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Dynamic Limited Dependent Variable Modeling and U.S. Monetary Policy

I estimate a forward-looking, dynamic, discrete-choice monetary policy reaction function for the U.S. economy that accounts for the fact that there are substantial restrictions in the period-to-period changes of the policy instrument. I find a substantial contrast between the periods before and after Paul Volcker's appointment as Fed chairman in 1979, both in terms of the Fed's response to expected inflation and in terms of its response to the (perceived) output gap. In the pre-Volcker era, the Fed's response to inflation was substantially weaker than in the Volcker–Greenspan era; conversely, the Fed seems to have been more responsive to (inaccurate real-time estimates of) the output gap in the pre-Volcker era than later. These results, which carry through a series of extensions and robustness checks, provide support for the "policy mistakes" hypothesis as an explanation of the stark contrast in U.S. macroeconomic performance between the pre-Volcker and the Volcker–Greenspan periods.

JEL codes: C15, C22, C25, E52, E58
Keywords: monetary policy rules, Taylor rule, real-time data, Greenbook forecasts, federal funds rate, discrete choice models, data augmentation, Markov Chain Monte Carlo, Gibbs sampling, time-varying parameter models, regime-switching models.

One question that has received much attention in recent work on U.S. monetary policy is that of the contrast in U.S. macroeconomic performance between the periods before and after the appointment of Paul Volcker as

I am indebted to James D. Hamilton for his advice and encouragement, and for many useful discussions. I am also grateful to Graham Elliott and to Allan Timmermann for their feedback and for useful discussions. I thank Kenneth D. West, three anonymous referees, Fabio Busetti, Carlos Capistrán, Takeo Hoshi, Bruce Lehmann, Valerie Ramey, Yixiao Sun, and seminar participants at UCSD, HEC Montréal, the Board of Governors of the Federal Reserve System, SUNY at Albany, SUNY at Binghamton, the 11th Conference of the Society of Computational Economics, the Seminar for Bayesian Inference in Econometrics and Statistics (SBIES 2005 conference), and the European Conference of the Econometrics Community (2006 EC^2 conference) for useful comments. Finally, I am grateful to Jean Boivin and to Athanasios Orphanides for generously providing me with their real-time data—the unemployment and inflation data for the early years used in this study come from Boivin's data set. Any errors are mine.

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Received November 2, 2007; and accepted in revised form November 16, 2010.

Journal of Money, Credit and Banking, Vol. 43, No. 2–3 (March–April 2011)

chairman of the Federal Reserve (Fed) in August of 1979, and of the causes of that contrast. As is well known, the late 1960s and the 1970s were a period of relative macroeconomic instability. This era of the *Great Inflation* contrasts starkly however with what followed after Volcker's appointment, namely, a period of low inflation and stable output growth. Understanding the causes of this dramatic change is essential both for a fair historical assessment of past policies and for the design of a better monetary policy for the future. This issue has thus justifiably been scrutinized in numerous studies, and various explanations have been proposed. One influential line of research focuses mainly on intertemporal differences in monetary policy and emphasizes the role that improved policies in the Volcker–Greenspan eras played in achieving better macroeconomic outcomes during the 1980s and the 1990s.

This literature that focuses mostly on the role of monetary policy makes extensive use of single equation reaction functions for the Fed, also known as Taylor rules (Taylor 1993), that link the Fed's policy instrument (typically taken to be monthly or quarterly averages of the federal funds rate) to measures of the inflation gap and of the real output gap (or of the unemployment gap). Such reaction functions are compatible with broadly held views about what the central goals of U.S. monetary policy are, and appropriately chosen rules from that family of reaction functions can have both a normative and a positive justification.

One of the better known papers from that literature that uses reaction functions is Clarida, Galí, and Gertler (2000) (henceforth CGG). CGG take a standard Taylor rule and augment it by introducing dynamics, in the form of lags of the dependent variable as additional explanatory variables (thus allowing for *interest rate smoothing*). They also employ a forward-looking framework (as they employ *forecasts* of inflation and the output gap for one or more periods ahead rather than contemporaneous or lagged values for these variables). They estimate such a dynamic and forward-looking reaction function for the postwar U.S. economy. Their central finding is that monetary policy prior to Volcker's appointment *accommodated inflation*—the Fed typically raised the nominal interest rates by less than the increase in expected inflation, which would thus result in a lower real interest rate, while in the Volcker–Greenspan era, the Fed drastically changed its approach and adopted a much more anti-inflationary stance, raising not only nominal, but also real interest rates in response to increases in expected inflation; it thus contributed to the transition from the volatile 1970s to the rosy 1980s and 1990s—a period of stability and low inflation.

