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James D. Hamilton
Department of Economics, 0508
University of California, San Diego
9500 Gilman Dr.
La Jolla, CA 92093-0508
e-mail: jhamilton@ucsd.edu

Òscar Jordà
Department of Economics
University of California, Davis
One Shields Avenue
Davis, CA 95616-8578
e-mail: ojorda@ucdavis.edu

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A Model of the Federal Funds Rate Target*

James D. Hamilton and Òscar Jordà

University of California at San Diego

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Abstract

This paper is a statistical analysis of the manner in which the Federal Reserve determines the level of the federal funds rate target, one of the most publicized and anticipated economic indicators in the financial world. The paper introduces new statistical tools for forecasting a discrete-valued time series such as the target, and suggests that these methods, in conjunction with a focus on the institutional details of how the target is determined, can significantly improve on standard VAR forecasts of the effective federal funds rate. We further show that the news that the Fed has changed the target has substantially different statistical content from the news that the Fed failed to make an anticipated target change, causing us to challenge some of the conclusions drawn from standard linear VAR impulse-response functions.

1 Introduction

This paper is a statistical analysis of the manner in which the Federal Reserve System (the Fed) determines the level of short-term interest rates in the U.S. In particular, we study when and how the Fed decides to change the level of the federal funds rate target, one of the most publicized and anticipated indicators for financial markets all over the world. The *target* (for short) is an internal objective that is set by the Chairman of the Federal Reserve System in compliance with the directives agreed upon at the Federal Open Market Committee (FOMC) meetings. The target is used by the Trading Desk of the Federal Reserve Bank of New York as a guide for the daily conduct of open market operations. We believe the target is of considerable economic interest precisely because it is not the outcome of the interaction of supply and demand of federal funds and it is not subject to technical fluctuations or extraneous sources of noise. Rather, it is an operational indicator of how the direction of monetary policy determined by the FOMC is translated into practice.

This paper introduces new statistical tools for forecasting a discrete-valued time series such as the target, and suggests that one can substantially improve on standard VAR forecasts of the effective federal funds rate by focusing on these aspects of the data along with institutional details of how the target gets set. We illustrate how our framework can be used as an alternative to the usual VAR impulse-response analysis to measure the effects of monetary policy. In a standard recursively-identified VAR, a monetary policy shock is measured as the difference between the federal funds rate and the rate that one would have predicted using the lagged and specified contemporaneous variables in the VAR. Such a linear representation makes no distinction between a forecast error that arises because the Fed unexpectedly raised the target and one where a drop in the target was anticipated but failed to materialize. In our nonlinear forecasting model, by contrast, the two events turn out to contain quite different statistical information. If the Fed unexpectedly raises the target, it would cause one to revise a forecast of future employment substantially downward. A 25-basis-point target hike would lead one to predict a 0.2 percent decrease in employment a year later, twice as large a drop as implied by a linear VAR. On the other hand, if one expected the Fed to lower the target 25 basis points and it did not, the new information should cause little change in the predicted level of employment. The rational expectation is that the Fed will go ahead and lower the target at the next FOMC meeting with the same implications for employment a year out. We argue that the usual linear VAR is actually measuring a combination of these two very different events.

A separate contribution of the paper is a new methodology for modeling the dynamics of limited dependent variables. One approach might be to use a conventional logit or probit model and assume that all of the relevant conditioning variables are included; see for example Dueker's (1999b) very useful study. The drawback is that significant serial correlation is likely to characterize the latent residuals. The dynamic probit specification (Eichengreen, Watson, and Grossman, 1985; Davutyan and Parke, 1995) is one way to deal with this, but has the disadvantage of requiring difficult numerical integrations. Monte Carlo Markov chain simulations (McCulloch and Rossi, 1994) and importance-sampling simulation estimators (Lee, 1999) are promising alternative estimation strategies. In particular, Cargnoni, Müller, and West (1997) proposed modeling the conditional probabilities as a nonlinear transformation of a latent Gaussian process, and simulated the Bayesian posterior distribution using a combination of the Gibbs sampler and Metropolis-Hastings algorithm. Fahrmeir (1992, 1994) and Lunde and Timmermann (2000) suggested a latent process for time-varying coefficients and also used numerical Bayesian methods for inference. Dueker (1999a) employed a latent Markov-switching process to model serial dependence in volatility, again analyzed with numerical Bayesian methods. Piazzesi (2001) proposed a linear-quadratic jump diffusion representation, though the technical demands for estimation of the latent continuous-time process from discretely sampled data are considerable.

In any of these numerically intensive methods, the ultimate object of interest is typically to form a forecast of the discrete event conditional on a set of available information, and this forecast will be some nonlinear function of the information. A logical shortcut is to hypothesize a data-generating process for which this nonlinear function is a primitive element rather than the outcome of millions of computations. The question is how to aggregate past realizations in a way that reduces the dimensionality of the problem but still could reasonably be expected to summarize the dynamics.

The autoregressive conditional duration (ACD) model of Engle and Russell (1997, 1998a) and Engle (2000) seems a very sensible approach for doing this. In the ACD specification, the forecast of the length of time between events is taken to be a linear distributed lag on previous observed durations. Given a sufficient number of lags, the forecast errors are serially uncorrelated by construction, thus directly solving the problem implicit in any latent variable formulation. For the ACD(1,1) model, the forecast duration is simply exponential smoothing applied to past durations. Although this seems a very promising way to model the serial dependence in discrete-valued time series, it is not clear how one should update such a forecast on the basis of information that has arrived since the most recent target change.

Engle and Russell's ACD specification poses the question, How much time is expected to pass before the next event (e.g., target change) occurs? Here we reframe the question as, How likely is it that the target will change tomorrow, given all that is known today? We describe this framework as the autoregressive conditional hazard (ACH) model.

Our proposed ACH framework is introduced in Section 2. This class of time-series processes includes as a special case a discrete-time version of the ACD framework. The appendix develops the formal connection between the ACH and ACD specifications of the likelihood function. Our ACH specification has the advantage over the ACD model that it readily allows one to incorporate updated explanatory variables in addition to lagged target changes in order to form a forecast of whether the Fed is likely to change the target again soon.

Section 3 shows how this framework can be used to forecast the value of the target itself, which requires predicting not only whether a change will occur but also the magnitude and direction of the change. We suggest that, conditional on a change in the target, one can use an ordered probit model to describe the size of the change.

Section 4 discusses the institutional background for the target, which motivates several details of the particular specification used in the empirical results presented in Section 5. The forecasting performance of these ACH estimates is evaluated in Section 6. The dynamics of the target described by our model are then used in a policy analysis exercise described in Section 7. Section 8 concludes.

2 The Autoregressive Conditional Hazard Model

The autoregressive conditional duration (ACD) model of Engle and Russell (1998a) describes the average interval of time between events. Let u_n denote the length of time between the nth and the $(n+1)$th time the Fed changed the target, and let ψ_n denote the expectation of u_n given past observations $u_{n-1}, u_{n-2}, ...$ The ACD(r, m) model posits that[1]

$$\psi_n = \sum_{j=1}^{m} \alpha_j u_{n-j} + \sum_{j=1}^{r} \beta_j \psi_{n-j}. \tag{1}$$

Engle and Russell show that the resulting process for durations u_n, when indexed by the cumulative number of target changes n, admits an ARMA$(\max\{m, r\}, r)$ representation with the jth autoregressive coefficient given by $\alpha_j + \beta_j$. Thus stationarity requires $\sum_{j=1}^{m} \alpha_j + \sum_{j=1}^{r} \beta_j < 1$.

If $\overline{u}$ denotes the average length of time between observed target changes, one can start the recursion (1) by setting the initial values $u_{1-j} = \overline{u}$ for $j = 1, 2, ..., m$ and $\psi_{1-j} = \overline{\psi}$ for

[1] The original ACD model also included a constant term in (1). We leave it out here, choosing instead always to include a constant term in $\mathbf{z}_{t-1}$ defined below. Dufour and Engle (1999) and Zhang, Russell and Tsay (2001) have recently suggested some nonlinear generalizations of the ACD for which it would be interesting to explore the ACH analogs.

$j = 1, 2, ..., r$ where

$$\overline{\psi} = \frac{\sum_{j=1}^{m} \alpha_j \overline{u}}{1 - \sum_{j=1}^{r} \beta_j}. \tag{2}$$

The basic premise of our approach is that observations on the process only occur at discrete points in time. Although one could use our method with daily data, little is lost by analyzing the target changes on a weekly frequency for the institutional reasons given in Section 5 below. Define $N(t)$ to be the cumulative number of target changes observed as of week t.[2] For example, if the first target change occurs in week 5, the second target change in week 8, and so on, then

$$N(t) = \begin{cases} 0 & \text{for } t = 1, 2, 3, 4 \\ 1 & \text{for } t = 5, 6, 7 \\ 2 & \text{for } t = 8, 9, ... \end{cases}$$

Equation (1) can then be rewritten in calendar time as

$$\psi_{N(t)} = \sum_{j=1}^{m} \alpha_j u_{N(t)-j} + \sum_{j=1}^{r} \beta_j \psi_{N(t)-j}. \tag{3}$$

Notice that, viewed as a function of t, expression (3) is a step function that only changes when the target was changed during week t, i.e., only when $N(t) \neq N(t-1)$.

Next consider the hazard rate h_t, which is defined as the conditional probability of a change in the target given $\boldsymbol{\Upsilon}_{t-1}$, which represents information observed as of time $t-1$:

$$h_t = \Pr[N(t) \neq N(t-1) | \boldsymbol{\Upsilon}_{t-1}]. \tag{4}$$

[2] $N(t)$ is the counting process associated with successive occurrences of "target change" events in the interval $(0, t]$. Hence, $N(0) = 0$; $N(t) = N(t-1)$ if the target remains unchanged in the interval $(t-1, t]$, and $N(t) = N(t-1) + 1$ if at time t the target is changed.

