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A regime-switching model for the federal funds rate target

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A regime-switching model for the federal funds rate target

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Abstract

This paper develops an ordered choice model for the federal funds rate target with endogenous switching among three latent regimes and possibly endogenous explanatory variables. Estimated for the Greenspan era (1987-2006), the new model detects recurring switches among three policy regimes (interpreted as loose, neutral and tight policy stances) in response to the state of economy, outperforms the Taylor rule and the existing discrete-choice models both in and out of sample, correctly predicts out of sample 90% of the Fed decisions during the next thirteen years, successfully handles the zero lower bound period by a prolonged switch to a loose policy regime with no-change to the target rate (while the Taylor rule and the conventional ordered probit model predict further cuts), and delivers markedly different inference. The empirical results suggest that the endogeneity of explanatory variables does matter in modelling monetary policy and can distort the inference: the marginal effects on the choice probabilities can differ by several times and even have the opposite signs.

Keywords: Federal funds rate target, ordinal responses, endogenous regime switching, endogenous regressors, control function, FOMC, real-time data.

JEL classification: C34, C35, C36, E52.

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1 Introduction

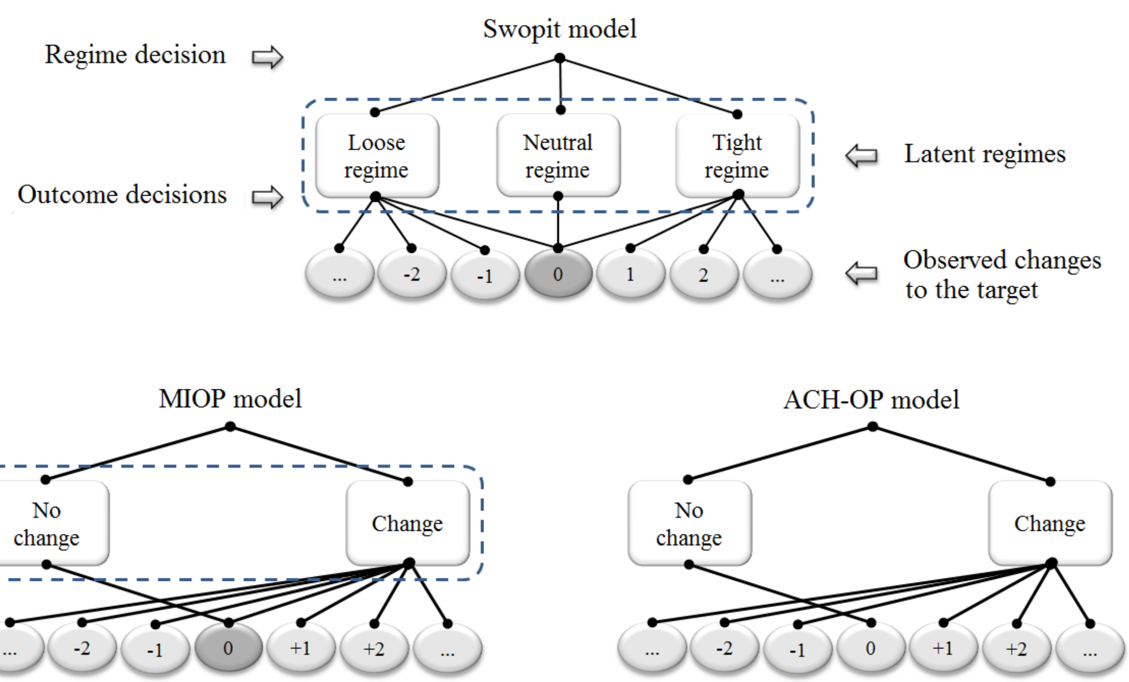
Despite the discrete nature of monetary policy interest rates, the regime-switching behavior of central banks and endogeneity of policy shocks, yet we lack a model that properly addresses all these three issues. The voluminous studies, which quantitatively formalize how the US Federal Reserve System (Fed) and other central banks set their policy interest rates, typically estimate monetary policy rules (central bank reaction functions) using a regression model for a continuous dependent variable. However, during the last three decades, the Fed has been and a growing number of other central banks have begun setting their policy rates by discrete increments, typically of 25 basis points (bp), i.e. a quarter of a percentage point. The discrete and censored nature of policy rates renders a regression model for a continuous dependent variable inappropriate, and has motivated the usage of latent class econometric techniques for an ordinal outcome (Dueker, 1999; Hamilton and Jorda, 2002; Hu and Phillips, 2004; Dolado *et al.,* 2005; Piazzesi, 2005; Gerlach, 2007, 2011; Monokroussos, 2011). The monetary policy studies typically employ a single-equation model that cannot let central bank actions be generated in different regimes, though a regime-switching approach, built on the seminal work of Hamilton (1989), is widely used in macroeconomic modeling. Besides, the existing literature largely ignores a problem of endogeneity (de Vries and Li, 2014), although the forward-looking behavior of the Fed and financial markets as well as the autocorrelation of monetary shocks can cause endogeneity due to a possible correlation between the shocks and regressors.

In order to fill the gap in the literature and adequately address these concerns, I develop a **Sw**itching **O**rdered **P**rob**it** (Swopit) model that allows for the discreteness of policy interest rates, the endogenous explanatory variables, and the endogenous regime switching among three latent policy regimes, generating three types of status quo (no-change) outcomes and asymmetric policy reactions. Methodologically, the Swopit model generalizes to discrete outcomes the endogenous regime switching models, developed for continuous outcomes by Kim *et al.* (2008) and Chang *et al.* (2017), and extends the existing two-equation discrete-choice models for policy rates (see Figure 1): the autoregressive conditional hazard – ordered probit (ACH-OP) model of Hamilton and Jorda (2002) and the middle-inflated ordered probit (MIOP) models of Brooks *et al.* (2012).

The Swopit model assumes three latent decisions represented by three ordered probit (OP) equations: a regime-switching equation and two regime-specific outcome equations. The regime switching among three latent regimes (interpreted as tight, neutral and loose policy stances) is endogenously driven by a central bank response to observed and unobserved economic data and has time-varying transition probabilities. The neutral regime generates only no-change outcomes. The outcome decisions in the tight and loose regimes 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).

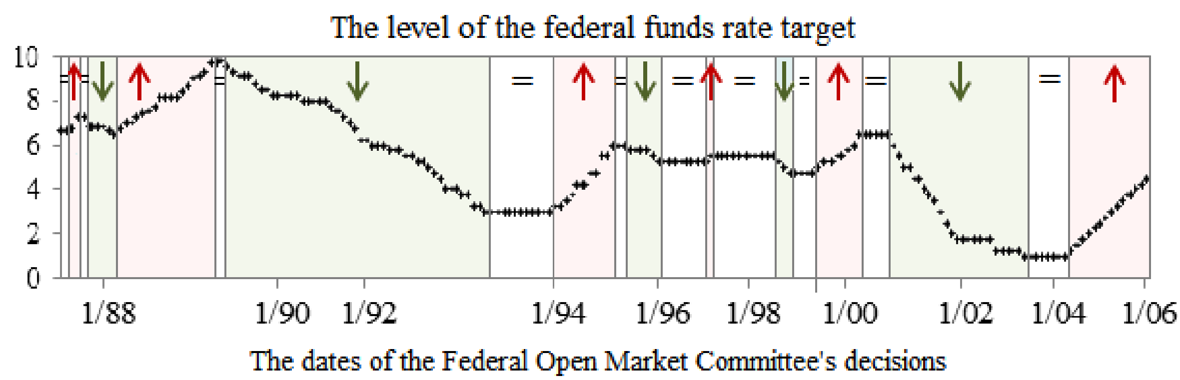
The rationale behind the three-regime approach can be motivated by a stylized fact that more than a half of the policy decisions of the Fed (and of many other central banks) are the no-change decisions, which are made in three different economic circumstances (and hence likely in different policy regimes), namely: in contractionary periods when the policy rate moves only up; in policy maintaining periods when the rate remains unchanged prior to policy reversals; and in expansionary periods when it moves only down (see Figure 2). Many of the no-change decisions, 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 expansion. Many of the status quo decisions, clustered prior to policy reversals during maintaining periods, are also likely to differ from those in expansionary or contractionary periods.

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



The Swopit model can accommodate the possible unobserved heterogeneity of abundant status quo decisions by allowing them to be generated by three distinct decision-making paths. In addition, the cuts and hikes can also be generated by distinct processes. A trichotomous regime decision seems to be more realistic than a binary decision (change or no change) if applied to ordinal data such as policy rate changes that assume negative, zero and positive values. The policymakers, who consider adjusting the policy rate, have already decided in which direction they are going to change it. Furthermore, a decision to increase or lower the rate may be driven by an 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 empirical rejection of MIOP model in favor of the Swopit model provides a compelling evidence of switching among three policy regimes and asymmetric effects of explanatory variables on the decisions to decrease or increase the policy rate. The conventional single-equation OP model leads to inferences that are markedly different from those in the Swopit model: for example, the marginal effects (ME) of the explanatory variables on the choice probabilities can differ by several times and can even have the opposite directions. A flexible three-regime structure of the Swopit model overcomes an important limitation of the single-equation ordered-choice models — the single crossing property — and lets the sign of the ME change more than once when moving from the lowest choice to the highest one.

Figure 2. FOMC decisions on federal funds rate target are made in different circumstances: during the expansionary (↓) , maintaining (=) or contractionary (↑) policy periods



Notes. Both scheduled and unscheduled FOMC decisions during the 7/1987–1/2006 period. The expansionary/contractionary periods are periods when the target changes in the same direction (down/up), from the first to the last sequential unidirectional change (decrease/increase, respectively). The maintaining periods are the status quo periods preceding the policy reversals

The federal funds rate target (*target* henceforth) is a principal tool of US monetary policy and a key determinant of other short-term market interest rates. The target is widely referenced and anticipated by financial markets all over the world. 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 target is set administratively by the chairman of the Fed according to the directives of the Federal Open Market Committee (FOMC). I use the FOMC scheduled decisions as sample observations, and estimate the Fed reaction to the observed published values of recent economic and daily financial data that the policymakers would have seen at each FOMC meeting, employing the vintages of real-time data that do not include subsequent revisions.

This approach is shown to provide a high economic relevance for modelling the target. Oscillating 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, while the zero lower bound (ZLB) period is tackled by a prolonged switch to a loose policy regime. I found that the next FOMC decision can be successfully predicted using the real-time values of the spread between the one-year treasury constant maturity rate and effective federal funds rate, the forecast ("nowcast") of the number of housing units started for current quarter, the "nowcast" of the growth rate in the nominal gross domestic product for current quarter, and the statement on monetary policy released after the previous FOMC meeting. According to the Swopit model, the average probability of neutral policy stance in the Greenspan era is 0.31, whereas the observed frequency of status quo decisions is 0.64. Only a half of the no-change decisions is generated by the neutral policy reaction to economic conditions; another half originates in the tight or loose policy regime. Even during the maintaining policy periods a half of the status quo responses is generated in the tight or loose regime. The outcome decisions tend to smooth the target by weakening the up- and downward policy inclinations and leaving the target unchanged.

The Swopit model clearly outperforms the existing models (the Taylor rule, the OP and MIOP models, and the models of Hu and Phillips (2004) and Piazzesi (2005)) in the in- and out-of-sample forecasting. The Swopit model estimated for the Greenspan era (7/1987-1/2006) predicts correctly about 90 percent of FOMC decisions to lower, leave unchanged or raise the target both in and out of sample during the next thirteen years. It is a challenging forecasting exercise because during the training sample the target was always well above the zero, while during the forecasting sample the target sharply approached the ZLB, stuck at it for seven years, and then began slowly moving up. The Swopit model beats the competitors before and after the ZLB period, and incorrectly predicts only four cuts during the ZLB period while the Taylor rule and the OP model incorrectly predict 25 and 19 cuts, respectively.

If our interest is not in forecasting the Fed decisions but rather in the ex-post estimation of the Fed policy rule, we must pay attention to a possible problem of endogeneity in order to avoid a bias in the estimates. To allow for the endogenous explanatory variables (EEV) in the Swopit model I implement the control function (CF) approach — a two-stage instrumental variable method. I obtain the instruments using a market-based proxy for monetary policy shocks — the difference between the observed and anticipated by the market FOMC decisions. The empirical results suggest that the endogeneity of explanatory variables does matter in the identification of the Fed policy rule and can distort the inference: the marginal effects on the choice probabilities in the Swopit model with controls for endogeneity can differ by several times and can have the opposite signs.

The performed Monte Carlo experiments suggest that the proposed maximum likelihood (ML) and CF estimators are consistent and provide a reliable inference in small samples.

2 The switching ordered probit model

2.1 Model

Let 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 ($t = 1, 2, ..., T$). The Fed increases or decreases its target by discrete increments, but leaves it unchanged at more than a half of FOMC meetings. Let y_t take positive, zero, or negative ordinal values coded by index j ($j = 1, 2, ..., J$), among which an abundant and potentially heterogeneous no-change outcome is coded as q ($1 < q < J$). Let y_t be generated by one of three unobserved regimes, coded by r_t ($r_t = 1, 2, 3$) and interpreted as monetary policy stances (loose, neutral, or tight, respectively). Let the regime decision r_t be determined by the continuous latent variable r^*_t, endogenously driven in response to the observed data and unobservables according to the OP regime equation. Let the correspondence between r^*_t and r_t be determined by unobserved thresholds in the usual ordered-response fashion according to the matching rules. Let $y_t = q$ (no change) in the neutral regime (if $r_t = 2$), $y_t \leq q$ (a decrease or no change) in the loose regime (if $r_t = 1$), and $y_t \geq q$ (an increase or no change) in the tight regime (if $r_t = 3$). In the loose and tight regimes, let y_t be determined (also in the usual ordered-response fashion) by the unobserved continuous latent variables $y^*_{1,t}$ and $y^*_{3,t}$, respectively, which represent the potential outcomes in each regime and are driven in response to the observed data and unobservables according to the OP outcome equations. Let the unobservables in the outcome equations be contemporaneously correlated with the unobservables in the regime equation.

