A discrete-choice regime-switching model for the federal funds rate target

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Abstract

I develop a three-equation discrete-choice model for federal funds rate target with endogenous regime switching. Recurring oscillating switches among three policy regimes evolving endogenously in response to the state of economy and interpreted as loose, neutral and tight policy stances are detected during a relatively stable policy period such as the Greenspan era. The model not only has a better in-sample fit for the Greenspan period than the existing models but also forecast better out of sample for the entire Bernanke tenure, and correctly predicts 91 percent of policy decisions including no-change decisions after reaching the zero-lower bound. A conventional single-equation discrete-choice model fails to accommodate the zero-lower bound and wrongly predicts further cuts to the rate target. I further show that the endogeneity of explanatory variables can cause a bias in the estimated policy rules.

KEYWORDS. Federal funds rate target, ordered discrete responses, endogenous switching, endogenous regressors, real-time data.

JEL CLASSIFICATION. C34, C35, C36, E52.

1 Introduction

The federal funds rate target (*target* henceforth) is a principal tool of monetary policy and a key determinant of other short-term market interest rates in the US. The target is widely referenced and anticipated by financial markets all over the world. It is set administratively by the chairman of the Federal Reserve System (Fed) according to the directives of the Federal Open Market Committee (FOMC). Unlike the *effective* federal funds rate determined by the interactions of supply of and demand for federal funds at the daily open market operations in the Federal Reserve Bank of New York, the

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target is set administratively, and is neither a market outcome nor subject to external disturbances and technical oscillations.

The Fed as many other central banks adjusts its target by discrete increments, typically of 25 basis points (bp). More than a half of Fed decisions are status quo (no change) decisions, which are made in different economic circumstances and likely in different policy regimes. The discrete nature of monetary policy interest rates during the last decades motivated the usage of nonlinear econometric techniques for a discrete ordered dependent variable (Vanderhart, 2000; Hu and Phillips, 2004; Dolado *et al.,* 2005; Piazzesi, 2005; Basu and de Jong, 2007; Gerlach, 2007, 2011; Kauppi, 2012; Van den Hauwe *et al.,* 2013). This literature employs single-equation models that cannot allow central bank actions to be generated by different policy regimes. Despite the increasing popularity of a regime-switching approach in macroeconomics, the existing regime-switching applications focus exclusively on models for continuous outcomes.

I develop a new model that predicts the next FOMC decision on the target and accommodates the discreteness of dependent variable, the abundant and possibly heterogeneous status quo outcomes, the asymmetric policy reactions, and the unobserved endogenous regime switching of data-generating process (DGP).

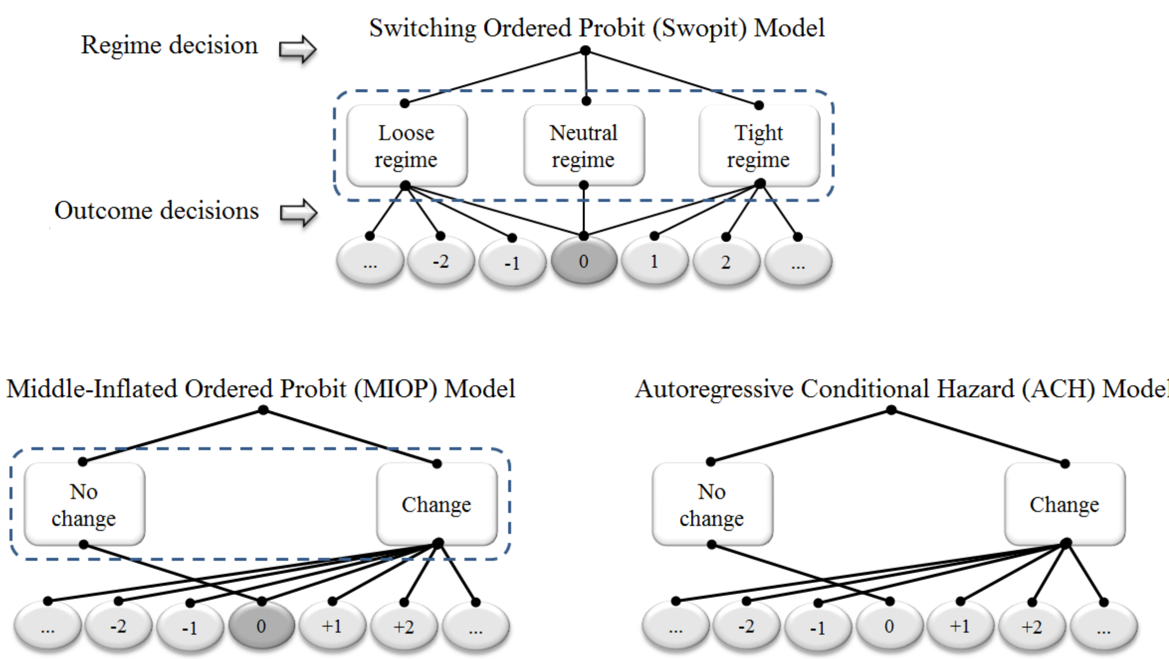
Such approach is shown to provide a high economic relevance for the identification of a monetary policy rule and prediction of the FOMC decisions. Recurring oscillating regime switches among three regimes evolving endogenously in response to the state of economy are detected during a relatively stable policy period such as the Greenspan era. The model correctly predicts 83 percent of FOMC decisions in the 11/1992–1/2006 period. The conventional single-equation ordered probit (OP) model leads to inferences that are markedly different from those in the new model, which also clearly outperforms the existing models in the out-of-sample forecasting. The new model estimated for the Greenspan era correctly predicts 91 percent of FOMC decisions (among five choices) during the Bernanke tenure, including all 41 status quo decisions after reaching the zero-lower bound (ZLB). The single-equation OP model makes no correct predictions after the onset of ZLB and wrongly predicts 41 cuts.

If our interest is not in forecasting the Fed decisions but rather in the ex-post estimation of structural policy parameters in the Fed monetary policy reaction function, we must address possible correlation between the regressors and unobserved monetary policy shocks in order to avoid a bias in the estimates. The literature on monetary policy rules, however, largely ignores the problem of endogeneity (de Vries and Li, 2014). To assess the effect of endogeneity on the identification of Fed policy decisions and avoid the problems of the lack, validity and strength of the instruments, I use market-based proxies for monetary shocks as controls for endogeneity. Following Bernanke and Kuttner (2005), I estimate monetary policy shocks by federal funds futures' reactions to the FOMC decisions on the days of policy actions. The empirical results suggest that the endogeneity of explanatory variables does matter and can cause a bias in the estimated monetary policy rules.

The FOMC makes interest rate decisions either at prescheduled meetings eight times per year or occasionally at unscheduled meetings and by the discretion of the chairman during intermeeting periods. Neither quarterly nor monthly interval matches a natural FOMC decision-making cycle. Modeling relationship between monthly or quarterly averages of the federal funds rate and economic variables can be subject to a problem of reverse causation, especially if financial market data are included. The Fed closely monitors daily market interest rates; on the other hand, market rates respond immediately to any Fed action. The identification of policy rules using aggregated (monthly or quarterly) financial market data is not plausible. Instead, I use the FOMC decisions on the target as sample observations, and forecast the next FOMC action using the vintages of real-time economic and daily financial data that do not include subsequent revisions and were truly available right before each FOMC decision (both scheduled and unscheduled ones).

The proposed Switching Ordered Probit (Swopit) model extends the autoregressive conditional hazard - ordered probit (ACH-OP) model of Hamilton and Jorda (2002), the zero-inflated ordered probit (ZIOP) model of Harris and Zhao (2007), and the middle-inflated ordered probit (MIOP) models of Brooks *et al.* (2012) and Bagozzi and Mukherjee (2012) as Figure 1 illustrates. The model consists of three latent OP equations: a regime-switching equation and two regime-specific outcome equations. The top panel of Figure 1 shows the decision tree of the Swopit model with three latent regimes (interpreted in the interest rate setting context as tight, neutral and loose policy stances). The regime decision is endogenously driven by a central bank response to observed and unobserved economic data. The outcome decisions, which are conditional on the regime, are driven by the observed data and the unobservables that can be contemporaneously correlated with the unobservables in the regime equation (in this sense the regime switching is endogenous).

Figure 1. The Swopit model is an extention of the ACH-OP and MIOP models



The Swopit model can be described as a three-part zero-inflated OP model. The two-part zero-inflated OP models, developed to address the unobserved heterogeneity of zeros, include the ZIOP model of Harris and Zhao (2007) for a non-negative ordinal outcome, and the MIOP models of Brooks *et al.* (2012) and Bagozzi and Mukherjee (2012) for an ordinal outcome, which ranges from negative to positive responses with an abundant zero response situated in the middle of the choice spectrum. In these models, the regime decision and the outcome decision are represented by the binary probit and OP equations, respectively, and the two latent regimes overlap at the zero outcome, generating "inflated" zeros.

The three-regime Swopit model is a natural extension of the two-regime MIOP and ACH-OP models (see bottom panel of Figure 1).[1] A trichotomous regime decision (no increase, no change, or no decrease) seems to be more realistic than a binary decision (change or no change) if applied to ordinal data that assume negative, zero and positive values. The policymakers, who consider adjusting the rate, have already decided in which direction they are going to change it. Furthermore, the decision to raise or cut the rate may be driven by asymmetric reaction to economic data. Combining these two distinct decisions into one category in the MIOP and ACH-OP models may seriously distort the inference. The formal comparison of the OP, MIOP and Swopit models is discussed in Section 2. The empirical rejections of the OP and MIOP models in favor of the Swopit model provide a compelling empirical evidence of switching among three policy regimes and asymmetric effects of explanatory variables on the decisions to cut or hike the target. The Monte Carlo experiments reported in Section 3 demonstrate a good performance of the Swopit models in small samples and its superiority with respect to the OP and MIOP models, which deliver asymptotically biased estimates if the underlying DGP is characterized by three switching regimes.

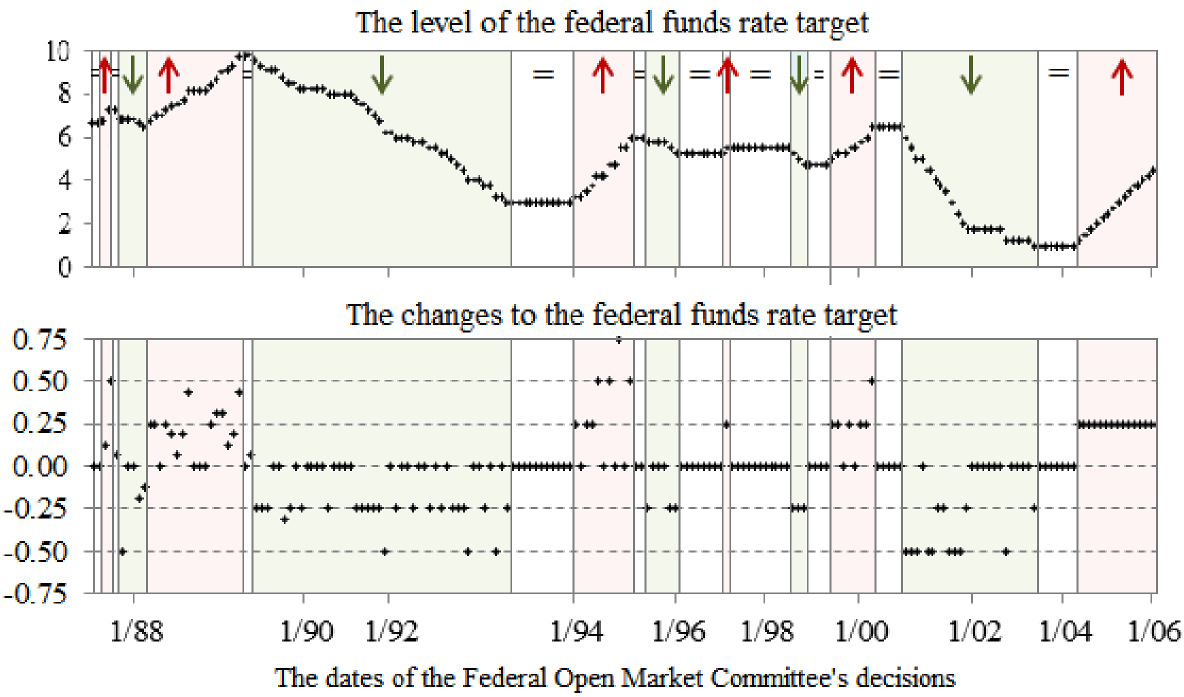
The rationale behind the three-regime zero-inflated approach can be motivated by the stylized fact that for many central banks the majority of policy decisions are status quo decisions (zeros), which are made in three different circumstances, namely: in contractionary periods when policy rate only moves up; in policy maintaining periods when policy rate remains unchanged between rate reversals; and in easing periods when it moves only down (see Figure 2). Many of the zeros, situated between rate hikes during policy contraction, are likely to be driven by different economic conditions compared with many of those that are situated between cuts during policy easing. Many of the zeros, clustered between rate reversals during maintaining periods, are also likely to differ from the zeros in easing or contractionary periods.

The zero-inflated Swopit model can accommodate the possible unobserved heterogeneity of abundant zeros by allowing them to be generated by three distinct regimes. In addition, the rate cuts and hikes can also be generated by distinct processes. According to the Swopit model, the average probability of neutral policy stance in the Greenspan era is 0.35, whereas the observed frequency of status quo decisions is 0.54. Only two thirds of zeros are the "neutral" zeros generated by the neutral policy reaction to economic conditions; the remaining zeros originate under the tight or loose policy regime. The contractionary/maintaining/easing periods are dominated by, respectively, the tight/neutral/loose regimes; however, in the maintaining periods one third of status quo outcomes are either the "tight" or "loose" zeros. One third of all outcomes in the

[1] If inflated response is located at the *end* of the ordered scale, the Swopit model reduces to the ZIOP model of Harris and Zhao (2007).

loose and tight regimes are zeros — the outcome decisions tend to smooth the target rate by weakening the up- and downward policy inclinations.

Figure 2. Federal funds rate target can remain unchanged in different circumstances: during the easing, maintaining or contractionary periods



Notes. ↓/=/↑ denote the easing/maintaining/contractionary periods. The easing/contractionary periods are periods when the rate only moves down/up, from the first to the last sequential unidirectional rate change (decrease/increase, respectively). The maintaining period is a status quo period between the rate reversals.

