; Phillips, 1996) as a model selection device. The chosen model successfully predicts the majority of the target rate changes during the time period considered (1985-2001) 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 and that the Fed is more conservative in raising interest rates than in lowering rates.

Keywords: Extended arc sine laws, Federal funds target rate, Interest rate, Monetary policy, Nonstationary discrete choice.

JEL Classification Numbers: C22, C25, E43, E52

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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 modeling 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 analyzing 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 rates rules and the dynamic behavior 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 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, the allowance for potentially nonstationary series that are monitored by the Fed in its decision making capacity, and the use of model selection criteria to determine a suitable empirical model.

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, and 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 VAR's 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 1990, 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 behavior 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.

The empirical approach in this paper is partly based on results obtained by Park and Phillips (2000) and further developed by the authors (2001) 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 behavior, 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 (2001) work is relevant. Moreover, if the explanatory variables actually trend upwards over time and there is a fixed threshold for determining decisions, then we would expect to eventually encounter an uninterrupted string of identical decisions. In that event, the likelihood is unbounded and has no maximum. The occurence of trending variables in the system seems inevitable in the present case since the Fed monitors a huge range of macroeconomic and financial data in making its evaluation of the state of the economy and the need for intervention, and some of the indicators they consider will certainly have nonstationary characteristics. On the other hand, Fed intervention decision outcomes are mixed over time although, as we know, there are periods where strings of similar decisions appear. In consequence, therefore, some detrending of the data is necessarily being undertaken by the Fed in making its decisions on intervention. In principle the empirical form of that detrending might be discovered by econometric model determination techniques through modeling the actual intervention decisions by the Fed in conjunction with a range of different trend elimination techniques.

There is also good reason to allow for some degree of nonstationarity in interest rates. In the finance literature it has been common to model short term interest rates or underlying state variables (factors) in terms of mean-reverting Ornstein-Uhlenbeck processes (e.g. Vasicek, 1977, Cox, Ingersoll and Ross, 1985, Dai and Singleton, 2000, among many others). According to these models, if the current interest rate is high, we may expect it eventually to fall, and if the current interest rate is low, we may expect it to rise. This specification usually works better in the long run than in the short run, especially in terms of its forecasting performance. For example, Fama and Bliss (1987) found that the forecasting power of this model seems to improve as the forecasting horizon is extended, due to the slow mean-reverting property of the interest rate. However, in many situations, we need to forecast in the short run and then we usually observe the opposite of mean-reversion. Indeed, as far as our present application is concerned, when the federal funds rate is increased, instead of expecting it to fall next period, it appears more likely that there will be further increases in the near future. The same is true for decreases in the rate. In summary, instead of a uniform mix of increases and decreases in the funds rate, we are far more likely to observe a sequence of rate adjustments in the same direction. The phenomenon seems to apply over extended periods of time and is confirmed by casual inspection of the evidence - see the lower panel of Fig. 1, which shows monthly target rate adjustments in the Federal funds rate over the period 1986:1-2001:6.

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 characterise 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 8 decisions to lower the rate target over 2001:1-2001:10, there have been some months where no change has been made in the rate. Hu and Phillips (2001) have 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 present paper also applies some econometric model determination techniques discussed in Phillips (1996). For example, we use the posterior information criterion (PIC) to choose which variables should be included in the empirical regression out of a large number of potential candidates that may be monitored by the Fed. We believe these techniques are hepful in letting the data reveal more about the latent decision making behavior of the Fed in the practice of the monetary policy.

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 (2001) on estimation and inference in potentially nonstationary discrete choice models. Some time series graphics of the data are included at the end of the paper.

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. Occasionally, the FOMC also holds unscheduled conferences and can change the interest rate target at these meetings also, two recent examples being the rate cuts of April 18 (with a target reduction from 5% to 4.5%) and September 2001 (with a target reduction from 4.0% to 3.5%). 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

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

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. The daily effective federal funds rate may not equal to the target rate set by FOMC, but the difference is very small, due to Fed's 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 treasure securities. In this way, the federal funds market rate is controlled 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. Whenever there is a change in this target rate, almost all other interest rates adjust correspondingly.

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.

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 labor 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 group of variables. The first group includes economic fundamentals that are believed to directly influence interest rate targets, such as the inflation rate and industrial growth rate. This group of variables are included in most regressions that are based on Taylor rule (1) formulations.

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 will consider 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.

Our approach takes the first group of variables as given for the regression index of the optimal interest rate and uses model selection methods to determine empirically which other explanatory variables should be included from a supplementary group that are likely to be monitored by the Fed.

3 The Model, Data and Estimation Results

3.1 The model

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

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

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

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 choise 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

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

where μ_{n0}^1 and μ_{n0}^2 are threshold parameters, which may be sample size (n) dependent in case y_t^* is nonstationary (c.f (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

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

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. In fact, our empirical findings indicate that in most cases $\Delta_t < |\hat{y}_t^*|$.

Equations (2), (3) and (4)-(5) constitute our basic model. The Appendix reviews some estimation and inference procedures from Hu and Phillips (2001) 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 literature. 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 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 behavior in determining the optimal interest rate and its behavior in actually implementing that policy separately. We will come back to this issue after we obtain estimated r_t^*.

We include current economic fundamentals at time t in the regression for r_t^*, and also include the lagged difference of the target rate, Δr_{t-1}, in the regression. This variable accounts for uncertainties faced by the Fed in forming opinions on the proper level of interest rate. As is apparent in the data (see the lower graph of Fig. 1), changes in target rates often occur consecutively. Intuitively, if there are several target rate cuts in a sequence, it is usually the first cut that is the hardest to predict, both in timing and magnitude, and in this respect may be different from the others. One explanation is that the Fed may hold back in order to be confident in their assessment of prevailing economic conditions before they modify their view of the desirable target rate and take action. In our specification, for the first intervention in a sequence, the lagged rate change variable Δr_{t-1} is zero, and so the information driving decisions comes only from prevailing economic indicators (and some noise). After the first intervention, the deviations (from prevailing economic conditions) needed to induce further actions in the same direction are less. So, for example, if we observe the first rate cut of a sequence in January, then even if the economic indicators are similar in December and February, the probability of a rate cut in December might be smaller than that in February because of the greater uncertainty in December. The lagged rate change Δr_{t-1} helps to account for this factor.