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

$$
\begin{array}{ll}
r^*_t = \mathbf{x}_{0,t}\boldsymbol{\beta}_0 + \varepsilon_{0,t} & \text{(regime equation),} \\
r_t = s \text{ if } \mu_{0,s-1} < r^*_t \leq \mu_{0,s},\ s = 1, 2, 3 & \text{(regime matching rule),} \\
y^*_{s,t} = \mathbf{x}_{s,t}\boldsymbol{\beta}_s + \varepsilon_{s,t},\ s = 1, 3 & \text{(outcome equations),} \\
y_t = j \text{ if } r_t = 1 \text{ and } \mu_{1,j-1} < y^*_{1,t} \leq \mu_{1,j},\ j \leq q & \text{(outcome} \\
y_t = q \text{ if } r_t = 2 & \text{matching} \\
y_t = j \text{ if } r_t = 3 \text{ and } \mu_{3,j-1} < y^*_{3,t} \leq \mu_{3,j},\ j \geq q & \text{rules),} \\
\begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{0,t} \end{bmatrix} \overset{iid}{\sim} \mathcal{N}\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{bmatrix} \sigma^2_s & \rho_s\sigma_0\sigma_s \\ \rho_s\sigma_0\sigma_s & \sigma^2_0 \end{bmatrix} \right),\ s = 1, 3 & \text{(interdependence between the regime and outcome decisions),}
\end{array}
\tag{1}
$$

where $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are the observed row vectors, which in addition to the predetermined covariance-stationary explanatory variables may also include the lags of y_t ($\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ may or may not contain common elements); $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_3$ are the vectors of unknown slope parameters; $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are the independently and identically distributed (iid) across t unobserved disturbance terms ($\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are mutually independent at leads and lags: $E(\varepsilon_{0,t}\varepsilon_{s,t+\tau}) = 0$, $s = 1, 3$ for $\forall\tau \neq 0$); and $-\infty = \mu_{0,0} \leq \mu_{0,1} \leq \mu_{0,2} \leq \mu_{0,3} = \infty$, $-\infty = \mu_{1,0} \leq \mu_{1,1} \leq ... \leq \mu_{1,q} = \infty$ and $-\infty = \mu_{3,q-1} \leq \mu_{3,q} \leq ... \leq \mu_{3,J} = \infty$ are the unknown threshold parameters. To allow for endogenous regime switching, let the joint distributions of $(\varepsilon_{0,t}; \varepsilon_{s,t})$, $s = 1, 3$ be bivariate normal:

$$
\Phi_2(\varepsilon_{0,t}; \varepsilon_{s,t}; \rho_s) = \frac{1}{2\pi\sigma_0\sigma_s\sqrt{1-\rho^2_s}} \int_{-\infty}^{\varepsilon_{0,t}} \int_{-\infty}^{\varepsilon_{s,t}} \exp\left(-\frac{u^2/\sigma^2_0 - 2\rho_s uv/\sigma_0\sigma_s + v^2/\sigma^2_s}{2(1-\rho^2_s)} \right) du dv,
$$

where Φ_2 is the cumulative distribution function (CDF) of a standardized bivariate normal distribution. Conditional on the observed data $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$, the probabilities of the outcome j are given by

$$
\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = I_{j\leq q}\Pr(r_t^* \leq \mu_{0,1} \text{ and } \mu_{1,j-1} < y_{1,t}^* \leq \mu_{1,j}|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}) \\
&+I_{j=q}\Pr(\mu_{0,1} < r_t^* \leq \mu_{0,2}|\mathbf{x}_{0,t}) + I_{j\geq q}\Pr(\mu_{0,2} < r_t^* \text{ and } \mu_{3,j-1} < y_{3,t}^* \leq \mu_{3,j}|\mathbf{x}_{0,t}, \mathbf{x}_{3,t}) \\
&= I_{j\leq q}\Pr(\varepsilon_{0,t} \leq \mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 \text{ and } \mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1 < \varepsilon_{1,t} \leq \mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1) \\
&+I_{j=q}\Pr(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 < \varepsilon_{0,t} \leq \mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) \qquad (2) \\
&+I_{j\geq q}\Pr(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 < \varepsilon_{0,t} \text{ and } \mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3 < \varepsilon_{3,t} \leq \mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3) \\
&= I_{j\leq q}[\Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1;\rho_1) - \Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1;\rho_1)] \\
&+I_{j=q}[\Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) - \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)] \\
&+I_{j\geq q}[\Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3; -\rho_3) - \Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3; -\rho_3)],
\end{aligned}
$$

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 $j > q$ ($I_{j=q}$ and $I_{j\leq q}$ are defined analogously). These probabilities can be computed as

$$
\begin{aligned}
&\Pr(y_t = 1|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1; \rho_1); \\
&\Pr(y_t = j|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) \\
&= I_{j\leq q}[\Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1;\rho_1) - \Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1;\rho_1)] \\
&+I_{j=q}[\Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) - \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)] + I_{j\geq q}[\Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3; -\rho_3) \\
&-\Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3; -\rho_3)] \text{ for } 1 < j < J; \\
&\Pr(y_t = J|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; -\mu_{3,J-1} + \mathbf{x}_{3,t}\boldsymbol{\beta}_3; \rho_3).
\end{aligned}
$$

If $\rho_1 = \rho_3 = 0$ then $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are mutually independent, and regime switching is exogenous. Under an assumption that $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$ are iid, the probabilities of the outcome j with exogenous switching are given by

$$
\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = I_{j\leq q}\Pr(r_t = 1|\mathbf{x}_{0,t})\Pr(y_t = j|\mathbf{x}_{s,t}, r_t = 1) \\
&+I_{j=q}\Pr(r_t = 2|\mathbf{x}_{0,t}) + I_{j\geq q}\Pr(r_t = 3|\mathbf{x}_{0,t})\Pr(y_t = j|\mathbf{x}_{s,t}, r_t = 3) \\
&= I_{j\leq q}\left\{\Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)[\Phi(\mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1) - \Phi(\mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1)]\right\} \\
&+I_{j=q}[\Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) - \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)] \\
&+I_{j\geq q}\left\{[1 - \Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)][\Phi(\mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3) - \Phi(\mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3)]\right\},
\end{aligned}
$$

where Φ is the CDF of the standard normal distribution. These probabilities can be computed as

$$
\begin{aligned}
&\Pr(y_t = 1|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)\Phi(\mu_{1,1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1); \\
&\Pr(y_t = j|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) \\
&= I_{j\leq q}\Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)[\Phi(\mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1) - \Phi(\mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1)] \\
&+I_{j=q}[\Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) - \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)] \\
&+I_{j\geq q}\left[1 - \Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)\right][\Phi(\mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3) - \Phi(\mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3)] \text{ for } 2 \leq j \leq J-1; \\
&\Pr(y_t = J|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \left[1 - \Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0)\right][1 - \Phi(\mu_{3,J-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3)].
\end{aligned}
$$

As is typical in the ordered-choice modelling, $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_3$ are identified only up to scale and location, i.e. only jointly with the corresponding threshold parameters $\boldsymbol{\mu}_0$, $\boldsymbol{\mu}_1$ and $\boldsymbol{\mu}_3$, and the variances σ_0^2, σ_1^2 and σ_3^2 of $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$. To identify the parameters, the intercept components of $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_3$ are fixed to zero, and the variances σ_0^2, σ_1^2 and σ_3^2 are fixed to one. The probabilities in (2), however, are absolutely estimable and invariant to the identifying assumptions. They can be estimated using an ML estimator of the vector of the parameters $\boldsymbol{\theta} = (\boldsymbol{\mu}_0; \boldsymbol{\beta}_0; \rho_0; \boldsymbol{\mu}_1; \boldsymbol{\beta}_1; \rho_1; \boldsymbol{\mu}_3; \boldsymbol{\beta}_3; \rho_3)$ that solves

$$\max_{\boldsymbol{\theta} \epsilon \boldsymbol{\Theta}} \sum_{t=1}^{T} \sum_{j=1}^{J} h_{t,j} \ln[\Pr(y_t = j | \mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, \boldsymbol{\theta})],$$

subject to the constraints: $-\infty = \mu_{0,0} \leq \mu_{0,1} \leq \mu_{0,2} \leq \mu_{0,3} = \infty$, $-\infty = \mu_{1,0} \leq \mu_{1,1} \leq \ldots \leq \mu_{1,q} = \infty$ and $-\infty = \mu_{3,q-1} \leq \mu_{3,q} \leq \ldots \leq \mu_{3,J} = \infty$, 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. In general, the parameters in $\boldsymbol{\theta}$ are separately identified (up to scale and location) 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 (ensuring that $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are not identical) to avoid collinearity problems. The performed Monte Carlo experiments (see Section 3) illustrate that the Swopit model is indeed identified without exclusion restrictions.

In practice, however, the collinearity problems might still exist if many observations lie within the middle quasi-linear range of normal CDF. If $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are identical, the simultaneous estimation of three OP equations may be subject to imperfect collinearity and weak identification (the common symptoms of this problem are close-to-singular Hessian matrix and large standard errors). The estimation can be cumbersome and infeasible if 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 may be desirable.

The starting values for the slope and threshold parameters in $\boldsymbol{\theta}$ can be obtained by, for example, using the independent OP estimations of each latent equation. The starting values for ρ_1 and ρ_3 can be computed by maximizing the likelihood function over a grid search, i.e. by changing the values of ρ_1 and ρ_3 in small increments while holding the other parameters at their estimates in the exogenous-switching model. The asymptotic standard errors of $\widehat{\boldsymbol{\theta}}$ can be estimated from the Hessian matrix. The performed Monte Carlo experiments suggest that the proposed estimator is consistent.

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 only three outcome categories, (ii) both $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ contain all regressors in the MIOP regime equation, and (iii) $\mathbf{x}_{0,t}$ contains all regressors 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.

2.2 Marginal effects

Let $\mathbf{x}_t^{all} = \mathbf{x}_{0,t} \bigcap \mathbf{x}_{1,t} \bigcap \mathbf{x}_{3,t}$ denote a vector that contains the values of all variables in $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ 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} = \frac{\partial \Pr(y_t=j|\boldsymbol{\theta})}{\partial \mathbf{x}_{t,k}^{all}} = I_{j\le 0}\left\{\left[\Phi\left(\frac{\mu_1-\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\rho_1(\mu_{1,j}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1)}{\sqrt{1-(\rho_1)^2}}\right)\phi(\mu_{1,j}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1)\right.\right. \\
&\left.-\Phi\left(\frac{\mu_1-\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\rho_1(\mu_{1,j+1}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1)}{\sqrt{1-(\rho_1)^2}}\right)\phi(\mu_{1,j+1}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1)\right]\boldsymbol{\beta}_{1,k}^{all} \\
&-\left[\Phi\left(\frac{\mu_{1,j+1}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1-\rho_1(\mu_{0,1}-\mathbf{x}_{0,t}\boldsymbol{\beta}_0)}{\sqrt{1-(\rho_1)^2}}\right)-\Phi\left(\frac{\mu_{1,j}-\mathbf{x}_{1,t}\boldsymbol{\beta}_1-\rho_1(\mu_{0,1}-\mathbf{x}_{0,t}\boldsymbol{\beta}_0)}{\sqrt{1-(\rho_1)^2}}\right)\right] \\
&\left.\times\phi(\mu_{0,1}-\mathbf{x}_{0,t}\boldsymbol{\beta}_0)\boldsymbol{\beta}_{0,k}^{all}\right\} \\
&-I_{j=0}[\phi(\mu_{0,2}-\mathbf{x}_{0,t}\boldsymbol{\beta}_0)-\phi(\mu_{0,1}-\mathbf{x}_{0,t}\boldsymbol{\beta}_0)]\boldsymbol{\beta}_{0,k}^{all} \\
&+I_{j\ge 0}\left\{\left[\Phi\left(\frac{\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\mu_{0,2}+\rho_3(\mu_{3,j-1}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3)}{\sqrt{1-(\rho_3)^2}}\right)\phi(\mu_{3,j-1}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3)\right.\right. \\
&\left.-\Phi\left(\frac{\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\mu_{0,2}+\rho_3(\mu_{3,j}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3)}{\sqrt{1-(\rho_3)^2}}\right)\phi(\mu_{3,j}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3)\right]\boldsymbol{\beta}_{3,k}^{all} \\
&+\left[\Phi\left(\frac{\mu_{3,j}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3+\rho_3(\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\mu_{0,2})}{\sqrt{1-(\rho_3)^2}}\right)-\Phi\left(\frac{\mu_{3,j-1}-\mathbf{x}_{3,t}\boldsymbol{\beta}_3+\rho_3(\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\mu_{0,2})}{\sqrt{1-(\rho_3)^2}}\right)\right] \\
&\left.\times\phi(\mathbf{x}_{0,t}\boldsymbol{\beta}_0-\mu_{0,2})\boldsymbol{\beta}_{0,k}^{all}\right\},
\end{aligned}
$$

where ϕ is the probability density function (PDF) of the standard normal distribution, and $\boldsymbol{\beta}_{0,k}^{all}$, $\boldsymbol{\beta}_{1,k}^{all}$ and $\boldsymbol{\beta}_{3,k}^{all}$ are the coefficients on the k^{th} explanatory variable from $\mathbf{x}_t^{all}$ in the regime equation, the outcome equation conditional on $r_t = 1$ and the outcome equation conditional on $r_t = 3$, respectively ($\boldsymbol{\beta}_{0,k}^{all}$, $\boldsymbol{\beta}_{1,k}^{all}$, 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 the others are held fixed.

A flexible three-part structure of the Swopit model is able to overcome a typical shortcoming of the single-regime ordered-choice models, in which the MEs on the probabilities of outcomes at the opposite ends of the ordered scale always have the opposite signs, and the sign of the ME can only change once when moving from the smallest category to the largest one (so-called single crossing property). In contrast, the Swopit model lets a certain variable have the same sign of the ME on the probabilities of both the largest and smallest choice categories, and also lets the sign of the ME change more than once when moving from the smallest category to the largest one.

2.3 Allowing for endogenous explanatory variables

The Swopit model can be extended by relaxing the assumption that the explanatory variables in $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are not correlated with the corresponding error terms $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$. Accounting for endogeneity in nonlinear models, even relatively simple ones, is more difficult to implement than in linear models. A simple mimicking of two-stage least squares estimation of linear models (i.e. inserting fitted values from the reduced form in place of endogenous regressors in the structural equations) does not generally work for nonlinear models and often makes the endogeneity bias worse (Bhattacharya *et al.,* 2006; Terza *et al.,* 2008).

To accommodate the EEVs in the Swopit model I implement the two-step CF approach, which was developed for nonlinear models by Smith and Blundell (1986), Newey (1987) and Rivers and Vuong (1988), among others, and extensively applied to the sample-selection, censored and disequilibrium models, as well as to the time-series models in the context of Markov-switching linear regressions (Kim, 2004). This method introduces residuals from the ordinary least squares (OLS) regressions of each EEV on the set of available instruments into the structural equations as additional regressors (bias correction terms). These residuals are ideally those components of the EEVs that are attributable to the unobserved monetary shocks. Although a joint ML estimation procedure is asymptotically most efficient, the two-step approach is computationally simpler, requires fewer assumptions and provides a reasonable alternative: the Monte Carlo experiments show that the two-step procedure can be more efficient than the joint one in finite samples (Kim, 2009). For a textbook exposition of CF method in discrete-choice, censored and sample-selection models see Wooldridge (2010). For an overview of CF approach in applied econometrics see Wooldridge (2015).