The flexible three-part structure of the Swopit model is also able to overcome some typical shortcomings of the conventional single-regime ordered-choice models. TheSwopit model allows a certain variable to have the same sign of the marginal effect (ME) on the probabilities of both the largest and smallest categories, and also allows the sign of the ME to change more than once when moving from the smallest category to the largest one. In the conventional models, the MEs on the probabilities of the outcomes at the opposite ends of the ordered scale always have the opposite sign, and the sign of the ME can only change once when moving from the smallest category to the largest one. The new model also overcomes another typical shortcoming of single-equation models, which tend to overfit the most popular choice.

The regime-switching applications in monetary economics focus exclusively on models for a continuous dependent variable. Policy regime change is often modelled as a permanent, non-stochastic switch; empirical studies divide data samples into regime-specific subperiods or employ a gradual regime switching approach with smoothed transitions between regimes. However, treating regime changes as breaks rather than as a slowly fluctuating stochastic process is largely a matter of convenience and even logically inconsistent, as Cooley *et al.* (1984) argue. The literature on modeling short-lived oscillating switches in monetary policy demonstrate that dividing the U.S. post-World War II sample into distinct regimes can distort qualitative and quantitative inferences, and that the U.S. monetary policy changes are better modeled as stochastic and repeated fluctuations between two or more regimes.

Building on the seminal work of Hamilton (1989), recurring policy regimes are typically modelled as the unobserved states generated by a stochastic exogenous Markov-chain process, which is independent of the endogenous economic variables and has constant probabilities of transition from one regime to another. This assumption is realistic in a wide range of contexts but highly unlikely in monetary policy applications. It is natural to assume that central banks react systematically to changes in the economic conditions; thus, regime switches are endogenous to the state of the economy and have time-varying transition probabilities. Models, in which the time-varying probabilities of regime changes are driven by the observed exogenous variables and past values of dependent variable, are considered by Diebold *et al.* (1994), Filardo (1994), Chib and Dueker (2004), and Bazzi *et al.* (2017). Kim *et al.* (2008) and Chang *et al.* (2017) develop the endogenous Markov regime-switching models, in which the regression disturbance is correlated with the disturbance to the latent state variable controlling the regime.

2 Econometric framework

This section describes the econometric framework of the Swopit model, and discusses the relationship and discrimination among the OP, MIOP and Swopit models.

2.1 Swopit model

Let t ($t = 1, 2, ..., T$) be one of the available T observations. Let y_t be an observed dependent variable — the change to the target made at an FOMC meeting t. The Fed increases or decreases its target by discrete increments, and leaves it unchanged at more than a half of FOMC meetings. Let y_t take a finite number J of positive, zero, and negative ordinal values coded by index j ($j = 1, 2, ..., J$), among which the abundant and potentially heterogeneous no-change response is coded as q. The observed outcome y_t can be generated in any of three unobserved regimes, coded by index s ($s = 1, 2, 3$) and interpreted as monetary policy stances (loose, neutral, or tight, respectively). The regime switching decision r_t ($r_t = 1, 2, 3$) is determined by the continuous latent variable r_t^*, endogenously driven in response to the observed data and unobservables according to the OP regime equation. The correspondence between r_t^* and r_t is determined by unobserved thresholds in the usual ordered-response fashion according to a matching rule. The only possible outcome of y_t in the neutral regime is $j = q$. The possible outcomes in the loose regime are $j \leq q$. The possible outcomes in the hawkish regime are $j \geq q$. In the loose and tight regimes, the observed outcome y_t is determined (also in the usual ordered-response fashion) by, respectively, the unobserved continuous latent variables $y_{1,t}^*$ and $y_{1,t}^*$, representing the potential outcomes in each regime, and driven in response to the observed data and unobservables according to outcome equations.

To summarize, the Swopit model can be described by the following system

$$
\begin{array}{ll}
r_t^* = \mathbf{x}_t'\boldsymbol{\beta} + \varepsilon_t & \text{(regime equation)},\\
r_t = s \text{ if } \mu_{s-1} < r_t^* \leq \mu_s,\ s = 1,2,3 & \text{(regime matching rule)},\\
y_{s,t}^* = \mathbf{x}_{s,t}'\boldsymbol{\beta}_s + \varepsilon_{s,t},\ s = 1,3 & \text{(outcome equations)},\\
y_t = j \text{ if } r_t = 1 \text{ and } \alpha_{1,j-1} < y_{1,t}^* \leq \alpha_{1,j},\ j \leq q & \text{(outcome}\\
y_t = q \text{ if } r_t = 2 & \text{matching}\\
y_t = j \text{ if } r_t = 3 \text{ and } \alpha_{3,j-1} < y_{3,t}^* \leq \alpha_{3,j},\ j \geq q & \text{rules)},\\
\begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_t \end{bmatrix} \overset{iid}{\sim} \mathcal{N}\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{bmatrix} \sigma_s^2 & \rho_s\sigma\sigma_s \\ \rho_s\sigma\sigma_s & \sigma^2 \end{bmatrix} \right),\ s = 1,3 & \text{(interdependence between the regime and outcome decisions)},
\end{array}
$$

where $\mathbf{x}_t$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are, respectively, the t^{th} rows of the observed data matrices $\mathbf{X}$, $\mathbf{X}_1$ and $\mathbf{X}_3$, which in addition to predetermined covariance-stationary explanatory variables may also include the lags of y_t; $\mathbf{X}$, $\mathbf{X}_1$ and $\mathbf{X}_3$ may or may not contain common elements; $\boldsymbol{\beta}$, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_3$ are the vectors of unknown slope parameters; ε_t, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are the t^{th} rows of the independently and identically distributed (iid) across t disturbance terms $\boldsymbol{\varepsilon}$, $\boldsymbol{\varepsilon}_1$ and $\boldsymbol{\varepsilon}_3$; ε_t, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are mutually independent at leads and lags: $E(\varepsilon_t\varepsilon_{s,t+\tau}) = 0$, $s = 1,3$ for $\forall\tau \neq 0$; $-\infty = \mu_0 \leq \mu_1 \leq \mu_2 \leq \mu_3 = \infty$, $-\infty = \alpha_{1,0} \leq \alpha_{1,1} \leq ... \leq \alpha_{1,q} = \infty$ and $-\infty = \alpha_{3,q-1} \leq \alpha_{3,q} \leq ... \leq \alpha_{3,J} = \infty$ are the unknown threshold parameters; the joint distribution of ε_t and each $\varepsilon_{s,t}$, $s = 1,3$ is bivariate normal with cumulative distribution function (CDF)

$$
\Phi_2(\varepsilon_t;\varepsilon_{s,t};\rho_s) = \frac{1}{2\pi\sigma\sigma_s\sqrt{1-\rho_s^2}} \int_{-\infty}^{\varepsilon_t}\int_{-\infty}^{\varepsilon_{s,t}} \exp\left(-\frac{u^2/\sigma^2 - 2\rho_s uv/\sigma\sigma_s + v^2/\sigma_s^2}{2(1-\rho_s^2)}\right) dudv.
$$

Conditional on the observed data $\mathbf{x}_t, \mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$, the probabilities of the outcome j are given by

$$
\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = I_{j\leq q}\Pr(r_t^* \leq \mu_1 \text{ and } \alpha_{1,j-1} < y_{1,t}^* \leq \alpha_{1,j}|\mathbf{x}_t, \mathbf{x}_{1,t})\\
&+I_{j=q}\Pr(\mu_1 < r_t^* \leq \mu_2|\mathbf{x}_t) + I_{j\geq q}\Pr(\mu_2 < r_t^* \text{ and } \alpha_{3,j-1} < y_{3,t}^* \leq \alpha_{3,j}|\mathbf{x}_t, \mathbf{x}_{3,t})\\
&= I_{j\leq q}\Pr(\varepsilon_t \leq \mu_1 - \mathbf{x}_t'\boldsymbol{\beta} \text{ and } \alpha_{1,j-1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1 < \varepsilon_{1,t} \leq \alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1)\\
&+I_{j=q}\Pr(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta} < \varepsilon_t \leq \mu_2 - \mathbf{x}_t'\boldsymbol{\beta})\\
&+I_{j\geq q}\Pr(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta} < \varepsilon_t \text{ and } \alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3 < \varepsilon_{3,t} \leq \alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)\\
&= I_{j\leq q}[\Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1;\rho_1) - \Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,j-1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1;\rho_1)]\\
&+I_{j=q}[\Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})]\\
&+I_{j\geq q}[\Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; -\rho_3) - \Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; -\rho_3)],
\end{aligned}
$$

where $I_{j\leq q}$ is an indicator function such that $I_{j\leq q} = 1$ if $j \leq q$, and $I_{j\leq q} = 0$ if $j > q$ (analogously for $I_{j=q}$ and $I_{j\leq q}$). These probabilities can be computed as

$$\Pr(y_t = 1|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1; \rho_1);$$

$$\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) \\
&= I_{j\leq q}[\Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1;\rho_1) - \Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,j-1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1;\rho_1)] \\
&+I_{j=q}[\Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})] + I_{j\geq q}[\Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; -\rho_3) \\
&-\Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; -\rho_3)] \text{ for } 1 < j < J;
\end{aligned} \tag{1}$$

$$\Pr(y_t = J|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; -\alpha_{3,J-1} + \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; \rho_3).$$

If $\rho_1 = \rho_3 = 0$ then $\boldsymbol{\varepsilon}$ and $\boldsymbol{\varepsilon}_s$ are mutually independent, and regime switching is exogenous. Under an assumption that $\boldsymbol{\varepsilon}$ and $\boldsymbol{\varepsilon}_s$ are iid with normal CDF Φ, the probabilities of the outcome j with exogenous switching are given by

$$\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = I_{j\leq q}\Pr(r_t = 1|\mathbf{x}_t)\Pr(y_t = j|\mathbf{x}_{s,t}, r_t = 1) \\
&+I_{j=q}\Pr(r_t = 2|\mathbf{x}_t) + I_{j\geq q}\Pr(r_t = 3|\mathbf{x}_t)\Pr(y_t = j|\mathbf{x}_{s,t}, r_t = 3) \\
&= I_{j\leq q}\left\{\Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})[\Phi(\alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1) - \Phi(\alpha_{1,j-1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1)]\right\} \\
&+I_{j=q}[\Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})] \\
&+I_{j\geq q}\left\{[1 - \Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta})][\Phi(\alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3) - \Phi(\alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)]\right\}.
\end{aligned}$$

These probabilities can be computed as

$$\Pr(y_t = 1|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})\Phi(\alpha_{1,1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1);$$

$$\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) \\
&= I_{j\leq q}\Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})[\Phi(\alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1) - \Phi(\alpha_{1,j-1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1)] \\
&+I_{j=q}[\Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})] \\
&+I_{j\geq q}[1 - \Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta})][\Phi(\alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3) - \Phi(\alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)] for 2 \leq j \leq J-1;
\end{aligned}$$

$$\Pr(y_t = J|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = [1 - \Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta})][1 - \Phi(\alpha_{3,J-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)].$$

As is typical in the discrete ordered choice models, the intercept components of $\boldsymbol{\beta}$ and $\boldsymbol{\beta}_s$ are identified only up to scale and location, i.e. only jointly with the corresponding threshold parameters $\boldsymbol{\mu}$ and $\boldsymbol{\alpha}_s$, and the variances σ^2 and σ_s^2 of $\boldsymbol{\varepsilon}$ and $\boldsymbol{\varepsilon}_s$. To identify the model, the intercept components of $\boldsymbol{\beta}$ and $\boldsymbol{\beta}_s$ are fixed to zero, and the variances σ^2 and σ_s^2 are fixed to one. The probabilities in (1), however, are absolutely estimable and invariant to the identifying assumptions. They can be estimated using an ML estimator of the vector of the parameters $\boldsymbol{\theta} = (\boldsymbol{\mu}', \boldsymbol{\beta}', \rho, \boldsymbol{\alpha}_1', \boldsymbol{\beta}_1', \rho_1, \boldsymbol{\alpha}_3', \boldsymbol{\beta}_3', \rho_3)'$ that solves

$$\max_{\boldsymbol{\theta}\epsilon\boldsymbol{\Theta}} \sum_{t=1}^{T}\sum_{j=1}^{J} h_{t,j} \ln[\Pr(y_t = j|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, \boldsymbol{\theta})],$$

where h_{tj} is an indicator function such that $h_{t,j} = 1$ if $y_t = j$ and $h_{tj} = 0$ otherwise, and $\boldsymbol{\Theta}$ is a parameter space, subject to the constraints: $-\infty = \mu_0 \leq \mu_1 \leq \mu_2 \leq \mu_3 = \infty$, $-\infty = \alpha_{1,0} \leq \alpha_{1,1} \leq ... \leq \alpha_{1,q} = \infty$ and $-\infty = \alpha_{3,q-1} \leq \alpha_{3,q} \leq ... \leq \alpha_{3,J} = \infty$.

In general, the parameters in $\boldsymbol{\theta}$ are separately identified (up to scale and location) by construction via the functional form due to the nonlinearity of the OP equations (Wilde, 2000). There is no need for exclusion restrictions on the specification of covariates in the latent equations to avoid collinearity problems. In practice, however, the collinearity problems might still exist if many observations lie within the middle quasi-linear range of normal CDF. Thus, if $\mathbf{X}$, $\mathbf{X}_1$and $\mathbf{X}_3$ are identical, the simultaneous estimation of three OP equations may be subject to the imperfect collinearity and weak identification (the common symptoms of this problem are large standard errors and close-to-singular Hessian matrix). The estimation can be cumbersome and infeasible if the sample size is not large enough as is often the case in monetary policy modeling. The Swopit estimator can suffer from problems with the invertibility of the Hessian matrix, because in small samples the likelihood function at the maximum can be flat for an infinitely wide range of parameters' values. In this case, the exclusion restrictions (ensuring that $\mathbf{X}$, $\mathbf{X}_1$and $\mathbf{X}_3$ are not identical) may be necessary. The starting values for $\boldsymbol{\theta}$ can be obtained by, for example, using the independent OP estimations of each latent equation. The asymptotic standard errors of $\widehat{\boldsymbol{\theta}}$ can be estimated from the Hessian matrix.