This is perhaps not a surprising finding to many—indeed the notion that Paul Volcker and Alan Greenspan did a superior job in conducting monetary policy than their predecessors may sound by now more like conventional wisdom than like a controversial proposition. Nevertheless, this result that CGG obtain using their *split-sample* estimation approach has been at the center of much attention and has been complemented, refined, or even challenged on several grounds in subsequent research. Such contributions include more elaborate modeling of the dynamics of the volatilities of nonpolicy shocks, of the dynamics of the Fed's responses to inflation and to the output gap, and more realistic representations of the Fed's actual information set in real time.

Indeed, papers such as Kim and Nelson (1999), Sims (1999), Blanchard and Simon (2001), Stock and Watson (2003), and Sims and Zha (2004) emphasize the role of nonpolicy shocks, whose volatility was higher in the pre-Volcker era than in the Volcker–Greenspan era, and argue that it was this, rather than any policy changes, that was the central factor behind the observed dramatic change in macroeconomic outcomes of the two periods. Another interesting line of work argues that changes in U.S. monetary policy were more gradual than suggested by CGG or that there were richer dynamics than suggested by the simple split-sample approach and concentrates on estimating reaction functions using time-varying parameter approaches (see *inter alia*, Cogley and Sargent 2001, 2002, Boivin 2006, and Jalil 2004).

Furthermore, and as Orphanides demonstrates in his influential 2001 paper, it is essential, when trying to reach policy conclusions on the basis of estimated reaction functions, to use real-time data, that is, data that were actually available to the Federal Open Markets Committee (FOMC) at the time their decisions were made, rather than revised data series that became available only *ex post*. Using this approach, he finds (Orphanides 2002, 2004) that, in contrast to the CGG conclusions, monetary policy in the pre-Volcker era, far from being accommodative to inflation, was in a similar manner to the Volcker–Greenspan era, activist, forward looking, and strong and decisive in its reaction to inflationary surges. While this contradicts the CGG conclusion that the instability of the 1970s was at least in part due to weak monetary policy, Orphanides also finds that monetary policy prior to Volcker's appointment was "too activist in reacting to perceived output gaps that retrospectively proved over-ambitious" (Orphanides 2004), which thus probably contributed to the inflationary pressures of that period.

All the contributions outlined above are not mutually exclusive and should be taken into account in careful attempts to assess the historical evolution of U.S. monetary policy and of its impact on the economy. However, one issue which, while equally important, has not been given nearly as much attention in the literature is that of characterizing the Fed's policy instrument and in particular of taking into account the specifics of its time-series behavior in estimation exercises of reaction functions.

The presumed policy instrument in most of the studies that investigate U.S. monetary policy with Taylor rules, including the ones outlined above, is the federal funds rate. Furthermore, related empirical work, including Bernanke and Blinder (1992) and Bernanke and Mihov (1998), establishes that with a possible exception of non-borrowed reserve targeting for a brief period during the first 3 years of Volcker's tenure, the Fed has indeed treated the Fed funds rate as its policy instrument.[1] Further evidence to this is provided by the fact that the Fed has been explicitly announcing a *target* for the Fed funds rate (henceforth the target). Announcements of changes or no changes to the target, and in general news related to the target and its movements has always been the subject of intense interest by the markets, *precisely because the*

1. Even for these 3 years at the start of Volcker's term, it is being argued (see, e.g., Goodfriend 1991) that the Fed had an implicit target for the federal funds rate.

Fed funds rate and its target in particular is understood to be the policy instrument of the Fed.

However, there are quite severe restrictions in the way the target changes from period to period: the target does not change at all for about half the time, and when it does change, it does so by multiples of 25 basis points (since November 1989 and by multiples of 6.25 basis points earlier). Thus, the period-to-period changes in the target have historically fallen into a small number of discrete categories.

These restrictions ought to be taken into account in modeling and estimation exercises of Fed reaction functions. Estimating linear reaction functions with Gaussian error terms ignores these restrictions to the support space of the dependent variable and may thus lead to serious biases. However, little work has been done in that direction. All of the literature outlined above, and nearly all of the rest of the literature in the area, employs linear specifications with Gaussian error terms. One exception to this paradigm is Hamilton and Jordà (2002), who propose the *autoregressive conditional hazard* approach which allows them to model the target as a discrete time-series variable. However, this approach is more geared toward forecasting and falls outside the Taylor rule framework of all the studies that have been outlined above. Also, Dueker (1999a) takes these restrictions into account as he models the reaction function using a multinomial ordered probit for the changes of the target (which is the approach adopted here too). However, he does not fully model the dynamics in this reaction function.

In general, most existing applied macroeconomic work, including the work on monetary policy reaction functions, either ignores the restrictions to the support space of the dependent variable under consideration and focuses on the needed time-series modeling requirements, or, conversely, employs limited dependent variable estimation techniques at the expense of time-series modeling. The main reason for this is that incorporating both of these at the same time results in an estimation task that presents the researcher with formidable computational challenges because of the need for integration of multiple integrals with no closed form solution whose dimensionality can be the same as the time-series dimension of the data, and/or because of the need for numerical optimization of difficult objective functions.