3.2 Data

Our sample data includes monthly observations of the target rate and other economic variables from January 1985 till June 2001. For the series that have trending behavior, like industrial production index, we track the data back as early as 1970. Because there are eight pre-scheduled FOMC meetings each year, we include the data for the months where there are scheduled meetings and also months where there are unscheduled FOMC meetings, thereby avoiding noise from 'non-meeting' months. In January 2001, the Fed cut the interest rate target by 50 bp twice in one month, with the second cut being made on January 30-31. We adjusted the timing of this second cut to February, so that instead of observing a single cut of 100 bp in January we treat these Fed interventions as two cuts in two consecutive months, each cut being 50 bp.

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]. Over the time period 1985:1 to 2001:6 we have 149 observations of the federal funds target rate, the remaining 49 months in this period being omitted because there were no meetings on those months. Since the adjustment indicator depends on the rate difference, we end up with 148 usable observations. Among these 148 observations, the rate has been hiked 28 times and has been cut 41 times. In Fig. 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.

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 cannot be used[4]. Of the remaining candidate variables, we included the following 11 series in the first estimation stage before model selection: annual inflation (computed from the core consumer price index), unemployment rate, initial claims for unemployment insurance, consumer confidence index, NAPM purchasing index, average weekly working hours, total industry capacity utilization percentage, consumer expectations, new housing unit starts, industrial production index, and lagged target rate changes.

The next section discusses how we use model selection methods to determine an empirical model from this group of 11 base variables. The model we end up selecting has the following 5 variables in the regression: inflation, consumer confidence, initial claims for unemployment insurance, industrial production growth, and the lagged target rate change. Since some of these series (like inflation and consumer confidence) have nonstationary behavior, we make use of spatial density estimation to summarize their main characteristics and discuss this approach in detail in section 3.6.

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

[2] `http://www.whitehouse.gov/fsbr/esbr.html.`

[3] `http://www.stls.frb.org/fred/`

[4] There is also a large category of data for inventories, shipments and orders that are relevant but were excluded from the empirical regressions because of a major change in classification in 1992.

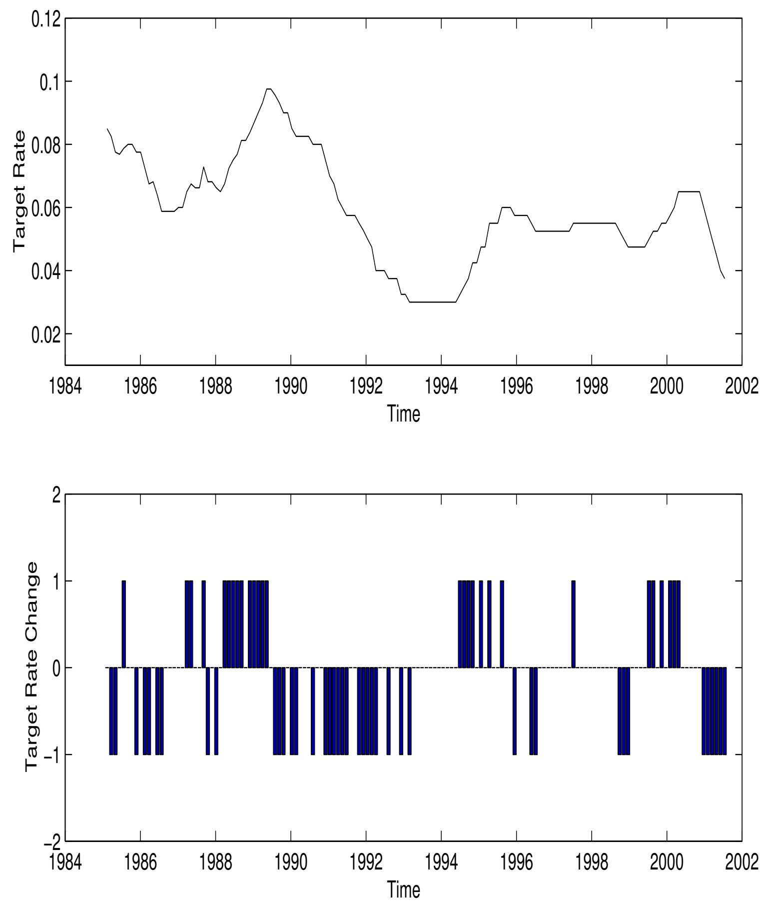

Figure 1: Federal Fund Target Rate and Change: 1985-2001

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 in predictive format.

3.3 Model Selection and Estimation Results

A key issue in the empirical formulation of (2) is the choice of variables to include as regressors. There is general agreement that some measure of inflation and output growth should be included in a policy rule for the determination of interest rates. While recognizing that many other variables may be relevant, there is less consensus about them. From a practical viewpoint, it is clear from congressional testimony and FOMC policy statements that many economic series and much financial data are considered in Fed decision making and, correspondingly, all such variables are potential candidates for inclusion. The determination of a suitable empirical model for Fed decision making therefore needs to take into account the explanatory power of such variables against the additional cost of including them.

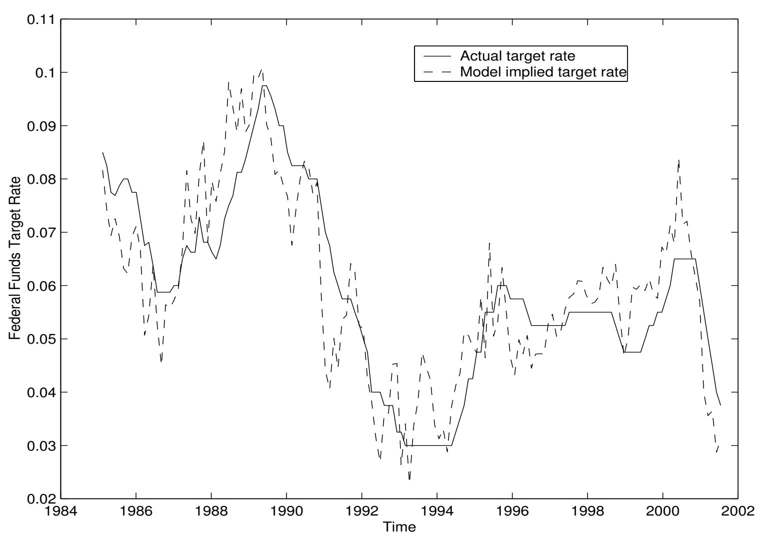

Figure 2: Actual Target Rate and Model Implied Optimal Target Rate: 1985.01-2001.06