Let $\mathbf{x}_t^{all}$ denote a vector that contains the values of all variables in $\mathbf{x}_t$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$. The ME of an explanatory variable k (the k^{th} element of $\mathbf{x}_t^{all}$) on the probability of choice j can be computed as

$$\begin{aligned}
ME_{k,j,t} = \tfrac{\partial \Pr(y_t=j|\boldsymbol{\theta})}{\partial \mathbf{x}_{t,k}^{all}} = I_{j\leq 0} \Bigg\{ \Bigg[\Phi\left(\tfrac{\mu_1 - \mathbf{x}_t'\boldsymbol{\beta} - \rho_1(\alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1)}{\sqrt{1-(\rho_1)^2}}\right) \phi(\alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1) \\
-\Phi\left(\tfrac{\mu_1 - \mathbf{x}_t'\boldsymbol{\beta} - \rho_1(\alpha_{1,j+1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1)}{\sqrt{1-(\rho_1)^2}}\right) \phi(\alpha_{1,j+1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1) \Bigg] \boldsymbol{\beta}_{1,k}^{all} \\
- \left[\Phi\left(\tfrac{\alpha_{1,j+1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1 - \rho_1(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})}{\sqrt{1-(\rho_1)^2}}\right) - \Phi\left(\tfrac{\alpha_{1,j} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1 - \rho_1(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})}{\sqrt{1-(\rho_1)^2}}\right)\right] \phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})\boldsymbol{\beta}_k^{all} \Bigg\} \\
- I_{j=0}[\phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta})]\boldsymbol{\beta}_k^{all} \\
+ I_{j\geq 0} \Bigg\{ \Bigg[\Phi\left(\tfrac{\mathbf{x}_t'\boldsymbol{\beta} - \mu_2 + \rho_3(\alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)}{\sqrt{1-(\rho_3)^2}}\right) \phi(\alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3) \\
-\Phi\left(\tfrac{\mathbf{x}_t'\boldsymbol{\beta} - \mu_2 + \rho_3(\alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3)}{\sqrt{1-(\rho_3)^2}}\right) \phi(\alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3) \Bigg] \boldsymbol{\beta}_{3,k}^{all} \\
+ \left[\Phi\left(\tfrac{\alpha_{3,j} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3 + \rho_3(\mathbf{x}_t'\boldsymbol{\beta} - \mu_2)}{\sqrt{1-(\rho_3)^2}}\right) - \Phi\left(\tfrac{\alpha_{3,j-1} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3 + \rho_3(\mathbf{x}_t'\boldsymbol{\beta} - \mu_2)}{\sqrt{1-(\rho_3)^2}}\right)\right] \phi(\mathbf{x}_t'\boldsymbol{\beta} - \mu_2)\boldsymbol{\beta}_k^{all} \Bigg\},
\end{aligned}$$

where ϕ is the probability density function of the standard normal distribution, and $\boldsymbol{\beta}_k^{all}$, $\boldsymbol{\beta}_{1,k}^{all}$ and $\boldsymbol{\beta}_{3,k}^{all}$ are the coefficients on the k^{th} explanatory variable in $\mathbf{x}_t^{all}$ in the regime equation, the outcome equation conditional on $s_t = 1$ and the outcome equation conditional on $s_t = 3$, respectively ($\boldsymbol{\beta}_k^{all}$, $\boldsymbol{\beta}_{1,k}^{all}$ or $\boldsymbol{\beta}_{3,k}^{all}$ is zero if the k^{th} explanatory variable in $\mathbf{x}_t^{all}$ is not included into the corresponding equation). For a discrete-valued explanatory variable, the ME should be computed as the change in the probabilities when this variable changes by one increment and all other explanatory variables are held fixed.

2.2 Discriminating among the OP, MIOP and Swopit models

In this section I discuss the relations among the OP, MIOP and Swopit models and the choice of a formal statistical test for model selection.

In general, neither the OP nor MIOP model is nested in the Swopit model, and vice versa. However, these models are not strictly non-nested. They overlap under certain parameter restrictions, namely, if their slope coefficients are all fixed to zero and only the thresholds are estimated. Therefore, the comparison of the OP or MIOP model with the Swopit model can be performed using a test for non-nested overlapping models, such as the Vuong test (Vuong, 1989).

An interesting special case when the Swopit model nests the MIOP model occurs under certain parameter restrictions provided (i) the dependent variable has three outcome categories, (ii) both $\mathbf{X}_1$ and $\mathbf{X}_3$ contain all covariates in the MIOP regime equation, and (iii) $\mathbf{X}$ includes all covariates in the MIOP outcome equation. See Online Appendix A for a proof. In this case, the comparison of the Swopit and MIOP models can be performed using a test for nested models, such as the likelihood ratio (LR) test.

The MIOP reduces to the OP model if (i) the outcome equation of the former contains all covariates in the latter and (ii) the threshold parameter in the regime equation of the former is infinitely close to the lower bound of its parameter space (that is close enough to $-\infty$) to ensure that all observations always occur in the "change" regime. In this special case, not only one parameter (the threshold in the regime equation) is not the interior point of the parameter space in the null hypothesis, but also all the slope coefficients in the regime equation become the nuisance parameters that are not identified under the null; therefore, since some standard regularity conditions of the classical LR test fail to hold, the comparison of the MIOP and OP models can be performed using the LR test with the adjusted critical values (Andrews, 2001).

3 Finite sample performance

This section summarizes the results of conducted Monte Carlo experiments to assess the finite sample performance of the ML estimator of the Swopit model. To assess the effect of exclusion restrictions, the repeated samples in the simulations are generated by the Swopit DGP under three different scenarios of the overlap among the covariates in three latent equations: "no overlap" (each covariate belongs only to one equation), "partial overlap" (each covariate belongs to two equations) and "complete overlap" (all three equations have the same set of covariates). Under each scenario, the samples are generated using the same number of observations per parameter: 25 (with 225, 300 and 375 observations, respectively), 50 (with 450, 600 and 750 observations, respectively) and 75 observations per parameter (with 675, 900 and 1125 observations, respectively).

The simulations suggest that (i) the proposed ML estimator is consistent and demonstrate good performance in small samples; (ii) it requires roughly twice as many observations per parameter for the Swopit model with no overlap among the covariates in latent equations (and four times as many observations per parameter with full overlap) to achieve the same accuracy of the estimates as in the standard OP model; (iii) the Swopit model is identified even with no exclusion restrictions; though, the more exclusion restrictions, the more accurate the estimates.

Unlike the parameters, which are identified up to scale and location only, and are of little interest in their own right, the choice probabilities and the MEs of covariates on them are absolutely estimable functions (invariant to the identifying assumptions), and are of main interest in empirical research. The reported Monte Carlo results assess the accuracy and uncertainty of the estimates of the MEs of covariates on choice probabilities, estimated at the population medians of the covariates. The following measures of finite sample performance (averaged for all covariates and choices, and across all replications) are reported: bias — the absolute difference between the estimated and true ME values; RMSE — the root mean square error of ME estimates relative to their true values; coverage probability — the percentage of times the estimated asymptotic 95% confidence intervals cover the true values of the MEs; and s.e. bias — the absolute difference between the average of estimated standard errors and standard deviation of ME estimates divided by the standard deviation of ME estimates, in percent.

Three vectors of covariates $\mathbf{v}_1$, $\mathbf{v}_2$ and $\mathbf{v}_3$ are drawn once and held fixed in all replications as $\mathbf{v}_1 \overset{iid}{\sim} \mathcal{N}(2,1)$, $\mathbf{v}_2 \overset{iid}{\sim} \mathcal{N}(0,1)$ and $\mathbf{v}_3 = $ -1 if $\mathbf{u} \leq 0.3$, $\mathbf{v}_3 = 0$ if $0.3 < \mathbf{u} \leq 0.7$, or $\mathbf{v}_3 = 1$ if $0.7 < \mathbf{u}$, where $\mathbf{u} \overset{iid}{\sim} \mathcal{U}[0,1]$. The repeated samples are generated as follows: under no overlap scenario — with $\mathbf{X} = \mathbf{v}_1$, $\mathbf{X}_1 = \mathbf{v}_2$, $\mathbf{X}_3 = \mathbf{v}_3$, $\boldsymbol{\beta} = 0.6$, $\boldsymbol{\beta}_1 = 0.8$, $\boldsymbol{\beta}_3 = 0.9$, $\boldsymbol{\mu} = (0.95,\ 1.45)'$, $\boldsymbol{\alpha}_1 = (-1.22,\ 0.03)'$, $\boldsymbol{\alpha}_3 = (-0.03,\ 1.18)'$, and $\rho_1 = \rho_3 = 0$; under partial overlap scenario — with $\mathbf{X} = (\mathbf{v}_1, \mathbf{v}_2)$, $\mathbf{X}_1 = (\mathbf{v}_1, \mathbf{v}_3)$, $\mathbf{X}_3 = (\mathbf{v}_2, \mathbf{v}_3)$, $\boldsymbol{\beta} = (0.6,\ 0.4)'$, $\boldsymbol{\beta}_1 = (0.2,\ 0.3)'$, $\boldsymbol{\beta}_3 = (0.3,\ 0.9)'$, $\boldsymbol{\mu} = (0.9,\ 1.5)'$, $\boldsymbol{\alpha}_1 = (-0.67,\ 0.36)'$, $\boldsymbol{\alpha}_3 = (0.02,\ 1.28)'$, and $\rho_1 = \rho_3 = 0$; and under complete overlap scenario — with $\mathbf{X} = \mathbf{X}_1 = \mathbf{X}_3 = (\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3)$, $\boldsymbol{\beta} = (0.6,\ 0.4,\ 0.8)'$, $\boldsymbol{\beta}_1 = (0.2,\ 0.8,\ 0.3)'$, $\boldsymbol{\beta}_3 = (0.4,\ 0.3,\ 0.9)'$, $\boldsymbol{\mu} = (0.85,\ 1.55)'$, $\boldsymbol{\alpha}_1 = (-1.2,\ 0.07)'$, $\boldsymbol{\alpha}_3 = (1.28,\ 2.5)'$, and $\rho_1 = \rho_3 = 0$. The samples are estimated using the exogenous Swopit model with the same specifications of the latent equations as in the above DGPs.

Table 1. Effect of exclusion restrictions on the performance of Swopit estimator

Number of observations per parameter:	25	50	75
The overlap among the covariates in the regime and amount equations:	no overlap | partial overlap | complete overlap		
Bias of ME estimates (=1 for "no overlap" with 25 obs/parameter)	1.0 | 1.5 | 1.6	0.4 | 0.8 | 0.7	0.3 | 0.6 | 0.6
RMSE of ME estimates (=1 for "no overlap" with 25 obs/parameter)	1.0 | 1.1 | 1.2	0.7 | 0.8 | 0.8	0.6 | 0.6 | 0.6
Coverage probability of ME estimates, % (at 95% level)	93.0 | 92.0 | 92.1	93.5 | 93.7 | 93.4	94.2 | 94.1 | 93.5
Bias of ME standard error estimates (=1 for "no overlap" with 25 obs/parameter)	1.0 | 1.4 | 2.5	0.9 | 0.8 | 2.2	0.4 | 0.6 | 1.4

The Monte Carlo results summarized in Table 1 suggest that the exclusion restrictions are not necessary for the identification and consistent estimation of the Swopit model.

As the sample size grows, the biases and RMSE reduce, and the coverage probability approaches the nominal value both with and without exclusion restrictions. Not surprisingly, the more exclusion restrictions, the more accurate the estimates — for example, without the exclusion restrictions (under the complete overlap) the bias is 100% larger, and the s.e. bias is 250% larger than in the case of no overlap among the covariates.

4 Empirical application

In this section, I apply the Swopit model to predict the next FOMC decision on the target during the Greenspan era, provide the out-of-sample forecast for the Bernanke tenure, compare the in- and out-of-sample performance of the OP, MIOP and Swopit models, and compare the fit of the Swopit and other discrete-choice models from the literature.

4.1 FOMC decisions as sample observations

I use all FOMC decisions (both scheduled and unscheduled) as sample observations, and estimate Fed reaction to recent economic and daily financial data truly available right before each FOMC decision, using the vintages of real-time data that do not include subsequent revisions.

The dates of FOMC decisions, the sizes of target changes, and the values of dependent variable y_t are reported in Table B1 of Online Appendix B. I use the chronology of FOMC decisions from the Fed's Board of Governors, available from ALFRED[2] and derived from Thornton (2005) prior to 1994 and from FOMC meeting transcripts and statements after 1994. I made the following consolidations of target changes: (i) the hikes by 37.5 basis points (bp) and 12.5 bp made on September 3$^{\text{rd}}$ and 4$^{\text{th}}$, 1987, respectively, are merged into a single 50 bp hike; (ii) no change on September 22$^{\text{nd}}$, 1987 and 6.25 bp hike on September 24$^{\text{th}}$, 1987 are merged into a single 6.25 bp hike; (iii) the hikes by 6.25 bp and 37.5 bp made on August 8$^{\text{th}}$ and 9$^{\text{th}}$, 1988, respectively, are merged into a single 43.75 bp hike; and (iv) two hikes by 6.25 bp and 18.75 bp made on November 17$^{\text{th}}$ and 22$^{\text{nd}}$, 1988, respectively, are merged into a single 25 bp hike. The sample consists of 190 observations during the 7/1987–1/2006 period under the Greenspan chairmanship.[3]

Prior to October 1989 the Fed often changed the target in multiples of 6.25 bp, but later on the changes have been always made in multiples of 25 bp. The sample frequencies of original target changes are as follows:

Change, bp	-50	-31.25	-25	-18.75	-12.5	0	6.25
Frequency	13	1	30	1	1	99	3

Change, bp	12.5	18.75	25	31.25	43.75	50	75
Frequency	2	3	27	2	2	5	1

[2]ALFRED, ArchivaL Federal Reserve Economic Data, is a collection of vintage versions of U.S. economic data, compiled by the Federal Reserve Bank of St. Louis (https://alfred.stlouisfed.org/).

[3]With an exception for the first observation in the sample – the FOMC meeting on July 7$^{\text{th}}$, 1987 under the Volcker chairmanship.