In this paper, I deviate from this pattern as I propose and estimate a model that accounts for both the discreteness and the dynamics in the Fed's reaction function. In contrast to past literature, I model the Fed's reaction function in a way that does not ignore the discrete nature of the changes in the target, while also taking into account contributions of past literature, such as the ones outlined earlier. Specifically, I estimate, using real-time data compiled from Greenbook forecasts of the Fed, a forward-looking, dynamic ordered probit reaction function, and I also consider a series of extensions and robustness checks. I overcome ensuing computational challenges by estimating the model using Markov Chain Monte Carlo (MCMC) methods and by going outside the extremum framework. I build on an approach proposed by Dueker (1999b): Dueker proposed an appealing and computationally attractive way of estimating dynamic probits by combining the ideas of *data augmentation* and *single-move Gibbs sampling* of the MCMC literature. This approach does not require any integration of multiple integrals or any numerical optimization, and it thus makes estimating dynamic probits a (computationally) feasible task.

My central finding is that the Volcker–Greenspan Fed avoided mistaken practices of the past in terms of its response to *both* inflation and the output gap. Thus, this result, which carries through the extensions and robustness checks, confirms the central conclusion of CGG in a way that is to a substantial extent robust to contributions and challenges of the relevant literature such as the ones outlined above (in addition to the discreteness issue).

The plan for the rest of the paper is as follows: Section 1 describes the benchmark model as well as the proposed estimation strategy. Section 2 describes the data used, Section 3 provides a discussion of the estimation results of the benchmark model, as well as a brief outline of results from a series of robustness checks and extensions, and Section 4 provides concluding remarks. The details of the additional results from the extensions and robustness checks, of the multiple integral problem, and the resulting computational challenges, as well as of the algorithms employed in this paper are included in a technical appendix that is available on request.

1. A FORWARD-LOOKING, DYNAMIC ORDERED PROBIT REACTION FUNCTION FOR THE FEDERAL RESERVE

The model I propose is a probit of a particular kind; namely, it is multinomial and ordered because there are several possible outcomes (a modest number of possible amounts by which the Fed can decide to change its target for the Fed funds rate), and these outcomes are ranked (as, for instance, it is recognized that an increase of 50 basis points is comparable to and ranks higher than an increase of 25 basis points). As is often done with probit models, I cast the model of this paper in terms of a continuous latent variable, the Fed's *desired level* for the federal funds rate, that governs the behavior of the observed discrete variable, the Fed's *target* for the federal funds rate. The dynamic and forward-looking aspects of the Fed reaction function are captured by the following equation on the desired level for the federal funds rate at time t, namely, ff_t^*:

$$ff_t^* = \alpha + \rho(L) ff_{t-1}^* + \beta\pi_{t,h} + \gamma y_{t,h}^{gap} + \varepsilon_t^*, \tag{1}$$

where $\rho(L) = \rho_1 + \rho_2 L + \cdots + \rho_n L^{n-1}$, and where all of the roots of the associated polynomial $1 - \rho_1 L - \rho_2 L^2 - \cdots - \rho_n L^n$ lie outside the unit circle. $\varepsilon_t^* \sim N(0, \sigma^2)$, $\pi_{t,h}$ is the h-period-ahead forecast of inflation that the Fed made at time t, and $y_{t,h}^{gap}$ is the h-period-ahead forecast of the output gap that the Fed made at time t. Thus, both of these are real-time forecasts, the definitions and details of which are provided in the data section that follows. Furthermore, and considering (1) in the context of Taylor rules, the intercept term α is modeled to capture both the natural real Fed funds rate, and the target inflation rate, which are therefore not separately identifiable.

While this latent variable ff_t^* is continuous, the observed policy instrument, the target, is discrete, and in particular it changes only when enough pressure for a change accumulates, that is, only when the difference between the actual value of the target and the level at which the Fed would like it to be is of a certain size. The size of that difference determines which out of a small possible number of changes will take place:

$$\Delta ff_t \in \text{category } j \text{ if } ff_t^* - ff_{t-1} \in (c_{j-1}, c_j), \; j = 1, \ldots, J, \tag{2}$$

where ff_t^* is the continuous latent variable of equation (1), and ff_t is *the observed target that changes only by one of J possible amounts at discrete points in time*, and where $c_0, c_1, \ldots, c_J$ are the threshold coefficients for movement between the J possible categories of change. So, the difference $ff_t^* - ff_{t-1}$ represents the distance between the desired level of the Fed funds rate this period (based on the reaction function of the Fed) and the actual level for the target last period; thus, and as mentioned above, it can be seen as a measure of the "pressure" to change the Fed funds rate in period t. The "intensity" of that pressure (i.e., which of the (c_{j-1}, c_j) intervals (for $j = 1, \ldots, J$) $ff_t^* - ff_{t-1}$ falls into) determines which of the J possible changes will take place.