To obtain the CF Swopit estimator, modify and augment system (1) with the reduced forms for EEVs as follows:

$$
\begin{array}{ll}
r_t^* = \mathbf{x}_{0,t}\boldsymbol{\beta}_0 + \mathbf{w}_{0,t}\boldsymbol{\gamma}_0 + \varepsilon_{0,t} & \text{(regime equation),} \\
r_t = s \text{ if } \mu_{0,s-1} < r_t^* \leq \mu_{0,s},\ s = 1,2,3 & \text{(regime matching rule),} \\
y_{s,t}^* = \mathbf{x}_{s,t}\boldsymbol{\beta}_s + \mathbf{w}_{s,t}\boldsymbol{\gamma}_s + \varepsilon_{s,t},\ s = 1,3 & \text{(outcome equations),} \\
y_t = j \ \text{ if } r_t = 1 \text{ and } \mu_{1,j-1} < y_{1,t}^* \leq \mu_{1,j},\ j \leq q & \text{(outcome} \\
y_t = q \text{ if } r_t = 2 & \text{matching} \\
y_t = j \ \text{ if } r_t = 3 \text{ and } \mu_{3,j-1} < y_{3,t}^* \leq \mu_{3,j},\ j \geq q & \text{rules),} \\
\mathbf{w}_{s,t} = \mathbf{z}_{s,t}\boldsymbol{\delta}_s + \boldsymbol{\nu}_{s,t},\ s = 0,1,3 & \text{(reduced forms for EEVs),} \\
\left[\begin{array}{c} \varepsilon_{s,t} \\ \varepsilon_{0,t} \end{array}\right] \overset{iid}{\sim} \mathcal{N}\left(\begin{array}{c} 0 \\ 0 \end{array}, \left[\begin{array}{cc} \sigma_s^2 & \rho_s\sigma_0\sigma_s \\ \rho_s\sigma_0\sigma_s & \sigma_0^2 \end{array}\right]\right),\ s = 1,3 & \text{(interdependence between the regime and outcome decisions),}
\end{array}
\tag{3}
$$

where $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are the observed row vectors that now contain only exogenous explanatory variables; $\mathbf{w}_{0,t}$, $\mathbf{w}_{1,t}$ and $\mathbf{w}_{3,t}$ are the observed row vectors that contain only EEVs; $\mathbf{z}_{0,t}$, $\mathbf{z}_{1,t}$ and $\mathbf{z}_{3,t}$ are the observed row vectors that contain all exogenous variables including those in $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$, respectively ($\mathbf{x}_{s,t}$ is a proper subset of $\mathbf{z}_{s,t}$: $\mathbf{x}_{s,t} \subset \mathbf{z}_{s,t}$, $s = 0,1,3$); $\boldsymbol{\gamma}_0$, $\boldsymbol{\gamma}_1$ and $\boldsymbol{\gamma}_3$ are the vectors of unknown parameters; $\boldsymbol{\delta}_0$, $\boldsymbol{\delta}_1$ and $\boldsymbol{\delta}_3$ are the matrices of unknown parameters; $\boldsymbol{\nu}_{0,t}$, $\boldsymbol{\nu}_{1,t}$ and $\boldsymbol{\nu}_{3,t}$ are the row vectors of normally distributed unobserved error terms with zero means; and the rest of variables and parameters are defined as in system (1).

Assume that each of three pairs $(\varepsilon_{s,t}; \boldsymbol{\nu}_{s,t})$, $s = 0, 1, 3$, is independent of $\mathbf{z}_{s,t}$ and jointly normally distributed with zero mean. The regressors $\mathbf{w}_{s,t}$ $(s = 0, 1, 3)$ are endogenous if the structural error terms $\varepsilon_{s,t}$ in the above three pairs are correspondingly correlated with the reduced form error terms $\boldsymbol{\nu}_{s,t}$. If there is no correlation in any of these pairs, there is no endogeneity problem. Under the joint normality of $(\varepsilon_{s,t}, \boldsymbol{\nu}_{s,t})$, assume $\varepsilon_{s,t} = \boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s + \zeta_{s,t}$ to obtain

$$
\begin{aligned}
r_t^* &= \mathbf{x}_{0,t}\boldsymbol{\beta}_0 + \mathbf{w}_{0,t}\gamma_0 + \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0 + \zeta_{0,t}, \\
y_{s,t}^* &= \mathbf{x}_{s,t}\boldsymbol{\beta}_s + \mathbf{w}_{s,t}\gamma_s + \boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s + \zeta_{s,t},\ s = 1, 3,
\end{aligned}
$$

where $\boldsymbol{\lambda}_0$, $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_3$ are the vectors of unknown parameters; $\zeta_{s,t}$ $(s = 0, 1, 3)$ are the error terms that are assumed to be normally distributed with zero means and independent of $\mathbf{z}_{s,t}$, $\mathbf{x}_{s,t}$ and $\boldsymbol{\nu}_{s,t}$ (and therefore independent of $\mathbf{w}_{s,t}$). Since $\varepsilon_{s,t}$ have unit variance due to normalization, $var(\zeta_{s,t}) = var(\varepsilon_{s,t} - \boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s) = 1 - var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s)$. Therefore, rewrite the probabilities to observe the outcome j in equation (2) as

$$
\begin{aligned}
&\Pr(y_t = j|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, \mathbf{w}_{0,t}, \mathbf{w}_{1,t}, \mathbf{w}_{3,t}) \\
&= I_{j\le q}\left[\Phi_2\left(\tfrac{\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 - \mathbf{w}_{0,t}\gamma_0 - \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}; \tfrac{\mu_{1,j} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1 - \mathbf{w}_{1,t}\gamma_1 - \boldsymbol{\nu}_{1,t}\boldsymbol{\lambda}_1}{\sqrt{1 - var(\boldsymbol{\nu}_{1,t}\boldsymbol{\lambda}_1)}}; \rho_1\right)\right. \\
&\left.-\Phi_2\left(\tfrac{\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 - \mathbf{w}_{0,t}\gamma_0 - \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}; \tfrac{\mu_{1,j-1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1 - \mathbf{w}_{1,t}\gamma_1 - \boldsymbol{\nu}_{1,t}\boldsymbol{\lambda}_1}{\sqrt{1 - var(\boldsymbol{\nu}_{1,t}\boldsymbol{\lambda}_1)}}; \rho_1\right)\right] \\
&+I_{j=q}\left(\Phi\left(\tfrac{\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 - \mathbf{w}_{0,t}\gamma_0 - \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}\right) - \Phi\left(\tfrac{\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0 - \mathbf{w}_{0,t}\gamma_0 - \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}\right)\right) \\
&+I_{j\ge q}\left[\Phi_2\left(\tfrac{-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0 + \mathbf{w}_{0,t}\gamma_0 + \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}; \tfrac{\mu_{3,j} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3 - \mathbf{w}_{3,t}\gamma_3 - \boldsymbol{\nu}_{3,t}\boldsymbol{\lambda}_3}{\sqrt{1 - var(\boldsymbol{\nu}_{3,t}\boldsymbol{\lambda}_3)}}; -\rho_3\right)\right. \\
&\left.-\Phi_2\left(\tfrac{-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0 + \mathbf{w}_{0,t}\gamma_0 + \boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0}{\sqrt{1 - var(\boldsymbol{\nu}_{0,t}\boldsymbol{\lambda}_0)}}; \tfrac{\mu_{3,j-1} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3 - \mathbf{w}_{3,t}\gamma_3 - \boldsymbol{\nu}_{3,t}\boldsymbol{\lambda}_3}{\sqrt{1 - var(\boldsymbol{\nu}_{3,t}\boldsymbol{\lambda}_3)}}; -\rho_3\right)\right].
\end{aligned}
$$

Since $\boldsymbol{\nu}_{0,t}$, $\boldsymbol{\nu}_{1,t}$ and $\boldsymbol{\nu}_{3,t}$ are not observed, in order to consistently estimate these probabilities perform the following two-step procedure:

1. Run the OLS regressions of each EEV in $\mathbf{w}_{0,t}$, $\mathbf{w}_{1,t}$ and $\mathbf{w}_{3,t}$ on all the exogenous variables in $\mathbf{z}_{0,t}$, $\mathbf{z}_{1,t}$ and $\mathbf{z}_{3,t}$, respectively, to consistently estimate $\boldsymbol{\delta}_0$, $\boldsymbol{\delta}_1$ and $\boldsymbol{\delta}_3$ and variances of $\boldsymbol{\nu}_{0,t}$, $\boldsymbol{\nu}_{1,t}$ and $\boldsymbol{\nu}_{3,t}$, and save the residuals $\widehat{\boldsymbol{\nu}}_{0,t}$, $\widehat{\boldsymbol{\nu}}_{1,t}$ and $\widehat{\boldsymbol{\nu}}_{3,t}$.

2. Run the Swopit regression with $\mathbf{x}_{0,t}$, $\mathbf{w}_{0,t}$, $\widehat{\boldsymbol{\nu}}_{0,t}$ in the regime equation and with $\mathbf{x}_{1,t}$, $\mathbf{w}_{1,t}$, $\widehat{\boldsymbol{\nu}}_{1,t}$ and $\mathbf{x}_{3,t}$, $\mathbf{w}_{3,t}$, $\widehat{\boldsymbol{\nu}}_{3,t}$ in the outcome equations to consistently estimate the scaled parameters $(\underline{\boldsymbol{\mu}_0}; \underline{\boldsymbol{\beta}_0}; \underline{\gamma_0}; \underline{\boldsymbol{\lambda}_0})$, $(\underline{\boldsymbol{\mu}_1}; \underline{\boldsymbol{\beta}_1}; \underline{\gamma_1}; \underline{\boldsymbol{\lambda}_1})$ and $(\underline{\boldsymbol{\mu}_3}; \underline{\boldsymbol{\beta}_3}; \underline{\gamma_3}; \underline{\boldsymbol{\lambda}_3})$.

The second-step parameters are scaled (because the variances of $\zeta_{s,t}$ do not equal one), and relate to the original (unscaled) parameters as

$$
\sqrt{1 - var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s)}(\underline{\boldsymbol{\mu}}_s; \underline{\boldsymbol{\beta}}_s; \underline{\gamma}_s; \underline{\boldsymbol{\lambda}}_s) \equiv (\mu_s; \boldsymbol{\beta}_s; \boldsymbol{\gamma}_s; \boldsymbol{\lambda}_s),\ s = 0, 1, 3.
$$

Since $\boldsymbol{\lambda}_s = \sqrt{1 - var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s)}\underline{\boldsymbol{\lambda}}_s$ it follows that $var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s) = [1 - var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s)]var(\boldsymbol{\nu}_{s,t}\underline{\boldsymbol{\lambda}}_s)$; hence, $1 - var(\boldsymbol{\nu}_{s,t}\boldsymbol{\lambda}_s) = 1/[1 + var(\boldsymbol{\nu}_{s,t}\underline{\boldsymbol{\lambda}}_s)]$. Thus, we can obtain the consistent estimators of the original parameters as

$$(\widehat{\boldsymbol{\mu}}_s; \widehat{\boldsymbol{\beta}}_s; \widehat{\boldsymbol{\gamma}}_s; \widehat{\boldsymbol{\lambda}}_s) \equiv (\underline{\widehat{\boldsymbol{\mu}}}_s; \underline{\widehat{\boldsymbol{\beta}}}_s; \underline{\widehat{\boldsymbol{\gamma}}}_s; \underline{\widehat{\boldsymbol{\lambda}}}_s)/\sqrt{1 + \widehat{var}(\widehat{\boldsymbol{\nu}}_{s,t}\underline{\widehat{\boldsymbol{\lambda}}}_s)},\ s = 0, 1, 3,$$

where all terms on the right-hand side are available from the two-step CF estimation procedure.

The usual t statistics on $\widehat{\boldsymbol{\nu}}_{0,t}$, $\widehat{\boldsymbol{\nu}}_{1,t}$ and $\widehat{\boldsymbol{\nu}}_{3,t}$ from the second step can be used to test the null hypotheses that $\mathbf{w}_{0,t}$, $\mathbf{w}_{1,t}$ and $\mathbf{w}_{3,t}$ are exogenous, that is $\boldsymbol{\lambda}_0 = \boldsymbol{\lambda}_1 = \boldsymbol{\lambda}_3 = \mathbf{0}$. Under the null of exogeneity, $\varepsilon_{0,t} = \zeta_{0,t}$, $\varepsilon_{1,t} = \zeta_{1,t}$ and $\varepsilon_{3,t} = \zeta_{3,t}$, so the distributions of $\widehat{\boldsymbol{\nu}}_{0,t}$, $\widehat{\boldsymbol{\nu}}_{1,t}$ and $\widehat{\boldsymbol{\nu}}_{3,t}$ do not matter. However, if $\mathbf{w}_{0,t}$, or $\mathbf{w}_{1,t}$, or $\mathbf{w}_{3,t}$ is endogenous, the normality of $\widehat{\boldsymbol{\nu}}_{0,t}$, or $\widehat{\boldsymbol{\nu}}_{1,t}$, or $\widehat{\boldsymbol{\nu}}_{3,t}$ is critical. The CF method imposes strong assumptions on the process generating EEVs and does not generally work if they are discrete. Allowing for discrete EEVs is notoriously difficult even in a single-equation instrumental-variable model of discrete choice (Bhattacharya *et al.,* 2006; Chesher and Smolinski, 2012). However, as suggested by Terza *et al.* (2008), for each discrete EEV $w_t^{disc} \in \mathbf{w}_{s,t}$ we can run an ordered probit (or logit) first-stage regression, estimate $\widehat{\boldsymbol{\delta}}^{disc} \in \widehat{\boldsymbol{\delta}}_s$, and then compute the generalized residuals $\widehat{\boldsymbol{\nu}}_t^{disc} \in \widehat{\boldsymbol{\nu}}_{s,t}$ as:

$$\sum_{t=1}^{T} \frac{[\mathbf{w}_t^{disc} - \Phi(\mathbf{z}_{s,t}\widehat{\boldsymbol{\delta}}^{disc})]\phi(-\mathbf{z}_{s,t}\widehat{\boldsymbol{\delta}}^{disc})}{[1 - \Phi(\mathbf{z}_{s,t}\widehat{\boldsymbol{\delta}}^{disc})]\Phi(\mathbf{z}_{s,t}\widehat{\boldsymbol{\delta}}^{disc})}\mathbf{z}_{s,t} \equiv \sum_{t=1}^{T} \widehat{\boldsymbol{\nu}}_t^{disc}\mathbf{z}_{s,t} = 0,\ s = 0, 1, 3. \qquad (4)$$

Derived from the first-order conditions that define the ML estimates in the probit and logit models, the generalized residuals, analogously to the OLS residuals in the linear regression model, satisfy the orthogonality condition with the explanatory variables. Wooldridge (2014) argues that the CF approach with generalized residuals might yield good estimates of average MEs and provide a reasonable approximate solution to the endogeneity problem with discrete EEVs.

3 Finite sample performance

This section summarizes the results of conducted Monte Carlo experiments to assess the finite sample performance of the ML and CF estimators of the Swopit model. The simulations suggest that (i) the proposed ML estimator is consistent and demonstrate a 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 a full overlap) to achieve the same accuracy of the estimates as in the conventional OP model; (iii) the Swopit model is identified even with no exclusion restrictions; though, the more exclusion restrictions, the more accurate the estimates; and (iv) the implemented CF Swopit estimator is consistent and provides a reliable small-sample inference in the presence of EEVs.