I classified these 190 observations into the following five categories of the dependent variable y_t:

y_t	large cut	small cut	no change	small hike	large hike
Frequency	14	32	102	32	10

where "large hike/cut" is an increase/decrease more than 25 bp, "small hike/cut" is an increase/decrease 25 bp or less but more than 6.25 bp, and "no change" is either no change or a change no more than 6.25 bp.[4]

4.2 Explanatory variables

The estimated models include the following four explanatory variables:

(1) $spread_t$ — the difference between the one-year treasury constant maturity rate and effective federal funds rate, five-business-day moving average. The studies that model target changes using a discrete choice approach report that the Taylor-rule variables (such as inflation and output gap) do not provide the best forecasting performance. Piazzesi (2005) finds that the two-year yield describes Fed policy better than the Taylor rules because: (i) yield data summarize the market anticipations of future target moves; (ii) these market anticipations are based on a wide spectrum of information, not just on a couple of variables; and (iii) yield data are available at higher frequencies and are less affected by measurement errors than macroeconomic variables. Hamilton and Jorda (2002), Kauppi (2012) and Van den Hauwe *et al.* (2013) report that despite an extensive literature relating Fed policy to such macroeconomic variables as inflation, output gap, capacity utilization, the spread between the six-month Treasury bill and federal funds rate appears to be by far the most important predictor of the target changes. The term spread can be seen as a low-dimension market-based precursor of future inflation and economic activity (Mishkin, 1990; Estrella and Hardouvelis, 1991; Frankel and Lown, 1994; Estrella and Mishkin, 1998). Bikbov and Chernov (2013) argue that monetary policy regimes may not be estimated precisely if one uses information from the short interest rate only. The real-time data on $spread_t$ are retrieved from ALFRED.

(2) $tight_{t-1}$ and (3) $ease_{t-1}$ — the two binary indicators derived from the "policy bias" statement or "balance-of-risks" assessment at the previous FOMC meeting. During the 1983–1999 period at each meeting the FOMC issued a statement in its domestic policy directive about its expectations for changes in the stance of monetary policy in the nearest future. The directive was symmetric if it is stated that a tightening or an easing of policy were equally likely; otherwise, the directive was asymmetric toward either a tightening or an easing (see Thornton and Wheelock (2000) for the history of the policy directive). Since 2000, the policy directive was replaced by the FOMC assessment of the balance of risks between heightened inflation pressure and economic weakness over the foreseeable future; and since 2003, the FOMC issued separate risk assessments for both inflation and economic growth. The balance-of-risks assessment indicates the FOMC evaluation of whether the risks for the economy are biased towards

[4] The estimations results are robust to the alternative classification: "large hike/cut" is an increase/decrease more than 25 bp, "small hike/cut" is an increase/decrease 25 bp or less, and "no change" is no change.

an economic slowdown (easing bias), towards higher inflationary pressure (tightening bias) or whether the both risks are balanced (symmetrical assessment). As the earlier policy bias directive, the balance-of-risks statements have persistently been interpreted as an indicator of the likely future policy actions. Lapp and Pearce (2000) and Pakko (2005) report that these FOMC statements have predictive power for the next decisions on the target. I classified the policy bias and balance-of-risks statements as "easing", "symmetrical" or "tightening" and constructed two indicator variables: $tight_{t-1}$ that takes value one if the statement at the previous FOMC meeting was tightening, and zero otherwise; and $ease_{t-1}$ that takes value one if the statement was easing, and zero otherwise. The indicators are derived from the FOMC statements and minutes.[5]

(4) $house_t$ — the total number of new privately owned housing units started — a critical leading indicator of economic strength, actively monitored by the Fed and frequently mentioned in FOMC statements. The real-time data on housing starts are retrieved from ALFRED and the Philadelphia Fed's real-time data set.[6]

The values of employed variables are shown in Table B1 of Online Appendix B. Sample descriptive statistics are reported in Table B2 of Online Appendix B. All variables are stationary at the 0.01 significance level according to the augmented Dickey-Fuller unit root test as documented in Table B3 of Online Appendix B.

4.3 Estimation results

Table 2. Modeling changes to federal funds rate target: the estimated parameters of the Swopit model

Variables	Regime equation	Outcome equations	
		Loose regime	Tight regime
tight $_{t-1}$	1.77 (0.37)***		2.44 (0.91)***
ease $_{t-1}$	-2.74 (0.73)***	-0.34 (0.34)	
spread $_t$	2.01 (0.37)***	0.99 (0.29)***	1.67 (0.72)**
house $_t$	5.21 (0.97)***		
threshold $_1$	7.09 (1.56)***	-1.52 (0.34)***	-2.33 (5.49)
threshold $_2$	9.95 (1.64)***	-0.22 (0.34)	3.18 (1.00)***

Notes. Sample period: 7/1987–1/2006 (190 observations). ***/**/* denote the statistical significance at the 1/5/10 percent level. The asymptotic standard errors are shown in parentheses. The explanatory variables are defined in Section 4.2.

Table 2 reports the estimated parameters of the Swopit model with exogenous switching ($\rho_1 = \rho_3 = 0$). The exogenous switching is preferred by the Bayesian information criteria (BIC). The regime equation contains all four above variables. The outcome equations

[5] https://www.federalreserve.gov/monetarypolicy/fomc_historical.htm

[6] https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/

contain $tight_{t-1}$ and $spread_t$ in the tight regime, and $ease_{t-1}$ and $spread_t$ in the loose regime. The exclusion restrictions are not imposed a priori but are completely data-driven: those variables, coefficients on which are not significantly different from zero at the 0.05 level, are excluded from the final specification (with an exception of $ease_{t-1}$ in the outcome equation in the loose regime). The estimation results without exclusion restrictions are reported in Table B4 of Online Appendix B. Among 190 FOMC actions during almost twenty years, the Swopit model correctly predicts 134 decisions (among five choices) with the 8.2 bp mean absolute error (MAE) and 71% hit rate. In terms of three policy choices (up, no change, down) the hit rate is 78%. The Swopit model never wrongly predicts the direction of change.

4.4 Comparison of alternative models

Table 3 compares the in-sample fit of the Swopit model, the standard OP model (estimated with all explanatory variables from the Swopit model), and the MIOP model (in which its both equations include all regressors from the Swopit model).[7] The OP model, as a natural starting point for discrete-choice modeling of monetary policy, is used in many studies (e.g., Vanderhart, 2000; Dolado *et al.,* 2005; Basu and de Jong, 2007; Gerlach, 2007). The MIOP model is applied in Brooks *et al.* (2012) to the policy rate of Bank of England.

Table 3. Comparison of competing models: the Swopit model is favoured by the data

Model:	OP	MIOP	Swopit
Log likelihood	-159.5	-149.8	-139.1
AIC	335.0	325.6	**306.2**
BIC	361.0	367.8	**351.6**
Vuong test versus OP model		-2.26**	**-4.41*** **
Vuong test versus MIOP model			**-2.46*** **
Hit rate (in terms of 5 choices)	0.64	0.66	**0.71**
MAE, bp	10.4	10.0	**8.2**
Adj. noise-to-signal ratio for cuts	**0.10**	0.11	**0.10**
Adj. noise-to-signal ratio for no changes	0.55	0.45	**0.37**
Adj. noise-to-signal ratio for hikes	0.08	0.05	**0.03**

Notes. Sample period: 7/1987–1/2006. ***/**/* denote the statistical significance at the 1/5/10 percent level. Hit rate is the percentage of correct predictions among five choices, where the predicted choice is that with the highest probability. MAE is the mean absolute difference between the observed change and expected change, computed as $\sum_j j\,\Pr(y_t = j|\mathbf{x}_t^{all})$. Adjusted noise-to-signal ratio (Kaminsky and Reinhart,1999), is defined as $[B/(B+D)]/[A/(A+C)]$, where A denotes the event that the decision is predicted and occurred, B denotes the event that the decision is predicted but not occurred, C denotes the event that the decision is not predicted but occurred, and D denotes the event that the decision is not predicted and not occurred.

[7] The OP and MIOP estimation results are shown in Table B5 of Online Appendix B.

For the 7/1987–1/2006 period, according to the Akaike information criteria (AIC), BIC and the Vuong test (at the 0.01 significance level), the Swopit model is clearly superior to the OP and MIOP models. The empirical rejection of the MIOP model in favor of the Swopit model implies that the impacts of explanatory variables on the outcome decisions are asymmetric; hence, combining these two distinct decisions into one branch of the decision tree, as implemented in the MIOP model, may seriously distort an inference. The Swopit model has the best hit rate, MAE and adjusted noise-to-signal ratios, especially for status quo outcomes. The OP and MOP models predict more zeros (130 and 121) than the Swopit model (119), but they correctly predict only 88 and 87 zeros, respectively, whereas the Swopit model correctly predicts 90 zeros.

How good is the fit of the Swopit model in comparison with the fit of other discrete-choice models for target changes in the literature? Hu and Phillips (2004) and Piazzesi (2005) model the target changes (in terms of three choices: 'decrease', 'no change' or 'increase') made only at the scheduled FOMC meetings in the 2/1994–12/2001 and 2/1994–12/1998 periods with 64 and 40 observations in the samples, respectively.

Though the Swopit model is estimated over the far longer 1987–2006 period with much larger sample size (190 observations), it has slightly better overall hit rate of 78% (in terms of three choices) and outperforms the competitors in terms of the adjusted noise-to-signal ratios.

Table 4. Comparison with Hu and Phillips (2004) and Piazzesi (2005): the Swopit model is favoured by the data

	Model (the number of observations in the sample)					
	Hu and Phillips (64 obs)	Piazzesi (40 obs)	Swopit model (114 obs)	Hu and Phillips (64 obs)	Piazzesi (40 obs)	Swopit model (114 obs)
Actual outcome	Hit rate			Adjusted noise-to-signal ratio		
Decrease	0.69	0.00	**0.84**	0.08	n/a	**0.03**
No change	0.90	**0.93**	0.91	0.45	0.72	**0.14**
Increase	0.50	0.57	**0.89**	**0.04**	0.11	0.05
All	0.78	0.75	**0.89**			

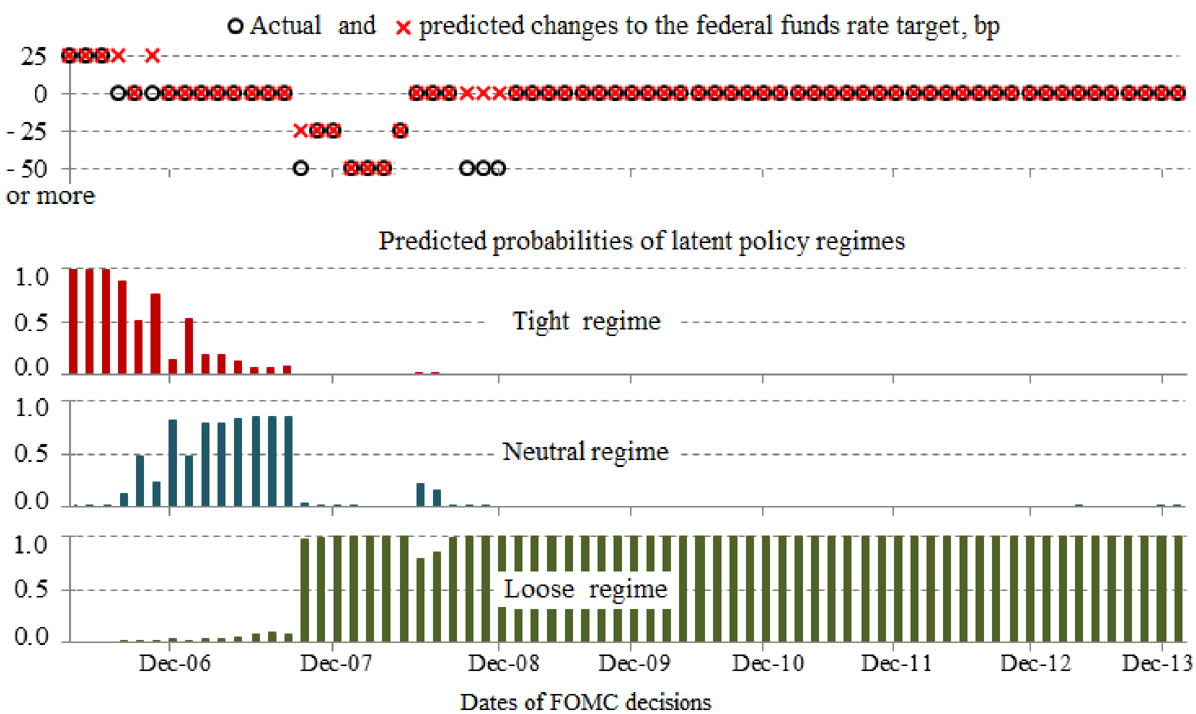
Notes. Hu and Phillips (2004) and Piazzesi (2005) estimate their models using scheduled FOMC decisions in the 2/1994–12/2001 and 2/1994–12/1998 periods, respectively. The Swopit model is estimated using both scheduled and unscheduled decisions in the 11/1992–1/2006 period with the same specification as in Table 2.

I re-estimated the Swopit model for a shorter period from 11/1992 to 1/2006 with 114 observations, still much more than in Hu and Phillips (2004) and Piazzesi (2005). I omitted the first 76 observations from 7/1987 to 10/1992, among which there are 33 decisions made at the unscheduled FOMC meetings and teleconferences; such intermeeting FOMC decisions are more difficult to predict (among 114 decisions from 11/1992 to 1/2006 there are seven intermeeting decisions only). As Table 4 reports, the Swopit model demonstrates much higher overall hit rate (89% versus 78% and 75% in Hu and Phillips (2004) and Piazzesi (2005), respectively), much higher hit rate for cuts (84% versus 69% and 0%, respectively) with better noise-to-signal ratio, much higher hit rate for hikes (89% versus 50% and 57%, respectively) with similar or better noise-to-signal ratio, and similar hit rate for no changes (but with much better noise-to-signal ratio of 0.14 versus 0.45 and 0.72, respectively). The models in Hu and Phillips (2004) and Piazzesi (2005) predict too many zeros, and many of these predictions are wrong. The Swopit model overcomes this typical shortcoming of discrete choice models, which tend to overfit the most popular choice.

4.5 Out-of-sample forecasting performance

How well does the Swopit model, estimated for the Greenspan era, forecast out of sample? Figure 3 shows the actual and predicted target changes as well as the predicted probabilities of latent regimes for the next 68 decisions (without recursive re-estimations), made during the 3/2006–12/2014 period under the Bernanke chairmanship. The Swopit model correctly predicts all three hikes, seven out of ten cuts, and 49 out of 51 status quo decisions.

Figure 3. Out-of-sample forecast for the Bernanke tenure (68 steps ahead): the Swopit model correctly predicts 91 percent of FOMC decisions



Notes. The 68-step ahead forecast for the 3/2006–12/2014 period is obtained from the Swopit model estimated for the 7/1897–1/2006 period (see Table 2).

Table 5 compares the out-of-sample forecasting performance of the competing models.