Suppose that the only information contained in $\boldsymbol{\Upsilon}_{t-1}$ were the dates of previous target changes, so that the hazard rate would not change until the next target change. In this case, one could calculate the expected length of time until the next target change as

$$\sum_{j=1}^{\infty} j(1-h_t)^{j-1}h_t = 1/h_t. \tag{5}$$

The hazard rate that is implied by the ACD model (1) would then be

$$h_t = 1/\psi_{N(t-1)}. \tag{6}$$

Notice that if one changes the units in which time is measured, the magnitude of ψ changes correspondingly. For example, the expected length of time until the next target change could equivalently be described as $\psi = 4$ weeks or 28 days or 672 hours, and the probability of a change within the next time period would correspondingly be described as a 1 in 4 chance of a change within the next week, a 1 in 28 chance of a change within the next day, and so on. The formal demonstration in the appendix that the ACH formulation (6) and the ACD formulation (1) imply the identical likelihood function is in fact a limiting result as the definition of a time period becomes arbitrarily short. If instead the time period becomes arbitrarily long – for example, if the expected duration were reported as $\psi = 1/12$ of a year, then (6) would imply a probability of a change within the next year of $h = 12$, obviously a nonsensical result. The problem is that as the definition of a time period becomes longer, the probability of more than one occurrence of an event within a single time period grows, invalidating the calculation in (5). We assume that the time interval is chosen to be sufficiently short so that no observed duration is ever less than one period and the probability of more than one event during a single period is negligible. This is simply a normalization of the units in which time is measured. With this normalization, the expected duration ψ cannot be smaller than unity and h must be between zero and one. In addition to this choice of units, we will want to impose the condition $\psi > 1$ on the maximum likelihood algorithm to ensure that the numerical search procedure does not make a poor guess of parameter values that would imply an expected duration of less than one period or, equivalently, a probability outside of $(0, 1)$.

The obvious advantage of describing the process in terms of calendar time and the hazard rate rather than in terms of event indexes and expected durations is that new information that appeared since the previous target change may also be relevant for predicting the timing of the next target change. A natural generalization of expression (6) is

$$h_t = \frac{1}{\psi_{N(t-1)} + \boldsymbol{\delta}'\mathbf{z}_{t-1}} \tag{7}$$

where $\mathbf{z}_{t-1}$ denotes a vector of variables that is known at time $t-1$.

It might appear from the unit coefficient on $\psi_{N(t-1)}$ in the denominator of (7) that this approach imposes a particular scale relation between durations u_n and hazard rates h_t. However, this is not the case. For example, if one solves (3) for $m = r = 1$ and substitutes the result into (7), the hazard can be written as

$$h_t = \frac{1}{\boldsymbol{\delta}'\mathbf{z}_{t-1} + \alpha\tilde{u}_{N(t-1)}}$$

where $\tilde{u}_{N(t-1)}$ is a weighted average of past durations:

$$\begin{aligned}\tilde{u}_{N(t-1)} &= u_{[N(t-1)-1]} + \beta u_{[N(t-1)-2]} + \beta^2 u_{[N(t-1)-3]} + ... \\ &\quad + \beta^{[N(t-1)-2]} u_1 + \beta^{[N(t-1)-1]} \overline{u} + \beta^{N(t-1)} \overline{u}/(1-\beta).\end{aligned}$$

Hence α is effectively a free parameter for translating from units of durations into a hazard rate.

It is important to ensure that a numerical search procedure does not select a value of h_t outside of $(0, 1)$. One way to do this would be simply to set h_t to a constant slightly below unity whenever the denominator of (7) gets too small. We have had success with pasting this constant together with (7) using a function that smoothes the transition so that the resulting expression is always differentiable, replacing (7) with[3]

$$h_t = \frac{1}{\lambda\{\psi_{N(t-1)} + \boldsymbol{\delta}'\mathbf{z}_{t-1}\}} \tag{8}$$

with $\psi_{N(t-1)}$ calculated from (3).

Given this hazard, it is then simple to evaluate the log likelihood function. Let $x_t = 1$ if the target changes during week t and zero otherwise. Notice from (4) that the probability of observing x_t given $\boldsymbol{\Upsilon}_{t-1}$ is

$$g(x_t|\boldsymbol{\Upsilon}_{t-1};\boldsymbol{\theta}_1) = (h_t)^{x_t}(1-h_t)^{1-x_t}$$

[3] Specifically, we use

$$\lambda(v) = \begin{cases} 1.0001 & v \leq 1 \\ 1.0001 + 2\Delta_0(v-1)^2/[\Delta_0^2 + (v-1)^2] & 1 < v \leq 1 + \Delta_0 \\ 0.0001 + v & v \geq 1 + \Delta_0 \end{cases}$$

with $\Delta_0 = 0.1$.

for $\boldsymbol{\theta}_1 = (\boldsymbol{\delta}', \boldsymbol{\alpha}', \boldsymbol{\beta}')'$. Thus the conditional log likelihood is

$$\mathfrak{L}_1(\boldsymbol{\theta}_1) = \sum_{t=1}^{T} \{x_t \log (h_t) + (1 - x_t) \log (1 - h_t)\} \tag{9}$$

which can then be maximized numerically with respect to $\boldsymbol{\theta}_1$. Robustness of numerical maximization routines likely requires further restricting $\alpha_j \geq 0$, $\beta_j \geq 0$, and $0 \leq \beta_1 + ... + \beta_r \leq 1$.

It is of interest to note that the ACH model includes the ACD model as a special case not only in terms of its implied value for the expected time separating target changes but also in terms of the value of the likelihood function (9) in the limit as the time interval used to discretize calendar time becomes arbitrarily small. This is demonstrated in the appendix.

3 Predicting the value of the target

Predicting the value of the federal funds rate target for any given week requires answering two questions. The first is the question analyzed up to this point: Is the Fed going to change the target this week or leave it in place? Second, if the Fed does change the target, by how much will the target change? Such a time series is sometimes described as a marked point process, in which "points" refers to the dates at which the target is changed (dates t for which $x_t = 1$) and "marks" refers to the sizes of the changes when they occur. Let y_t be the mark, or the magnitude of the target change if one occurs in week t. As before, let $\boldsymbol{\Upsilon}_{t-1}$ denote information up to time $t-1$, which in addition to the endogenous variables x_t and y_t will include a vector of exogenous variables such as production, prices, and unemployment, that influence the Fed's decision on the target. Our task is to model the joint probability distribution of x_t and y_t conditional on the past. Without loss of generality, this probability can be factored as:

$$f(x_t, y_t|\boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = g(x_t|\boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_1)q(y_t|x_t, \boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_2). \tag{10}$$

Our objective is to choose $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ so as to maximize the log likelihood,

$$\sum_{t=1}^{T} \log f(x_t, y_t|\boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = \mathfrak{L}_1(\boldsymbol{\theta}_1) + \mathfrak{L}_2(\boldsymbol{\theta}_2) \tag{11}$$

where

$$\mathfrak{L}_1(\boldsymbol{\theta}_1) = \sum_{t=1}^{T} \log g(x_t|\boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_1) \tag{12}$$

is described in equation (9) while

$$\mathfrak{L}_2(\boldsymbol{\theta}_2) = \sum_{t=1}^{T} \log q(y_t|x_t, \boldsymbol{\Upsilon}_{t-1}; \boldsymbol{\theta}_2). \tag{13}$$

If $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ have no parameters in common, then maximization of (11) is equivalent to maximization of (12) and (13) separately. If they do have parameters in common, then separate maximization would not be efficient but would still lead to consistent estimates.[4]

Consider, then, the determinants of the marks, or the size of a target change given that one occurs. Target changes typically occur in discrete increments of 25 basis points, though changes as small as 6.25 basis points were sometimes observed prior to 1990. The

[4] An interesting approach that models $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ jointly is the autoregressive multinomial framework of Engle and Russell (1998b).

discreteness of the target suggests the use of an ordered response model as in Hausman, Lo, and MacKinlay (1992).

Let $\mathbf{w}_{t-1}$ denote a vector of variables observed in the week prior to t that includes predetermined and exogenous variables. We hypothesize the existence of an unobserved latent variable y_t^* that depends on $\mathbf{w}_{t-1}$ according to

$$y_t^* = \mathbf{w}_{t-1}'\boldsymbol{\pi} + \varepsilon_t \tag{14}$$

where $\varepsilon_t|\mathbf{w}_{t-1} \sim$ i.i.d. $N(0,1)$.

Suppose that there are k different discrete amounts by which the Fed may change the target. Denote the possible changes in the target by $s_1, s_2, ..., s_k$ where $s_1 < s_2 < ... < s_k$. Conditional on $x_t = 1$, we hypothesize that the observed discrete target change y_t is related to the latent continuous variable y_t^* according to

$$y_t = \begin{cases} s_1 & \text{if} \quad y_t^* \in (-\infty, c_1] \\ s_2 & \text{if} \quad y_t^* \in (c_1, c_2] \\ \vdots & \\ s_k & \text{if} \quad y_t^* \in (c_{k-1}, \infty) \end{cases} \tag{15}$$

where $c_1 < c_2 < ... < c_k$. Notice that the probability that the target changes by s_j is given by

$$\Pr(y_t = s_j|\mathbf{w}_{t-1}, x_t = 1) = \Pr(c_{j-1} < \mathbf{w}_{t-1}'\boldsymbol{\pi} + \varepsilon_t \leq c_j)$$

for $j = 1, 2, ..., k$, with $c_0 = -\infty$ and $c_k = \infty$. If $\Phi(z)$ denotes the probability that a standard Normal variable takes on a value less than or equal to z, then these probabilities can be written

$$\begin{aligned}\Pr(y_t &= s_j|\mathbf{w}_{t-1}, x_t = 1) \\ &= \begin{cases} \Phi(c_1 - \mathbf{w}'_{t-1}\boldsymbol{\pi}) & \text{for} \quad j = 1 \\ \Phi(c_j - \mathbf{w}'_{t-1}\boldsymbol{\pi}) - \Phi(c_{j-1} - \mathbf{w}'_{t-1}\boldsymbol{\pi}) & \text{for} \quad j = 2, 3, ..., k-1 \\ 1 - \Phi(c_{k-1} - \mathbf{w}'_{t-1}\boldsymbol{\pi}) & \text{for} \quad j = k. \end{cases}\end{aligned}$$

Note that this specification implies that the bigger the value of $\mathbf{w}'_{t-1}\boldsymbol{\pi}$, the greater the probability that the latent variable y_t^* takes on a value in a higher bin and so the greater the probability of observing a big increase in the target y_t. Thus if an increase in the unemployment rate tends to cause the Fed to lower the target, then we would expect the coefficient in $\boldsymbol{\pi}$ that multiplies the unemployment rate to be negative.