3.1 Effect of exclusion restrictions

To assess the effect of exclusion restrictions the repeated samples in the simulations are generated by the Swopit data-generating process (DGP) in three different scenarios of the overlap among the explanatory variables in three latent equations: "no overlap" (each variable belongs only to one equation), a "partial overlap" (each variable belongs to two equations) and a "complete overlap" (all three equations have the same set of explanatory variables). Three sets of experiments are simulated; in each set the samples are generated with the same number of observations per parameter in each scenario: 25 (with 225, 300 and 375 observations in the samples in the "no overlap", "partial overlap" and "complete overlap" scenarios, respectively), 50 (with 450, 600 and 750 observations, respectively) and 75 observations per parameter (with 675, 900 and 1125 observations, respectively).

Unlike the parameters, which are identified only up to scale and location, and are of little interest in their own right, the choice probabilities and the MEs of regressors 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 explanatory variables on choice probabilities, estimated at the population medians of the covariates. The following measures of finite sample performance (averaged for all regressors and choices, and across all replications) are reported: bias — the absolute difference between the estimated and true values of MEs; RMSE — the root mean square error of ME estimates relative to their true values; coverage probability (CP) — 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 in the repeated samples divided by the standard deviation of ME estimates, in percent.

Three explanatory variables $v_{1,t}$, $v_{2,t}$ and $v_{3,t}$ are drawn once and held fixed in all replications as $v_{1,t} \overset{iid}{\sim} \mathcal{N}(2,1)$, $v_{2,t} \overset{iid}{\sim} \mathcal{N}(0,1)$, and $v_{3,t}$ = -1 if $u_t \leq 0.3$, $v_{3,t} = 0$ if $0.3 < u_t \leq 0.7$, or $v_{3,t} = 1$ if $0.7 < u_t$, where $u_t \overset{iid}{\sim} \mathcal{U}[0,1]$. The repeated samples are generated as follows: under the "no overlap" scenario — with $\mathbf{x}_{0,t}$=$v_{1,t}$, $\mathbf{x}_{1,t}$=$v_{2,t}$, $\mathbf{x}_{3,t}$=$v_{3,t}$, $\boldsymbol{\beta}_0 = 0.6$, $\boldsymbol{\beta}_1 = 0.8$, $\boldsymbol{\beta}_3 = 0.9$, $\boldsymbol{\mu}_0 = (0.95,\ 1.45)'$, $\boldsymbol{\mu}_1 = (-1.22,\ 0.03)'$, $\boldsymbol{\mu}_3 = (-0.03,\ 1.18)'$, and $\rho_1 = \rho_3 = 0$; under the "partial overlap" scenario — with $\mathbf{x}_{0,t}$=$(v_{1,t}, v_{2,t})$, $\mathbf{x}_{1,t}$= $(v_{1,t}, v_{3,t})$, $\mathbf{x}_{3,t}$= $(v_{2,t}, v_{3,t})$, $\boldsymbol{\beta}_0 = (0.6,\ 0.4)'$, $\boldsymbol{\beta}_1 = (0.2,\ 0.3)'$, $\boldsymbol{\beta}_3 = (0.3,\ 0.9)'$, $\boldsymbol{\mu}_0 = (0.9,\ 1.5)'$, $\boldsymbol{\mu}_1 = (-0.67,\ 0.36)'$, $\boldsymbol{\mu}_3 = (0.02,\ 1.28)'$, and $\rho_1 = \rho_3 = 0$; and under the "complete overlap" scenario — with $\mathbf{x}_{0,t}$= $\mathbf{x}_{1,t}$= $\mathbf{x}_{3,t}$= $(v_{1,t}, v_{2,t}, v_{3,t})$, $\boldsymbol{\beta}_0 = (0.6,\ 0.4,\ 0.8)'$, $\boldsymbol{\beta}_1 = (0.2,\ 0.8,\ 0.3)'$, $\boldsymbol{\beta}_3 = (0.4,\ 0.3,\ 0.9)'$, $\boldsymbol{\mu}_0 = (0.85,\ 1.55)'$, $\boldsymbol{\mu}_1 = (-1.2,\ 0.07)'$, $\boldsymbol{\mu}_3 = (1.28,\ 2.5)'$, and $\rho_1 = \rho_3 = 0$. For each sample, the exogenous Swopit model is estimated using the same specifications of the latent equations as in the above true DGPs.

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 bias and RMSE reduce, and the CP 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" scenario) the bias is 100% larger, and the s.e. bias is 250% larger than in the case of no overlap among the regressors.

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

Number of observations per parameter:	25	50	75
The overlap among the regressors in the regime and outcome 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

3.2 Performance with endogenous explanatory variables

To analyze the finite sample performance of the CF Swopit estimator in the presence of EEVs, the repeated samples in this set of experiments are generated according to the system (3) with $\mathbf{x}_{0,t}= \mathbf{0}$, $\mathbf{x}_{1,t}= \mathbf{x}_{3,t}=v_2$, $\mathbf{z}_{1,t}= \mathbf{z}_{2,t}= (v_{1,t},v_{3,t})$, $v_{1,t} \overset{iid}{\sim} \mathcal{N}(2,1)$, $v_{2,t} \overset{iid}{\sim} \mathcal{N}(0,1)$, $v_{3,t} \overset{iid}{\sim} \mathcal{N}(0,1)$, $\boldsymbol{\gamma}_0 = (0.6,\ 0.4)'$, $\boldsymbol{\gamma}_1 = 0.5$, $\boldsymbol{\gamma}_3 = 0.5$, $\boldsymbol{\beta}_1 = 0.6$, $\boldsymbol{\beta}_3 = 0.6$, $\boldsymbol{\mu}_0 = (0.91,\ 1.49)'$, $\boldsymbol{\mu}_1 = (\text{-}1.25,\ \text{-}0.04)'$, $\boldsymbol{\mu}_3 = (0.4,\ 1.25)'$, $\sigma_0^2 = \sigma_1^2 = \sigma_3^2 = 1$, $\rho_1 = \rho_3 = 0$, $\boldsymbol{\lambda}_0 = (0.75,\ 0.75)'$, $\boldsymbol{\lambda}_1 = \boldsymbol{\lambda}_3 = 0.75$, $var(\nu_{1,t}) = var(\nu_{3,t}) = 0.36$, and $\boldsymbol{\delta}_1 = \boldsymbol{\delta}_3 = \begin{pmatrix} 0.9 & 0 \\ 0 & 0.9 \end{pmatrix}$.

There are two EEVs: the first one (instrumented by $v_{1,t}$) enters $\mathbf{w}_{0,t}$ and belongs only to the regime equation, the second one (instrumented by $v_{3,t}$) enters $\mathbf{w}_{0,t}$, $\mathbf{w}_{1,t}$ and $\mathbf{w}_{3,t}$ and belongs to all three equations. The only exogenous regressor $v_{2,t}$ is included in $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ in the outcome equations. The values of $v_{1,t}$, $v_{2,t}$ and $v_{3,t}$ are drawn repeatedly and independently for each replication. The estimations are performed using the standard and CF Swopit estimators.

In the first round of experiments, the repeated samples are generated with 250, 500, 1000 and 2000 observations. The Monte Carlo results demonstrate (see Table 2) that the CF estimator is consistent and provides reliable estimates in small samples: as the sample size grows from 250 to 2000, the bias reduces by 90%; the RMSE and s.e. bias reduce by 70%; and the CP moves from 91.8% to 94.4%, closer to the 95% nominal value. The standard estimator that ignores the endogeneity performs much worse: the bias reduces only by 5%; the RMSE reduces only by 30%; the s.e. bias reduces by 70%; and the CP moves from 61.7% to 39.0%, away from the nominal level. The relative performance of the standard estimator with respect to the CF one worsens as the sample size grows: with 250 observations, its bias is eleven times as large as the bias of the CF estimator, whereas with 2000 observations, it is hundred times as large. The bias of the s.e. estimates in the standard estimator is only twice as small as that in the CF one.

Table 2. Performance of standard and CF Swopit estimators in the presense of endogenous explanatory variables

	Estimator	Sample size 250	500	1000	2000
Bias of ME estimates	Standard	10.9	10.6	10.5	10.4
(= 1 for CF estimator with 250 observations)	CF	1.0	0.5	0.3	0.1
RMSE of ME estimates	Standard	1.8	1.6	1.4	1.3
(= 1 for CF estimator with 250 observations)	CF	1.0	0.7	0.4	0.3
Coverage probability of ME estimates,	Standard	61.7	48.9	41.8	39.0
% (at 95% level)	CF	91.8	93.4	94.0	94.4
Bias of ME standard error estimates	Standard	1.0	0.7	0.5	0.3
(= 1 for standard estimator with 250 observations)	CF	2.6	1.4	1.0	0.7

In the second round of experiments, the repeated samples are generated with 1000 observations but with the various degree of endogeneity strength (measured by the values of $\boldsymbol{\lambda}_0$, $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_3$). The simulations show (see Table 3) that as endogeneity becomes stronger, the performance of the CF estimator decreases but not sharply: the bias grows by 10%; the RMSE grows by 20%; the s.e. bias is affected more severe — it increases by 170%; consequently, the CP slowly moves from 94.5% to 93.7%, away from the nominal value. The performance of the standard Swopit estimator deteriorates much severe: the bias almost doubles; the RMSE increases by 80%; the CP stays around 40%; the s.e. bias, however, remains low. The relative performance of the standard estimator with respect to the CF one worsens as the endogeneity strengthens: for instance, when it is weak (strong) the bias of ME estimates is 29 (51) times as large as the bias of the CF estimator.

Table 3. Effect of endogeneity strength on the performance of standard and CF Swopit estimators

	Estimator	The strength of endogeneity (the values of $\lambda = \lambda^+ = \lambda^-$) 0.10	0.25	0.50	0.75	0.90
Bias of ME estimates	Standard	29.4	31.9	39.3	49.1	57.4
(=1 for CF estimator with λ = 0.1)	CF	1.0	1.0	1.0	1.2	1.1
RMSE of ME estimates	Standard	2.3	2.5	2.9	3.6	4.2
(=1 for CF estimator with λ = 0.1)	CF	1.0	1.0	1.0	1.1	1.2
Coverage probability of ME	Standard	43.6	39.9	37.4	41.8	43.7
estimates, % (at 95% level)	CF	94.5	94.5	94.4	94.0	93.7
Bias of ME standard error estimates	Standard	1.0	1.0	0.8	1.1	0.9
(=1 for standard estimator with λ = 0.1)	CF	1.3	1.2	1.7	2.5	3.5

In the third round of experiments, the repeated samples are generated with 1000 observations but with the various degree of instruments' strength (measured by the values of parameters in $\boldsymbol{\delta}_1$ and $\boldsymbol{\delta}_3$). The simulations suggest (see Table 4) that as the instruments become stronger, the performance of the CF estimator improves sharply: the bias reduces by 94%; the RMSE reduces by 87%; the s.e. bias decreases by 84%; and the CP moves from 79% to 94%, closer to the nominal value. The performance of the standard estimator also improves but not so sharply — the CP changes from 29% to only 42%, and its relative performance with respect to the CF estimator worsens significantly: with weak (strong) instruments the bias of ME estimates is 8 (40) times as large as that in the CF estimator, the RMSE is larger by 37% (220%), and the s.e. bias is smaller by 328% (122%).

Table 4. Effect of the strength of instruments on the performance of standard and CF Swopit estimators

	Estimator	The strength of instruments (the values of $\boldsymbol{\delta}_{11} = \boldsymbol{\delta}_{22}$)				
		0.10	0.25	0.50	0.75	0.90
Bias of ME estimates	Standard	8.2	7.1	4.6	3.0	2.4
(= 1 for CF estimator with $\boldsymbol{\delta}$ = 0.1)	CF	1.0	0.2	0.07	0.05	0.06
RMSE of ME estimates	Standard	1.4	1.2	0.8	0.5	0.4
(= 1 for CF estimator with $\boldsymbol{\delta}$ = 0.1)	CF	1.0	0.4	0.2	0.14	0.13
Coverage probability of ME	Standard	29.0	35.5	37.0	38.5	41.8
estimates, % (at 95% level)	CF	79.3	90.9	93.1	93.9	94.0
Bias of ME standard error estimates	Standard	1.0	0.5	0.4	0.4	0.3
(= 1 for standard estimator with δ = 0.1)	CF	4.3	1.0	1.0	0.8	0.7

4 Data and empirical results

This section estimates the Taylor rule, OP, MIOP and Swopit models to predict the next FOMC decision on the target during the Greenspan's era, provides the out-of-sample forecasts for the next thirteen years during the Bernanke's, Yelen's and Powell's terms, compares the in- and out-of-sample performance of the competing models, contrasts the fit of the Swopit model and the discrete-choice models for the target from the literature, and accesses the effect of endogeneity.

4.1 FOMC decisions as sample observations

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 meetings as the sample observations, and forecast the next FOMC decision 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 scheduled meeting.

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[1] and derived from Thornton (2005) prior to 1994 and from the FOMC meeting transcripts and statements after 1994. The sample consists of 150 observations during the 7/1987–1/2006 period under the Greenspan's chairmanship (with an exception for the first observation in the sample — the FOMC meeting on July 7$^{\text{th}}$, 1987 under the Volcker's chairmanship).

Prior to 10/1989 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	-25	-12.5	0	6.25	12.5	25	31.25	50	75
Frequency	9	14	1	93	3	1	23	1	4	1

I classified these 150 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	9	15	96	24	6

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.[2]

4.2 Explanatory variables and estimation results

A common simple benchmark in setting the monetary policy is the so-called Taylor (1993) rule, according to which the Fed alters the federal funds rate ffr_t using the following formula: $ffr_t = r^* + infl_t + 0.5gap_t + 0.5(infl_t - \pi^*)$, where r^* – the equilibrium real interest rate, $infl_t$ – the inflation rate over the previous four quarters, π^* – the long-run inflation target, and gap_t – the output gap (the percent deviation of the real gross domestic product (GDP) from the potential one). Taylor assumed $r^* = 2$ and $\pi^* = 2$. Originally, Taylor's point was that the Fed certainly does not follow a simple mechanical rule and considers wider information in setting monetary policy, although inflation and output gap are the only variables it should consistently and systematically respond to.

[1] 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/).

[2] The empirical results are similar with the alternative classifications, for example, such as: "large hike/cut" is an increase/decrease more than 37.5 bp, "small hike/cut" is an increase/decrease between 37.5 bp and 12.5 bp, and "no change" is no change or change no more than 12.5 bp.

The performance of the original version of the Taylor rule actually broke down after 1993, i.e. immediately out of sample (Ball and Tchaidze, 2002).