The Swopit model correctly predicts 91% of the decisions (in terms of five choices) and clearly outperforms the OP (29%) and MIOP (78%) models. The MAE of the forecast in the OP and MIOP models are, respectively, six times and two times as large as in the Swopit model. If we compare the forecasts only for the first 27 decisions before the onset of the zero-lower-bound (ZLB) period in December 2008, the Swopit model also has the best hit rate of 78%, whereas the OP and MIOP models correctly predict 74% and 48% of the policy decisions, respectively. Among the next 41 decisions after December 2008 during the ZLB period (all of them were status quo outcomes), the Swopit and MIOP models correctly predict 100% and 98% of them, respectively, while the OP model makes no correct predictions (it predicts 41 cuts). According to the Swopit forecast, the status quo decisions in the 8/2006–8/2007 period are either the "tight" or "neutral" zeros, while since 1/2009 the zeros are generated exclusively by the loose regime. The Swopit model predicts that the probability of a loose regime is close to one during the entire 10/2007–12/2014 period; nevertheless, it predicts no cuts during the ZLB period when there was actually no scope for reducing target further.

Table 5. Comparison with the OP and MIOP models: the Swopit model provides the best out-of-sample forecast for the Bernanke tenure

Model:	OP	MIOP	Swopit
Hit rate (in terms of 5 choices)	0.29	0.78	**0.91**
MAE, basis points	19.5	7.0	**3.3**

Notes. The 68-step ahead forecasts for the 3/2006–12/2014 period are obtained from the models estimated for the 7/1897–1/2006 period without recursive re-estimations.

4.6 Surmounting the endogeneity problem

The model is cast in a predictive format. If we are not interested in forecasting per se but rather in estimating the structural policy reaction to economic and financial developments, we must pay attention to possible correlation between the regressors and monetary policy shocks in order to avoid a bias in the estimates.[8] Although the model explains the next Fed decision using the predetermined values of explanatory variables as they were known prior to each FOMC meeting (so there is no reverse causal effect from the shocks to the regressors), we however should worry about the possible endogeneity problem for two reasons. First, the FOMC policy bias directives or balance-of-risks assessments may contain internal Fed information about monetary shock at the next policy meeting; hence, the variables $tight_{t-1}$ and $ease_{t-1}$ may be endogenous to the shocks. Second, according to the efficient market hypothesis, the market participants use all available information to predict the upcoming policy actions, and the market

[8] See de Vries and Li (2014) for a discussion of the problem of endogeneity and an assessment of the magnitude of the bias in the conventional estimates of linear monetary policy rules; see also Kim (2004) for endogeneity problem in the estimation of a forward-looking linear reaction function of the Fed with an unknown break date.

interest rates may move in anticipation of FOMC decisions; thus, the variable $spread_t$ may be endogenous.

To overcome the possible endogeneity problem, we could apply the control function estimation approach (Smith and Blundell, 1986; Rivers and Vuong, 1988) that introduces residuals from the reduced form for the endogenous regressors into the structural equation as controls for endogeneity. These residuals are presumably those components of the endogenous variables that are attributable to the unobserved monetary policy shocks. The estimation of the reduced forms in this application, however, raises a host of issues such as the lack, validity and strength of the instruments. As Sims and Zha (2006) point out, identification in instrumental variable model is based on claiming that a list of instrumental variables is available to control for the endogeneity of explanatory variables, but these instruments are available only because of a claim that we know a priori that they do not belong directly to the central bank reaction function and can affect monetary policy only through their effects on the future values of regressors. However, it seems inherently implausible that, for instance, the central bank response to an expected future 3-percent inflation rate does not depend on whether the past inflation rate was 1.5 percent or 6 percent. We can avoid these issues by computing instead the market-based proxies for monetary shocks in order to use them as controls for endogeneity.

Cochrane and Piazzesi (2002) point out that monetary shocks derived from daily interest rate data are nearly the ideal measures of unanticipated changes to the target. Financial markets can flexibly employ the boundless spectrum of information in order to predict Fed decisions, surmounting the omitted-variable and time-varying-parameter problems common in econometric estimations. Krueger and Kuttner (1996) document that the federal funds futures rates provide the efficient forecasts of funds rate changes. Gürkaynak *et al.* (2007) report that the federal funds futures dominate the other securities in forecasting monetary policy at horizons up to six months.

Measuring monetary policy shocks.

I estimate monetary policy shocks as surprises, that is as FOMC decisions on the target unanticipated by the market. Following Bernanke and Kuttner (2005), the one-day surprises are measured by market reaction to FOMC actions using the change in the implied rate of current-month federal funds futures on the day of policy action:

$$surprise_\tau = \frac{n}{n-\tau}(f_\tau - f_{\tau-1}), \tag{2}$$

where τ is the day of month when the policy action became known to market participants, n is the number of days in the current month, f_τ and $f_{\tau-1}$ are the current-month futures rate on the day of policy action and on the day prior to policy action, respectively. The futures rate is computed as 100 minus the contract's settlement price. The contracts, known as "30 day federal funds futures", are traded on the Chicago Mercantile Exchange. Each contract is for interest on federal funds for one month calculated on a 30-day basis at a rate equal to the average overnight effective federal funds rate for the contract month. The data are retrieved from Quandl.[9] The first multiplier is a scaling factor

[9] https://www.quandl.com

that accounts for the number of remaining days in the month affected by a policy action. If a policy action occurs on the first day of the month, the one-month futures rate on the last day of the previous month is subtracted from the current-month futures rate on the first day of the current month. If an FOMC decision comes on one of the last three days of the month, the unscaled difference in the one-month futures rates is used instead.

The timing of Fed actions (the dates when the market participants became aware of them) is crucial for measuring monetary policy surprises. The effective dates of Fed actions and the estimated monetary policy shocks are reported in Table B1 of Online Appendix B. The employed chronology is taken from the Board of Governors of the Fed (via ALFRED) with several adjustments suggested by Kuttner (2001, 2003) on the basis of the analysis of market reaction.[10]

Controlling for endogeneity.

The exogeneity of estimated monetary policy shocks is first tested by regressing them on all explanatory variables. The null hypothesis of exogeneity is rejected (the p-value of F-test is 0.0000).

Table 6. Endogeneity does matter: the estimated paremeter of the Swopit model with bias correction

Variables	Regime equation	Output equations	
		Loose regime	Tight regime
tight $_{t-1}$	2.03 (0.46)***		2.56 (1.23)**
ease $_{t-1}$	-4.04 (1.44)***	-0.14 (0.38)	
spread $_t$	2.90 (0.59)***	1.36 (0.33)***	0.46 (0.75)
house $_t$	5.44 (1.22)***		
surprise $_t$	13.45 (3.98)***	8.68 (1.66)***	22.00 (7.02)***
threshold $_1$	7.17 (2.04)***	-2.48 (0.46)***	-2.21 (1.35)
threshold $_2$	10.56 (2.11)***	-0.61 (0.38)	3.60 (1.37)***
Log likelihood	AIC	BIC	Hit rate
-104.3	242.7	297.9	0.79

Notes. Sample period: 7/1987–1/2006 (190 observations). ***/**/* denote the statistical significance at the 1/5/10 percent level. The asymptotic standard errors are shown in parentheses.

Table 6 reports the estimated parameters of the Swopit model with exogenous switching ($\rho_1 = \rho_3 = 0$) and with monetary policy surprises included as controls for endogeneity in all three equations. The usual t statistics for the coefficients on monetary policy surprises can also be used to test exogeneity. The coefficients on $surprise_t$ are significant

[10] See notes to Table B1 of Online Appendix B for the details.

at the 0.001 level in each equation. The null of exogeneity is rejected again.[11] The inclusion of $surprise_t$ substantially improves the model fit: the log likelihood increases from -139.1 to -104.3, the hit rate rises from 0.71 to 0.79, and the MAE decreases from 8.2 bp to 5.5 bp. The Swopit model with bias correction is clearly preferred to the standard Swopit model by the AIC and BIC.

The endogeneity of explanatory variables causes a severe bias in the standard estimates of the Swopit model. The null hypothesis that the parameters in the standard model (Table 2) and in the model with bias correction (Table 6) do not differ jointly is rejected by the LR test (the p-value is 0.0000); the slope parameters in two models do also differ jointly (the p-value is 0.0000). Individually, only three slope parameters differ in two models at the 0.001 significance level: the coefficients on $spread_t$ and $house_t$ in the regime equation and on $spread_t$ in the output equation under the hawkish regime. The other slope parameters are not individually different from their counterparts at the 0.10 significance level. The null hypothesis that the policy reactions are symmetrical (that is, the coefficients on $spread_t$ are equal and coefficients on $tight_{t-1}$ and $ease_{t-1}$ have the same absolute value but opposite signs in the dovish and hawkish regimes) is rejected by the LR-test (the p-value is 0.003). The Swopit model with bias correction is also preferred to the MIOP and OP models with bias correction by the AIC, the BIC and the Vuong test (the p-values are 0.007 and 0.000, respectively).

The estimates of the MEs of the covariates on choice probabilities can differ significantly in the OP, MIOP and Swopit models. For example, as Table 7 shows, the ME of $ease_{t-1}$ on the probability of no change in the Swopit model is -0.23. It means that if the policy bias directive at the last FOMC meeting changes from "symmetrical" to "easing", the probability of no change reduces by 0.23 (holding all other covariates at their sample medians). In the OP and MIOP models, the ME estimates are five times as small as in the Swopit model, and statistically insignificant even at the 0.2 level.

Table 7. The marginal effects of the covariates on choice probabilities can differ significantly in the competing models

Model	OP	MIOP	Swopit
ME of $ease_{t-1}$ on $\Pr(y_t = 0)$	-0.05 (0.04)	-0.04 (0.04)	-0.23 (0.09)***

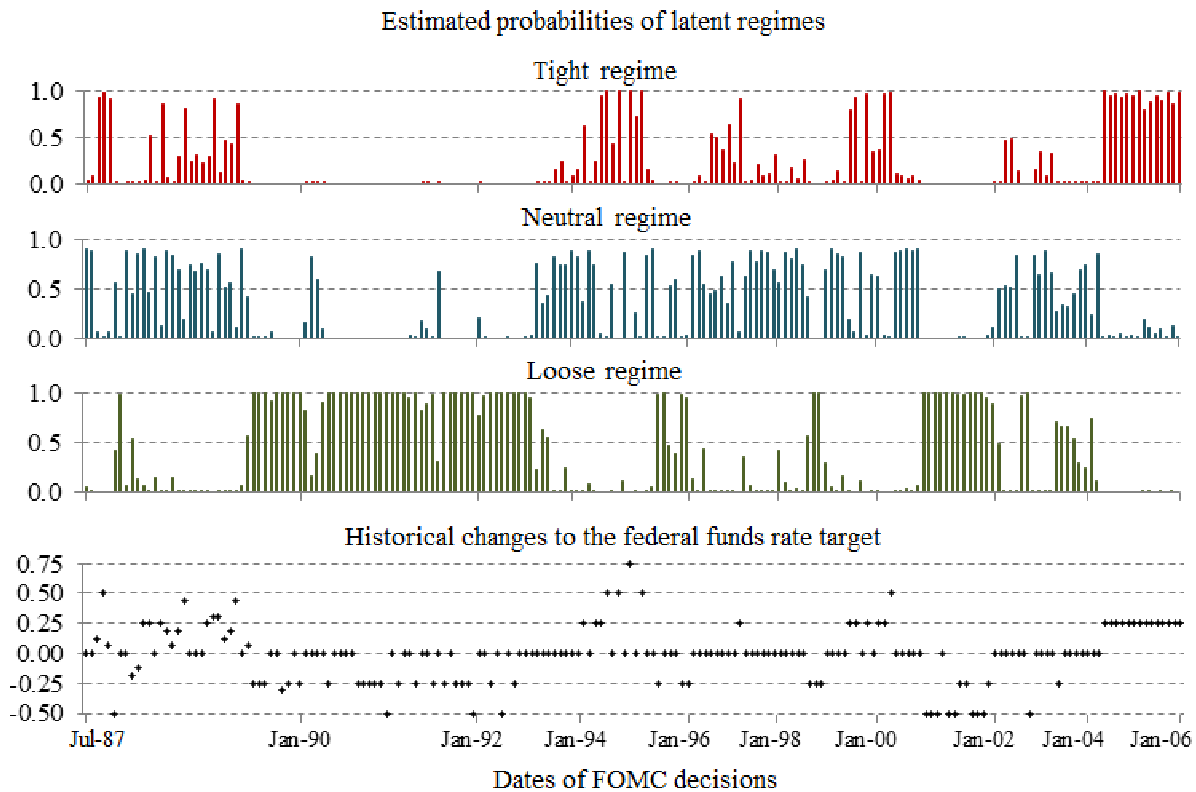
Notes. Sample period: 7/1987–1/2006 (190 observations). ***/**/* denote the statistical significance at the 1/5/10 percent level. The MEs are computed using estimations with bias correction (see Table 6) and fixing the other variables at their sample median values.

Figure 4 shows the estimated probabilities of latent policy regimes for each FOMC decision in the Greenspan era. The average probabilities of the tight, neutral and loose regimes are 0.23, 0.35 and 0.42, whereas the observed frequencies of hikes, zeros and cuts are 0.22, 0.54 and 0.24, respectively. On average, the ratio of the probability of no

[11] Evidence in favor of endo/exogeneity should be interpreted conditional on the correct model specification.

change conditional on the neutral regime to the unconditional probability of no change $\Pr(y_t = 0|r_t = 0)/\Pr(y_t = 0)$ is 0.66. It means that only about two thirds of zeros are the neutral zeros; one third of zeros are generated in either loose or tight policy regime. It turns out that one third of all outcomes in the loose and tight regimes are zeros — the outcome decisions tend to leave the rate unchanged by weakening the tightening and easing policy inclinations.

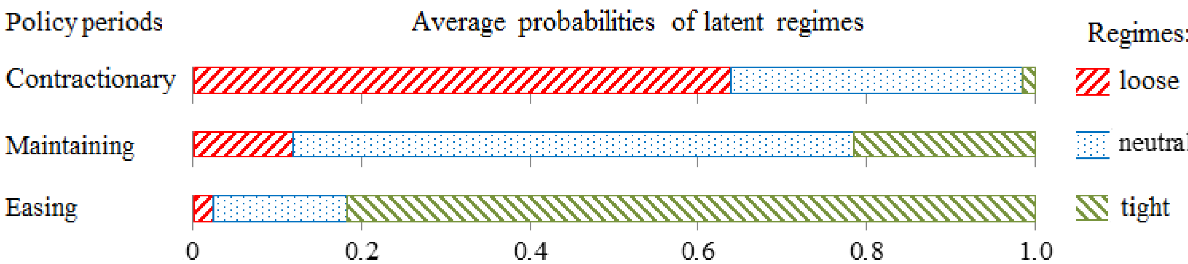
Figure 4. Estimated probabilities of latent regimes and actual FOMC decisions during the Greenspan era



Notes. Sample period: 7/1987–1/2006 (190 observations). The estimates are obtained from the Swopit model with bias correction (Table 6).