A natural way to proceed in this assessment is to use model selection methods to find a suitable empirical model. In the present application, we used the PIC criterion (Phillips and Ploberger, 1996, and Phillips, 1996) of model determination to select the 'best' set of explanatory variables. The PIC criterion chooses the model that maximizes the penalized log likelihood, viz. $l_n(\hat{\theta}_n) - (1/2)\ln|B_n|$, where $l_n(\hat{\theta}_n)$ is the log likelihood evaluated at the MLE and B_n is the sample information about the parameters. This criterion is valid in models with stationary and nonstationary regressors. Including all of the 11 variables listed above produces a probit likelihood of -115.88 and PIC value of -182.66. Applying the PIC criterion we then choose the empirical model with the best 5 of these 11 variables in terms of penalized likelihood. The log likelihood and PIC for the chosen model is -123.98 and -161.27 and the variables selected are: inflation, consumer confidence, unemployment claims and industrial production growth.

variable	estimator	std	t-stat
Inflation	1.6355	0.0826	19.8073
Consumer Confidence	0.0580	0.0066	8.7492
Unemployment Claim	-0.0067	0.0032	-2.0896
Industrial Growth	0.1193	0.0698	1.7097
Δr_{t-1}	2.1884	0.3915	5.5905
μ_{1n}	-0.0068	0.0015	-4.5601
μ_{2n}	0.0107	0.0015	7.2031

Table 1: Probit regression and threshold parameter estimates

The estimation results are shown in Table 1. The most significant variable turns out to be inflation, as might be expected in an empirical model of monetary policy intervention where there is inflation targeting. However, it may be surprising that consumer confidence is also very significant. In fact, it is the most significant variable after inflation. 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 estimates of the threshold parameters for market intervention are also highly significant and they are asymmetric. Thus, the threshold for a rate cut is 68 bp whereas for a rate hike it is 107 bp. In contrast, working directly from the data, we compute that for a rate cut the average magnitude is 35 bp and the largest movement is 75 bp; whereas, for a rate hike, the average magnitude is 33 bp and the largest movement is also 75 bp. So statistics for actual cuts and hikes are almost symmetric. Therefore, our first conclusion is that the deviations (in the index) needed to induce a change in the current target rate are greater than the average magnitude of the actual changes and that greater deviations in the index are generally needed to induce an increase than a decrease in the target rate. In other words, the Fed is more conservative in raising the target interest rate.

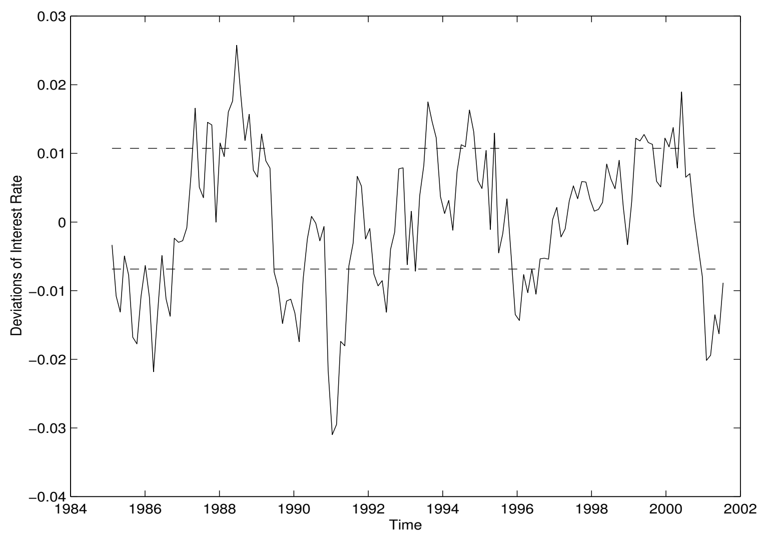

Figure 3: y_t^* and Thresholds for Adjustment: 1985.01-2001.06

Fig. 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. 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.

Fig. 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 interventions. In Fig. 4, the upper graph plots the actual decision y_t from the data and the lower graph plots

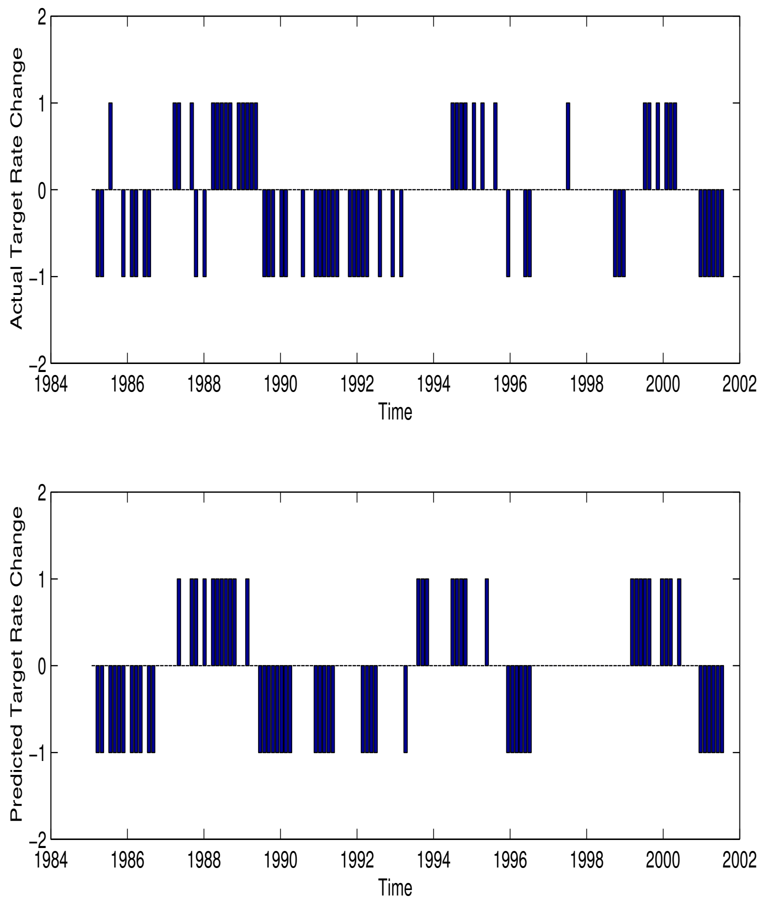

Figure 4: Actual and Predicted FOMC Decisions: 1985.01-2001.06

the model predicted decision $\hat{y}_t$ inferred from $\hat{y}_t^*$ and $\hat{\mu}_{in}$, $i = 1, 2$. Comparing this two graphs, we see again that $\hat{y}_t$ apparently leads y_t by a short time period, especially in the case of rate hikes.