Let $\ell(y_t|\mathbf{w}_{t-1}; \boldsymbol{\theta}_2)$ denote the log of the probability of observing y_t conditional on $\mathbf{w}_{t-1}$ and $x_t = 1$,

$$\ell(y_t|\mathbf{w}_{t-1}; \boldsymbol{\theta}_2) = \begin{cases} \log[\Phi(c_1 - \mathbf{w}'_{t-1}\boldsymbol{\pi})] & \text{if} \quad y_t = s_1 \\ \log[\Phi(c_j - \mathbf{w}'_{t-1}\boldsymbol{\pi}) - \Phi(c_{j-1} - \mathbf{w}'_{t-1}\boldsymbol{\pi})] & \text{if} \quad y_t = s_2, s_3, ..., s_{k-1} \\ \log[1 - \Phi(c_{k-1} - \mathbf{w}'_{t-1}\boldsymbol{\pi})] & \text{if} \quad y_t = s_k \end{cases} \qquad (16)$$

where $\boldsymbol{\theta}_2 = (\boldsymbol{\pi}', c_1, c_2, ..., c_{k-1})'$. The conditional log likelihood of the marks (the second term in equation (11)) can thus be written

$$\mathcal{L}_2(\boldsymbol{\theta}_2) = \sum_{t=1}^{T} x_t \ell(y_t|\mathbf{w}_{t-1}; \boldsymbol{\theta}_2). \qquad (17)$$

The vector of population parameters is then estimated by maximizing (17) subject to the constraint that $c_j > c_{j-1}$ for $j = 1, 2, ..., k - 1$.

4 Data and Institutional Framework

The U.S. Federal Reserve requires banks to hold deposits in their accounts with the Fed so as to exceed a minimum required level based on the volume of transactions deposits held by the banks' customers. Calculation of whether a bank satisfies these reserve requirements is based in part on the bank's average Federal Reserve deposits held over a two-week period beginning on a Thursday and ending on a Wednesday. If the Fed sells Treasury securities to the public, the payments it receives from banks' customers force banks to reduce their Fed deposits. Given the need to continue to meet reserve requirements, banks are then forced to try to borrow the reserves from other banks on the federal funds market or from the Fed at the Fed's discount window, or to manage with a lower level of excess reserves. Banks' aversion to the second and third options causes the equilibrium interest rate on loans of federal funds to be bid up in response to the initial sale of securities by the Fed. The Trading Desk of the Federal Reserve Bank of New York carefully monitors banks' reserve requirements and available Fed deposits, and implements purchases or sales of Treasury securities (open market operations) in order to achieve a particular target for the federal funds rate.[5]

The raw data for our study are the dates and sizes of federal funds target changes for

[5] See Feinman (1993) or Meulendyke (1998) for further details.

1984-2001 compiled by Glenn Rudebusch (1995) and updated by Volker Wieland.[6] These values are reported in Table 1. The nature of the target and details of its implementation have changed considerably during our sample period. In the early part of the sample, the directive for the Trading Desk at the Federal Reserve Bank of New York was often framed in terms of a desired level of "reserve pressure," interpreted as an expected level of borrowing from the Fed's discount window (see for example Heller, 1988, or Meulendyke, 1998, pp. 139-142). Given a relatively stable positive relation between discount window borrowing and the federal funds rate, this usually translated fairly directly into a target for the federal funds rate itself. However, a borrowed reserves target requires frequent adaptation of the procedure to changes in market conditions. Table 1 reveals that, in the early part of the sample, target changes almost always came on Thursday, either at the beginning of a new two-week reserve maintenance period or halfway through in response to new market information. Moreover, the target was characterized by small and frequent adjustments over this period. Dates of FOMC meetings are given in Table 2. In the latter part of our sample, the FOMC directives were almost always implemented immediately. In the early part of our sample, the FOMC directives usually were not implemented until the week following the FOMC meeting, and additional changes often came much later, evidently reflecting decisions made by the Chairman of the Federal Reserve under the broad guidelines of earlier FOMC directives.

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[6] We thank Volker Wieland for graciously providing us with these data. These data are now publicly available from the Federal Reserve Bank of New York at http://www.ny.frb.org/pihome/statistics/dlyrates/fedrate.htm

In principle, it would be possible to apply our ACH model to daily data with careful modeling of these strong day-of-the-week effects. We felt that little was lost by converting our data to a weekly series, where for compatibility with the reserve-requirement cycle we define a week as beginning on a Thursday and ending on a Wednesday. The target we associate with any given week is the value for the target on the final Wednesday of that seven-day period. For eight weeks in our sample, there were two target changes within this seven-day period, which in our constructed data were treated as a single large change.[7]

Small, frequent changes in the target were perhaps a necessary aspect of the borrowed reserves operating procedure, but they served another function as well, namely helping to provide for Fed secrecy. When Chairman Paul Volcker allowed the federal funds rate to reach 20% in 1981, he did not want the evening news reporting how much the Fed had deliberately decided to kick up interest rates each day. The target changes in the early part of our sample were virtually never announced publicly.

This does not mean that the market did not know about the changes in the target. On the contrary, if the Fed made a large injection of reserves on a day when the federal funds rate was already trading below the previous target, market participants would quite accurately and immediately know that the target had been lowered. Indeed, the *Wall Street Journal* would report each day whether the target had been raised or lowered. Cook and Hahn (1989) constructed a time series for the target based exclusively on market inferences as reported in the *Wall Street Journal,* and the series is quite close to the official Trading Desk

[7] These consolidated weeks correspond to the following observations: 5/16/1985; 9/3/1987; 10/22/1987; 8/4/1988; 11/17/1988; 2/9/1989; 2/23/1989; and 10/31/1991.

figures used here. Thus, Fed "secrecy" did not mean keeping the market confused about what the Fed was up to; indeed, giving the market a clear understanding of the FOMC target helped the Fed considerably to implement its goals. Instead, "secrecy" meant that the nature of the inference was sufficiently arcane and subtle that detailed Fed directives were not reported by the nonfinancial press and thus the Fed was insulated slightly from political criticism for its weekly decisions.

Secrecy issues aside, a borrowed reserves operating procedure ultimately had to be disbanded for the simple reason that banks became virtually unwilling to borrow from the discount window regardless of the level of the federal funds rate.[8] Discount window borrowing came to be viewed by a bank's creditors as a signal of financial weakness, inducing banks to pay almost any cost to avoid it. The dashed line in the top panel of Figure 1 plots monthly values for the level of discount window borrowing for adjustment purposes. By 1991 discount window adjustment borrowing had essentially fallen to zero. Internal Fed documents reveal that by 1989 the Fed was increasingly coming to ignore the borrowed reserves target and effectively target the federal funds rate directly.[9]

When Alan Greenspan became Chairman in 1987, the Fed initially continued the policy of borrowed reserves targeting and small, semi-secret target changes. Some key events for the transition to the current operating procedure occurred in the fall of 1989. During October 13-19, there was confusion about the Fed response to the stock market fall. The next month,

[8] This distaste for discount window borrowing is a likely consequence of the collapse of the Continental Illinois Bank and Trust Company and other similar bank failures in the mid-eighties.

[9] Federal Reserve Bank of New York, 1990, pp. 34-35, 56-57.

the Fed added reserves on November 22 at a time when the rate was below its 8-1/2 % target. The market interpreted this as a signal that the target had been lowered, and a Fed policy change was announced in the business press (*Wall Street Journal*, November 24, 1989, p. 2; November 28, 1989, p. 1). In fact the Fed had not changed its target, but had added reserves because of its analysis of the demand for borrowed reserves. These market reactions prompted a re-examination of Fed procedure. One change shows up quite dramatically in the series for the assumption that the Trading Desk made about the level of discount window borrowing in forming its implementation of monetary policy each day, which appears as the solid line in the top panel of Figure 1.[10] Up until November 1989 this borrowing assumption series tracked adjustment borrowing as best it could. After November, the Fed essentially assumed zero adjustment borrowing, so that the borrowing assumption series becomes nearly identical to the level of seasonal borrowing (Panels B and C of Figure 1). One further sees no change in the target that is smaller than 25 basis points after November 1989, and no repeat of the market confusion in interpreting Fed policy. Indeed, since 1994, the Fed has announced its target in complete openness.

5 Empirical Results

5.1 ACH estimates

For reasons just discussed, we suspected a break in the process associated with the change in Fed operating procedures and indeed found dramatically different serial correlation prop-

[10] Data for the Trading Desk borrowing assumption are from Thornton (2001). We thank Daniel Thornton for graciously sharing these data.

erties of target durations associated with the two regimes. We therefore report the results from ACH models fit to two different subsamples, the first corresponding to the borrowed-reserves target regime (March 1,1984 to November 23, 1989) and the second to the explicit funds-rate target regime (November 30, 1989 to April 26, 2001).

For each subsample we considered a number of variables to include in the vector $\mathbf{z}_{t-1}$ in equation (8) to try to predict the timing of changes in the target. The variables we considered fall in three general categories: (1) variables reflecting the overall state of the macroeconomy that may influence interest rates and the Fed's broad policy objectives; (2) monetary and financial aggregates; and (3) variables specific to the Trading Desk operating procedures. For macroeconomic variables, we used the most recent figures available as of week t. For example, the January CPI is not released until the second week of February. Thus, for t the second through last week of January or first week of February, the component of $\mathbf{z}_{t-1}$ corresponding to inflation would be that based on the December CPI. For the second week of February, $\mathbf{z}_{t-1}$ would use the January CPI.