Unfortunately, the Taylor rule is based on an unrealistic assumption that policymakers possess reliable information on the equilibrium real interest rate and output gap. In fact, the equilibrium real rate and potential output are unobservable, and the FOMC members typically have different judgments. The reliability of equilibrium real rate and output gap estimates in real time is quite low. To provide a better description of FOMC decisions I estimate using OLS a more general inertial version of the Taylor rule from the observed real-time data: $target_t = \alpha_0 + \alpha_1 target_{t-1} + \alpha_2 infl_t + \alpha_3 gap_t$, where $target_t$ – the target set at the FOMC meeting t, annualized percentage points; $target_{t-1}$ – the target observed prior to the meeting t, annualized percentage points; $infl_t$ – the real-time forecast of the core inflation rate for the current quarter, seasonally adjusted, annualized percentage points (before 1/2000 — the Greenbook projection for quarter-over-quarter core consumer price index (CPI) inflation rate; from 1/2000 through 12/2013 — the Greenbook projection for quarter-over-quarter core personal consumption expenditures (PCE) inflation rate, chain weight; since 1/2014 — the median forecast of the annualized quarter-over-quarter percent changes of the core PCE inflation rate for the current quarter the Survey of Professional Forecasters (SPF) provided by Philadelphia Fed); gap_t – the real-time forecast of the output gap, the difference between the actual and potential output expressed as a percent of potential output, for current quarter (before 1/2014 — the Greenbook projections for current quarter of the output gap; since 1/2014 the projection of the output gap for current quarter is derived from the Congressional Budget Office's estimate of potential real GDP level and median forecast of the real GDP level in the SPF, seasonally adjusted); and $\alpha_0, \alpha_1, \alpha_2$ and α_3 – the unknown OLS parameters to be estimated. The real-time data on $target_t$, $target_{t-1}$, $infl_t$ and gap_t are retrieved from Philadelphia Fed's real-time data set[3] and ALFRED. The forecasts of $infl_t$ and gap_t for the current quarter provided similar or better explanatory power than the one-, two-, three- and four-quarter ahead forecasts.

The estimated OLS parameters of the Taylor rule are reported in Table 5.

Table 5. Modeling the target level: estimated parameters of the Taylor rule

Variables	OLS estimates	Dependent variable:	$target_t$
		Probability of F-stat.:	0.000
$constant$	0.11 (0.04)**	R-squared:	0.993
$target_{t-1}$	0.93 (0.02)***	Rbar-squared:	0.993
$infl_t$	0.09 (0.03)***	Residual SS:	5.36
gap_t	0.07 (0.01)***	SER:	0.192

Notes. Sample period: 7/1987–1/2006 (150 observations). ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses.

The studies that model target changes using a discrete choice approach report that

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

the Taylor-rule variables (inflation and output gap) do not provide the best forecasting performance. Piazzesi (2005) finds that the two-year yield describes the 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.

To estimate the OP, MIOP and Swopit models I selected the following four explanatory variables that exhibit a far more predictive power than the Taylor-rule measures of inflation and output gap:

(1) $spread_t$ — the difference between the one-year treasury constant maturity rate and effective federal funds rate, three-business-day moving average. 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 only the short interest rate. The real-time data on $spread_t$ are retrieved from ALFRED.

(2) $pbias_{t-1}$ — the binary indicator derived from the "policy bias" or "balance-of-risks" statement made at the previous FOMC meeting that takes value 1 if the statement was "tightening", 0 if the statement was "symmetrical", and -1 if the statement was "easing". 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 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 the heightened inflation pressure and economic weakness over the foreseeable future; and since 2003, the FOMC issued the 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 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 took the values of $pbias_{t-1}$ up to 1999 from Thornton and Wheelock (2000) and derived them after 1999 from the FOMC statements and minutes.[4] For example, the "policy bias" directive released on May 18, 1999 was "tightening":

> "While the FOMC did not take action today to alter the stance of mone-

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

tary policy, the Committee was concerned about the potential for a buildup of inflationary imbalances that could undermine the favorable performance of the economy and therefore adopted a directive that is tilted toward the possibility of a firming in the stance of monetary policy."

By contrast, the "balance-of-risks" statement released on January 31, 2001 was "easing":

> "Nonetheless, the Committee continues to believe that against the background of its long-run goals of price stability and sustainable economic growth and of the information currently available, the risks are weighted mainly toward conditions that may generate economic weakness in the foreseeable future."

The "balance-of-risks" statement released on January 29, 2003 was "symmetrical":

> "In these circumstances, the Committee believes that, against the background of its long-run goals of price stability and sustainable economic growth and of the information currently available, the risks are balanced with respect to the prospects for both goals for the foreseeable future."

(3) $house_t$ — the forecast of the total number of new privately owned housing units started (in thousands) for current quarter [5] — a critical leading indicator of economic strength, actively monitored by the Fed and frequently mentioned in the FOMC statements (before 1/2014 — the Greenbook projections for the current quarter; since 1/2014 — the latest available data on housing starts at monthly frequency[6]). The real-time data are retrieved from ALFRED and the Philadelphia Fed's real-time data set.

(4) gdp_t — the forecast of the quarter-over-quarter growth in the nominal gross domestic product for the current quarter, percent change at annual rate, seasonally adjusted (before 1/1992 — the Greenbook projections for the gross national product; from 1/1992 through 12/2013 — the Greenbook projections for the GDP; since 1/2014 — the forecast of the GDP provided by the Atlanta Fed). The real-time data are retrieved from the Philadelphia Fed's real-time data set and ALFRED.

The values of employed variables are shown in Table B1 of Online Appendix B. The sample descriptive statistics are reported in Table B2 of Online Appendix B. All variables included in the OP, MIOP and Swopit models 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.

Table 6 reports the estimated parameters of the Swopit model with exogenous switching ($\rho_1 = \rho_3 = 0$).[7] The regime equation contains $pbias_{t-1}$, $spread_t$ and $house_t$. The

[5] The forecast for the current quarter provides more explanatory power than for one, two, three and four quarters ahead.

[6] It is highly correlated with the Greenbook projections for the current quarter (the first-order autocorrelation coefficient is 0.97), and provides similar results if used for the entire sample.

[7] The short sample size (only 150 observations for 13 parameters) does not allow to accurately estimate the correlations between the unobservables in the tight and loose regimes of the Swopit model with exogenous regime switching. More data are needed to identify ρ_1 and ρ_3 more precisely: the Monte Carlo experiments indicate that the precision of correlation coefficients' estimates are the most sensitive to the small sample size among all parameters.

outcome equations contain $spread_t$ and gdp_t in both regimes. Among the 150 FOMC actions during almost twenty years, the Swopit model predicts correctly 122 decisions (among five choices) with the 5.4 bp mean absolute error (MAE) and 81% accuracy (the percentage of correct predictions). In terms of three policy choices ("decrease", "no change" or "increase") the accuracy is 87%. The Swopit model never wrongly predicts the direction of target change.

Table 6. Modeling target changes: estimated parameters of the Swopit model

Variables	Regime equation	Output equations	
		Loose regime	Tight regime
$pbias_{t-1}$	1.89 (0.37)***		
$spread_t$	1.93 (0.52)***	1.47 (0.40)***	3.30 (0.95)***
$house_t$	5.72 (1.24)***		
gdp_t		0.42 (0.11)***	0.78 (0.34)*
$threshold_1$	8.72 (2.00)***	-0.09 (0.43)	3.98 (1.98)*
$threshold_2$	10.73 (2.18)***	1.03 (0.45)*	8.01 (2.65)**

Notes. Sample period: 7/1987–1/2006 (150 observations). ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses. Exogenous switching: ρ_1=ρ_3=0.

The estimation output for the OP and MIOP models, which are estimated using the same set of explanatory variables as in the Swopit model, are shown in Table 7. In the MIOP model, its outcome equation includes all regressors from the Swopit model, and its regime equation includes $house_t$ and gdp_t.

Table 7. Modeling target changes: estimated parameters of the OP and MIOP models

Variables	OP model	MIOP model	
		Regime equation	Outcome equation
$pbias_{t-1}$	0.82 (0.19)***		1.06 (0.25)***
$spread_t$	1.89 (0.26)***		2.23 (0.33)***
$house_t$	1.54 (0.45)***	4.72 (2.07)*	1.82 (0.59)**
gdp_t	0.30 (0.08)***	-0.38 (0.20)	0.35 (0.10)***
$threshold_1$	0.97 (0.72)	3.95 (2.06)	1.38 (0.87)
$threshold_2$	2.01 (0.71)**		2.80 (0.92)**
$threshold_3$	5.62 (0.88)***		6.19 (1.07)***
$threshold_4$	7.23 (0.95)***		8.18 (1.16)***

Notes. Sample period: 7/1987–1/2006 (150 observations). ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses.

4.3 In- and out-of-sample comparison of competing models

The top panel of Table 8 compares the in-sample fit of the Swopit model, the OP and MIOP models (which are estimated with the same set of regressors as in the Swopit model), and the inertial Taylor-type rule estimated by OLS. The Taylor-type rules are widely used (and abused) in monetary economics literature and central banking. 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; Gerlach, 2007). The MIOP model is applied in Brooks *et al.* (2012) to the policy rate of Bank of England.

Table 8. In- and out-of-sample comparison with the OP and MIOP models: the FOMC desicions favor the Swopit model

Model:	Taylor rule	OP	MIOP	Swopit
In-sample forecast for 7/1987--1/2006 period				
McFadden R^2		0.42	0.46	**0.51**
AIC		209.1	201.8	**188.1**
BIC		233.2	235.0	**227.2**
Adj. noise-to-signal ratio for cuts		0.05	0.02	**0.01**
Adj. noise-to-signal ratio for no changes		0.44	0.41	**0.29**
Adj. noise-to-signal ratio for hikes		0.06	0.03	**0.03**
Accuracy (% of correct predictions)	0.62	0.71	0.76	**0.81**
MAE, basis points	11.5	8.1	6.6	**5.4**
Out-of-sample forecast for 3/2006--12/2008 period (before ZLB period)				
Accuracy (% of correct predictions)	0.43	0.78	0.74	**0.83**
MAE, basis points	21.7	9.8	9.8	**7.6**
Out-of-sample forecast for 1/2009--12/2015 period (during ZLB period)				
Accuracy (% of correct predictions)	0.54	0.64	**0.95**	0.91
MAE, basis points	11.6	12.1	**1.8**	3.6
Out-of-sample forecast for 1/2016--6/2019 period (after ZLB period)				
Accuracy (% of correct predictions)	0.61	0.71	0.71	**0.82**
MAE, basis points	9.8	7.1	7.1	**4.5**

Notes. MAE is the mean absolute difference between the observed and predicted choices (the predicted choice is that with the highest predicted probability). 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.

Among the four competing models, the Taylor rule demonstrates the worst accuracy and MAE, which is more than twice as large as that in the Swopit model. To compute the discrete-choice predictions for the Taylor rule and make them compatible with the OP, MIOP and Swopit predictions, I rounded the continuous-valued Taylor rule's predictions to the nearest discrete-valued choice.

The Swopit model is clearly superior to the OP and MIOP models according to the McFadden R^2, Akaike information criteria (AIC), BIC and the Vuong test (at the 0.01 and 0.05 significance levels, respectively), has the highest accuracy, the lowest MAE, and the lowest adjusted noise-to-signal ratios, especially for the no-change outcomes. The OP and MIOP models predict more no-change outcomes (110 and 113) than the Swopit model (107), but they correctly predict only 88 and 92 of them, respectively, whereas the Swopit model correctly predicts 92 no-change decisions. 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. Indeed, the null hypothesis that the Fed policy reactions are symmetrical (that is all parameters in the loose and tight regimes are equal) is rejected by the LR-test (the p-value is 10^{-8}). The OP model makes predictions that are markedly different from those in the Swopit model: for example, as Figure 9 reports, the predicted MEs of the explanatory variables on the choice probabilities can differ by several times and can even have the opposite directions.

Table 9. The MEs on the choice probabilities in the Swopit and OP models can differ by several times and have opposite signs

	ME of $spread_t$		ME of gdp_t	
Model:	Swopit	OP	Swopit	OP
$\Pr(y_t$ = "small cut")	-0.33 (0.14)*	0.30 (0.21)	-0.09 (0.03)**	0.05 (0.04)
$\Pr(y_t$ = "large cut")	-0.25 (0.08)**	-0.75 (0.30)***	-0.07 (0.03)*	-0.12 (0.03)***

Notes. ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses. The speciffications of the Swopit and OP models are reported in Tables 5 and 6. The MEs are predicted for the values of explanatory variables observed at the FOMC meeting on November 3, 2010.

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 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. I re-estimated the Swopit model for the same samples as in Hu and Phillips (2004) and Piazzesi (2005).

As Table 10 reports, the Swopit model yields a substantially higher accuracy and far better adjusted noise-to-signal ratios for all three choices, and especially for the no-change outcomes. 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 single-equation discrete-choice models, which tend to overfit the most popular choice — in the Swopit model the noise-to-signal ratios for no-change outcome is 0.20 versus 0.45 in Hu and Phillips (2004), and 0.17 versus 0.72 in Piazzesi (2005).

Table 10. Comparison with Hu and Phillips (2004) and Piazzesi (2005): the FOMC decisions favor the Swopit model

Sample:	2/1994 - 12/2001		2/1994 - 12/1998	
Observed choice	Hu and Phillips (2004)	Swopit model	Piazzesi (2005)	Swopit model
	Accuracy (% of correct predictions)			
Decrease	0.69	**0.92**	0.00	**1.00**
No change	0.90	**0.95**	0.93	**0.96**
Increase	0.50	**0.69**	0.57	**0.71**
All choices	0.78	**0.89**	0.75	**0.93**
	Adjusted noise-to-signal ratios			
Decrease	0.08	**0.02**	n/a	**0.00**
No change	0.45	**0.20**	0.72	**0.17**
Increase	0.04	**0.03**	0.11	**0.04**

Notes. The Swopit model is reestimated for the same samples as in Hu and Phillips (2004) and Piazzesi (2005) with three choices ("decrease", "no change" or "increase") and with the same specification as in Table 6.

How well does the Swopit model, estimated for the Greenspan term, forecast out of sample the next 107 FOMC decisions during the 3/2006–6/2019 period under the Bernanke's, Yellen's and Powell's chairmanships (using the actual real-time values of explanatory variables as they were known one day before each FOMC meeting)? During the forecasting period, the target approaches the ZLB in December 2008 and remains at the ZLB until December 2015. It is intriguing to see whether the three competing model, estimated for the Greenspan period, in which the target was far above the zero, will be able (i) to predict the FOMC decisions when the target was approaching the ZLB (the 3/2006–12/2008 period), (ii) to avoid predicting a negative level of the target during the ZLB period (the 1/2009–12/2015 period), and (iii) to predict the FOMC decisions when the Fed began slowly increasing the target (the 1/2016–6/2019 period). The forecasts for the 3/2006–12/2008 period are obtained from the models estimated for the 7/1987–1/2006 period without the recursive re-estimations, the forecasts for the 1/2009–12/2015 period — from the models estimated for the 7/1987–12/2008 period without the recursive re-estimations, and the forecasts for the 1/2016–6/2019 period — using the one-step ahead forecasts with recursive re-estimations for the entire sample since 1/1987.