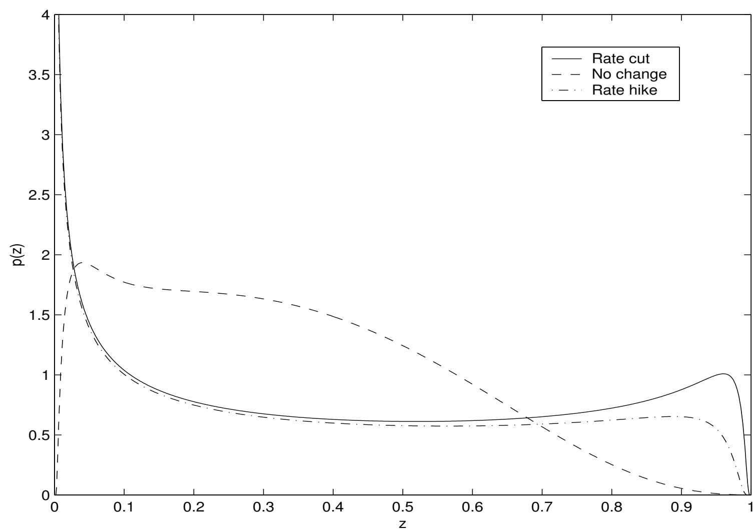

Figure 5: Extended Arc Sine Limit Laws for the Sampe Proportions of Intervention Decisions

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 (2001) 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 $W(r)$

$$\begin{aligned} r_n(-1) &\rightarrow_d \int_0^1 1\left\{W(r) < \frac{\mu_0^1}{\omega_x}\right\} dr, \\ r_n(1) &\rightarrow_d \int_0^1 1\left\{W(r) > \frac{\mu_0^2}{\omega_x}\right\} dr, \\ r_n(0) &\rightarrow_d \int_0^1 1\left\{\frac{\mu_0^1}{\omega_x} < W(r) < \frac{\mu_0^2}{\omega_x}\right\} dr, \end{aligned}$$

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 Fig. 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 there is no peak in the density as the proportion approaches unity (the probability of getting lots of rate hikes is less than that for rate cuts). This difference in the two distributions manifests the asymmetry in Fed policy intervention between rate cuts, for which the Fed appears to adopt a more liberal policy position, and rate hikes, over which the Fed appears to be more conservative. It also 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 (c.f. Figs. 1 and 6).

3.4 Goodness of Fit

In analyzing the results of a forecasting exercise relating to a future event or action, the following matrix recording successes and failures is useful in the assessment.

	Action	No action
Action was predicted	A	B
Action was not predicted	C	D

Outcomes in this table are preferred when entries A and D are large while entries B and C are small. A ratio based on these quantities can then be used as a criterion for goodness of fit. In evaluating the performance of forecast indicators of currency crises, Kaminsky, Lizondo and Reinhart (1997) recently used an 'adjusted noise to signal ratio' as a summary criterion computed from the entries of this matrix according to the formula $[B/(B+D)]/[A/(A+C)]$. This statistic is computed in Table 2, where we report the results of our forecasts of Fed monetary policy intervention.

	Cut at time t	No Cut at time t	Noise/signal ratio
Cut was predicted	27	14	19.87%
Cut was not predicted	14	93	
	Hike at time t	No Hike at time t	Noise/signal ratio
Hike was predicted	16	12	17.50%
Hike was not predicted	12	108	

Table 2: Policy Intervention Predictions

In Table 2, the phrase 'at time t' in the headings emphasizes the timing of the action. This is important because, as is apparent from Fig. 2, there is evidence of a lag between the model implied target rate and the actual target rate. Table 2 records as successful predictions only those cases where the actions occurred exactly in the months where they were predicted to take place. The percentage of correct predictions of cuts and hikes is then 67% and 57%, respectively. If we were to allow a two-month lag, then 36 out of 41 predicted cuts and 22 out of 28 predicted hikes took place within three months from the time they were predicted. The ratio of 'correctly' predicted cuts and hikes would then be 88% and 79%, respectively.

In reporting within-sample forecasting performance of the model in Table 2, 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 j is made because it has the largest probability as a possible outcome. So in Table 2 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 Fig. 6 where the estimated probabilities of (rate cut and rate hike) interventions are shown against the background of the actual Fed decision.

3.5 Detrending

One of the variables chosen in the regression is industrial production growth. Since Nelson and Plosser's (1982) study, industrial production is commonly assessed as a trend stationary (rather than difference stationary) series. Industrial production growth can then be calculated by regression on a linear trend, giving a constant (average) growth rate over the period or by recursive calculations over shorter subperiods. In evaluating empirical evidence

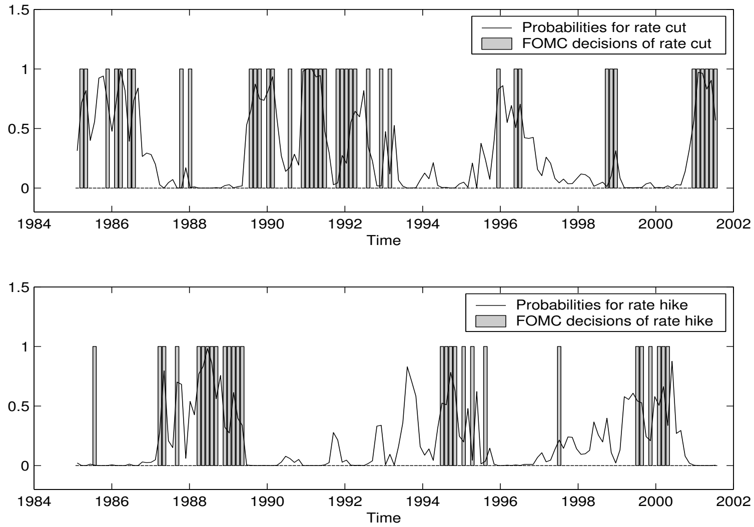

Figure 6: Estimated Probabilities of Rate Cuts and Rate Hikes

on industrial production growth, observers such as the Fed will make ongoing assessments of the latest realized growth rate against some benchmark based on 'recent' as well as longer term evidence. Fig. 7 plots the semi-annual growth rate of industrial production (quoted as an annual rate) estimated recursively with a rolling period of four years against the benchmark average growth rate estimated from the full data series over 1985-2001.