Another issue is whether to use the final revised figures or those initially released. Initial release data are difficult to obtain for most of the series we investigated, and raise a host of other modeling issues that seemed better to avoid in this application.[11] For this reason, all estimates use final revised data, but dated as of the week of the initial release. Our final models keep only those parameters that are statistically significant. A detailed list of all the variables we tried is provided in Table 3.

[11] For further discussion, see Amato and Swanson (2001), Diebold and Rudebusch (1991), Koenig, Dolmas, and Piger (2000), and Runkle (1998).

Many of the variables that fall into the first category are motivated by papers that investigate the properties of Taylor rules (such as Clarida, Gali and Gertler (2000), McCallum and Nelson (1999), Rudebusch and Svensson (1999), and Dueker (1999b)). It is common in this literature to model the Fed's reaction as a function of an inflation measure (we tried a four-quarter average of the log-change in the GDP deflator, the 12-month average of the log-change in the personal consumption expenditures deflator, the 12-month average of the log-change in the consumer price index less food and energy), and an output gap measure (such as the percentage distance of actual GDP from potential GDP as measured by the Congressional Budget Office). In addition, to allow for forward looking behavior, we investigated the 12-month inflation forecasts from the Consumer Survey collected by the University of Michigan along with consumer expectations on the unemployment rate and on business conditions. To complement these data, we also experimented with the National Association of Purchasing Manager's composite index, and the composite indices of coincident and leading indicators published by the Conference Board. To allow for the possibility that the Fed reacts to deviations above or below some norm, we tried using the absolute value of deviations from a norm (e.g., capacity utilization from 85%, GDP growth from 2.5%, inflation from 2%, and so on).

In category (2), monetary and financial aggregates, we considered lagged values of the federal funds rate, M2, and the spread between 6-month Treasury Bill and the federal funds rate. Finally, the data contained in category (3) consisted of the dates of FOMC meetings, Strongin's (1995) measure of borrowed reserve pressure, the size of the previous target change, and the number of weeks since the previous change.

Despite an extensive literature relating Fed policy to such macroeconomic variables, we find that for the specific task of predicting whether the Fed is going to change the target during any given week, institutional factors and simple time-series extrapolation appear to be far more useful than most of the above variables. Table 4 reports maximum likelihood estimates for our favored model for the first subsample. The estimates suggest persistent serial correlation in the durations or hazards, with $\alpha + \beta = 0.95$. Of the variables other than lagged durations that we investigated, only one appeared to be statistically significant, specifically, there is a significant increased probability of a target change in the week following an FOMC meeting during this period. The average value for $\psi_{N(t)}$ in this subsample is 2.460, implying a typical hazard of $1/(2.460 + 2.257) = 0.21$, or a one in five chance that the Fed would change its target next week. By contrast, in the week following an FOMC meeting, this probability goes up to $1/(2.460 + 2.257 - 2.044) = 0.37$.

By contrast, we found much less serial correlation in the durations in the 1989-2001 subsample, as reported in Table 5. The coefficient β on $\psi_{N(t)-1}$ is in fact estimated to be zero,[12] and the coefficient α on the lagged duration is quite small (though statistically significant). The primary explanatory power comes from two simple variables. Over this period, the Fed has tended to implement target changes during the week of FOMC meetings rather than the week after. The other variable that we found useful for forecasting target changes over this period is $|SP6_{t-1}|$, the absolute value of the spread between the effective

[12] Our program restricts $0 \leq \beta \leq 1$ and the MLE fell on the boundary.

federal funds rate and the six month Treasury bill rate.

To get a sense of these estimates, the average absolute spread over this subperiod is 0.495 and the mean duration $\overline{u}$ is 1.74, implying a typical hazard of $1/[(0.067)(1.74) + 30.391 - (8.209)(0.495)] = 1/26.444 = 0.038$; the Fed is extremely unlikely to change the target during a week without an FOMC meeting, under the current regime. With an FOMC meeting, the probability of a target change rises to $1/(26.444 - 23.046) = 0.294$. If there is an FOMC meeting in week t and the previous week the spread had been 100 basis points or higher, a change in the target is virtually a sure thing.

5.2 Ordered probit estimates

Next we turn to empirical estimates of our ordered probit model for the marks, or the size of Fed target changes when they occur. Our first step was to consolidate the number of possible categories for changes in the target. Historical changes occurred in increments of 6.25 basis points until December 1990 and in increments of 25 basis points afterwards. We consolidated these earlier data (along with the one change of 75 basis points on November 15, 1994) as follows. If $y_t^{\#}$ denotes the actual value for the target change in Table 1, then our analyzed data y_t were defined as

$$
y_t = \begin{cases} -0.50 & \text{if } -\infty < y_t^{\#} \leq -0.5 \\ -0.25 & \text{if } -0.4375 \leq y_t^{\#} < -0.125 \\ 0.00 & \text{if } -0.125 \leq y_t^{\#} < 0.0625 \\ 0.25 & \text{if } 0.0625 \leq y_t^{\#} < 0.375 \\ 0.50 & \text{if } 0.4375 \leq y_t^{\#} < \infty \end{cases} . \tag{18}
$$

We then maximized the likelihood function $\mathcal{L}_2(\boldsymbol{\theta}_2)$ in expression (17) with respect to $\boldsymbol{\pi}$, the coefficients on the explanatory variables in (14), and the threshold parameters c_j in (16). The explanatory variables $\mathbf{w}_{t-1}$ use the value of the variable for the week prior to the target change. Results are reported in Table 6. Most of the ACH explanatory variables proved insignificant for explaining the size of target changes and were dropped. We find an extremely strong effect of $y_{t_{N(t-1)}}$; if the previous change raised the target, then this week's change is much more likely to be an increase than a decrease. We find an equally dramatic influence of the spread between the six month Treasury bill and the federal funds rate (the variable $SP6_{t-1}$): if the 6-month Treasury bill rate is above the federal funds rate, then we can expect the Fed to raise the target.

6 Forecast evaluations

One advantage of the ACH framework is that it generates a closed-form expression for the one-period-ahead forecast of the target i_{t+1} based on time t information $\boldsymbol{\Upsilon}_t$, where

$\mathbf{w}_t = (y_{t_{N(t)}}, \mathbf{z}_t)'$ with $\mathbf{z}_t = SP6_t$. Specifically,

$$E(i_{t+1}|\boldsymbol{\Upsilon}_t) = (1 - h_{t+1})i_t + h_{t+1} \sum_{j=1}^{5} (i_t + s_j)[\Phi(c_j - \mathbf{w}_t^{'}\boldsymbol{\pi}) - \Phi(c_{j-1} - \mathbf{w}_t^{'}\boldsymbol{\pi})] \tag{19}$$

where h_{t+1} is calculated from (8), $s_j = (0.25)(j-3)$, c_j are as given in Table 6 with $c_0 = -\infty$ and $c_5 = \infty$ and $\mathbf{w}_t^{'}\boldsymbol{\pi} = 2.545 y_{t_{N(t)}} + 0.541\ SP6_t$.

Multiperiod-ahead forecasts are substantially less convenient. One first requires forecasts of the explanatory variables $\mathbf{z}_{t+j}$. These can be generated with a VAR (with contemporaneous values of i_t included), estimated over the complete sample In our application, there is only a single exogenous explanatory variable ($SP6_t$) whose forecast equation is (standard errors in parenthesis):

$$SP6_t = \underset{(0.032)}{0.129} + \underset{(0.083)}{0.228}\ i_t - \underset{(0.083)}{0.267}\ i_{t-1} + \underset{(0.023)}{0.723}\ SP6_{t-1}. \tag{20}$$

Unfortunately, the forecast $E(i_{t+j+1}|\boldsymbol{\Upsilon}_{t+j})$ in (19) is a nonlinear function of $\boldsymbol{\Upsilon}_{t+j}$, so simulation methods are necessary for multiperiod-ahead forecasts. Specifically, (19) is derived from a discrete probability distribution for $i_{t+1}|\boldsymbol{\Upsilon}_t$ and one can generate a value $i_{t+1}^{(1)}$ from this distribution. If one further assumes that the error in (20) is Gaussian, then, given this value $i_{t+1}^{(1)}$, one can generate a value $\mathbf{z}_{t+1}^{(1)}$ from (20), which represents a draw from the distribution of $\mathbf{z}_{t+1}|\boldsymbol{\Upsilon}_t$. Using $\mathbf{z}_{t+1}^{(1)}$ one can again use the distribution behind (19) to generate a value $i_{t+2}^{(1)}$, which now represents a draw from the distribution $i_{t+2}|\boldsymbol{\Upsilon}_t$. Iterating on this sequence produces at step j a value $i_{t+j}^{(1)}$ which represents a single draw from the distribution $f(i_{t+j}|\boldsymbol{\Upsilon}_t)$. One can then go back to the beginning to generate a second value $i_{t+1}^{(2)}$ from $f(i_{t+1}|\boldsymbol{\Upsilon}_t)$ as in (19) and iterate to obtain a second draw $i_{t+j}^{(2)}$ from $f(i_{t+j}|\boldsymbol{\Upsilon}_t)$. The average value from M simulations, $M^{-1}\sum_{m=1}^{M} i_{t+j}^{(m)}$, represents the forecast $E(i_{t+j}|\boldsymbol{\Upsilon}_t)$.

Most of the macro literature has focused on monthly values for the effective federal funds rate rather than the weekly federal funds target as here. For purposes of comparison, we estimated a monthly VAR similar to that used by Evans and Marshall (1998). The Evans-Marshall VAR uses monthly data on the logarithm of nonagricultural employment (EM); the logarithm of personal consumption expenditures deflator in chain-weighted 1992 dollars (P); the change in the index of sensitive materials prices ($PCOM$); the effective federal funds rate (f); the ratio of nonborrowed reserves plus extended credit to total reserves ($NBRX$); and the log growth rate of the monetary aggregate M2 ($M2$). The model has twelve lags and is estimated over the sample February 1960 to February 2001. The mean squared errors for 1- to 12-month ahead forecasts for this VAR are reported in the first column of Table 7.