This model falls within the dynamic probit reaction function framework of, *inter alia*, Eichengreen, Watson, and Grossman (1985), and Dueker (1999a, 1999b). In that respect, it is not directly comparable to the linear Taylor rule literature, as it accounts for the discreteness in the observed target level for the policy instrument and it explicitly distinguishes this target from a latent, and continuous, desired level for the policy instrument. However, it also captures crucial aspects of standard linear Taylor rule models. Similarly, to CGG, for instance, this model employs inflation and the output gap as explanatory variables, in a forward-looking framework. Furthermore, it allows for dynamic behavior for the Fed through the lags of ff_t^* in equation (1). Note that this is not interest rate smoothing in the standard sense of linear Taylor rule models (see, *inter alia*, Judd and Rudebusch 1998, Sack and Wieland 2000, Piazzesi 2001), which employ lags of the *actual* Fed funds rate instead to deliver gradual adjustment of that variable to the level dictated by inflation and the output gap. Still, the present specification does not imply any immediate adjustment to the Fed funds rate level dictated by inflation and the output gap either: note that the latent variable ff_t^* adjusts to that level only gradually, because of equation (1), and it does not deviate much from the observed discrete target because of equation (2). These two observations suggest that the current specification is in practice compatible with an *actual* Fed funds rate that also adjusts gradually, and not immediately, to the level dictated by inflation and the output gap (as the Fed typically ensures (through Open Market Operations) that the actual Fed funds rate does not deviate much from its set target level at any point in time either).

Estimating such a dynamic probit model is a daunting computational task, however, because it requires integrating high-order multiple integrals with no closed-form solution; the computational challenge would be even higher in a standard maximum likelihood framework because of the associated need for numerical optimization. Thus, I adopt an MCMC approach that overcomes both the need for numerical optimization and the multiple integral problem through a *Gibbs sampling algorithm with data augmentation*. Previous work that employs Gibbs sampling techniques for limited dependent variable and time-series models includes Albert and Chib (1993a, 1993b), Dueker (1999b), and Dueker and Wesche (2003). The specifics of the algorithm are as follows.[2]

1.1 The MCMC Estimation Strategy

Divide the set of parameters into a multiblock setup of one block per latent variable, $\lambda_{1_t} = \{ff_t^*\}, t = 1, \ldots, T$, one block for the variance, $\lambda_2 = \{\sigma^2\}$, and one block for the coefficients of the explanatory variables, $\lambda_3 = \{\alpha, \beta, \gamma, \rho_1, \ldots\rho_n\}$. Then:

Step 1: Specify arbitrary initial values $\lambda_1^{(0)}, \lambda_2^{(0)}, \lambda_3^{(0)}$, and set $i = 0$.

Step 2: Cycle through the following conditional distributions, drawing:

$$\lambda_{1_1}^{(i+1)} \text{ from } p_{ff_1^*}\left(\lambda_{1_1} | \lambda_{1_2}^{(i)}, \ldots, \lambda_{1_T}^{(i)}, \lambda_2^{(i)}, \lambda_3^{(i)}, Y_T\right), \ldots,$$
$$\lambda_{1_T}^{(i+1)} \text{ from } p_{ff_T^*}\left(\lambda_{1_T} | \lambda_{1_1}^{(i)}, \ldots, \lambda_{1_{T-1}}^{(i)}, \lambda_2^{(i)}, \lambda_3^{(i)}, Y_T\right)$$

$$\lambda_2^{(i+1)} \text{ from } p_2\left(\lambda_2 | \lambda_{1,\ldots,T}^{(i+1)}, \lambda_3^{(i)}, Y_T\right), \text{ and } \lambda_3^{(i+1)} \text{ from } p_3\left(\lambda_3 | \lambda_{1,\ldots,T}^{(i+1)}, \lambda_2^{(i+1)}, Y_T\right),$$

where Y_T denotes the entire history of the data for periods $1, \ldots, T$, and superscript i indicates the iteration of the Gibbs sampler. This choice of blocks is dictated by the fact that the resulting conditional posteriors are easy to sample from.

The multiblock setup of one block per latent variable is employed to implement the technique of *data augmentation*, introduced by Tanner and Wong (1987), whereby the latent variables are generated from their model implied conditional distributions $p_{ff_1^*}, \ldots, p_{ff_T^*}$. Note that these distributions are conditioned on the entire history of the data and thus that a smoothing algorithm is required. The standard way to approach a problem of this sort is with a state-space framework and using the Kalman filter; however, it is unclear how to usefully cast the system in a state-space form so as to employ the Kalman filter in this context. Thus, in a manner similar to Dueker (1999b) and Dueker and Wesche (2003), I implement the smoothing algorithm for the latent variables by exploiting simplifications that occur in the conditional distributions of these latent variables, and then by observing that functional forms for these simplified conditional distributions can be obtained from the joint distribution of all the error terms where each latent variable appears.