It is apparent from Fig. 7 that growth rates estimated with a rolling window fluctuate over time, so that the benchmark provided by recent evidence on growth is itself evolving. To show how this time-varying growth rate benchmark affects the interpretation of empirical evidence, consider the following example. Suppose in year 1993, we observed a realized growth rate of 2%. We might have assessed this growth rate as a bad indicator if it were compared to the overall sample average of 2.9%. However, against 'recent evidence' from the recursive estimate, we see that 2% growth is actually not that bad because its expected value from the rolling assessment is less than 1% due to the 1991 recession.

Fig. 8 plots the deviations of the realized growth rate from its 'recent' expected value, as estimated recursively. We included this variable in our final regression. The evidence of a downturn in realized growth against recent expectations is very apparent in this figure, providing confirmation of the recession downturns in 1991 and in 2001 which is less evident in Fig. 7.

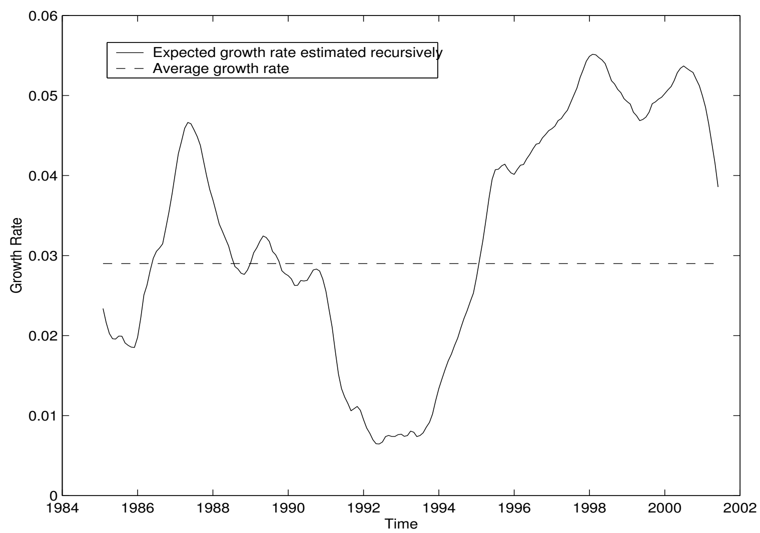

Figure 7: The Growth Rate of Industrial Production

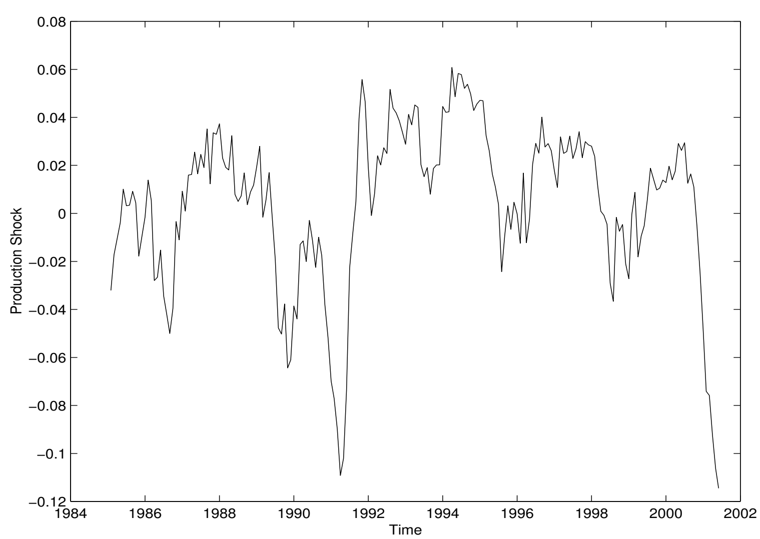

Figure 8: The Deviations of Realized Growth Rate from its Expectation

3.6 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 behavior 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.

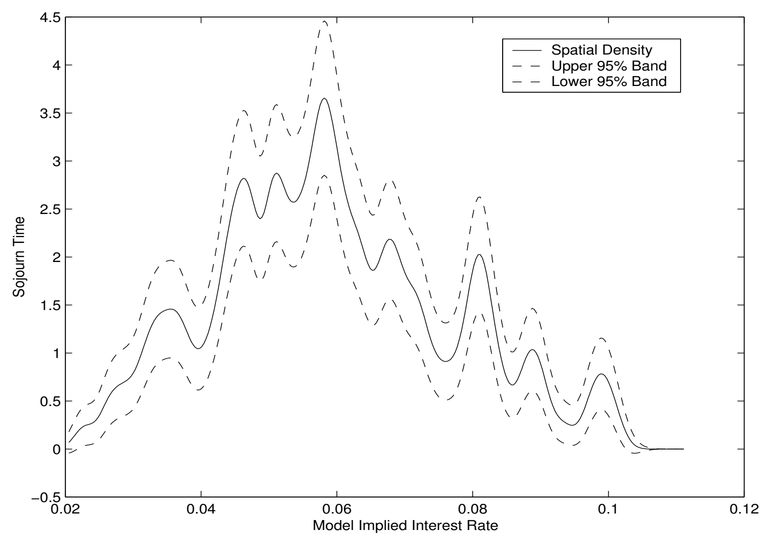

Figure 9: The Spatial Density of $\hat{r}_t^*$

Fig. 9 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% to 8% with some significant peaks at higher levels. Using the same methods, Figs. 4- 4 show spatial densities for each of the component variables included in r_t^*. The most significant components of r_t^* are inflation and consumer confidence. Inflation shows two major peak densities around 2.5% and 4.5%, and consumer confidence randomly wanders over its support with numerous peak density levels.

Fig. 10 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 Figs. 11 and 12 . 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 200 bp above r_{t-1}), and that the lower is $\hat{y}_t^*$ the greater the chance of a cut (to around 240 bp below r_{t-1}).