We then ask, How good a job can our weekly model of the target do at predicting the monthly values of the effective federal funds rate? We used our ACH and ordered-probit model to forecast the value that the target would assume the last week of month $\tau + j$ based on information available as of the last week of month τ. We then calculated the squared difference between this forecast for the target and the actual value for the effective federal funds rate for month $\tau + j$ and report the MSE's in the second column of Table 7.

This would seem to be a tough test for our model, given that (a) the estimation criteria for the VAR is minimizing the MSE whereas the estimation criteria for our model is maximizing the likelihood function; and (b) the VAR is specifically optimized for forecasting monthly values of f whereas ours is designed to describe weekly changes in the target. On the other hand, our weekly model has the advantages of (a) using the most up-to-date weekly values of variables as of the end of month τ, (b) using the value of the spread (not included as an explanatory variable in the Evans-Marshall VAR), (c) using the target rather than the funds rate itself (which we argue is more central to the actual process by which the funds rate is generated), and (d) incorporating the detailed institutional features of target setting selected by our model, including the change in regime in 1989. We find that the weekly approach yields substantially superior forecasts of the monthly f at all horizons, though the advantage deteriorates as the horizon increases.[13]

We conclude that the ACH specification is worth considering as a realistic description of the dynamics of the target. It thus seems of interest to revisit some of the policy questions that have been addressed using linear VAR's, to which we turn in the next section.

7 Estimating the effects of monetary policy shocks

A great number of papers have attempted to measure the effects of monetary policy based on linear vector autoregressions. Let $\mathbf{y}_\tau$ denote a vector of macro variables for month τ; in the Evans and Marshall (1998) VAR, $\mathbf{y}_\tau = (EM_\tau, P_\tau, PCOM_\tau, f_\tau, NBRX_\tau, M2_\tau)'$. Let $\mathbf{y}_{1\tau} = (EM_\tau, P_\tau, PCOM_\tau)'$ denote the variables that come before the effective federal funds rate f_τ and $\mathbf{y}_{2\tau} = (NBRX_\tau, M2_\tau)'$ the variables that come after. An estimate of the effects of a monetary policy shock based on a Cholesky decomposition of the residual

[13] See Rudebusch (1995) for further discussion of the properties of forecasts of the target over intermediate horizons.

variance-covariance matrix would calculate the impulse-response function,

$$\frac{\partial E(\mathbf{y}_{\tau+s}|f_\tau, \mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...)}{\partial f_\tau}.$$

This is equivalent to finding the effect on $\mathbf{y}_{\tau+s}$ of an orthogonalized shock to f_τ, where an orthogonalized shock is defined as

$$u_\tau^f = f_\tau - E\left(f_\tau|\mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...\right).$$

Note that the shock can be written as

$$u_\tau^f = f_\tau - f_{\tau-1} - [E\left(f_\tau|\mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...\right) - f_{\tau-1}]. \tag{21}$$

A positive value for u_τ^f could thus come from two sources. On the one hand, the Fed could have changed the target ($f_\tau - f_{\tau-1} > 0$) when no change was expected ($E\left(f_\tau|\mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...\right) - f_{\tau-1} = 0$). On the other hand, the Fed may not have changed the target ($f_\tau - f_{\tau-1} = 0$) even though a drop of $E\left(f_\tau|\mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...\right) - f_{\tau-1} < 0$ had been expected. Either event would produce a positive u_τ^f. The two events are predicted to have the same effect if the data were generated from a linear VAR.

In a nonlinear model such as our ACH specification, however, the two events are not forced to have the same effects, and it is an interesting exercise to see what the model says about their respective consequences. To do so, we start with the linear VAR,

$$\mathbf{y}_\tau = \mathbf{c} + \mathbf{\Phi}_1\mathbf{y}_{\tau-1} + \mathbf{\Phi}_2\mathbf{y}_{\tau-2} + ... + \mathbf{\Phi}_{12}\mathbf{y}_{\tau-12} + \boldsymbol{\varepsilon}_\tau.$$

We estimate the parameters $(\mathbf{c}, \mathbf{\Phi}_1, \mathbf{\Phi}_2, ..., \mathbf{\Phi}_{12})$ by OLS equation by equation. We also need the forecast of $\mathbf{y}_{2\tau}$ given $\mathbf{y}_{1\tau}$ and i_τ. This can be obtained by estimating the following system by OLS, one equation at a time,

$$\mathbf{y}_{2\tau} = \mathbf{d} + \mathbf{d}_1 i_\tau + \mathbf{D}_0 \mathbf{y}_{1\tau} + \mathbf{B}_1 \mathbf{y}_{\tau-1} + \mathbf{B}_2 \mathbf{y}_{\tau-2} + ... + \mathbf{B}_{12} \mathbf{y}_{\tau-12} + \mathbf{u}_{2\tau}, \tag{22}$$

where $\mathbf{d}_1$ in the Evans-Marshall example is a (2×1) vector, $\mathbf{D}_0$ is a (2×3) matrix, and $\mathbf{B}_j$ are (2×6) matrices. Given any hypothesized value for i_τ and the historical values for $\mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...,$ one can then calculate the forecast $\tilde{\mathbf{y}}_{2\tau|\tau}(i_\tau)$ from (22). Collect these forecasts along with the historical $\mathbf{y}_{1\tau}$ and the hypothesized i_τ in a vector

$$\tilde{\mathbf{y}}_{\tau|\tau}(i_\tau) = (\mathbf{y}_{1\tau}^{'}, i_\tau, \tilde{\mathbf{y}}_{2\tau|\tau}^{'}(i_\tau))'. \tag{23}$$

The one-step-ahead VAR forecast conditional on the hypothetical i_τ is:

$$\hat{E}(\mathbf{y}_{\tau+1}|i_\tau, \mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...) = \mathbf{c} + \mathbf{\Phi}_1 \tilde{\mathbf{y}}_{\tau|\tau}(i_\tau) + \mathbf{\Phi}_2 \mathbf{y}_{\tau-1} + ... + \mathbf{\Phi}_{12} \mathbf{y}_{\tau-11}. \tag{24}$$

We then replace the fourth element of the vector of conditional forecasts in (24), corresponding to the forecast of the effective federal funds rate $f_{\tau+1}$, with the forecast target rate for the last week of month $\tau+1$. This forecast is calculated as in the previous section based on historical values of variables available at date τ, with the historical value for the target at date τ replaced by the hypothesized value of i_τ. Call the resulting vector $\tilde{\mathbf{y}}_{\tau+1|\tau}(i_\tau)$. Next, we use the VAR coefficients to generate two-step-ahead forecasts conditional on i_τ:

$$\hat{E}(\mathbf{y}_{\tau+2}|i_\tau, \mathbf{y}_{1\tau}, \mathbf{y}_{\tau-1}, \mathbf{y}_{\tau-2}, ...) = \mathbf{c} + \mathbf{\Phi}_1 \tilde{\mathbf{y}}_{\tau+1|\tau}(i_\tau) + \mathbf{\Phi}_2 \tilde{\mathbf{y}}_{\tau|\tau}(i_\tau) + ... + \mathbf{\Phi}_{12} \mathbf{y}_{\tau-10}. \tag{25}$$

We again replace the fourth element of (25) with the forecast of $i_{\tau+2}$ implied by the ACH model and call the result $\tilde{\mathbf{y}}_{\tau+2|\tau}(i_\tau)$. Iterating in this manner, we can calculate $\tilde{\mathbf{y}}_{\tau+j|\tau}(i_\tau)$, which summarizes the dynamic consequences of the forecast time path for $i_\tau, i_{\tau+1}, ...$ implied by the ACH model for other macroeconomic variables of interest.

To measure the consequences of the first term in (21), we ask, What difference does it make if the Fed raises the target by 25 basis points during month τ ($i_\tau = i_{\tau-1} + 0.25$) compared to if it had kept the target constant ($i_\tau = i_{\tau-1}$)? We then normalize the answer in units of a derivative, as

$$(0.25)^{-1}\left[\tilde{\mathbf{y}}_{\tau+j|\tau}(i_\tau)\left|_{i_\tau=i_{\tau-1}+0.25} - \tilde{\mathbf{y}}_{\tau+j|\tau}(i_\tau)\right|_{i_\tau=i_{\tau-1}}\right]. \tag{26}$$

If we had not replaced the fourth element of (24) and (25) at each iteration with the ACH forecast, the resulting value in (26) would not depend on τ or $i_{\tau-1}$ and would be numerically identical to the standard VAR impulse-response function based on the Cholesky decomposition. As is, the value of (26) does depend on τ and $i_{\tau-1}$, and to report results we therefore average (26) over the historical values $\tau = 1, ..., T$ and $\mathbf{y}_1, ..., \mathbf{y}_T$ in our sample.

The second term in (21) asks, What would happen if we predicted a change in the target but none occurred? Letting $\hat{i}_{\tau|\tau-1}$ denote the forecast for the target in month τ based on historical information available at date $\tau - 1$, we thus calculate

$$\omega_\tau\left[\tilde{\mathbf{y}}_{\tau+j|\tau}(i_\tau)\left|_{i_\tau=i_{\tau-1}} - \tilde{\mathbf{y}}_{\tau+j|\tau}(i_\tau)\right|_{i_\tau=\hat{i}_{\tau|\tau-1}}\right] \tag{27}$$

where

$$\omega_\tau = \begin{cases} (i_{\tau-1} - \hat{i}_{\tau|\tau-1})^{-1} & \text{if } |i_{\tau-1} - \hat{i}_{\tau|\tau-1}| > 0.05 \\ 0 & \text{otherwise} \end{cases}.$$

The effect of the weight ω_τ in (27) is to ignore observations for which no change was expected and to rescale positive or negative forecast errors into units comparable to (26). Again if we had not replaced the VAR forecasts of $f_{\tau+j}$ with the ACH forecasts of $i_{\tau+j}$, the magnitude in (27) would not depend on τ and would be numerically identical to the VAR impulse-response function.