To detect convergence of the Gibbs sampling algorithm, I adopt an approach similar to that of McCulloch and Rossi (1994), whereby the empirical distributions of the

2. Note that the details of the multiple integral problem as well as of the Gibbs sampling algorithm (including all the distributional assumptions, proofs, and robustness checks) are included in a technical appendix that is available on request.

simulated values are compared when the Gibbs sampler is initiated from different starting points, and as the number of simulations increases, looking for evidence of nontrivial changes in these distributions.

Once convergence has been established according to the criteria just outlined, statistics based on the simulated sample can be constructed and can serve as estimators of the parameters of interest. The point estimates and confidence intervals of the parameters of this paper are based on the means and the quantiles of their simulated marginal posterior distributions.

2. DATA

The dependent variable is the target for the federal funds rate and the explanatory variables are, in addition to lags of the latent, desired level for the federal funds rate, and real-time forecasts of inflation and of the output gap. The data series used span the period from January 1969 to June 1998. The rest of this section provides details on these time series.

2.1 The Fed Funds Rate Target

The time series on the target is not available for the entire period considered in this study, and not for the early part of the sample in particular. The Fed began to announce the target explicitly only in 1994, although even before 1994 changes in the target were quite accurately inferred by the market and indeed news on such changes would even be published in the financial press. Researchers have used such historical information to compile time series of target changes for periods prior to 1994 (such as Cook and Hahn 1989 for the mid and late 1970s and Rudebusch 1995 for the mid 1980s and later), but there is no complete such series for the entire period considered in this study.

Thus, the dependent variable that I use is the (annualized) averages of the Fed funds rate at the "FOMC frequency," that is, monthly averages for the months during which there was an FOMC meeting.[3] These averages, for which there is a complete series for the period of interest, can thus be viewed as proxying for averages of the target. One would expect, given that the Fed typically ensures that the Fed funds rate does not deviate too much from the set target at any given period, that the loss from such a strategy is only minimal.[4]

3. The choice of frequency is dictated by the explanatory variables: in particular, the Greenbook forecasts (from which the explanatory variables are constructed) are available only for the months during which there was an FOMC meeting.

4. Indeed, and as can be seen in time-series plots of the two variables (Figure 2 of the paper's technical appendix, available on request), the Fed funds rate tracks the target quite closely. Additional evidence to this is available in estimates of the benchmark reaction function for the Greenspan period using the monthly averages for the Fed funds rate; these estimates are quite similar to their respective estimates obtained when using the target as the dependent variable, either as averages at the FOMC frequency, or as end-of-month values for months during which there was an FOMC meeting.

2.2 *Real-Time Data on Fed Forecasts of Inflation and of the Output Gap*

The data used are real-time Greenbook forecasts of the Federal Reserve for the GDP deflator and for unemployment. The Greenbooks and the forecasts contained therein are prepared by staff of the Fed before each FOMC meeting and thus contain estimates based on real-time information. The forecasts are for varying forecast horizons, but only short horizons are consistently available—in this study, I use three-quarter-ahead forecasts for the benchmark specification, but I also conduct robustness checks for zero, one, and two quarters ahead.

The inflation variable used is based on the GDP deflator (up to 10/91) and the GNP deflator after that date.[5] Also, and as in past literature, such as Boivin (2006) and Orphanides (2002), I construct a proxy for the output gap variable using forecasts for unemployment, and specifically, I take the output gap at time t to be proxied by the difference between the natural unemployment rate (the time t natural rate of unemployment is taken to be the historical average of the unemployment series up to that point) and the forecast for the unemployment rate[6] at time t.

Quite clearly, using such Greenbook forecasts is central to our approach, as it enables us to estimate a real time, forward-looking reaction function. Still, this approach is not free of pitfalls. Most notably, endogeneity issues are a valid concern. A plausible case can be made for potential correlation between the explanatory variables and the error term in the reaction function that could result if, for instance, macro shocks affect the Greenbook forecasts themselves. Unfortunately, and as Boivin (2006) argues, the validity of such claims cannot be checked in a definitive manner as there is not much detailed information in the public domain regarding how these Greenbook forecasts are constructed. However, and as Boivin argues again, it is reasonable to expect that these forecasts are constructed prior to FOMC meetings and independently of decisions reached there; thus, it is precisely the real-time nature of these data that can be invoked to support an assumption of the explanatory variables being contemporaneously uncorrelated with the error term. Similarly, and if, as is likely, there are lags in the monetary transmission mechanism, then zero-period-ahead Greenbook forecasts will not be contemporaneously correlated with the error term; and results based on such zero-period-ahead forecasts are indeed quite similar to the respective estimates using three-period-ahead forecasts (of the following section). Finally, and while ours may be an imperfect approach, note that similar issues and concerns arise everywhere in the Taylor rule literature. Indeed, it is not clear that even alternative approaches that employ instruments, such as that of CGG, are preferable (see, e.g., Mavroeidis 2004).