Figure 5 illustrates the correspondence of latent regimes to the contractionary, maintaining and easing policy periods shown in Figure 2. The profiles of regime probabilities differ considerably. Monetary policy decisions in the contractionary/maintaining/easing periods are dominated by the tight/neutral/loose regimes, respectively; however, in the maintaining periods one third of status quo outcomes are the "tight" or "loose" zeros.

Figure 5. Average probabilities of latent regimes in different policy periods



Notes. Sample period: 7/1987–1/2006 (190 observations). The estimates are obtained from the Swopit model with bias correction (Table 6). The policy periods are shown in Figure 2.

Concluding remarks

This paper introduced a regime-switching ordered probit model for analyzing ordinal outcomes such as changes in the federal funds rate target. The empirical results demonstrate that ignoring the regime-switching process and the endogeneity of explanatory variables can lead to a seriously distorted statistical inference in the estimated monetary policy rules. The model overwhelmingly outperforms the existing ordered-choice models both in and out of sample. It can be used to more adequately represent monetary policy rules of many central banks, can be embedded in multivariate macroeconomic models to better understand the monetary policy effects, and can be fruitfully applied to various ordinal data with a regime-switching environment.

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Supplementary Online Material

for
"A discrete-choice regime-switching model for the federal funds rate target"
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Online Appendix A. A special case when the Swopit model nests the MIOP model

In general, the Swopit and MIOP models (see the upper panel of Figure 1) are not nested in each other, but they are not strictly non-nested. They overlap if their slope coefficients are all fixed to zero, and only the thresholds are estimated. However, there is an interesting special case when the Swopit model does nest the MIOP model. The special case arises under certain parameter restrictions provided (i) there are only three outcome categories of the dependent variable, (ii) both $\mathbf{X}_1$ and $\mathbf{X}_3$ in the Swopit outcome equations contain all covariates in the MIOP regime equation, and (iii) $\mathbf{X}$ in the Swopit regime equation includes all covariates in the MIOP outcome equation.

To begin, I first describe the MIOP econometric framework. Then I explain under which conditions the Swopit model nests the MIOP model.

The MIOP model

Let t $(t = 1, 2, ..., T)$ be one of the available T observations. Let y_t be an observed dependent variable that can take on a finite number J of ordinal values, coded by index j $(j = 1, 2, ..., J,\ J > 2)$, among which a potentially heterogeneous ("inflated") and often predominant response is coded as q, $1 < q < J$. The observed outcome y_t can be generated in any of two states, coded as 1 or 0 and interpreted as latent regimes in the time-series context or as latent segments of population in the cross-section context. The realized states (regimes) r_t^m are only partially observed and of an ordinal nature. The regime switching decision is determined by the continuous latent variable r_t^{m*}, endogenously driven in response to the observed data and unobservables according to the binary probit regime equation. The correspondence between r_t^{m*} and r_t^m is determined by an unobserved threshold in the usual binary-response fashion. For each t, only one out of two potential realizations of y_t is observed. Conditional on being in the regime $r_t^m = 1$, the observed outcome y_t is determined (in the usual OP fashion) by a continuous latent variable y_t^{m*}, which is driven in response to the observed data and unobservables according to an outcome equation. Conditional on being in the regime $r_t^m = 0$, the observed outcome y_t is always q.

To summarize, the MIOP model can be described by the following system

$$
\begin{array}{ll}
r_t^{m*} = \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m + \varepsilon_t^m & \text{(regime equation),} \\
r_t^m = \begin{cases} 1 \text{ if } \mu^m < r_t^{m*} \\ 0 \text{ if } r_t^{m*} \leq \mu^m \end{cases} & \text{(regime matching rule)} \\
y_{1,t}^{m*} = \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m + \varepsilon_{1,t}^m & \text{(outcome equation),} \\
y_t = j \text{ if } r_t^m = 1 \text{ and } \alpha_{1,j-1}^m < y_{1,t}^{m*} \leq \alpha_{1,j}^m,\ j = 1, 2, ..., J & \text{(outcome matching} \\
y_t = q, \text{ if } r_t^m = 0 \text{ and } 1 < q < J & \text{rules),} \\
\begin{bmatrix} \varepsilon_{1,t}^m \\ \varepsilon_t^m \end{bmatrix} \overset{iid}{\sim} \mathcal{N}\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{bmatrix} 1 & \rho^m \\ \rho^m & 1 \end{bmatrix} \right) & \text{(interdependence between the regime and outcome decisions),}
\end{array}
$$

where $\mathbf{x}_t^m$ and $\mathbf{x}_{1,t}^m$ are the t^{th} rows of the observed data matrices $\mathbf{X}^m$ and $\mathbf{X}_1^m$, respectively; $\boldsymbol{\beta}^m$ and $\boldsymbol{\beta}_1^m$ are the vectors of unknown slope parameters; ε_t^m and $\varepsilon_{1,t}^m$ are the t^{th} rows of the iid across t disturbance terms $\boldsymbol{\varepsilon}^m$ and $\boldsymbol{\varepsilon}_1^m$; ε_t^m is independent of $\varepsilon_{1,t}^m$ at leads and lags: $E(\varepsilon_t^m \varepsilon_{1,t+\tau}^m) = 0$ for $\forall \tau \neq 0$; μ^m and $-\infty \equiv \alpha_{1,0}^m \leq \alpha_{1,1}^m \leq ... \leq \alpha_{1,J}^m \equiv \infty$ are the unknown threshold parameters; the joint probability density between ε_t^m and $\varepsilon_{1,t}^m$ is standardized bivariate normal with CDF $\Phi_2(\varepsilon^m;\varepsilon_1^m;\rho^m)$.

The probabilities of the outcome j in the MIOP model are given by

$$
\begin{aligned}
&\Pr(y_t^m = j|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Pr(r_t^{m*}|\mathbf{x}_t^m > \mu^m \text{ and } \alpha_{1,j-1}^m < y_{1,t}^{m*}|\mathbf{x}_{1,t}^m \leq \alpha_{1,j}^m) \\
&+I_{j=q} \Pr(r_t^{m*}|\mathbf{x}_t^m \leq \mu^m) \\
&= \Pr(\varepsilon_t > \mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m \text{ and } \alpha_{1,j-1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m < \varepsilon_{1,t}^m \leq \alpha_{1,j}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) \\
&+I_{j=q} \Pr(\varepsilon_t^m \leq \mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m) \\
&= \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,j}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) \\
&-\Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,j-1} - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) + I_{j=q}\Phi(\mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m),
\end{aligned} \tag{A1}
$$

where $I_{j=q}$ is an indicator function such that $I_{j=q} = 1$ if $j = q$, and $I_{j=q} = 0$ if $j \neq q$.

A special case

Suppose a dependent variable y_t^m takes only three discrete values j coded as $\{1, 2, 3\}$, and an inflated response is coded as 2 ($q = 2$).

The probabilities of observing the outcome j in the MIOP model are given according to (A1) as

$$
\begin{aligned}
&\Pr(y_t = 1|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m); \\
&\Pr(y_t = 2|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi(\mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m) \\
&+\Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,2}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) \\
&-\Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m); \\
&\Pr(y_t = 3|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; -\alpha_{1,2}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m;\rho^m).
\end{aligned} \tag{A2}
$$

The probabilities of observing the outcome j in the Swopit model are given according to (1) as

$$\Pr(y_t = 1|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{1,1} - \mathbf{x}_{1,t}'\boldsymbol{\beta}_1; \rho_1);$$

$$\begin{aligned} &\Pr(y_t = 2|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}; -\alpha_{1,1} + \mathbf{x}_{1,t}'\boldsymbol{\beta}_1; -\rho_1) \\ &+\Phi(\mu_2 - \mathbf{x}_t'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_t'\boldsymbol{\beta}) + \Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; \alpha_{3,2} - \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; -\rho_3); \end{aligned} \tag{A3}$$

$$\Pr(y_t = 3|\mathbf{x}_t, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(-\mu_2 + \mathbf{x}_t'\boldsymbol{\beta}; -\alpha_{3,2} + \mathbf{x}_{3,t}'\boldsymbol{\beta}_3; \rho_3).$$

Suppose now that the matrices $\mathbf{X}_1$ and $\mathbf{X}_3$ in the Swopit outcome equations are identical to the matrix $\mathbf{X}^m$ in the MIOP regime equation, and that the matrix $\mathbf{X}$ in the Swopit regime equation is identical to the matrix $\mathbf{X}_1^m$ in the MIOP outcome equation. Then $\mathbf{x}_{1,t} = \mathbf{x}_{3,t} = \mathbf{x}_t^m$ and $\mathbf{x}_t = \mathbf{x}_{1,t}^m$. Impose the following restrictions on the Swopit parameters:

$$\begin{aligned} &\boldsymbol{\beta}_3 = -\boldsymbol{\beta}_1 = \boldsymbol{\beta}^m,\ \boldsymbol{\beta} = \boldsymbol{\beta}_1^m,\ \mu_1 = \alpha_{1,1}^m,\ \mu_2 = \alpha_{1,2}^m, \\ &\alpha_{3,2} = -\alpha_{1,1} = \mu^m \text{ and } -\rho_1 = \rho_3 = \rho^m. \end{aligned} \tag{A4}$$

Then, using that $\Phi(-\theta) = 1 - \Phi(\theta)$, the probabilities of observing the outcome j in the Swopit model according to (A3) can be written as

$$\Pr(y_t = 1|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m);$$

$$\begin{aligned} &\Pr(y_t = 2|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi_2(\alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; \mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \rho^m) \\ &+\Phi(\alpha_{1,2}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) - \Phi(\alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) + \Phi_2(-\alpha_{1,2}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; \mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; -\rho^m) \\ &= 1 - \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) - \Phi(-\alpha_{1,1}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) \\ &+\Phi(\alpha_{1,2}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) - \Phi(\alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) \\ &+1 - \Phi(\alpha_{1,2}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m) - \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; -\alpha_{1,2}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; \rho^m) \\ &= 1 - \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) - \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; -\alpha_{1,2}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; \rho^m) \\ &= \Phi(\mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m) + \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,2}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m) \\ &-\Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; \alpha_{1,1}^m - \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; -\rho^m); \end{aligned}$$

$$\Pr(y_t = 3|\mathbf{x}_t^m, \mathbf{x}_{1,t}^m) = \Phi_2(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m; -\alpha_{1,2}^m + \mathbf{x}_{1,t}^{m\prime}\boldsymbol{\beta}_1^m; \rho^m),$$

which are identical to the probabilities in the MIOP model given by (A2).

In more general cases, when $\mathbf{X}_1$ and $\mathbf{X}_3$ are not identical to the matrix $\mathbf{X}^m$, but contain all variables in $\mathbf{X}^m$, and when $\mathbf{X}$ is not identical to $\mathbf{Z}^m$, but contains all variables in $\mathbf{Z}^m$, we can use additional restrictions by fixing the values of the coefficients on all extra variables in $\mathbf{X}$, $\mathbf{X}_1$ and $\mathbf{X}_3$ to zero. With these additional parameter restrictions, the selected set of the explanatory variables in each Swopit outcome equation is identical to the set of the variables in the MIOP regime equation, the selected set of the explanatory variables in the Swopit regime equation is identical to the set of the variables in the

MIOP outcome equation, and the probabilities in the MIOP and Swopit models are identical.

Notice that the restrictions in (A4), namely $\boldsymbol{\beta}_3 = -\boldsymbol{\beta}_1 = \boldsymbol{\beta}^m$ and $\alpha_{3,2} = -\alpha_{1,1} = \mu^m$, impose a sort of symmetry on the policy reactions in the hawkish and dovish policy stances in the Swopit model, since they imply that the conditional probability of a hike in the hawkish regime $\Pr(y_t = 3|\mathbf{x}_t, \mathbf{x}_{3,t}, r_t = 3)$ is determined by the same mechanisms as the conditional probability of a cut in the dovish regime $\Pr(y_t = 1|\mathbf{x}_t, \mathbf{x}_{1,t}, r_t = 1)$:

$$\Pr(y_t = 3|\mathbf{x}_t, \mathbf{x}_{3,t}, r_t = 3) = 1 - \Phi(\alpha_{3,2} - \mathbf{x}'_{3,t}\boldsymbol{\beta}_3) = 1 - \Phi(\mu^m - \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m)$$
$$= \Phi(-\mu^m + \mathbf{x}_t^{m\prime}\boldsymbol{\beta}^m) = \Phi(\alpha_{1,1} - \mathbf{x}'_{1,t}\boldsymbol{\beta}_1) = \Pr(y_t = 1|\mathbf{x}_t, \mathbf{x}_{1,t}, r_t = 1).$$

Online Appendix B. Supporting material for empirical application

Table B1. Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
07-Jul-87	0	no change	08-Jul-87	-0.040	0	0	0.164	1.620
18-Aug-87	0	no change	19-Aug-87	-0.020	0	0	0.228	1.611
27-Aug-87	0.125	small hike	27-Aug-87	0.040	1	0	0.260	1.611
03-Sep-87	0.5	large hike	3-Sep-87: 0.125 4-Sep-87: 0.375	0.090	1	0	0.426	1.611
22-Sep-87	0.0625	no change	24-Sep-87	0.010	1	0	0.426	1.582
03-Nov-87	-0.5	large cut	04-Nov-87	-0.130	0	0	0.008	1.669
16-Dec-87	0	no change	17-Dec-87	-0.140	0	1	0.534	1.637
05-Jan-88	0	no change	05-Jan-88	-0.050	0	0	0.130	1.637
28-Jan-88	-0.1875	small cut	28-Jan-88	-0.060	0	0	0.134	1.374
10-Feb-88	-0.125	small cut	11-Feb-88	0.030	0	0	0.146	1.374
29-Mar-88	0.25	small hike	30-Mar-88	0.010	0	0	0.144	1.494
09-May-88	0.25	small hike	09-May-88	0.050	0	0	0.540	1.543
17-May-88	0	no change	18-May-88	-0.040	0	0	0.110	1.543
25-May-88	0.25	small hike	25-May-88	-0.020	1	0	0.482	1.561
22-Jun-88	0.1875	small hike	22-Jun-88	-0.010	1	0	-0.108	1.384
30-Jun-88	0.0625	no change	01-Jul-88	-0.070	1	0	-0.136	1.384
19-Jul-88	0.1875	small hike	19-Jul-88	0.000	1	0	0.028	1.454
08-Aug-88	0.4375	large hike	8-Aug-88: 0.0625 9-Aug-88: 0.375	0.090	1	0	0.100	1.454
16-Aug-88	0	no change	17-Aug-88	-0.040	1	0	0.166	1.454
20-Sep-88	0	no change	21-Sep-88	0.020	1	0	-0.110	1.489
01-Nov-88	0	no change	02-Nov-88	0.032	1	0	-0.192	1.453
17-Nov-88	0.25	small hike	17-Nov-88: 0.0625 22-Nov-88: 0.1875	-0.078	1	0	0.208	1.554
14-Dec-88	0.3125	large hike	15-Dec-88	0.018	1	0	0.450	1.554
05-Jan-89	0.3125	large hike	05-Jan-89	-0.024	1	0	-0.270	1.563
08-Feb-89	0.125	small hike	09-Feb-89	0.000	1	0	0.058	1.524
14-Feb-89	0.1875	small hike	14-Feb-89	0.020	1	0	-0.070	1.524
24-Feb-89	0.4375	large hike	24-Feb-89	0.070	1	0	-0.158	1.693