Figure 2 calculates the effects of three different kinds of monetary policy shocks. The solid line is the linear VAR impulse-response function, describing the effects of a 100-basis-point increase in f_τ on each of the five other variables in $\mathbf{y}_{\tau+j}$ for $j = 0$ to 11 months. This replicates the conventional results – an increase in the federal funds rate is associated with an initial decrease in nonborrowed reserves and in M2, and is followed within 6 months by a decline in employment and prices. The dashed line records the average values of (26) over all the dates τ in our sample, which we interpret as the answer to the question, What happens when the Federal Reserve deliberately raises its target for the federal funds rate? The effects are qualitatively similar to the VAR impulse-response function, but quantitatively are much bigger – a policy change implies a bigger contraction in NBRX or M2 than the orthogonalized VAR innovations u_τ^f, and the negative consequences for employment are much bigger as well. The dotted line records the average values of (27), which answers the question, What happens if one would have predicted that the Fed was going to lower the target, but in fact it did not? The results are completely different, and suggest that the Fed's decision not to lower the target typically has little lasting consequences for how one would forecast the federal funds rate or other macro variables more than one month into the future. The linear VAR, which essentially is an average of these two scenarios, thus appears to be mixing together the answers to two very different experiments.

This latter result is consistent with the evidence presented in Kuttner (2001) and Demiralp and Jordà (2001). These authors distinguish between cases in which (1) the Fed changed the rate in a way that took the market completely by surprise, and (2) the market believed a policy change would take place, but misjudged the exact date on which it would occur. They argued that the first development should have a much bigger effect on longer term interest rates than the second, and presented a variety of evidence consistent with this interpretation. It may be that our measure in (26) (the dashed line in Figure 2) typically represents an example of the first experiment, whereas (27) (the dotted line in Figure 2) typically represents an example of the second.

8 Conclusions

This paper introduced the autoregressive conditional hazard model for generating a time-varying serially dependent probability forecast for a discrete event such as a change in the federal funds rate targeted by the Federal Reserve. The advantage over the closely related autoregressive conditional duration specification is the ability to incorporate new information on other variables into the forecast.

We find that the change in Federal Reserve operating procedures from borrowed reserves targeting over 1984-1989 to an explicit federal funds rate target since 1989 show up quite dramatically through this investigation. We also find that, in our nonlinear model, "innovations" in monetary policy are not all the same. Specifically, an increase in the target results in a much more dramatic effect on employment and prices than does the prediction of a target decrease that fails to materialize. Traditional linear VAR measures of monetary innovations fail to differentiate between the response to these two radically different events.

9 Appendix: Relation to Continuous-Time Models.

Throughout the paper we adopted the perspective that time is discrete. Suppose instead that time is continuous but we sample it in discrete intervals of length Δ; (note that Δ was fixed at unity in the text). Let t_n denote the date of the nth target change and t_{n+1} the date of the $(n+1)$th target change. Then the log likelihood as calculated by the ACH model for the observations between these dates would be

$$\sum_{\tau=t_n+\Delta}^{t_{n+1}} \{x_\tau \log (h_\tau(\Delta)) + (1-x_\tau) \log (1-h_\tau(\Delta))\} \tag{28}$$

where $h_\tau(\Delta)$ denotes the probability of a change between τ and $\tau+\Delta$ and where the summation over τ is in increments of Δ. Note that from the definition of t_n and t_{n+1}, the term x_τ in (28) is zero for all but the last τ. Furthermore, if there are no exogenous covariates, then $h_\tau(\Delta)$ would be constant for all τ, that is, $h_\tau(\Delta) = h_{t_n}(\Delta)$ for $\tau = t_n+\Delta, t_n+2\Delta, ..., t_{n+1}$. Thus in the absence of exogenous covariates, expression (28) would become

$$\begin{aligned} \log (h_{t_n}(\Delta)) &\quad + \log (1-h_{t_n}(\Delta)) \sum_{\tau=t_n+\Delta}^{t_{n+1}} (1-x_\tau) \\ = &\quad \log (h_{t_n}(\Delta)) + \log (1-h_{t_n}(\Delta)) \frac{(t_{n+1}-t_n-\Delta)}{\Delta}. \end{aligned} \tag{29}$$

The probability $h_\tau(\Delta)$ of a change between τ and $\tau+\Delta$ of course vanishes as the time increment Δ becomes arbitrarily small. Suppose that associated with the sequence $\{h_{t_n}(\Delta)\}$ for succeedingly smaller values of Δ there exists a value ψ_{t_n} such that

$$h_{t_n}(\Delta) = \psi_{t_n}^{-1}\Delta + o(\Delta). \tag{30}$$

Expression (30) represents an assumption about the limiting continuous-time probability law governing events that is often described as the Poisson postulate (see for example Chiang, 1980, p. 250). Notice by Taylor's theorem,

$$\log\left[1 - h_{t_n}(\Delta)\right] \frac{(t_{n+1} - t_n - \Delta)}{\Delta} = -\left(t_{n+1} - t_n\right)\psi_{t_n}^{-1} + O(\Delta). \tag{31}$$

Substituting (31) into (29), it is clear that (29) differs from

$$\log\left[h_{t_n}(\Delta)\right] - \left(t_{n+1} - t_n\right)\psi_{t_n}^{-1}$$

by $O(\Delta)$. Thus if we use the ACH model to evaluate the log likelihood for the observed target changes between t_n and t_{n+1} for the fixed interval $\Delta = 1$, and if (30) is a good approximation for $\Delta = 1$, then

$$\sum_{\tau=t_n+1}^{t_{n+1}} \left\{x_\tau \log[h_\tau(1)] + (1 - x_\tau)\log[1 - h_\tau(1)]\right\} \tag{32}$$

$$\simeq \log(\psi_{t_n}^{-1}) - \left(t_{n+1} - t_n\right)\psi_{t_n}^{-1}.$$

The ACH likelihood for the complete sample is thus

$$\sum_{\tau=1}^{T} \left\{x_\tau \log[h_\tau(1)] + (1 - x_\tau)\log[1 - h_\tau(1)\right\} \simeq \sum_{n=1}^{N} \left\{\log\psi_n^{-1} - \frac{u_n}{\psi_n}\right\} \tag{33}$$

where the approximation becomes arbitrarily good as the discrete sampling frequency on which the left-hand side is based becomes finer and finer. The right-hand side of (33) will be recognized as identical to equation (17) in Engle (2000), which is the form of the log likelihood as calculated under the exponential autoregressive conditional duration specification. Thus (33) reproduces the familiar result that one can reparametrize the likelihood function for such processes equivalently in terms of durations or in terms of hazards, where from (30) the expected duration is essentially the reciprocal of the single period ($\Delta = 1$) hazard.

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Table 1 - Calendar of Changes in the Federal Funds Rate Target

Date of Change	Target Value	Target Change	Duration in days	Day of the Week	Date of Change	Target Value	Target Change	Duration in days	Day of the Week
1-Mar-84	9.5	na		Thursday	28-Jan-88	6.625	-0.1875	85	Thursday
15-Mar-84	9.875	0.375	14	Thursday	11-Feb-88	6.5	-0.125	14	Thursday
22-Mar-84	10	0.125	7	Thursday	30-Mar-88	6.75	0.25	48	Wednesday
29-Mar-84	10.25	0.25	7	Thursday	9-May-88	7	0.25	40	Monday
5-Apr-84	10.5	0.25	7	Thursday	25-May-88	7.25	0.25	16	Wednesday
14-Jun-84	10.625	0.125	70	Thursday	22-Jun-88	7.5	0.25	28	Wednesday
21-Jun-84	11	0.375	7	Thursday	19-Jul-88	7.6875	0.1875	27	Tuesday
19-Jul-84	11.25	0.25	28	Thursday	8-Aug-88	7.75	0.0625	20	Monday
9-Aug-84	11.5625	0.3125	21	Thursday	9-Aug-88	8.125	0.375	1	Tuesday
30-Aug-84	11.4375	-0.125	21	Thursday	20-Oct-88	8.25	0.125	72	Thursday
20-Sep-84	11.25	-0.1875	21	Thursday	17-Nov-88	8.3125	0.0625	28	Thursday
27-Sep-84	11	-0.25	7	Thursday	22-Nov-88	8.375	0.0625	5	Tuesday
4-Oct-84	10.5625	-0.4375	7	Thursday	15-Dec-88	8.6875	0.3125	23	Thursday
11-Oct-84	10.5	-0.0625	7	Thursday	29-Dec-88	8.75	0.0625	14	Thursday
18-Oct-84	10	-0.5	7	Thursday	5-Jan-89	9	0.25	7	Thursday
8-Nov-84	9.5	-0.5	21	Thursday	9-Feb-89	9.0625	0.0625	35	Thursday
23-Nov-84	9	-0.5	15	Friday	14-Feb-89	9.3125	0.25	5	Tuesday
6-Dec-84	8.75	-0.25	13	Thursday	23-Feb-89	9.5625	0.25	9	Thursday
20-Dec-84	8.5	-0.25	14	Thursday	24-Feb-89	9.75	0.1875	1	Friday
27-Dec-84	8.125	-0.375	7	Thursday	4-May-89	9.8125	0.0625	69	Thursday
24-Jan-85	8.25	0.125	28	Thursday	6-Jun-89	9.5625	-0.25	33	Tuesday
14-Feb-85	8.375	0.125	21	Thursday	7-Jul-89	9.3125	-0.25	31	Friday
21-Feb-85	8.5	0.125	7	Thursday	27-Jul-89	9.0625	-0.25	20	Thursday
21-Mar-85	8.625	0.125	28	Thursday	10-Aug-89	9	-0.0625	14	Thursday
28-Mar-85	8.5	-0.125	7	Thursday	18-Oct-89	8.75	-0.25	69	Wednesday
18-Apr-85	8.375	-0.125	21	Thursday	6-Nov-89	8.5	-0.25	19	Monday
25-Apr-85	8.25	-0.125	7	Thursday	20-Dec-89	8.25	-0.25	44	Wednesday
16-May-85	8.125	-0.125	21	Thursday	13-Jul-90	8	-0.25	205	Friday
20-May-85	7.75	-0.375	4	Monday	29-Oct-90	7.75	-0.25	108	Monday
11-Jul-85	7.6875	-0.0625	52	Thursday	14-Nov-90	7.5	-0.25	16	Wednesday
25-Jul-85	7.75	0.0625	14	Thursday	7-Dec-90	7.25	-0.25	23	Friday
22-Aug-85	7.8125	0.0625	28	Thursday	19-Dec-90	7	-0.25	12	Wednesday
29-Aug-85	7.875	0.0625	7	Thursday	9-Jan-91	6.75	-0.25	21	Wednesday
6-Sep-85	8	0.125	8	Friday	1-Feb-91	6.25	-0.5	23	Friday
18-Dec-85	7.75	-0.25	103	Wednesday	8-Mar-91	6	-0.25	35	Friday
7-Mar-86	7.25	-0.5	79	Friday	30-Apr-91	5.75	-0.25	53	Tuesday
10-Apr-86	7.125	-0.125	34	Thursday	6-Aug-91	5.5	-0.25	98	Tuesday
17-Apr-86	7	-0.125	7	Thursday	13-Sep-91	5.25	-0.25	38	Friday
24-Apr-86	6.75	-0.25	7	Thursday	31-Oct-91	5	-0.25	48	Thursday
22-May-86	6.8125	0.0625	28	Thursday	6-Nov-91	4.75	-0.25	6	Wednesday
5-Jun-86	6.875	0.0625	14	Thursday	6-Dec-91	4.5	-0.25	30	Friday
11-Jul-86	6.375	-0.5	36	Friday	20-Dec-91	4	-0.5	14	Friday
14-Aug-86	6.3125	-0.0625	34	Thursday	9-Apr-92	3.75	-0.25	111	Thursday
21-Aug-86	5.875	-0.4375	7	Thursday	2-Jul-92	3.25	-0.5	84	Thursday
4-Dec-86	6	0.125	105	Thursday	4-Sep-92	3	-0.25	64	Friday
30-Apr-87	6.5	0.5	147	Thursday	4-Feb-94	3.25	0.25	518	Friday
21-May-87	6.75	0.25	21	Thursday	22-Mar-94	3.5	0.25	46	Tuesday
2-Jul-87	6.625	-0.125	42	Thursday	18-Apr-94	3.75	0.25	27	Monday
27-Aug-87	6.75	0.125	56	Thursday	17-May-94	4.25	0.5	29	Tuesday
3-Sep-87	6.875	0.125	7	Thursday	16-Aug-94	4.75	0.5	91	Tuesday
4-Sep-87	7.25	0.375	1	Friday	15-Nov-94	5.5	0.75	91	Tuesday
24-Sep-87	7.3125	0.0625	20	Thursday	1-Feb-95	6	0.5	78	Wednesday
22-Oct-87	7.125	-0.1875	28	Thursday	6-Jul-95	5.75	-0.25	155	Thursday
28-Oct-87	7	-0.125	6	Wednesday	19-Dec-95	5.5	-0.25	166	Tuesday
4-Nov-87	6.8125	-0.1875	7	Wednesday	31-Jan-96	5.25	-0.25	43	Wednesday