5. This is dictated by the availability of these variables, as GNP deflator data replace GDP deflator data in the Greenbooks starting October 1991, and it is likely to have only a negligible effect on the results.

6. This is standard practice in the literature and indeed Okun's Law guarantees that there is a close relationship between this "unemployment gap" proxy and the output gap.

TABLE 1

Benchmark Model

Variable	Mean	Std. dev.	Median	2.5% qntl	5% qntl	10% qntl	90% qntl	95% qntl	97.5% qntl
				Pre-Volcker period					
Intercept	0.9683	0.4682	0.9663	0.0331	0.1835	0.3787	1.5685	1.7377	1.8991
Variance	1.1417	0.228	1.1208	0.7607	0.8024	0.8703	1.4515	1.5632	1.6344
1st lag	0.866	0.0493	0.8685	0.7675	0.7821	0.8043	0.9286	0.9463	0.9572
Inflation	0.0649	0.0798	0.064	−0.0926	−0.0617	−0.0377	0.1708	0.1939	0.2167
Output gap	**0.2933**	0.1064	0.296	0.0844	0.129	0.1624	0.4254	0.467	0.4993
				Volcker–Greenspan period					
Intercept	−0.0371	0.2806	−0.0356	−0.5725	−0.4862	−0.399	0.3261	0.4517	0.5297
Variance	1.2245	0.1949	1.2072	0.8979	0.9415	0.987	1.4802	1.5754	1.6704
1st lag	0.7681	0.047	0.7701	0.6724	0.6857	0.7088	0.8278	0.8432	0.8606
Inflation	**0.4524**	0.0896	0.4527	0.2789	0.3068	0.3381	0.5744	0.6016	0.6311
Output gap	0.1107	0.0884	0.1109	−0.0738	−0.034	−0.0026	0.225	0.2531	0.2768

Notes: This table presents estimates of the benchmark model (equation (1)). The variable "variance" refers to the variance of the error of equation (1). The variable "1st lag" refers to the 1st lag of the dependent variable (as an explanatory variable of equation (1)). When the inflation and/or "output gap" explanatory variables are significant they appear in bold. The last seven columns are quantiles of the posterior distribution.

TABLE 2

Benchmark Model—Alternative Threshold Values

Variable	Mean	Std. dev.	Median	2.5% qntl	5% qntl	10% qntl	90% qntl	95% qntl	97.5% qntl
				Pre-Volcker period					
Intercept	0.9067	0.3976	0.9103	0.1087	0.2406	0.4097	1.3954	1.5409	1.6632
Variance	0.9206	0.2014	0.9015	0.5891	0.6396	0.6814	1.1815	1.2671	1.3798
1st lag	0.8894	0.0451	0.8906	0.7935	0.8138	0.8321	0.9465	0.9605	0.9705
Inflation	0.0396	0.068	0.0385	−0.0894	−0.0687	−0.0473	0.1287	0.1499	0.1694
Output gap	**0.2826**	0.0882	0.283	0.1086	0.1391	0.1686	0.3969	0.4317	0.4541
				Volcker–Greenspan period					
Intercept	−0.0472	0.2662	−0.0462	−0.5563	−0.4766	−0.3985	0.2985	0.4208	0.4922
Variance	1.0991	0.1743	1.0865	0.8058	0.8369	0.886	1.3302	1.4274	1.4997
1st lag	0.7823	0.0442	0.7829	0.6936	0.7071	0.7254	0.839	0.853	0.8683
Inflation	**0.4288**	0.084	0.4289	0.2676	0.2904	0.3216	0.5433	0.572	0.5983
Output gap	0.1076	0.0834	0.107	−0.0612	−0.0295	0.0021	0.2144	0.2406	0.2657

Notes: Same as in Table 1. This table uses ±25 basis points to divide the categories of small change and of bigger change for the Fed funds rate target (rather than ±18 basis points as in Table 1).

3. ESTIMATION RESULTS AND DISCUSSION

The results for the benchmark model (equations (1) and (2)) are reported in Tables 1 and 2.[7] These tables contain panels with quantiles and statistics of the posterior distributions of the parameters of interest. Several panels such as those of Tables 1

7. The benchmark model of Tables 1 and 2 has one lag only of the latent dependent variable (as in an experiment with two lags (the two-lag specification being the one used by CGG), the second lag is insignificant).

and 2, together with their respective histograms of the posterior distributions,[8] are produced for different starting values that initiate the Gibbs sampler and for different numbers of iterations of the sampler, and they are compared and evidence of any substantial changes in the results is sought for. The results change very little as different starting values and different numbers of iterations are considered.[9] This serves as evidence of convergence, at least according to the criteria outlined in Section 1.