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
28-Mar-89	0	no change	29-Mar-89	-0.070	1	0	-0.194	1.498
16-May-89	0.0625	no change	17-May-89	-0.022	1	0	-0.744	1.361
05-Jun-89	-0.25	small cut	05-Jun-89	-0.036	0	0	-1.086	1.361
06-Jul-89	-0.25	small cut	07-Jul-89	-0.026	0	0	-1.446	1.311
26-Jul-89	-0.25	small cut	26-Jul-89	-0.062	0	0	-1.224	1.400
22-Aug-89	0	no change	23-Aug-89	0.000	0	0	-0.708	1.430
03-Oct-89	0	no change	04-Oct-89	0.034	0	1	-0.720	1.353
16-Oct-89	-0.3125	large cut	16-Oct-89	-0.207	0	1	-0.854	1.353
06-Nov-89	-0.25	small cut	07-Nov-89	-0.104	0	1	-0.940	1.263
14-Nov-89	0	no change	15-Nov-89	-0.020	0	1	-0.652	1.263
19-Dec-89	-0.25	small cut	20-Dec-89	-0.169	0	1	-0.828	1.361
07-Feb-90	0	no change	08-Feb-90	-0.014	0	0	-0.110	1.235
27-Mar-90	0	no change	28-Mar-90	0.000	0	0	0.034	1.477
15-May-90	0	no change	16-May-90	0.000	0	0	0.084	1.321
03-Jul-90	0	no change	04-Jul-90	0.000	0	0	-0.248	1.207
13-Jul-90	-0.25	small cut	13-Jul-90	-0.138	0	1	-0.118	1.207
21-Aug-90	0	no change	22-Aug-90	0.000	0	1	-0.464	1.148
07-Sep-90	0	no change	07-Sep-90	0.039	0	1	-0.594	1.148
17-Sep-90	0	no change	17-Sep-90	-0.023	0	1	-0.286	1.148
02-Oct-90	0	no change	03-Oct-90	0.021	0	1	-0.480	1.127
29-Oct-90	-0.25	small cut	29-Oct-90	-0.020	0	1	-0.472	1.135
13-Nov-90	-0.25	small cut	16-Nov-90	0.000	0	1	-0.484	1.135
07-Dec-90	-0.25	small cut	07-Dec-90	-0.271	0	1	-0.274	1.041
18-Dec-90	-0.25	small cut	19-Dec-90	-0.233	0	1	-0.206	1.041
08-Jan-91	-0.25	small cut	08-Jan-91	-0.175	0	1	0.122	1.129
01-Feb-91	-0.5	large cut	01-Feb-91	-0.259	0	1	-0.918	0.987
06-Feb-91	0	no change	07-Feb-91	0.000	0	1	-0.244	0.987
08-Mar-91	-0.25	small cut	08-Mar-91	-0.162	0	1	0.096	0.850
26-Mar-91	0	no change	27-Mar-91	0.000	0	1	0.170	0.989
12-Apr-91	0	no change	12-Apr-91	-0.100	0	0	0.452	0.989
30-Apr-91	-0.25	small cut	30-Apr-91	-0.170	0	0	0.310	0.901
14-May-91	0	no change	15-May-91	0.019	0	0	0.374	0.901
03-Jul-91	0	no change	05-Jul-91	0.000	0	0	0.198	0.982
05-Aug-91	-0.25	small cut	06-Aug-91	-0.149	0	0	0.384	1.040
20-Aug-91	0	no change	21-Aug-91	0.124	0	0	0.052	1.070

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
13-Sep-91	-0.25	small cut	13-Sep-91	-0.053	0	1	0.070	1.070
01-Oct-91	0	no change	02-Oct-91	-0.011	0	1	0.102	1.065
30-Oct-91	-0.25	small cut	30-Oct-91	-0.060	0	1	0.104	1.033
05-Nov-91	-0.25	small cut	06-Nov-91	-0.125	0	1	0.114	1.033
06-Dec-91	-0.25	small cut	06-Dec-91	-0.087	0	1	-0.190	1.096
17-Dec-91	-0.5	large cut	20-Dec-91	-0.238	0	1	-0.086	1.066
05-Feb-92	0	no change	06-Feb-92	-0.013	0	0	0.190	1.103
31-Mar-92	0	no change	01-Apr-92	0.010	0	1	0.674	1.304
09-Apr-92	-0.25	small cut	09-Apr-92	-0.243	0	1	0.418	1.304
19-May-92	0	no change	20-May-92	0.000	0	1	0.120	1.115
01-Jul-92	-0.5	large cut	02-Jul-92	-0.363	0	0	0.144	1.230
18-Aug-92	0	no change	19-Aug-92	0.026	0	1	0.122	1.119
04-Sep-92	-0.25	small cut	04-Sep-92	-0.219	0	1	0.106	1.119
06-Oct-92	0	no change	07-Oct-92	0.052	0	1	-0.528	1.237
17-Nov-92	0	no change	18-Nov-92	-0.100	0	1	0.648	1.256
22-Dec-92	0	no change	23-Dec-92	0.039	0	1	0.732	1.242
03-Feb-93	0	no change	04-Feb-93	-0.012	0	0	0.330	1.302
23-Mar-93	0	no change	24-Mar-93	-0.044	0	0	0.290	1.208
18-May-93	0	no change	19-May-93	-0.026	0	0	0.270	1.213
07-Jul-93	0	no change	08-Jul-93	0.027	1	0	0.146	1.244
17-Aug-93	0	no change	18-Aug-93	0.000	1	0	0.428	1.212
21-Sep-93	0	no change	22-Sep-93	0.000	0	0	0.228	1.323
16-Nov-93	0	no change	17-Nov-93	0.023	0	0	0.546	1.351
21-Dec-93	0	no change	22-Dec-93	0.000	0	0	0.604	1.432
04-Feb-94	0.25	small hike	04-Feb-94	0.117	0	0	0.324	1.540
28-Feb-94	0	no change	28-Feb-94	-0.050	0	0	0.736	1.294
22-Mar-94	0.25	small hike	22-Mar-94	-0.034	0	0	1.104	1.309
18-Apr-94	0.25	small hike	18-Apr-94	0.100	0	0	1.282	1.309
17-May-94	0.5	large hike	17-May-94	0.133	0	0	1.678	1.455
06-Jul-94	0	no change	06-Jul-94	-0.050	0	0	0.986	1.510
16-Aug-94	0.5	large hike	16-Aug-94	0.145	1	0	1.340	1.415
27-Sep-94	0	no change	27-Sep-94	-0.200	0	0	1.112	1.442
15-Nov-94	0.75	large hike	15-Nov-94	0.140	1	0	1.444	1.525
20-Dec-94	0	no change	20-Dec-94	-0.169	0	0	1.758	1.540
01-Feb-95	0.5	large hike	01-Feb-95	0.052	1	0	1.208	1.529

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
28-Mar-95	0	no change	28-Mar-95	0.103	0	0	0.326	1.323
23-May-95	0	no change	23-May-95	0.000	1	0	0.012	1.236
06-Jul-95	-0.25	small cut	06-Jul-95	-0.012	0	0	-0.610	1.239
22-Aug-95	0	no change	22-Aug-95	0.000	0	1	0.080	1.380
26-Sep-95	0	no change	26-Sep-95	0.000	0	0	-0.122	1.398
15-Nov-95	0	no change	15-Nov-95	0.060	0	0	-0.324	1.390
19-Dec-95	-0.25	small cut	19-Dec-95	-0.103	0	0	-0.394	1.337
31-Jan-96	-0.25	small cut	31-Jan-96	-0.070	0	0	-0.466	1.420
26-Mar-96	0	no change	26-Mar-96	-0.031	0	0	0.198	1.490
21-May-96	0	no change	21-May-96	0.000	0	0	0.316	1.519
03-Jul-96	0	no change	03-Jul-96	-0.050	0	0	0.060	1.434
20-Aug-96	0	no change	20-Aug-96	-0.042	1	0	0.448	1.455
24-Sep-96	0	no change	24-Sep-96	-0.125	1	0	0.666	1.525
13-Nov-96	0	no change	13-Nov-96	0.000	1	0	0.128	1.438
17-Dec-96	0	no change	17-Dec-96	0.011	1	0	0.182	1.514
05-Feb-97	0	no change	05-Feb-97	-0.030	1	0	0.328	1.329
25-Mar-97	0.25	small hike	25-Mar-97	0.026	1	0	0.458	1.528
20-May-97	0	no change	20-May-97	-0.113	0	0	0.354	1.473
02-Jul-97	0	no change	02-Jul-97	-0.016	1	0	-0.272	1.397
19-Aug-97	0	no change	19-Aug-97	-0.013	1	0	0.008	1.447
30-Sep-97	0	no change	30-Sep-97	0.000	1	0	-0.070	1.363
12-Nov-97	0	no change	12-Nov-97	-0.042	1	0	-0.126	1.500
16-Dec-97	0	no change	16-Dec-97	-0.010	1	0	-0.058	1.531
04-Feb-98	0	no change	04-Feb-98	0.000	0	0	-0.310	1.519
31-Mar-98	0	no change	31-Mar-98	0.000	0	0	-0.150	1.636
19-May-98	0	no change	19-May-98	-0.026	1	0	-0.150	1.538
01-Jul-98	0	no change	01-Jul-98	-0.005	1	0	-0.480	1.530
18-Aug-98	0	no change	18-Aug-98	0.012	1	0	-0.370	1.615
29-Sep-98	-0.25	small cut	29-Sep-98	0.060	0	0	-0.896	1.613
15-Oct-98	-0.25	small cut	16-Oct-98	-0.262	0	1	-0.906	1.613
17-Nov-98	-0.25	small cut	17-Nov-98	-0.058	0	1	-0.542	1.576
22-Dec-98	0	no change	22-Dec-98	-0.017	0	0	-0.362	1.649
03-Feb-99	0	no change	03-Feb-99	0.000	0	0	-0.182	1.720
30-Mar-99	0	no change	30-Mar-99	0.000	0	0	-0.116	1.799
18-May-99	0	no change	18-May-99	-0.036	0	0	0.018	1.574

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
30-Jun-99	0.25	small hike	30-Jun-99	-0.040	1	0	0.284	1.676
24-Aug-99	0.25	small hike	24-Aug-99	0.022	1	0	0.232	1.661
05-Oct-99	0	no change	05-Oct-99	-0.042	0	0	-0.064	1.676
16-Nov-99	0.25	small hike	16-Nov-99	0.086	1	0	0.138	1.618
21-Dec-99	0	no change	21-Dec-99	0.016	0	0	0.426	1.600
02-Feb-00	0.25	small hike	02-Feb-00	-0.054	0	0	0.564	1.712
21-Mar-00	0.25	small hike	21-Mar-00	-0.031	1	0	0.398	1.781
16-May-00	0.5	large hike	16-May-00	0.052	1	0	0.322	1.663
28-Jun-00	0	no change	28-Jun-00	-0.020	1	0	-0.372	1.592
22-Aug-00	0	no change	22-Aug-00	-0.017	1	0	-0.294	1.512
03-Oct-00	0	no change	03-Oct-00	0.000	1	0	-0.500	1.531
15-Nov-00	0	no change	15-Nov-00	0.000	1	0	-0.394	1.530
19-Dec-00	0	no change	19-Dec-00	0.052	1	0	-0.810	1.532
03-Jan-01	-0.5	large cut	03-Jan-01	-0.382	0	1	-1.052	1.562
31-Jan-01	-0.5	large cut	31-Jan-01	0.005	0	1	-1.208	1.575
20-Mar-01	-0.5	large cut	20-Mar-01	0.056	0	1	-1.186	1.647
11-Apr-01	0	no change	11-Apr-01	0.016	0	1	-1.014	1.647
18-Apr-01	-0.5	large cut	18-Apr-01	-0.425	0	1	-0.852	1.613
15-May-01	-0.5	large cut	15-May-01	-0.078	0	1	-0.680	1.613
27-Jun-01	-0.25	small cut	27-Jun-01	0.050	0	1	-0.472	1.622
21-Aug-01	-0.25	small cut	21-Aug-01	0.016	0	1	-0.290	1.672
17-Sep-01	-0.5	large cut	17-Sep-01	-0.323	0	1	-0.306	1.672
02-Oct-01	-0.5	large cut	02-Oct-01	-0.069	0	1	-0.508	1.527
06-Nov-01	-0.5	large cut	06-Nov-01	-0.100	0	1	-0.460	1.574
11-Dec-01	-0.25	small cut	11-Dec-01	0.000	0	1	0.322	1.552
30-Jan-02	0	no change	30-Jan-02	0.015	0	1	0.434	1.570
19-Mar-02	0	no change	19-Mar-02	-0.026	0	1	0.846	1.678
07-May-02	0	no change	07-May-02	0.000	0	0	0.528	1.646
26-Jun-02	0	no change	26-Jun-02	0.000	0	0	0.378	1.733
13-Aug-02	0	no change	13-Aug-02	0.034	0	0	-0.032	1.672
24-Sep-02	0	no change	24-Sep-02	0.025	0	1	0.006	1.609
06-Nov-02	-0.5	large cut	06-Nov-02	-0.194	0	1	-0.252	1.843
10-Dec-02	0	no change	10-Dec-02	0.000	0	0	0.282	1.603
29-Jan-03	0	no change	29-Jan-03	0.000	0	0	0.066	1.835
18-Mar-03	0	no change	18-Mar-03	0.048	0	0	-0.080	1.622