Table 1 - (continued)

Date of Change	Target Value	Target Change	Duration in days	Day of the Week
25-Mar-97	5.50	0.25	419	Tuesday
29-Sep-98	5.25	-0.25	553	Tuesday
15-Oct-98	5.00	-0.25	16	Thursday
17-Nov-98	4.75	-0.25	33	Tuesday
30-Jun-99	5.00	+0.25	225	Tuesday
24-Aug-99	5.25	+0.25	55	Tuesday
16-Nov-99	5.50	+0.25	84	Tuesday
2-Feb-00	5.75	+0.25	78	Wednesday
21-Mar-00	6.00	+0.25	48	Tuesday
16-May-00	6.50	+0.50	56	Tuesday
3-Jan-01	6.00	-0.50	232	Wednesday
31-Jan-01	5.50	-0.50	28	Wednesday
20-Mar-01	5.00	-0.50	48	Tuesday
18-Apr-01	4.50	-0.50	29	Wednesday

Table 2: Dates of Federal Open Markets Committee Meetings

Year	FOMC Dates	Year	FOMC Dates	Year	FOMC Dates	Year	FOMC Dates
1984	January 30-31	**1989**	February 6-7	**1994**	February 3-4	**1999**	February 3- 4
	March 26-27		March 28		March 22		March 30
	May 21-22		May 16		May 17		May 18
	July 16-17		July 5-6		July 5-6		June 29 – 30
	August 21		August 22		August 16		August 24
	October 2		October 3		September 27		October 5
	November 7		November 14		November 15		November 16
	December 17-18		December 18-19		December 20		December 21
1985	February 12-13	**1990**	February 6-7	**1995**	January 31-1	**2000**	February 1-2
	March 26		March 27		March 28		March 21
	May 21		May 15		May 23		May 16
	July 9-10		July 2-3		July 5-6		June 27 – 28
	August 20		August 21		August 22		August 22
	October 1		October 2		September 26		October 3
	November 4-5		November 13		November 15		November 15
	December 16-17		December 17-18		December 19		December 19
1986	February 11-12	**1991**	February 5-6	**1996**	January 30-31	**2001**	January 30 – 31
	April 1		March 26		March 26		March 20
	May 20		May 14		May 21		May 15
	July 8-9		July 2-3		July 2-3		June 26 – 27
	August 19		August 20		August 20		August 21
	September 23		October 1		September 24		October 2
	November 5		November 5		November 13		November 6
	December 15-16		December 17-18		December 17		December 11
1987	February 10-11	**1992**	February 4-5	**1997**	February 4-5		
	March 31		March 31		March 25		
	May 19		May 19		May 20		
	July 7		June 30-31		July 1-2		
	August 18		August 18		August 19		
	September 22		October 16		September 30		
	November 3		November 17		November 12		
	December 15-16		December 22		December 16		
1988	February 9-10	**1993**	February 2-3	**1998**	February 3-4		
	March 29		March 23		March 31		
	May 17		May18		May 19		
	June 29-30		July 6-7		June/July 30-1		
	August 16		August 17		August 18		
	September 30		September 21		September 29		
	November 1		November 16		November 17		
	December 13-14		December 21		December 22		

Table 3

List of candidate explanatory variables in the specification of the ACH model

Inflation Measures:

- *GDP Deflator* (yearly average of the annualized log-change, in percent)
- *CPI Index*, less food and energy (yearly average of the annualized log-change, in percent)
- *Personal Consumption Expenditures Deflator* (yearly average of the annualized log-change, in percent)
- *Employment Cost Index* (annualized, quarterly log-change, in percent)
- *12-month ahead inflation forecasts* (Consumer Survey, University of Michigan)

Output Measures:

- *Output Gap* (log difference between actual and potential GDP, Congressional Budget Office estimates, in percent)
- *GDP growth* (annualized quarterly growth rate, in percent)
- *Total Capacity Utilization* (in deviations from an 80% norm)
- *12-month ahead consumer expectations on business conditions* (Consumer Survey, University of Michigan)

- *National Association of Purchasing Manager's composite index*

Employment Measures:

- *Unemployment Rate*

- *12-month ahead consumer expectations on unemployment* (Consumer Survey, University of Michigan)

Other Activity Measures:

- *Budget Deficit/Surplus*

- *Composite Index of coincident and leading indicators* (The Conference Board)

Monetary Variables:

- *M2* (log change in percent)

- *Federal funds rate*

- *6-month Treasury Bill Spread* (relative to the federal funds rate).

Trading Desk Variables:

- *Discount Window borrowing* (normalized by lagged total reserves)

- *FOMC meeting dates*

Table 4

Parameter Estimates for ACH(1,1) Model for 1984-1989

parameter	variable	estimate	(standard error)
α	$u_{N(t-1)-1}$	0.090	(0.056)
β	$\psi_{N(t-1)-1}$	0.847	(0.078)
δ_1	constant	2.257	(1.160)
δ_2	$FOMC_{t-1}$	-2.044	(0.631)

log likelihood: -162.85

Variable Definitions:

- $u_{N(t-1)-1}$: duration between the two most recent target changes as of week $t-1$.
- $\psi_{N(t-1)-1}$: lagged value of the latent index ψ, dated as of the time of the last target change observed as of date $t-1$.
- $FOMC_{t-1}$: dummy variable that takes the value of 1 if in week $t-1$, there was an FOMC meeting, 0 otherwise.

Table 5

Parameter Estimates for ACH(0,1) Model for 1989-2001

parameter	**variable**	**estimate**	**(standard error)**
α	$u_{N(t-1)-1}$	0.067	(0.024)
δ_1	constant	30.391	(7.119)
δ_2	$FOMC_t$	-23.046	(7.295)
δ_3	$\lvert SP6_{t-1}\rvert$	-8.209	(2.462)

log likelihood: -117.37

Variable definitions:

- $FOMC_t$: dummy variable that takes the value of 1 if in week t, there was an FOMC meeting, 0 otherwise.
- $|SP6_{t-1}|$: absolute value of the spread between the six month T-Bill and the federal funds rate. Fed funds rate used is an average of the daily effective fed funds rate for the week ending on Wednesday (where a holiday occurs during the week, it is an average of 4 observations). $TB6_t$ is an average of the 6-month treasury bill rate on the secondary market for the week ending on Wednesday.

Table 6

Parameter Estimates for Ordered Probit Model for 1984-2001

parameter	**variable**	**estimate**	**(standard error)**
π_1	$y_{t_{N(t-1)}}$	2.545	(0.426)
π_2	$SP6_{t-1}$	0.541	(0.263)
c_1		-1.895	(0.259)
c_2		-0.420	(0.245)
c_3		-0.005	(0.267)
c_4		1.517	(0.256)

log likelihood: -122.44

Variable Definitions:

- $y_{t_{N(t-1)}}$: magnitude of the last target change as of date $t-1$.
- $SP6_{t-1}$:value of the the six-month T-Bill rate minus the effective federal funds rate.