As discussed earlier, the forecast horizon of the benchmark model is three quarters ahead. Furthermore, I assume that there are five categories of change for the observed variable, namely, a no change category, a small change (positive or negative) category, and a bigger change (positive or negative) category: one realizes, simply by observing the actual time series of target changes that there have been no changes in the target[10] for roughly half of the time, and that for the other half of the time there have been either small changes in the target, or bigger changes, that is, changes whose magnitude has been greater than one times 25 basis points after 1989, and greater than three times 6.25 basis points before 1989. So, the threshold coefficients I use in Table 1 are -18, -5, 5, and 18 basis points. Thus, and for example, the "no change" category is the one where the change in the observed variable is between -5 and 5 basis points. While there might be little loss associated with exogenously imposing a number of categories of change in the present context, the same is not necessarily true with exogenously imposing the threshold values that define these categories. Indeed, there have been several target changes that took place before 1989 and that were equal to ± 18.75 basis points. So, Table 2 reports results obtained when the threshold coefficients are -25, -5, 5, and 25 basis points; these results are very similar to those of Table 1.

The results of Table 1 (and of Table 2) point toward substantial differences in monetary policy between the two periods before and after Volcker's appointment as chairman of the Fed in August 1979: Specifically, the pre-Volcker period is characterized by a weak overall response to inflation: for instance, the inflation coefficient is not significantly different from 0, and the implied long-run inflation coefficient is $\beta/(1-\rho_1) = 0.0649/(1-0.866) = 0.4843$. This is well below 1 and thus does not satisfy the Taylor property; it suggests that the pre-Volcker Fed "accommodated" inflation, as it would raise the nominal interest rate by less than increases in expected inflation, thus effectively allowing the real short-term interest rate to decline.

8. These histograms, which provide a more complete picture of the marginal distributions, are available from the author.

9. The results reported are based on 1,300 iterations of the Gibbs sampler, with 300 "burn-in" states, as all the available evidence in various experiments I conducted showed that this was a sufficient number of iterations, based on the criteria that are used in this study to establish convergence (which were outlined earlier) and also based on experiments and comparisons with higher numbers of iterations. For instance, for the benchmark model, results based on 130,000 iterations were very similar to the results reported in Table 1 (which were based on 1,300 iterations).

10. Or almost no changes when FOMC monthly averages of the Fed funds rate are used.

These results contrast starkly, however, with the estimated response of the Fed toward inflation during the Volcker–Greenspan era. The inflation coefficient is substantially higher than before and is now significant, and the implied long-run inflation coefficient is now $0.4524/(1 - 0.7681) = 1.9508$, which suggests that the Volcker–Greenspan Fed adopted a very strong anti-inflationary stance, as it would substantially raise *both* the nominal *and* the real interest rate in response to increases in anticipated inflation.

Quite clearly, these findings confirm the central message of CGG that there were substantial differences in the Fed's response toward expected inflation between the two periods. These results are thus compatible with CGG's theory that the pre-Volcker's Fed accommodative policy stance was destabilizing, as it allowed for the possibility of expectations-based inflationary spirals, and also as it was less effective in countering negative shocks to the economy, and that the dramatic shift toward a much stronger anti-inflationary stance of the Fed that took place when Volcker became chairman of the Fed was a central factor behind the improved macroeconomic outcomes and the greater stability of the 1980s and 1990s.

Conversely, the coefficient of the output gap was low (0.1107) and insignificant during the Volcker–Greenspan period, and substantially higher (0.2933) and significant during the pre-Volcker period. Thus, and on the basis of these results, it can be argued that the Fed effectively pursued a pure inflation targeting policy during the 1980s and 1990s, while it was much more responsive toward the output gap during the pre-Volcker period.

Given that the data used for the construction of the output gap variable are real-time Greenbook forecasts on unemployment, and since, as demonstrated by Orphanides (2002), estimates of the output gap based on Greenbook data on unemployment are downwardly biased, the results of Table 1 (and of Table 2) on the coefficient of the output gap are consistent with the explanation put forth by Orphanides in his recent papers (Orphanides 2002, 2004). Orphanides argues that the main difference between the two periods before and after Volcker's appointment is that the pre-Volcker Fed was essentially too activist in its response to real-time output gap estimates that *ex post* proved to be overambitious, and thus that this excessive activism of the pre-Volcker Fed contributed to the poor macroeconomic outcomes and the Great Inflation of the 1970s. Following Volcker's appointment, the Fed adopted a more cautious approach toward possibly inaccurate real-time estimates of the output gap and in general a more realistic stance in the sense that it better recognized the limitations of monetary policy in attempting to achieve output stabilization. However, and in contrast to CGG, Orphanides finds that the Fed had a strong anti-inflationary stance both in the 1960s and 1970s and later.

Both CGG and Orphanides essentially adopt a "policy mistakes"[11] view to explain the great inflation and the contrast in macroeconomic performance between the 1970s and the 1980s–90s in that they argue that the pre-Volcker Fed made mistakes in its

11. The terms "policy mistakes view" and "bad luck view" are taken from Primiceri (2006).

conduct of monetary policy, and that starting with Volcker's appointment, the Fed to a large extent avoided mistaken practices of the past. CGG and Orphanides differ, however, in terms of their assessments on what these policy mistakes were.