The bottom panels of Table 8 compare the out-of-sample forecasting performance of the Taylor rule, OP, MIOP and Swopit models separately for the three periods. Before and after the ZLB period, the Swopit model correctly predicts 83% and 82% of FOMC decisions (among the five choices), respectively, and clearly outperforms the Taylor rule

(43% and 61%), the OP model (78% and 71%) and the MIOP model (74% and 71%) model. The MAE of the forecasts in the OP and MIOP models are 29% greater before the ZLB and 58% greater after the ZLB than in the Swopit model. The MAE in the Taylor rule are greater by far more than 100%. Among the 55 status quo outcomes during the ZLB period when there was no scope for reducing the target further, the Swopit model (without imposed restrictions that do not allow for further cuts and a negative level of the rate target) correctly predicts 51 of them and incorrectly predicts only four cuts, while the Taylor rule and OP model incorrectly predict 25 and 19 cuts, respectively, and fail to adequately address the outset of the ZLB. The MIOP model correctly predicts 53 out of 55 status quo outcomes during the ZLB period, but performs much worse than the Swopit model before and after it. Overall, for the entire 3/2006–6/2019 period, the Swopit model predicts correctly out-of-sample 90% of the FOMC decisions among three choices ("decrease", "no change", "increase").

4.4 Surmounting the endogeneity problem

The model is cast in a predictive format. If we are instead interested in estimating the Fed policy reactions to economic and financial developments, we must pay attention to a 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 a possible endogeneity of the regressors. The FOMC "policy bias" directives or "balance-of-risks" assessments may contain internal Fed information about a monetary shock at the next policy meeting; and the FOMC projections of economic indicators may be correlated with the future monetary shocks. Hense, the variables $pbias_{t-1}$, $house_t$ and gdp_t may be endogenous to the error terms. Since the market participants use all available information to predict the upcoming policy actions, the market interest rates may move in anticipation of FOMC decisions; thus, the variable $spread_t$ may also be endogenous.

Choice of instruments

To overcome a possible endogeneity problem, we can apply a CF estimation approach. The CF method introduces residuals from the regressions of EEVs on the set of instruments into the structural equations as controls for endogeneity. These residuals are presumably those components of the EEVs that are correlated with the unobserved monetary shocks. The estimation of these residuals in this application raises a host of issues such as the lack, validity and strength of the instruments. The typical instruments employed in the literature are the lags of inflation, output gap, and other variables. As Sims and Zha (2006) point out, identification in instrumental variables 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

[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.

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 percent or 5 percent.

We can avoid these problems by using a market-based proxy for monetary shocks (the differences between the actual Fed actions and the actions anticipated by the market) in order to obtain the strong and valid instruments. Suppose we have an estimate of monetary shocks, denoted by $surprise_t$. If the shocks are well estimated and our model is well specified, the estimate of shocks should be correlated with the disturbances in the model:

$$surprise_t = \varepsilon_{s,t}\varphi_s + \xi_{s,t},\ s = 0, 1, 3,$$

where φ_s are the OLS coefficients; $\xi_{s,t}$ are the zero-mean error terms, which are neither correlated with $\varepsilon_{s,t}$ nor with any explanatory variable in $\mathbf{x}_{s,t}$ and $\mathbf{w}_{s,t}$, and have variances that are much smaller than those of $\varepsilon_{s,t}\varphi_0$. The instruments in $\mathbf{z}_{0,t}$, $\mathbf{z}_{1,t}$ and $\mathbf{z}_{3,t}$ can be obtained for each continuous-valued EEV $w_t^{cont} \in \mathbf{w}_{0,t} \bigcup \mathbf{w}_{1,t} \bigcup \mathbf{w}_{3,t}$ (for example, such as $house_t$) as the OLS residuals from the regression of w_t^{cont} on $surprise_t$, and for the each discrete-valued EEV $w_t^{disc} \in \mathbf{w}_{0,t} \bigcup \mathbf{w}_{1,t} \bigcup \mathbf{w}_{3,t}$ (such as $pbias_{t-1}$) as the generalized residuals from the ordered probit (or logit) regression of w_t^{disc} on $surprise_t$:

$$z_t^{cont} = w_t^{cont} - w_t^{cont} \times cov(w_t^{cont}, surprise_t)/var(surprise_t),$$
$$z_t^{disc} = \frac{[w_t^{disc} - F(surprise_t \times \widehat{\delta}_{disc})]f(-surprise_t \times \widehat{\delta}_{disc})}{[1 - F(surprise_t \times \widehat{\delta}_{disc})]F(surprise_t \times \widehat{\delta}_{disc})},$$

where $\widehat{\delta}_{disc}$ is the slope coefficient in the ordered probit (or logit) regression of w_t^{disc} on $surprise_t$; and F and f are the CDF and PDF of standard normal (or logistic) distribution, respectively. Since $var(\varepsilon_{s,t}\varphi_s)$, $s = 0, 1, 3$ is much larger than $var(\xi_{s,t})$, and since $cov(w_t^{cont}, \xi_{s,t}) = 0$ and $cov(\varepsilon_{s,t}, \xi_{s,t}) = 0$,

$$cov(z_t^{cont}, \varepsilon_{s,t}) = cov(w_t^{cont} - (\varepsilon_{s,t}\varphi_s + \xi_{s,t})\frac{cov(w_t^{cont}, \varepsilon_{s,t}\varphi_s + \xi_{s,t})}{var(\varepsilon_{s,t}\varphi_s + \xi_{s,t})}, \varepsilon_{s,t})$$
$$\approx cov(w_t^{cont}, \varepsilon_{s,t}) - cov(\varepsilon_{s,t}\frac{cov(w_t^{cont}, \varepsilon_{s,t})}{var(\varepsilon_{s,t})}, \varepsilon_{s,t}) - cov(\xi_{s,t}\frac{cov(w_t^{cont}, \varepsilon_{s,t})}{\varphi_s var(\varepsilon_{s,t})}, \varepsilon_{s,t}) = 0.$$

Thus, z_t^{cont} is correlated with w_t^{cont} but not correlated with the error terms $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$. Similarly, z_t^{disc} is correlated with w_t^{disc} but not correlated with the error terms $\varepsilon_{0,t}$, $\varepsilon_{1,t}$ and $\varepsilon_{3,t}$, because the generalized residual z_t^{disc} is a discrete-choice counterpart of the OLS residual in the linear models and is orthogonal to the regressor $surprise_t$. For example, in the case of generalized logit residuals we have:

$$cov(z_t^{disc}, \varepsilon_{s,t}) = cov(z_t^{disc}, \tfrac{1}{\varphi_s} surprise_t - \tfrac{1}{\varphi_s}\xi_{s,t}) = \tfrac{-1}{\varphi_s} cov(z_t^{disc}, \xi_{s,t})$$
$$= \tfrac{-1}{\varphi_s} cov(w_t^{disc} - F(surprise_t \delta_{disc}), \xi_{s,t}) = \tfrac{1}{\varphi_s} cov(F(surprise_t \delta_{disc}), \xi_{s,t})$$
$$= \frac{1}{\varphi_s}\sum_{t=1}^{T} \frac{1}{1+\exp(-surprise_t \delta_{disc})}\xi_{s,t} = \frac{1}{\varphi_s}\sum_{t=1}^{T} \frac{1}{1+\exp(-\varepsilon_{s,t}\varphi_s\delta_{disc})\exp(-\xi_{s,t}\delta_{disc})}\xi_{s,t}$$

$$\approx \frac{1}{\varphi_s}\sum_{t=1}^{T}\frac{1}{1+\exp(-\varepsilon_{s,t}\varphi_s\delta_{disc})}\xi_{s,t} = 0,\ s = 0, 1, 3,$$

because $var(\varepsilon_{s,t}\varphi_s)$ is much larger than $var(\xi_{s,t})$, $cov(w_t^{disc}, \xi_{s,t}) = 0$, $cov(\varepsilon_{s,t}, \xi_{s,t}) = 0$ and

$$F(surprise_t\delta_{disc}) = 1/(1 + \exp(-surprise_t\delta_{disc})),$$
$$f(surprise_t\delta_{disc}) = F(surprise_t\delta_{disc})[1 - F(surprise_t\delta_{disc})],$$
$$z_t^{disc} = \frac{[w_t^{disc} - F(surprise_t\delta_{disc})]f(-surprise_t\delta_{disc})}{[1-F(surprise_t\delta_{disc})]F(surprise_t\delta_{disc})} = w_t^{disc} - F(surprise_t\delta_{disc}).$$

Therefore, z_t^{cont} and z_t^{disc} are both the relevant and exogenous instruments, and can be employed to estimate the Swopit model using a two-step CF approach.

The explanatory variables $pbias_{t-1}$, $house_t$ and gdp_t are more endogenous to monetary shocks (the coefficients of correlation with $surprise_t$ are about 0.15) than $spread_t$ (coefficients of correlation with $surprise_t$ is only 0.06).

Measuring monetary policy shocks

Monetary shocks derived from the daily interest rate data are nearly the ideal measures of unanticipated changes to the target (Cochrane and Piazzesi, 2002). Financial markets can flexibly employ a boundless spectrum of information in order to predict the Fed decisions, surmounting the omitted-variable and time-varying-parameter problems common in econometric estimations. Financial market instruments provide forecasts that are clearly outperform those of the sophisticated time-series models and monetary policy rules (Evans, 1998). A growing number of studies employs financial market reactions to Fed announcements to identify monetary policy shocks. Following Kuttner (2001), Faust *et al.* (2004), Bernanke and Kuttner (2005) and Piazzesi and Swanson (2008) I estimate the monetary shocks as policy surprises around FOMC decisions, that is as the FOMC decisions unanticipated by the federal funds futures' market. The federal funds futures rates dominate all the other financial securities in forecasting Fed monetary policy (Gürkaynak *et al.*, 2007) and provide the efficient forecasts of target changes (Krueger and Kuttner, 1996). The use of the federal funds futures is attractive also because obtaining the forecasts is simple, and there are no model-specification problems (Kuttner 2001). The one-day surprises are measured by market reaction to FOMC actions using the change in the implied rate of current-month (or one-month-ahead) federal funds futures on the day of policy action:

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

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. This measure of monetary policy shock, suggested by Kuttner (2001), differences out any constant risk premia and other technical features in the federal funds market, is unpredictable by financial market instruments known to market participants right before the FOMC announcement, and is not distorted by time-varying risk premia over such small interval (Piazzesi and Swanson, 2008).

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 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.[10] The dates when the FOMC decisions became effective do not completely coincide with the dates when these decisions were made. Up to 1994, the 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 decisions became effective on the same day. The employed chronology of FOMC actions is taken from the Board of Governors of the Fed (via ALFRED) with the following adjustment suggested by Kuttner (2001, 2003) on the basis of the analysis of market reaction: a 25 bp cut on December 18, 1990 instead of December 19, 1990 as in ALFRED.

Controlling for endogeneity: CF estimation results

To control for endogeneity with the above instruments it is sufficient to include only one bias correction term in each Swopit equation.[11] At the first step of the CF estimation procedure, I obtain the controls for endogeneity: $\widehat{\nu}_{0,t}$ — as the OLS residuals from the reduced-form regression of $house_t$ on the constant and the instruments z_t^{pbias}, z_t^{spread} and z_t^{house}; and $\widehat{\nu}_{1,t}$ and $\widehat{\nu}_{3,t}$ — as the OLS residuals from the regression of gdp_t on the constant and the instruments z_t^{spread} and z_t^{gdp}. At the second step of the CF procedure, the residual $\widehat{\nu}_{s,t}$ is included in the corresponding equations of the Swopit model as the bias correction terms.

Table 11 reports the estimated consistent (unscaled) CF Swopit parameters with exogenous switching ($\rho_1 = \rho_3 = 0$).[12] The usual t statistics for the coefficients on $\widehat{\nu}_{s,t}$ can be used to test for exogeneity. The coefficients on $\widehat{\nu}_{0,t}$, $\widehat{\nu}_{1,t}$ and $\widehat{\nu}_{3,t}$ are significant at the 0.020, 0.001 and 0.023 significance levels, respectively. The null of exogeneity of the

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

[10] The reported values of $surprise_t$ are multiplied by 10 in all estimations.

[11] The bias corection terms — the residuals in the reduced form regressions of each EEV on the instruments at the first step of CF procedure are all highly correlated with $surprise_t$ and hence with each other because all the instruments are constructed as the residuals in the regressions of each EEV on $surprise_t$ only. Including all of them into the structural equations at the second step of CF procedure would introduce strong multicollinearity and is not necessary.

[12] The scaled parameters from the second step of CF procedure are reported in Table B4 in Online Appendix B.

regressors is rejected.[13] The inclusion of the controls for endogeneity substantially improves the fit: the McFadden pseudo R^2 increases from 0.51 to 0.62, the MAE decreases from 5.4 bp to 3.4 bp, and the accuracy increases from 0.81 to 0.87. In terms of three choices ("increase", "no change", "decrease") the CF Swopit model with the controls for endogeneity correctly predicts 93% of the next FOMC decisions, and is clearly preferred to the standard Swopit model by AIC and BIC.

Table 11. Endogeneity does matter: the estimated parameters of the Swopit model using CF approach

Variables	Regime equation	Output equations	
		Loose regime	Tight regime
$pbias_{t-1}$	1.45 (0.31)***		
$spread_t$	1.75 (0.53)***	1.49 (0.37)***	1.69 (0.73)*
$house_t$	6.14 (1.39)***		
gdp_t		0.55 (0.11)***	0.84 (0.32)**
$v_{s,t}$	-4.47 (1.92)*	-0.95 (0.25)***	-1.45 (0.64)*
$threshold_1$	9.61 (2.32)***	0.23 (0.41)	4.25 (1.74)*
$threshold_2$	11.03 (2.38)***	1.57 (0.47)***	7.34 (2.52)**

Notes. Sample period: 7/1987–1/2006 (150 observations). ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses. Exogenous switching: ρ_1=ρ_3=0. The explanatory variables are defined in Section 4.2. The dependent variable is defined in Section 4.1. $\nu_{s,t}$ are the controls for endogeneity.

Table 12. Endogeneity does matter: the MEs on the choice probabilities in the standard and CF Swopit models can differ by several times and have opposite signs

	ME of $spread_t$		ME of gdp_t	
Model:	Swopit	CF Swopit	Swopit	CF Swopit
Pr(y_t = "no change")	0.58 (0.16)***	0.13 (0.13)	0.17 (0.04)***	0.05 (0.04)
Pr(y_t = "small cut")	-0.25 (0.13)	0.54 (0.18)**	-0.07 (0.03)*	0.20 (0.06)**
Pr(y_t = "large cut")	-0.34 (0.11)**	-0.67 (0.19)***	-0.10 (0.04)*	-0.25 (0.05)***

Notes. ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses. The speciffications of the Swopit and CF Swopit models are reported in Tables 6 and 11. The MEs are estimated at the values of explanatory variables observed at the FOMC meeting on December 17, 1991.