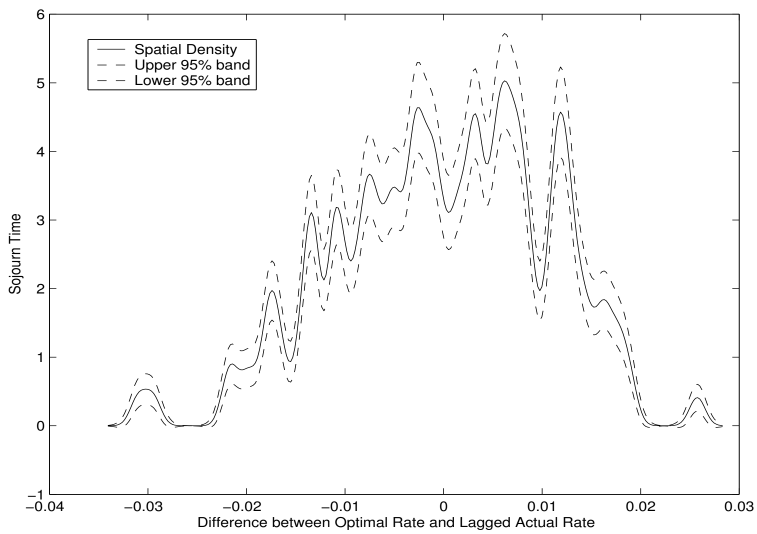

Figure 10: The Spatial Density of $\hat{y}_t^*$

3.7 Out-of-sample Forecasting

All the results we have reported so far are from within-sample forecasting. It is also of interest to check the model's out-of-sample (ex ante) forecasting performance by recursive estimation. The disadvantage of recursive estimation is that the results inevitably suffer from small sample bias and imprecision during the earlier years of the sample when there are only a few observations of rate changes. Another shortcoming is that there are differences in how the Fed adjusted the target rate before 1990 and after 1990, as will be discussed in the Conclusion. Since our sample time period is sixteen and a half years, we used the first eight years (1985-1993) to calibrate the likelihood and model and then checked out-of-sample performance over

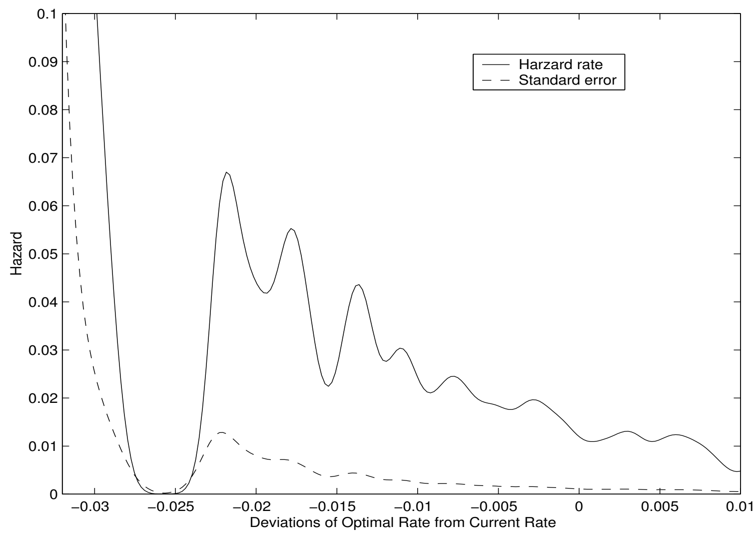

Figure 11: Hazards for Target Rate Cut

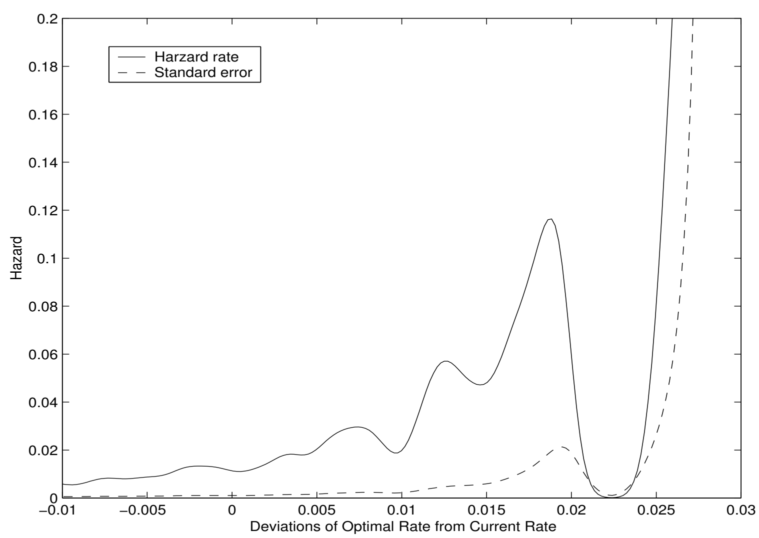

Figure 12: Hazards for Target Rate Hike

the remaining eight and half years. We do not report detailed results here. But, in general, the forecasting performance is not as good as it is in the within-sample case. The model correctly predicted 6 out of the 12 cuts and 9 out of the 14 hikes during this period.

4 Conclusion

This paper proposes a discrete choice approach to model the dynamics of federal funds target rates. Our methods permit the regressors to be nonstationary as well as stationary variables, we use model selection methods that accommodate these data characteristics and we seek to let the data speak about the determining factors in Fed decisions on market intervention. 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 indicate that the empirical model approximates the market intervention decisions fairly well using a small number of economic variables and they reveal the prominent role played by inflation and consumer confidence in Fed intervention decisions. For some periods like that of the year from June 2000 to June 2001, we predicted all FOMC decisions correctly.

Several aspects of our work suggest further research. First, we assume that monetary policy is consistent over the period 1985 - 2001. However, regarding the adjustments made in target rates, there are some differences between the 1980's and 1990's. The data suggest that there are more frequent adjustments of smaller magnitude in the 1980's and that rate cuts and rate hikes are sometimes close to each other during that period. However, since the early 1990's, the Fed appears to have been more cautious in changing the target rate and the magnitude of adjustments has been in multiples of 25 bp. Our model does not account for these factors. As time passes and we have more data, we may be able to conduct tests of the consistency of policy and determine whether the model needs to be adjusted for subperiods like the 1980's.

Second, this work is mostly concerned with the 'qualitative' side of Fed intervention and focusses on whether there is a change in the target rate and the direction 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 smaller sample sizes for each group. In our present data set, for example, there are only 8 hikes of magnitude 50 bp or higher, compared with 148 observations in total.