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
06-May-03	0	no change	06-May-03	0.037	0	0	-0.028	1.780
25-Jun-03	-0.25	small cut	25-Jun-03	0.150	0	1	-0.280	1.732
12-Aug-03	0	no change	12-Aug-03	0.000	0	1	0.342	1.803
16-Sep-03	0	no change	16-Sep-03	0.000	0	1	0.204	1.872
28-Oct-03	0	no change	28-Oct-03	0.000	0	1	0.288	1.888
09-Dec-03	0	no change	09-Dec-03	0.000	0	1	0.374	1.960
28-Jan-04	0	no change	28-Jan-04	0.000	0	1	0.182	2.088
16-Mar-04	0	no change	16-Mar-04	0.000	0	1	0.158	1.855
04-May-04	0	no change	04-May-04	-0.006	0	1	0.536	2.007
30-Jun-04	0.25	small hike	30-Jun-04	-0.010	0	0	1.116	1.967
10-Aug-04	0.25	small hike	10-Aug-04	0.022	0	0	0.752	1.802
21-Sep-04	0.25	small hike	21-Sep-04	0.017	0	0	0.528	2.000
10-Nov-04	0.25	small hike	10-Nov-04	0.000	0	0	0.636	1.898
14-Dec-04	0.25	small hike	14-Dec-04	0.000	0	0	0.546	2.027
02-Feb-05	0.25	small hike	02-Feb-05	0.000	0	0	0.502	2.004
22-Mar-05	0.25	small hike	22-Mar-05	0.000	0	0	0.658	2.195
03-May-05	0.25	small hike	03-May-05	0.000	0	0	0.480	1.837
30-Jun-05	0.25	small hike	30-Jun-05	0.000	0	0	0.286	2.009
09-Aug-05	0.25	small hike	09-Aug-05	0.000	0	0	0.462	2.004
20-Sep-05	0.25	small hike	20-Sep-05	0.015	0	0	0.252	2.009
01-Nov-05	0.25	small hike	01-Nov-05	0.000	0	0	0.424	2.108
13-Dec-05	0.25	small hike	13-Dec-05	0.000	0	0	0.256	2.014
31-Jan-06	0.25	small hike	31-Jan-06	0.000	1	0	0.142	1.933
28-Mar-06	0.25	small hike	28-Mar-06	0.000	1	0	0.136	2.120
10-May-06	0.25	small hike	10-May-06	-0.007	1	0	0.170	1.960
29-Jun-06	0.25	small hike	29-Jun-06	-0.015	1	0	0.264	1.957
08-Aug-06	0	no change	08-Aug-06	-0.040	1	0	-0.150	1.850
20-Sep-06	0	no change	20-Sep-06	0.000	1	0	-0.228	1.665
25-Oct-06	0	no change	25-Oct-06	0.000	1	0	-0.170	1.772
12-Dec-06	0	no change	12-Dec-06	0.000	1	0	-0.326	1.486
31-Jan-07	0	no change	31-Jan-07	0.000	1	0	-0.156	1.642
21-Mar-07	0	no change	21-Mar-07	0.000	1	0	-0.328	1.525
09-May-07	0	no change	09-May-07	0.000	1	0	-0.314	1.518
28-Jun-07	0	no change	28-Jun-07	0.000	1	0	-0.308	1.474
07-Aug-07	0	no change	07-Aug-07	0.026	1	0	-0.460	1.467

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
10-Aug-07	0	no change	10-Aug-07	0.000	1	0	-0.490	1.467
17-Aug-07	0	no change	17-Aug-07	0.155	1	0	-0.202	1.381
18-Sep-07	-0.5	large cut	18-Sep-07	-0.150	0	0	-1.008	1.381
31-Oct-07	-0.25	small cut	31-Oct-07	-0.020	0	0	-0.848	1.191
11-Dec-07	-0.25	small cut	11-Dec-07	0.008	0	0	-1.246	1.229
22-Jan-08	-0.75	large cut	22-Jan-08	-0.741	0	0	-1.394	1.006
30-Jan-08	-0.5	large cut	30-Jan-08	-0.095	0	1	-1.182	1.006
18-Mar-08	-0.75	large cut	18-Mar-08	0.167	0	1	-1.420	1.065
30-Apr-08	-0.25	small cut	30-Apr-08	-0.055	0	1	-0.324	0.947
25-Jun-08	0	no change	25-Jun-08	-0.030	0	0	0.604	0.975
05-Aug-08	0	no change	05-Aug-08	-0.006	0	0	0.260	1.066
16-Sep-08	0	no change	16-Sep-08	0.059	0	0	-0.202	0.965
08-Oct-08	-0.5	large cut	08-Oct-08	-0.142	0	0	-0.154	0.895
29-Oct-08	-0.5	large cut	29-Oct-08	-0.060	0	1	0.734	0.817
16-Dec-08	-0.75	large cut	16-Dec-08	-0.119	0	1	0.356	0.625
28-Jan-09	0	no change	28-Jan-09	0.000	0	1	0.252	0.550
18-Mar-09	0	no change	18-Mar-09	-0.006	0	1	0.508	0.583
29-Apr-09	0	no change	29-Apr-09	-0.005	0	1	0.342	0.510
24-Jun-09	0	no change	24-Jun-09	-0.025	0	1	0.262	0.532
12-Aug-09	0	no change	12-Aug-09	-0.008	0	1	0.324	0.582
23-Sep-09	0	no change	23-Sep-09	0.000	0	1	0.244	0.598
04-Nov-09	0	no change	04-Nov-09	0.000	0	1	0.270	0.590
16-Dec-09	0	no change	16-Dec-09	-0.010	0	1	0.230	0.574
27-Jan-10	0	no change	27-Jan-10	-0.019	0	1	0.188	0.557
16-Mar-10	0	no change	16-Mar-10	0.000	0	1	0.234	0.575
28-Apr-10	0	no change	28-Apr-10	0.000	0	1	0.248	0.626
23-Jun-10	0	no change	23-Jun-10	0.000	0	1	0.110	0.593
10-Aug-10	0	no change	10-Aug-10	0.000	0	1	0.080	0.549
21-Sep-10	0	no change	21-Sep-10	0.000	0	1	0.052	0.598
03-Nov-10	0	no change	03-Nov-10	0.003	0	1	0.028	0.610
14-Dec-10	0	no change	14-Dec-10	0.000	0	1	0.126	0.519
26-Jan-11	0	no change	26-Jan-11	0.000	0	1	0.096	0.529
15-Mar-11	0	no change	15-Mar-11	0.000	0	1	0.108	0.596
27-Apr-11	0	no change	27-Apr-11	0.000	0	1	0.132	0.549
22-Jun-11	0	no change	22-Jun-11	-0.009	0	1	0.084	0.560

Table 14 (contd). Data used in estimations

Date of FOMC decision	Change to federal funds rate target	Dependent variable y_t	Effective date of FOMC action	$surprise_t$	$tight_{t-1}$	$ease_{t-1}$	$spread_t$	$house_t$
09-Aug-11	0	no change	09-Aug-11	0.000	0	1	0.024	0.629
21-Sep-11	0	no change	21-Sep-11	0.008	0	1	0.002	0.571
02-Nov-11	0	no change	02-Nov-11	0.000	0	1	0.052	0.658
13-Dec-11	0	no change	13-Dec-11	-0.004	0	1	0.032	0.628
25-Jan-12	0	no change	25-Jan-12	0.000	0	1	0.022	0.657
13-Mar-12	0	no change	13-Mar-12	0.017	0	1	0.064	0.699
25-Apr-12	0	no change	25-Apr-12	0.000	0	1	0.042	0.654
20-Jun-12	0	no change	20-Jun-12	0.000	0	1	0.008	0.708
01-Aug-12	0	no change	01-Aug-12	0.005	0	1	0.032	0.760
13-Sep-12	0	no change	13-Sep-12	0.009	0	1	0.028	0.746
24-Oct-12	0	no change	24-Oct-12	0.000	0	1	0.030	0.872
12-Dec-12	0	no change	12-Dec-12	0.000	0	1	0.014	0.894
30-Jan-13	0	no change	30-Jan-13	0.000	0	1	0.016	0.954
20-Mar-13	0	no change	20-Mar-13	0.000	0	1	-0.004	0.917
01-May-13	0	no change	01-May-13	0.000	0	1	-0.012	1.036
19-Jun-13	0	no change	19-Jun-13	0.014	0	1	0.034	0.914
31-Jul-13	0	no change	31-Jul-13	0.000	0	1	0.026	0.836
18-Sep-13	0	no change	18-Sep-13	0.000	0	1	0.046	0.891
30-Oct-13	0	no change	30-Oct-13	0.000	0	1	0.032	0.891
18-Dec-13	0	no change	18-Dec-13	0.006	0	1	0.050	1.091
29-Jan-14	0	no change	29-Jan-14	0.000	0	1	0.040	0.999

Notes. The dependent variable y_t is defined in Section 4.1; the explanatory variables $tight_{t-1}$, $ease_{t-1}$, $spread_t$ and $house_t$ are defined in Section 4.2; the monetary shock $surprise_t$ is defined in (2 in Section 4.6).

The dates when FOMC decisions became effective do not completely coinside with the dates when these decisions were made. Up to 1994, the FOMC decisions, made at scheduled meetings, became effective on the next day. Since February 1994, when the Fed began announcing its decision immediately after each FOMC scheduled meeting, the FOMC decisions became effective on the same day. The target changes made at unscheduled meetings were typically implemented by the Fed and recognized by futures market participants on the same day (with two exceptions for FOMC decisions on November 6, 1989 (technical factors delayed market reaction to the next day) and on October 15, 1998 (which was implemented after the close of futures market, so the market reacted on the next day). The employed chronology of FOMC actions is taken from the Board of Governors of the Fed (via ALFRED) with several adjustments suggested by Kuttner (2001, 2003): (i) 25 bp cut on June 5, 1989 instead of June 6, 1989 as in ALFRED; (ii) 25 bp cut on July 26, 1989 instead of July 27, 1989; (iii) 31.25 bp cut on October 16, 1989 instead of October 19, 1989; (iv) 25 bp cut on November 7, 1989 instead of November 6, 1989; (v) 25 bp cut on December 18, 1990 instead of December 19, 1990; (vi) 25 bp cut on January 8, 1991 instead of January 9, 1991; and (vii) 25 bp cut on October 30, 1991 instead of October 31, 1991.

Table B2. Sample descriptive statistics

Variable	Mean	Median	Standard deviation	Minimum	Maximum	First-order autocorrelation coefficient
y_t	-0.04	0.00	0.92	-0.50	0.50	0.50
$tight_{t-1}$	0.26	0.00	0.44	0.00	1.00	0.63
$ease_{t-1}$	0.32	0.00	0.47	0.00	1.00	0.73
$spread_t$	0.05	0.11	0.54	-1.45	1.76	0.82
$house_t$	1.48	1.51	0.27	0.85	2.20	0.92
$surprise_t$	-0.03	0.00	0.09	-0.43	0.15	-0.02

Notes. Sample period: 7/1987–1/2006 (190 observations). For the definitions of the variables see Section 4.2.

Table B3. Tests for unit roots

Variable	Sample period (and size)	The Augmented Dickey-Fuller (ADF) unit root tests				
		Data frequency	Deterministic terms*	Lag length	t-statistic	P-value**
y_t	7/87-1/06 (254 obs.)	FOMC decisions	C	3	-4.30	0.0005
$tight_{t-1}$	7/87-1/06 (256 obs.)	FOMC decisions	C	1	-4.72	0.0001
$ease_{t-1}$	7/87-1/06 (257 obs.)	FOMC decisions	C	0	-5.29	0.0000
$spread_t$	1/62-2/17 (14341 obs.)	daily	C	41	-7.84	0.0000
$house_t$	1/59-1/17 (680 obs.)	monthly	C, LT	16	-4.23	0.0043
$surprise_t$	7/87-1/06 (254 obs.)	FOMC decisions	C	3	-6.44	0.0000

Notes. * C - constant, LT - linear trend; ** MacKinnon (1996) one-sided p-values. For the definitions of the variables see Section 4.2. The lag order of the lagged first differences of the dependent variable in the ADF tests is selected according to a criterion of no serial correlation among the ADF regression residuals.

Table B4. Modeling changes to federal funds rate target: the estimated parameters of the Swopit model without exclusion restrictions

Variables	Regime equation	Outcome equations	
		Loose regime	Tight regime
tight $_{t-1}$	1.61 (0.38)***	5.25 (136.22)	2.33 (1.00)**
ease $_{t-1}$	-1.85 (0.68)***	-0.36 (0.37)	-10.38 (297.67)
spread $_t$	2.06 (0.37)***	0.64 (0.39)*	1.52 (0.74)**
house $_t$	5.06 (1.00)***	-1.45 (0.82)*	-1.38 (1.96)
threshold $_1$	6.91 (1.67)***	-3.32 (1.01)***	-7.07 (172.75)
threshold $_2$	9.63 (1.68)***	-1.91 (0.93)**	0.83 (3.31)

Notes. Sample period: 7/1987–1/2006 (190 observations). ***/**/* denote the statistical significance at the 1/5/10 percent level. The asymptotic standard errors are shown in parentheses. The explanatory variables are defined in Section 4.2.

Table B5. Modeling changes to federal funds rate target: the estimated parameters of the OP and MIOP models

Variables	OP model	MIOP model	
		Regime equation	Outcome equation
tight $_{t-1}$	1.41 (0.25)***	-8.00 (201.73)	2.77 (0.60)***
ease $_{t-1}$	-0.89 (0.23)***	-5.18 (201.73)	-1.25 (0.28)***
spread $_t$	1.56 (0.20)***	1.52 (0.55)	1.74 (0.25)***
house $_t$	1.55 (0.36)***	4.11 (1.36)***	1.70 (0.41)***
threshold $_1$	-0.11 (0.55)	-1.57 (201.73)	-0.11 (0.60)
threshold $_2$	1.09 (0.53)**		1.39 (0.61)**
threshold $_3$	3.91 (0.64)***		4.06 (0.73)***
threshold $_4$	5.29 (0.69)***		6.29 (0.88)***

Notes. Sample period: 7/1987–1/2006 (190 observations). ***/**/* denote the statistical significance at the 1/5/10 percent level. The asymptotic standard errors are shown in parentheses. The explanatory variables are defined in Section 4.2.