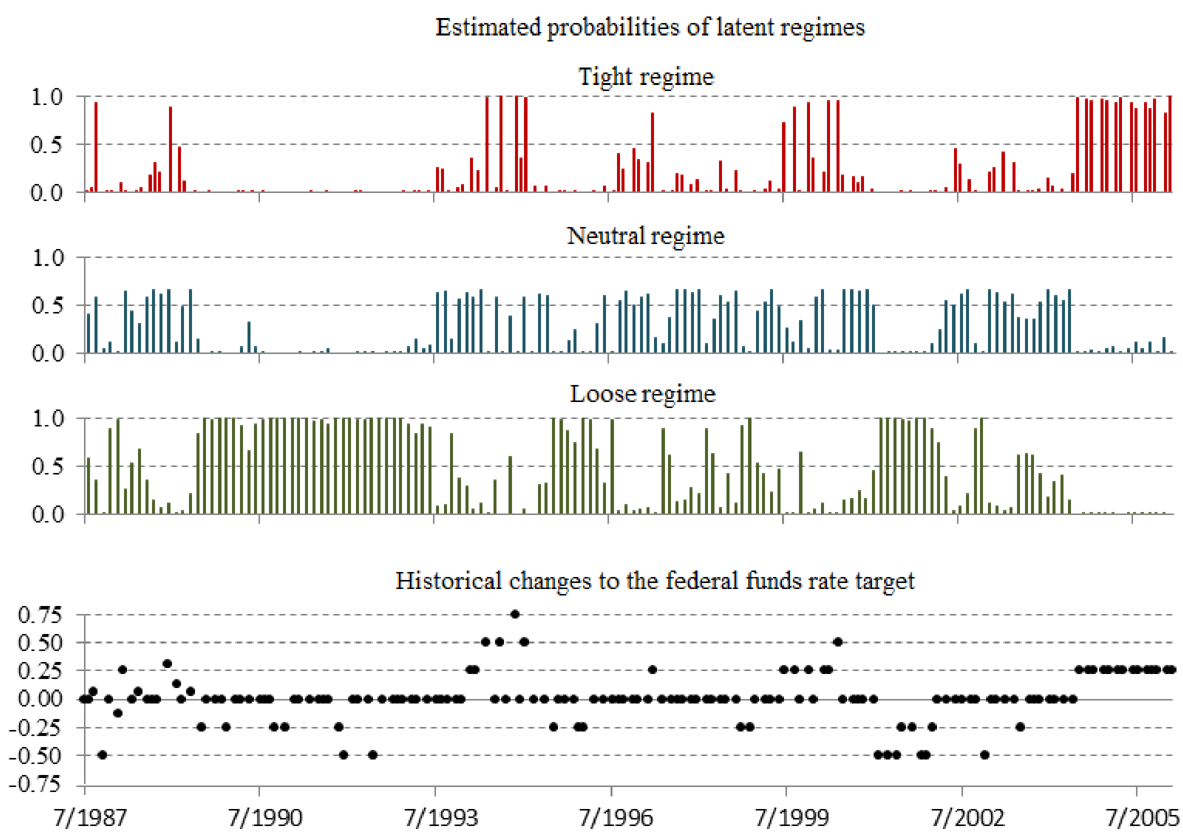
[13] Of course, the evidence in favor of endo/exogeneity should be interpreted conditional on the correct model specification.

The endogeneity of explanatory variables can cause a severe bias in the inference: the MEs of the regressors on the choice probabilities in the standard Swopit model and in the model with the controls for endogeneity can differ by several times, and can even have the opposite signs, as Table 12 shows.

4.5 Probabilities of latent regimes

Figure 3 shows the estimated probabilities of latent policy regimes in the CF Swopit model for each scheduled FOMC decision during the Greenspan term. The average probabilities of the loose, neutral and tight regimes are 0.49, 0.28 and 0.23, whereas the observed frequencies of cuts, no-change decisions and hikes are 0.16, 0.64 and 0.20, respectively. On average in the sample, the ratio of the probability of no change conditional on the neutral regime to the unconditional probability of no change $\Pr(y_t = 0|r_t = 0)/\Pr(y_t = 0) = 0.33/0.64 = 0.51$. Loosely speaking, it means that only about a half of no-change outcomes is generated in the neutral regime, and another half of them is generated in either loose or tight policy regime. The outcome decisions tend to leave the target unchanged by weakening the tightening and easing policy inclinations.

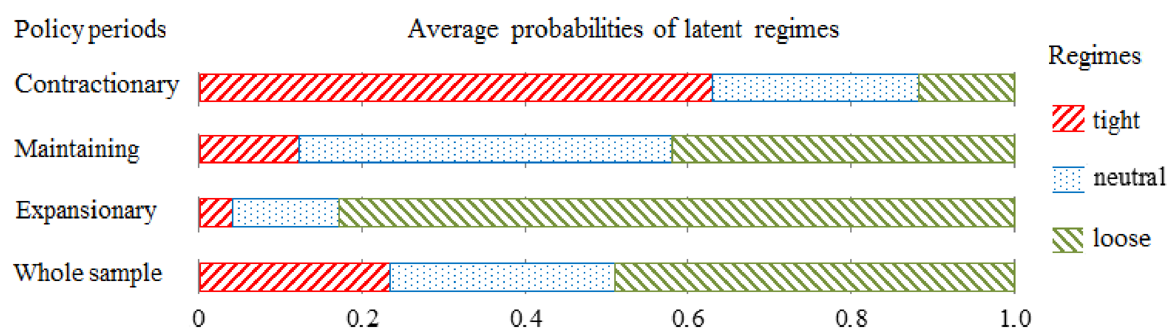
Figure 3. Estimated probabilities of latent regimes and actual FOMC decisions



Notes. Sample period: 7/1987–1/2006 (150 observations). The estimates are obtained from the Swopit model with the controls for endogeneity using CF approach (Table 11).

Figure 4 illustrates the correspondence of latent regime probabilities to the contractionary, maintaining and expansionary policy periods shown in Figure 2. The profiles of regime probabilities differ considerably across the three policy periods. The Fed actions in the contractionary, maintaining and expansionary periods are dominated by the tight, neutral and loose regimes, respectively. However, in the maintaining periods, the average probability of neutral regime is only 0.46, hence about a half of the status quo outcomes is generated by the tight or loose regimes even in the maintaining periods.

Figure 4. Average probabilities of latent regimes in different policy periods



Notes. Sample period: 7/1987–1/2006 (150 observations). The estimates are obtained from the CF Swopit model with controls for endogeneity (Table 11). The policy periods are shown in Figure 2.

Concluding remarks

This paper introduces a regime-switching ordered probit model with possibly endogenous regressors for analyzing ordinal outcomes such as changes to the federal funds rate target. The empirical results demonstrate that ignoring the regime-switching environment and the endogeneity of explanatory variables can lead to a seriously distorted statistical inference. The new model outperforms the existing models for the federal funds rate target both in and out of sample. It can be used to more adequately represent the monetary policy rules of many central banks, can be embedded in the multivariate macroeconomic models to better understand the monetary policy effects, can significantly improve the forecasts of Taylor-like rules and standard linear vector autoregressions, can challenge the inference from vector autoregression impulse-response functions, and can also be fruitfully applied to other ordinal data such as responses to treatment, changes to the rankings, indices and prices, etc.

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Supplementary Online Material

for
"A 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 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 $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ in the Swopit outcome equations contain all covariates in the MIOP regime equation, and (iii) $\mathbf{x}_{0,t}$ 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

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

where $\mathbf{x}_t^m$ and $\mathbf{x}_{1,t}^m$ are the observed data row vectors; $\boldsymbol{\beta}^m$ and $\boldsymbol{\beta}_1^m$ are the vectors of unknown slope parameters; ε_t^m and $\varepsilon_{1,t}^m$ are the iid (across t) unobserved disturbance terms; 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 $-\infty \equiv \mu_{1,0}^m \leq \mu_{1,1}^m \leq ... \leq \mu_{1,J}^m \equiv \infty$ 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

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

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 (2) as

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

The probabilities of observing the outcome j in the Swopit model are given according to (2) as

$$
\begin{aligned}
&\Pr(y_t = 1|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{1,1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1; \rho_1);\\
&\Pr(y_t = 2|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0; -\mu_{1,1} + \mathbf{x}_{1,t}\boldsymbol{\beta}_1; -\rho_1)\\
&+\Phi(\mu_{0,2} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) - \Phi(\mu_{0,1} - \mathbf{x}_{0,t}\boldsymbol{\beta}_0) + \Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; \mu_{3,2} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3; -\rho_3);\\
&\Pr(y_t = 3|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}) = \Phi_2(-\mu_{0,2} + \mathbf{x}_{0,t}\boldsymbol{\beta}_0; -\mu_{3,2} + \mathbf{x}_{3,t}\boldsymbol{\beta}_3; \rho_3).
\end{aligned}
\tag{A3}
$$

Suppose now that $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ in the Swopit outcome equations are identical to $\mathbf{x}_t^m$ in the MIOP regime equation, and that $\mathbf{x}_{0,t}$ in the Swopit regime equation is identical to $\mathbf{x}_{1,t}^m$ in the MIOP outcome equation. Impose the following restrictions on the Swopit parameters:

$$
\begin{aligned}
&\boldsymbol{\beta}_3 = -\boldsymbol{\beta}_1 = \boldsymbol{\beta}^m,\ \boldsymbol{\beta}_0 = \boldsymbol{\beta}_1^m,\ \mu_{0,1} = \mu_{1,1}^m,\ \mu_{0,2} = \mu_{1,2}^m,\\
&\mu_{3,2} = -\mu_{1,1} = \mu^m \text{ and } -\rho_1 = \rho_3 = \rho^m.
\end{aligned}
\tag{A4}
$$

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

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

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

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

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

In more general cases, when $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ are not identical to $\mathbf{x}_t^m$, but contain all variables in $\mathbf{x}_t^m$, and when $\mathbf{x}_{0,t}$ is not identical to $\mathbf{x}_{1,t}^m$, but contains all variables in $\mathbf{x}_{1,t}^m$, we can use additional restrictions by fixing the values of the coefficients on all extra variables in $\mathbf{x}_{0,t}$, $\mathbf{x}_{1,t}$ and $\mathbf{x}_{3,t}$ 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 $\mu_{3,2} = -\mu_{1,1} = \mu^m$, impose a sort of symmetry on the policy reactions in the tight and loose policy regimes in the Swopit model, since they imply that the conditional probability of a hike in the tight regime $\Pr(y_t = 3|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, r_t = 3)$ is determined by the same mechanisms as the conditional probability of a cut in the loose regime $\Pr(y_t = 1|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, r_t = 1)$:

$$\Pr(y_t = 3|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, r_t = 3) = 1 - \Phi(\mu_{3,2} - \mathbf{x}_{3,t}\boldsymbol{\beta}_3) = 1 - \Phi(\mu^m - \mathbf{x}_t^m\boldsymbol{\beta}^m)$$
$$= \Phi(-\mu^m + \mathbf{x}_t^m\boldsymbol{\beta}^m) = \Phi(\mu_{1,1} - \mathbf{x}_{1,t}\boldsymbol{\beta}_1) = \Pr(y_t = 1|\mathbf{x}_{0,t}, \mathbf{x}_{1,t}, \mathbf{x}_{3,t}, r_t = 1).$$

Online Appendix B. Supporting material for empirical application

Table B1. Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action	$target_{t-1}$	$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$	$infl_t$	gap_t
07-Jul-87	0	no change	08-Jul-87	6.6250	0	0.00	1.61	5.90	-0.040	4.60	-1.10
18-Aug-87	0	no change	19-Aug-87	6.6250	0	0.13	1.61	6.40	-0.020	3.70	-1.10
22-Sep-87	0.0625	no change	24-Sep-87	7.2500	1	0.50	1.60	6.80	0.010	3.90	-0.90
03-Nov-87	-0.5	large cut	04-Nov-87	7.3125	0	0.12	1.55	5.00	-0.130	4.10	-0.90
16-Dec-87	0	no change	17-Dec-87	6.8125	-1	0.57	1.54	5.40	-0.140	4.50	-0.60
10-Feb-88	-0.125	small cut	11-Feb-88	6.6250	0	0.16	1.55	4.90	0.030	4.10	-0.50
29-Mar-88	0.25	small hike	30-Mar-88	6.5000	0	0.16	1.46	6.10	0.010	4.50	-0.10
17-May-88	0	no change	18-May-88	7.0000	0	0.12	1.51	7.10	-0.040	5.30	0.10
30-Jun-88	0.0625	no change	01-Jul-88	7.4375	1	-0.18	1.49	8.20	-0.070	4.70	0.50
16-Aug-88	0	no change	17-Aug-88	8.1250	1	0.01	1.47	7.30	-0.040	4.50	0.50
20-Sep-88	0	no change	21-Sep-88	8.1250	1	-0.11	1.47	6.50	0.020	4.40	0.40
01-Nov-88	0	no change	02-Nov-88	8.1250	1	-0.25	1.46	6.70	0.032	5.00	0.00
14-Dec-88	0.3125	large hike	15-Dec-88	8.3750	1	0.50	1.51	7.00	0.018	5.10	0.30
08-Feb-89	0.125	small hike	09-Feb-89	9.0000	1	0.10	1.50	8.90	0.000	4.80	0.80
28-Mar-89	0	no change	29-Mar-89	9.7500	1	-0.18	1.56	9.40	-0.070	5.20	0.80
16-May-89	0.0625	no change	17-May-89	9.7500	1	-0.85	1.44	7.30	-0.022	5.00	1.00
06-Jul-89	-0.25	small cut	07-Jul-89	9.5625	0	-1.48	1.40	5.10	-0.026	4.60	0.60
22-Aug-89	0	no change	23-Aug-89	9.0625	0	-0.62	1.43	5.80	0.000	4.20	0.91
03-Oct-89	0	no change	04-Oct-89	9.0625	-1	-0.74	1.43	5.30	0.034	4.40	1.10
14-Nov-89	0	no change	15-Nov-89	8.5000	-1	-0.60	1.38	4.90	-0.020	4.00	0.90
19-Dec-89	-0.25	small cut	20-Dec-89	8.5000	-1	-0.88	1.39	4.50	-0.169	4.20	0.70
07-Feb-90	0	no change	08-Feb-90	8.2500	0	-0.07	1.37	5.20	-0.014	4.30	0.20
27-Mar-90	0	no change	28-Mar-90	8.2500	0	0.04	1.47	7.60	0.000	5.80	0.60
15-May-90	0	no change	16-May-90	8.2500	0	0.00	1.30	6.80	0.000	4.70	0.60
03-Jul-90	0	no change	04-Jul-90	8.2500	0	-0.28	1.21	5.70	0.000	4.70	0.30
21-Aug-90	0	no change	22-Aug-90	8.0000	-1	-0.42	1.19	5.70	0.000	5.00	0.30
02-Oct-90	0	no change	03-Oct-90	8.0000	-1	-0.48	1.09	2.60	0.021	4.90	0.20
13-Nov-90	-0.25	small cut	16-Nov-90	7.7500	-1	-0.42	1.10	1.30	0.000	5.00	-0.90
18-Dec-90	-0.25	small cut	19-Dec-90	7.2500	-1	-0.24	1.02	0.90	-0.233	4.20	-1.10
06-Feb-91	0	no change	07-Feb-91	6.2500	-1	0.28	1.00	3.30	0.000	5.20	-2.80
26-Mar-91	0	no change	27-Mar-91	6.0000	-1	0.25	0.95	2.10	0.000	7.00	-3.00
14-May-91	0	no change	15-May-91	5.7500	0	0.37	1.01	3.00	0.019	3.70	-3.60
03-Jul-91	0	no change	05-Jul-91	5.7500	0	-0.03	1.05	8.10	0.000	4.10	-3.50
20-Aug-91	0	no change	21-Aug-91	5.5000	0	-0.01	1.05	4.90	0.124	4.20	-3.30