Finally, 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 (2001) - hereafter HP- on estimation and inference in potentially nonstationary discrete choice models. The model considered in that work has the form

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

where x_t is a (m by 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

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

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 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

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

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 different rates, with some components converging at the slower rate $n^{1/4}$, others at the faster rate $n^{3/4}$. More specifically, HP show that as $n \to \infty$ and under certain regularity conditions

$$\begin{pmatrix} n^{1/4}(\hat{\beta}_n - \beta_0) \\ n^{3/4}(\hat{\mu}_n - \mu_0) \end{pmatrix} \to_d \text{MN}(0, V), \tag{10}$$

where the limit distribution is mixed normal with conditional covariance matrix V whose distribution depends on the local time of a Brownian motion arising from the limit process of a standardized version of the index $x_t'\beta_0$. Standard methods of inference are justified asymptotically by (10) because as $n \to \infty$

$$-[E_n^{-1}J_n(\hat{\theta}_n)E_n^{-1}]^{-1} \to_d V$$

where $E_n = \text{Diag}(n^{1/4}I_m, n^{3/4}I_J)$ and $J_n(\hat{\theta}_n)$ is the usual hessian matrix evaluated at the MLE $\hat{\theta}_n = (\hat{\beta}_n', \hat{\mu}_n')'$.

Readers are refered to HP for proofs and discussion of these and other results that are applicable in a nonstationary choice models. As discussed in Park and Phillips (2000), if there are additional explanatory variables that are stationary in the regression, then the scale for the estimation of the coefficients of these variables is also $n^{1/4}$ provided there is at least one $I(1)$

variable among the regressors. The Park-Phillips and HP techniques were developed for models with $I(1)$ and $I(0)$ variables. Although we do not provide the extension here, these techniques extend to cases where the explanatory variables have long memory with memory parameter $d \in [0,1]$, with changes in rates of convergence and the limit theory that reflect the order of the regressors and probit functions of them. The case where $d \in (1/2, 1)$ involves nonstationary long range dependence may be particularly important in applications like the present one because earlier work (Phillips, 1998) provides evidence that inflation and interest rates have memory parameters in this range.

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^*. ADF, Z_α, and Z_t unit root tests of the fitted series $\hat{y}_t^* = x_t'\widehat{\beta} - r_{t-1}$ all reject the null hypothesis of a unit root at the 5% level[5]. On the other hand, a KPSS test of stationarity rejects the null of stationarity for $\hat{y}_t^*$ at the 5% level. Thus, there is some uncertainty about the stochastic order of $\hat{y}_t^*$. Since the observed series $\hat{y}_t^*$ shows evidence of some random wandering behavior (see Fig. 3) and since both unit root and stationary behavior were rejected, long memory behvior is an alternate possibility. We therefore computed log periodogram (LP) and Whittle semiparametric estimates of the memory parameter, d, for the series $\hat{y}_t^*$. Both these estimators are known to be consistent (Kim and Phillips, 2000, and Phillips and Shimotsu, 2000) for values of d in the interval $[0,1]$, and this is the range of values for d suggested by the empirical results of the unit root and stationarity tests. The estimates obtained by these methods (using a band of $m = [n^{0.75}]$ frequencies near the origin) are given in Table 3. Both LP and Whittle estimates confirm that there is evidence of nonstationarity in the series $\hat{y}_t^*$.

	Log periodogram	Whittle
$\widehat{d}$	0.57	0.72
st. error	0.10	0.06
95% Confidence Band	(0.37,0.76)	(0.60,0.84)

Table 3: Memory Parameter Estimates for $\hat{y}_t^*$

[5]Neither of these tests take account of the presence of the fitted regression coefficient in $\hat{y}_t^*$.