Table 7

Mean Squared Errors for 1-12 Month-Ahead Forecasts Based on

the ACH model and the VAR from Evans and Marshall (1998)

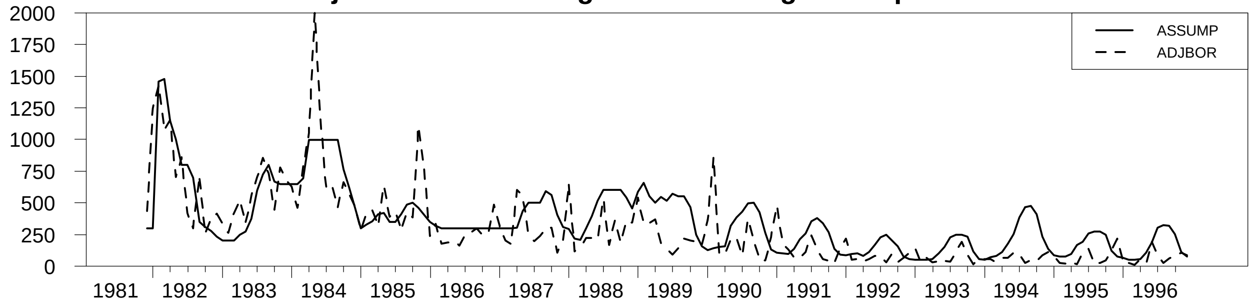
Forecast horizon	*VAR*	*ACH*
1 Month Ahead	0.207	0.037
2 Months Ahead	0.590	0.097
3 Months Ahead	0.950	0.171
4 Months Ahead	1.238	0.263
5 Months Ahead	1.446	0.373
6 Months Ahead	1.621	0.481
7 Months Ahead	1.772	0.606
8 Months Ahead	1.886	0.766
9 Months Ahead	2.004	0.924
10 Months Ahead	2.176	1.080
11 Months Ahead	2.419	1.235
12 Months Ahead	2.697	1.389

Figure Captions

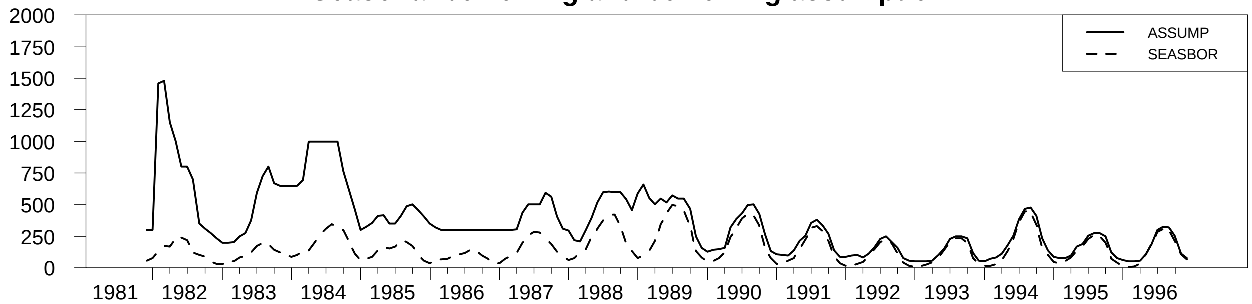
Figure 1. Top panel: adjustment borrowing at the Fed discount window (dashed line) and the Fed Trading Desk's borrowing assumption (solid line). Middle panel: seasonal borrowing at the Fed discount window (dashed line) and the Fed Trading Desk's borrowing assumption (solid line). Bottom panel: the borrowing assumption minus seasonal borrowing.

Figure 2. Effect of $\mathbf{y}_{t+j}$ for $j = 0, 1, ..., 11$ of different definitions of an "innovation" in the Fed funds rate. Solid line: innovation means a forecast error in the VAR. Dashed line: innovation means that the Fed raised the Fed funds target. Dotted line: innovation means a forecast target change that failed to materialize. Different panels correspond to the different elements of $\mathbf{y}$.

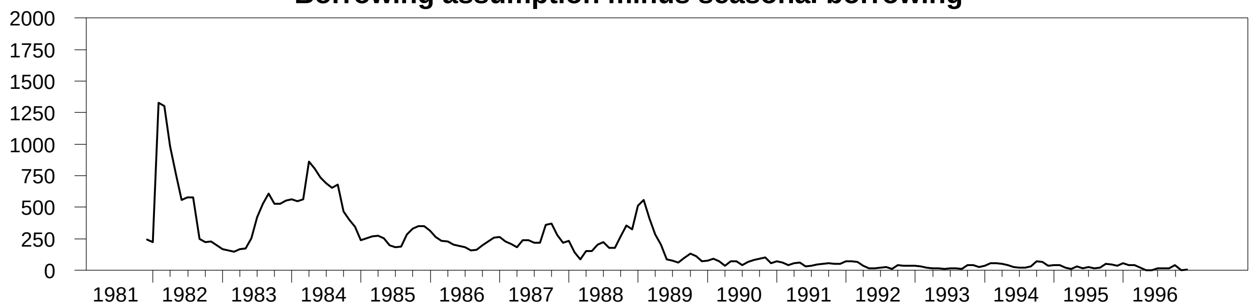
Adjustment borrowing and borrowing assumption

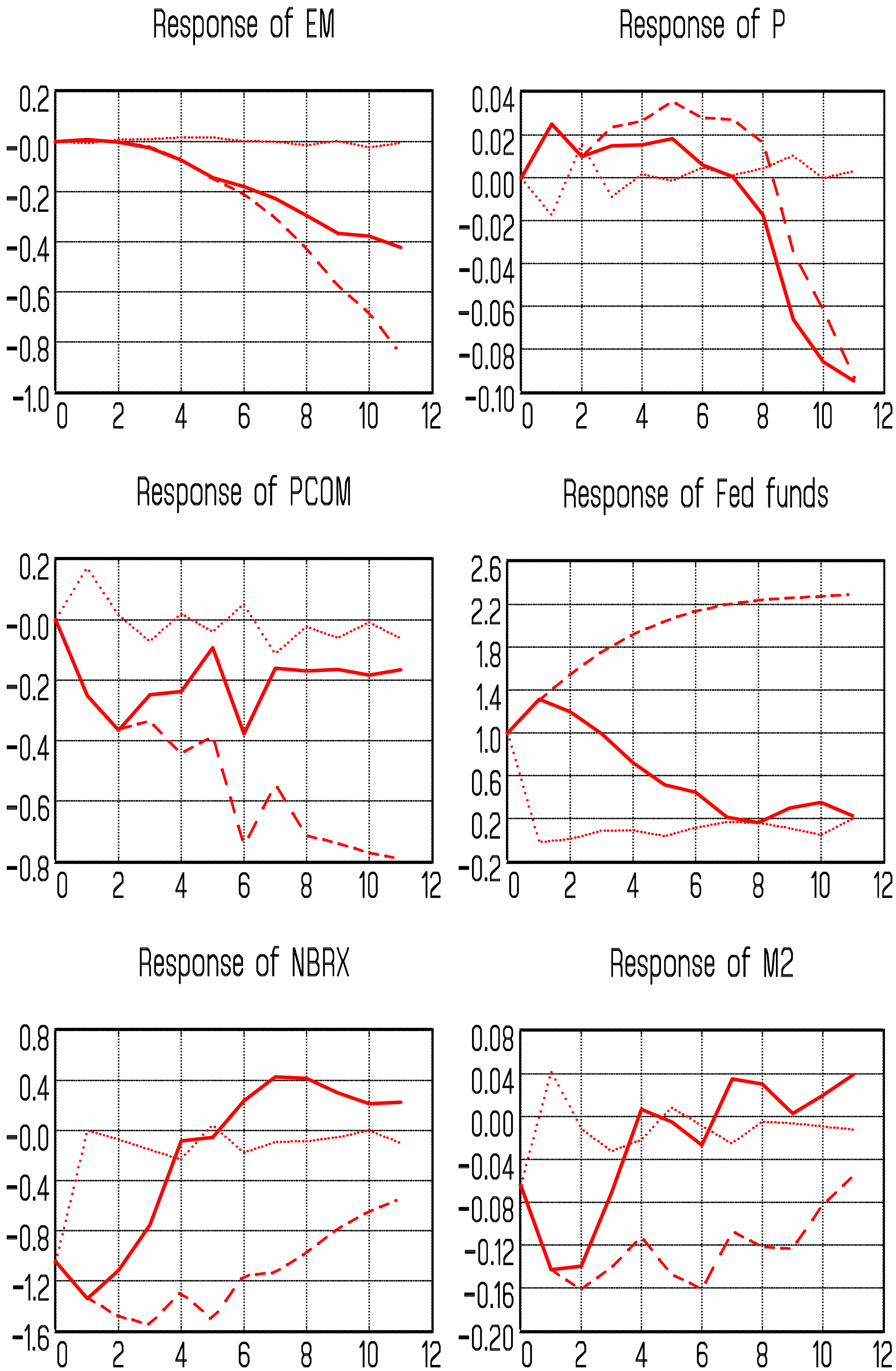


Seasonal borrowing and borrowing assumption



Borrowing assumption minus seasonal borrowing





Response of EM
0.2
-0.0
-0.2
-0.4
-0.6
-0.8
-1.0
0 2 4 6 8 10 12
Response of P
0.04
0.02
0.00
-0.02
-0.04
-0.06
-0.08
-0.10
0 2 4 6 8 10 12
Response of PCOM
0.2
-0.0
-0.2
-0.4
-0.6
-0.8
0 2 4 6 8 10 12
Response of Fed funds
2.6
2.2
1.8
1.4
1.0
0.6
0.2
-0.2
0 2 4 6 8 10 12
Response of NBRX
0.8
0.4
-0.0
-0.4
-0.8
-1.2
-1.6
0 2 4 6 8 10 12
Response of M2
0.08
0.04
0.00
-0.04
-0.08
-0.12
-0.16
-0.20
0 2 4 6 8 10 12