The results presented here provide further evidence for such a policy mistakes view in terms of *both* the inflation *and* the output gap variables. They are thus compatible with and provide motivation for learning models in which the monetary authority initially has wrong perceptions in real time about both the output gap and the output–inflation trade-off and eventually corrects such misperceptions.

A question that naturally arises at this point is how these results mesh with those of the existing literature. More specifically, what sets apart the benchmark model from the existing literature is primarily the discreteness issue. Nevertheless, the results presented here are qualitatively similar to those of earlier studies, such as those of CGG and Orphanides, as discussed above. So, does accounting for discreteness matter in practice in this particular context? The best way to answer this question would be to compare our results to those from a specification that assumes a continuous interest rate setting, *ceteris paribus*. A comparison with CGG does not help us answer this question; CGG's specification differs from ours not only on the discreteness issue, but along two other dimensions as well: CGG use quarterly time-series data (as opposed to our "FOMC frequency," as discussed above) and which are not real time either. Orphanides uses real-time data in his work, but at a quarterly frequency. However, using data that are not just real time, but at the FOMC frequency as well is crucial in the context of our specification, as a quarterly frequency is likely to confound variations in target changes by bundling together successive and distinct such changes. Indeed, it is only a comparison with Boivin's results that can best help us assess the practical significance of the discreteness issue in our context: Boivin (2006) employs a continuous setting using data that are both real time and at the FOMC frequency. His results (discussed in the first part of his paper, where he follows a split-sample approach such as that of the benchmark model of this paper) are qualitatively similar to those of Orphanides in that they imply a monetary policy response to inflation in the pre-Volcker period that is not too different from that in the Volcker–Greenspan period. These results and conclusions are clearly different from those reached here, as discussed above.[12]

In a nutshell, the results of the benchmark model thus indicate that discreteness matters in practice, and they also provide empirical support for the policy mistakes hypothesis. Furthermore, the essence of these results essentially carries through

12. However, Boivin (2006) also reports that such constant-parameter, split-sample results are very fragile and very sensitive in particular to the starting and ending points of the pre-Volcker periods. In light of this, I conducted two sets of exercises. First, I estimated the "linear counterpart" to my benchmark specification (i.e., equation (1) estimated with ordinary least squares (OLS) using the same data for the explanatory variables, and replacing the latent dependent variable with the actual Fed funds rate). I obtained such OLS estimates for 16 different combinations of alternative starting points (the first 4 "FOMC" months in 1969) and ending points (July 1979 and the subsequent 3 "FOMC months" in 1979). These OLS estimates are indeed very fragile. However, I also estimated my benchmark probit model (of equations (1) and (2)) for the same 16 combinations of alternative starting points and ending points. These results are both much more stable (and similar to the results reported in Table 1) and also very different from the OLS results.

several extensions and robustness checks that are mostly inspired by the existing literature on Taylor rules (as discussed in the introduction). These include, in addition to the threshold coefficient issue (also discussed above), estimating the model for different forecast horizons, allowing for possible heteroskedasticity by augmenting the benchmark specification with a two-state regime-switching framework (Hamilton 1989) for the variance of the error term, and allowing the coefficients of equation (1) to be time varying (where I model these time-varying parameters as driftless random walks). Implementing such extensions requires augmenting the Gibbs sampler of Section 1 with additional blocks; the paper's technical appendix (available on request) provides the relevant details of all these algorithms and additional results.

4. CONCLUDING REMARKS

This paper proposes and estimates a forward-looking, dynamic probit reaction function for the Federal Reserve that accounts for the observed discreteness in the target series and provides evidence that supports the "policy mistakes" hypothesis as an explanation of the Great Inflation and of the stark contrast in U.S. macroeconomic performance between the 1970s and the 1980s–90s. There is strong evidence that prior to Volcker's appointment as chairman of the Fed in August 1979, the Fed was too weak in its response to anticipated inflation and that under Volcker the Fed adopted a much stronger anti-inflationary stance. The results also suggest that the pre-Volcker Fed was too activist in its response to real-time estimates of the output gap that were proved *ex post* to have been too optimistic, while starting with Volcker, the Fed adopted a more cautious approach toward such real-time estimates.

These results are of course obtained from just a single-equation framework, which, as discussed earlier, is not free of pitfalls. At a minimum, however, they are consistent with the widely held view that monetary policy played a role in securing the improved macroeconomic performance of the Volcker–Greenspan period. Furthermore, they also provide motivation for a more fully specified model of the economy, which includes a monetary policymaking authority that initially has incorrect perceptions in real time about the structure of the economy and eventually corrects such misperceptions through accumulated knowledge coming from past policy mistakes and from the experience of the impact of these mistakes on the economy.

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