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Data and Spatial Densities

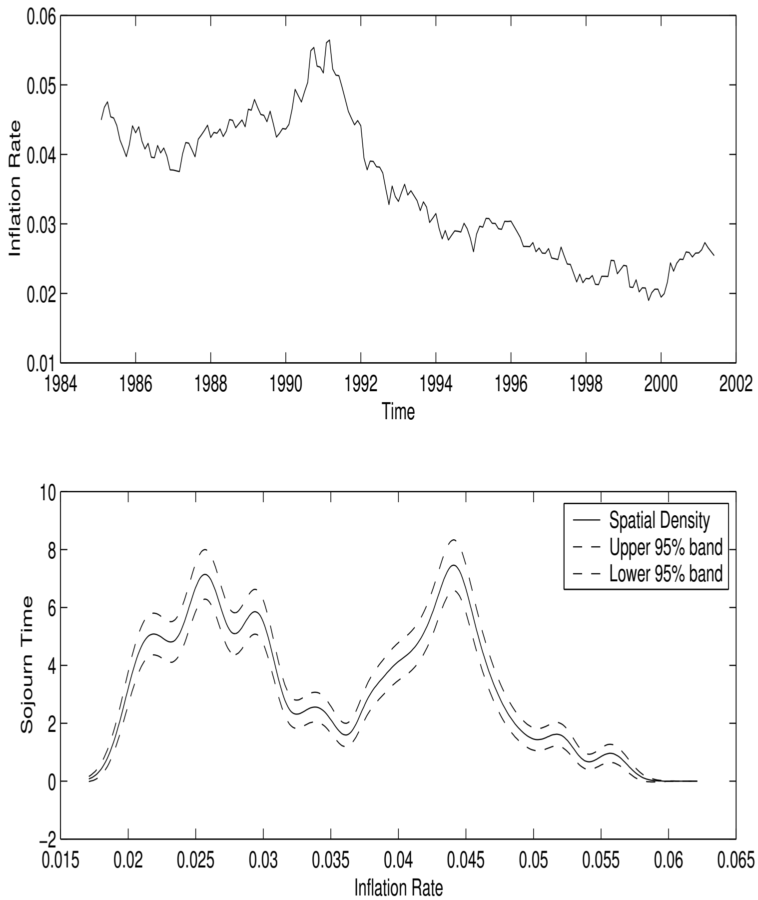

Figure 13: Monthly Year to Year Inflation Rate: 1985-2001

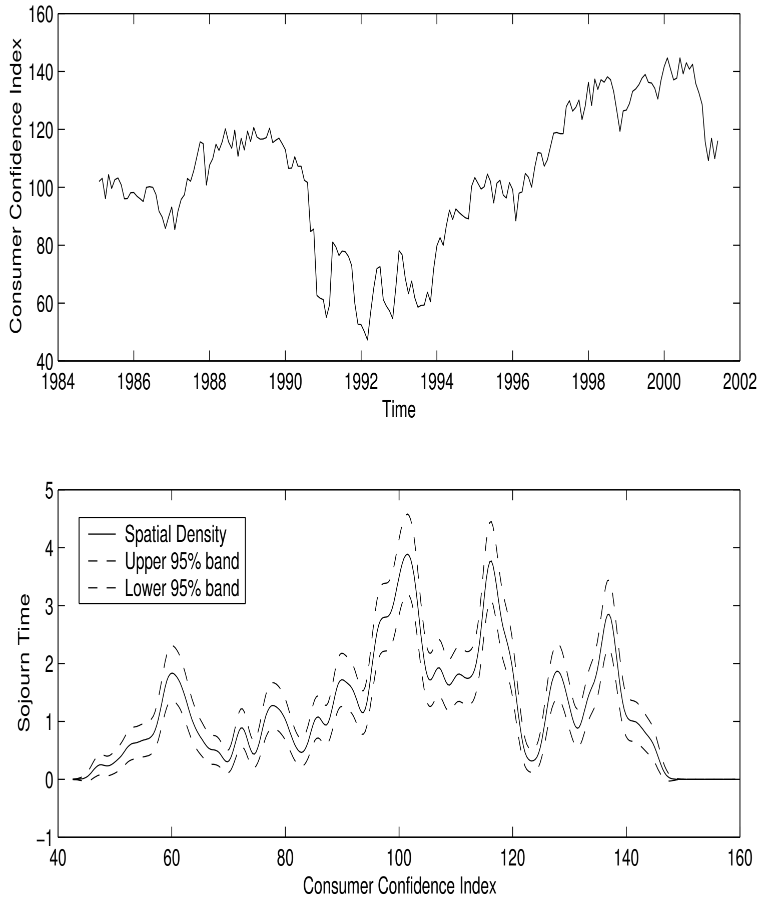

Figure 14: Consumer Confidence Index: 1985-2001

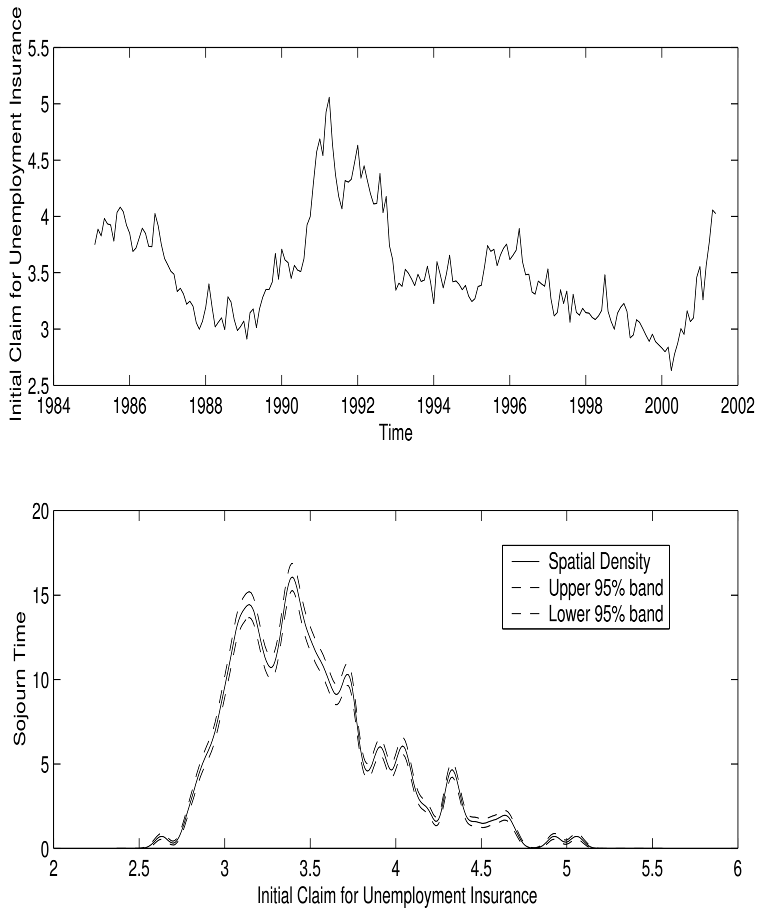

Figure 15: Initial Claim for Unemployment Insurance: 1985-2001

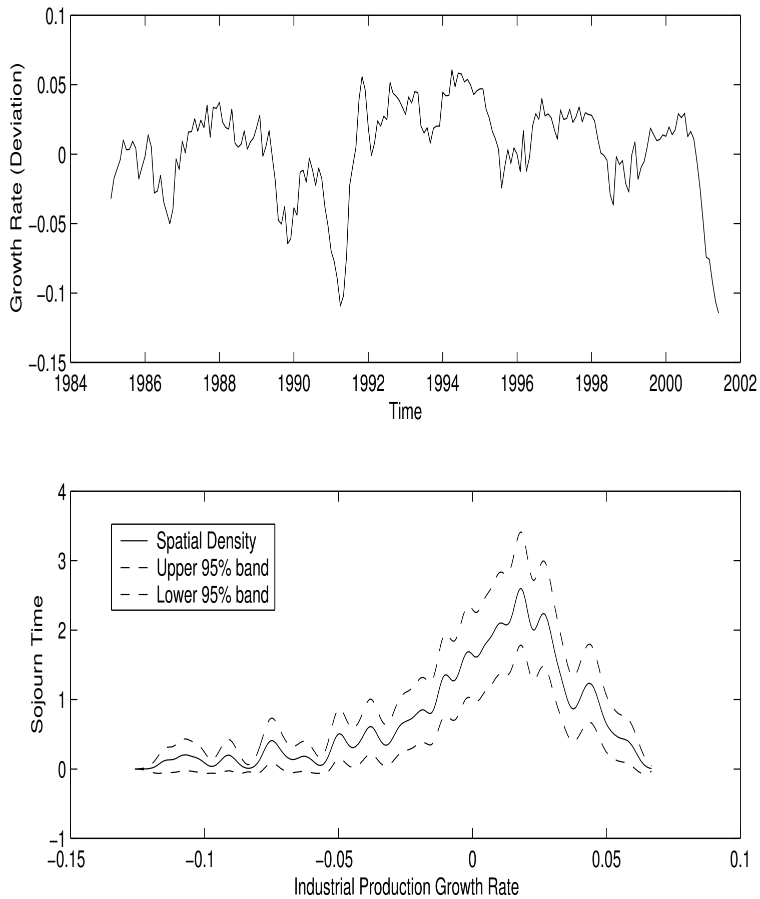

Figure 16: Industrial Production Growth Rate (Deviation): 1985-2001