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
01-Oct-91	0	no change	02-Oct-91	5.2500	-1	0.03	1.06	4.50	-0.011	4.20	-3.50
05-Nov-91	-0.25	small cut	06-Nov-91	5.0000	-1	-0.07	1.02	3.50	-0.125	3.90	-4.00
17-Dec-91	-0.5	large cut	20-Dec-91	4.5000	-1	-0.12	1.08	2.70	-0.238	3.40	-4.50
05-Feb-92	0	no change	06-Feb-92	4.0000	0	0.15	1.14	4.30	-0.013	4.10	-4.50
31-Mar-92	0	no change	01-Apr-92	4.0000	-1	0.63	1.25	4.70	0.010	3.80	-3.90
19-May-92	0	no change	20-May-92	3.7500	-1	0.16	1.21	4.90	0.000	4.30	-3.80
01-Jul-92	-0.5	large cut	02-Jul-92	3.7500	0	0.07	1.17	4.80	-0.363	4.00	-3.70
18-Aug-92	0	no change	19-Aug-92	3.2500	-1	0.06	1.23	3.40	0.026	2.90	-4.20
06-Oct-92	0	no change	07-Oct-92	3.0000	-1	-0.34	1.24	3.40	0.052	3.50	-4.10
17-Nov-92	0	no change	18-Nov-92	3.0000	-1	0.62	1.23	4.50	-0.100	2.70	-3.90
22-Dec-92	0	no change	23-Dec-92	3.0000	-1	0.78	1.24	6.20	0.039	3.70	-3.30
03-Feb-93	0	no change	04-Feb-93	3.0000	0	0.26	1.30	6.20	-0.012	2.90	-2.80
23-Mar-93	0	no change	24-Mar-93	3.0000	0	0.34	1.22	6.70	-0.044	4.30	-2.60
18-May-93	0	no change	19-May-93	3.0000	0	0.26	1.26	4.20	-0.026	3.30	-2.90
07-Jul-93	0	no change	08-Jul-93	3.0000	1	0.25	1.28	4.40	0.027	2.80	-3.10
17-Aug-93	0	no change	18-Aug-93	3.0000	1	0.34	1.28	4.80	0.000	2.50	-3.30
21-Sep-93	0	no change	22-Sep-93	3.0000	0	0.24	1.28	3.50	0.000	2.20	-2.70
16-Nov-93	0	no change	17-Nov-93	3.0000	0	0.50	1.36	6.60	0.023	2.80	-1.90
21-Dec-93	0	no change	22-Dec-93	3.0000	0	0.60	1.40	7.40	0.000	2.70	-1.70
04-Feb-94	0.25	small hike	04-Feb-94	3.0000	0	0.42	1.44	7.20	0.117	3.40	-1.10
22-Mar-94	0.25	small hike	22-Mar-94	3.2500	0	1.07	1.37	5.70	-0.034	2.60	-0.90
17-May-94	0.5	large hike	17-May-94	3.7500	0	1.46	1.41	6.20	0.133	3.10	-0.70
06-Jul-94	0	no change	06-Jul-94	4.2500	0	0.78	1.38	5.20	-0.050	3.30	-0.70
16-Aug-94	0.5	large hike	16-Aug-94	4.2500	1	1.31	1.33	4.40	0.145	3.10	-0.20
27-Sep-94	0	no change	27-Sep-94	4.7500	0	1.14	1.41	4.80	-0.200	3.00	-0.10
15-Nov-94	0.75	large hike	15-Nov-94	4.7500	1	1.20	1.41	6.10	0.140	3.50	0.50
20-Dec-94	0	no change	20-Dec-94	5.5000	0	1.71	1.42	6.90	-0.169	2.60	0.80
01-Feb-95	0.5	large hike	01-Feb-95	5.5000	1	1.06	1.49	6.40	0.052	3.30	0.80
28-Mar-95	0	no change	28-Mar-95	6.0000	0	0.26	1.34	5.80	0.103	3.50	0.50
23-May-95	0	no change	23-May-95	6.0000	1	0.04	1.27	3.50	0.000	3.60	0.20
06-Jul-95	-0.25	small cut	06-Jul-95	6.0000	0	-0.84	1.33	3.90	-0.012	3.00	-0.50
22-Aug-95	0	no change	22-Aug-95	5.7500	-1	0.15	1.37	4.60	0.000	2.70	-0.30
26-Sep-95	0	no change	26-Sep-95	5.7500	0	-0.07	1.40	5.10	0.000	2.60	-0.20
15-Nov-95	0	no change	15-Nov-95	5.7500	0	-0.26	1.45	4.80	0.060	2.70	0.00

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
19-Dec-95	-0.25	small cut	19-Dec-95	5.7500	0	-0.44	1.38	3.90	-0.103	2.7	0.1
31-Jan-96	-0.25	small cut	31-Jan-96	5.5000	0	-0.45	1.39	4.30	-0.070	2.6	-0.3
26-Mar-96	0	no change	26-Mar-96	5.2500	0	0.17	1.47	4.50	-0.031	2.7	-0.4
21-May-96	0	no change	21-May-96	5.2500	0	0.38	1.48	5.60	0.000	2.7	0.4
03-Jul-96	0	no change	03-Jul-96	5.2500	0	-0.28	1.39	4.50	-0.050	3.0	0.4
20-Aug-96	0	no change	20-Aug-96	5.2500	1	0.37	1.43	4.50	-0.042	3.0	0.5
24-Sep-96	0	no change	24-Sep-96	5.2500	1	0.55	1.43	4.20	-0.125	2.6	0.7
13-Nov-96	0	no change	13-Nov-96	5.2500	1	0.19	1.45	4.00	0.000	2.9	0.7
17-Dec-96	0	no change	17-Dec-96	5.2500	1	0.12	1.41	4.50	0.011	2.7	0.8
05-Feb-97	0	no change	05-Feb-97	5.2500	1	0.25	1.41	4.60	-0.030	2.3	1.0
25-Mar-97	0.25	small hike	25-Mar-97	5.2500	1	0.50	1.45	6.40	0.026	2.2	1.4
20-May-97	0	no change	20-May-97	5.5000	0	0.30	1.43	3.90	-0.113	2.9	1.7
02-Jul-97	0	no change	02-Jul-97	5.5000	1	-0.57	1.44	4.80	-0.016	2.6	1.7
19-Aug-97	0	no change	19-Aug-97	5.5000	1	-0.04	1.44	3.90	-0.013	2.2	1.9
30-Sep-97	0	no change	30-Sep-97	5.5000	1	-0.09	1.43	4.50	0.000	1.9	2.0
12-Nov-97	0	no change	12-Nov-97	5.5000	1	-0.08	1.43	5.40	-0.042	2.4	1.9
16-Dec-97	0	no change	16-Dec-97	5.5000	1	-0.22	1.47	6.10	-0.010	2.2	1.9
04-Feb-98	0	no change	04-Feb-98	5.5000	0	-0.30	1.48	4.40	0.000	2.0	2.0
31-Mar-98	0	no change	31-Mar-98	5.5000	0	-0.12	1.56	4.50	0.000	2.5	2.1
19-May-98	0	no change	19-May-98	5.5000	1	-0.17	1.60	4.20	-0.026	2.3	2.0
01-Jul-98	0	no change	01-Jul-98	5.5000	1	-0.68	1.55	3.70	-0.005	2.7	1.9
18-Aug-98	0	no change	18-Aug-98	5.5000	1	-0.40	1.58	3.60	0.012	2.0	1.7
29-Sep-98	-0.25	small cut	29-Sep-98	5.5000	0	-0.98	1.63	4.20	0.060	2.1	2.0
17-Nov-98	-0.25	small cut	17-Nov-98	5.0000	-1	-0.66	1.57	3.20	-0.058	2.2	2.0
22-Dec-98	0	no change	22-Dec-98	4.7500	0	-0.24	1.69	4.20	-0.017	2.5	2.3
03-Feb-99	0	no change	03-Feb-99	4.7500	0	-0.18	1.68	4.40	0.000	2.7	2.7
30-Mar-99	0	no change	30-Mar-99	4.7500	0	-0.11	1.75	5.10	0.000	1.7	2.7
18-May-99	0	no change	18-May-99	4.7500	0	-0.03	1.66	4.80	-0.036	1.8	2.7
30-Jun-99	0.25	small hike	30-Jun-99	4.7500	1	0.21	1.64	4.70	-0.040	2.5	2.7
24-Aug-99	0.25	small hike	24-Aug-99	5.0000	1	0.19	1.64	5.00	0.022	1.8	2.4
05-Oct-99	0	no change	05-Oct-99	5.2500	0	-0.07	1.61	6.10	-0.042	2.6	2.6
16-Nov-99	0.25	small hike	16-Nov-99	5.2500	1	0.06	1.64	5.90	0.086	2.7	2.5
21-Dec-99	0	no change	21-Dec-99	5.5000	0	0.45	1.62	6.40	0.016	2.6	2.2
02-Feb-00	0.25	small hike	02-Feb-00	5.5000	0	0.54	1.64	6.10	-0.054	1.8	2.3

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
21-Mar-00	0.25	small hike	21-Mar-00	5.7500	1	0.43	1.74	7.30	-0.031	2.0	2.7
16-May-00	0.5	large hike	16-May-00	6.0000	1	0.25	1.65	7.90	0.052	2.4	3.2
28-Jun-00	0	no change	28-Jun-00	6.5000	1	-0.40	1.61	6.80	-0.020	2.1	3.0
22-Aug-00	0	no change	22-Aug-00	6.5000	1	-0.26	1.53	4.80	-0.017	1.3	2.2
03-Oct-00	0	no change	03-Oct-00	6.5000	1	-0.55	1.57	5.70	0.000	2.1	1.8
15-Nov-00	0	no change	15-Nov-00	6.5000	1	-0.41	1.56	5.90	0.000	2.2	1.7
19-Dec-00	0	no change	19-Dec-00	6.5000	1	-0.89	1.52	4.70	0.052	2.2	1.3
31-Jan-01	-0.5	large cut	31-Jan-01	6.0000	-1	-1.19	1.59	2.40	0.005	1.9	0.1
20-Mar-01	-0.5	large cut	20-Mar-01	5.5000	-1	-1.22	1.65	4.20	0.056	2.4	0.1
15-May-01	-0.5	large cut	15-May-01	4.5000	-1	-0.65	1.62	3.80	-0.078	1.9	-0.1
27-Jun-01	-0.25	small cut	27-Jun-01	4.0000	-1	-0.43	1.62	3.50	0.050	1.6	-0.1
21-Aug-01	-0.25	small cut	21-Aug-01	3.7500	-1	-0.26	1.64	2.50	0.016	1.9	-0.4
02-Oct-01	-0.5	large cut	02-Oct-01	3.0000	-1	-0.49	1.56	-0.50	-0.069	1.9	-0.6
06-Nov-01	-0.5	large cut	06-Nov-01	2.5000	-1	-0.42	1.51	-2.00	-0.100	3.0	-1.8
11-Dec-01	-0.25	small cut	11-Dec-01	2.0000	-1	0.36	1.54	-1.80	0.000	3.0	-1.9
30-Jan-02	0	no change	30-Jan-02	1.7500	-1	0.47	1.57	3.30	0.015	1.3	-1.8
19-Mar-02	0	no change	19-Mar-02	1.7500	-1	0.85	1.65	5.40	-0.026	1.0	-1.1
07-May-02	0	no change	07-May-02	1.7500	0	0.55	1.65	4.10	0.000	1.3	-1.5
26-Jun-02	0	no change	26-Jun-02	1.7500	0	0.38	1.65	3.20	0.000	1.7	-1.6
13-Aug-02	0	no change	13-Aug-02	1.7500	0	-0.01	1.65	3.50	0.034	1.1	-1.5
24-Sep-02	0	no change	24-Sep-02	1.7500	-1	-0.03	1.67	4.30	0.025	1.8	-1.3
06-Nov-02	-0.5	large cut	06-Nov-02	1.7500	-1	-0.22	1.68	2.90	-0.194	1.5	-1.7
10-Dec-02	0	no change	10-Dec-02	1.2500	0	0.26	1.66	3.10	0.000	1.8	-1.7
29-Jan-03	0	no change	29-Jan-03	1.2500	0	0.07	1.77	3.80	0.000	1.2	-2.4
18-Mar-03	0	no change	18-Mar-03	1.2500	0	-0.07	1.82	4.30	0.048	0.7	-2.3
06-May-03	0	no change	06-May-03	1.2500	0	-0.02	1.76	3.10	0.037	1.6	-2.6
25-Jun-03	-0.25	small cut	25-Jun-03	1.2500	-1	-0.27	1.70	2.40	0.150	1.0	-2.7
12-Aug-03	0	no change	12-Aug-03	1.0000	-1	0.28	1.74	4.60	0.000	1.4	-2.4
16-Sep-03	0	no change	16-Sep-03	1.0000	-1	0.16	1.80	5.90	0.000	1.7	-2.7
28-Oct-03	0	no change	28-Oct-03	1.0000	-1	0.27	1.84	5.20	0.000	1.3	-2.0
09-Dec-03	0	no change	09-Dec-03	1.0000	-1	0.35	1.93	5.50	0.000	1.2	-1.9
28-Jan-04	0	no change	28-Jan-04	1.0000	-1	0.18	1.92	6.60	0.000	1.0	-1.6
16-Mar-04	0	no change	16-Mar-04	1.0000	-1	0.15	1.90	6.60	0.000	1.3	-2.0
04-May-04	0	no change	04-May-04	1.0000	-1	0.54	1.89	6.20	-0.006	1.6	-1.6

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
30-Jun-04	0.25	small hike	30-Jun-04	1.0000	0	1.12	1.97	7.40	-0.010	1.6	-1.2
10-Aug-04	0.25	small hike	10-Aug-04	1.2500	0	0.67	1.93	4.90	0.022	1.7	-1.3
21-Sep-04	0.25	small hike	21-Sep-04	1.5000	0	0.48	1.98	4.50	0.017	1.0	-1.4
10-Nov-04	0.25	small hike	10-Nov-04	1.7500	0	0.67	1.98	5.20	0.000	1.5	-1.4
14-Dec-04	0.25	small hike	14-Dec-04	2.0000	0	0.51	1.98	5.60	0.000	1.5	-1.3
02-Feb-05	0.25	small hike	02-Feb-05	2.2500	0	0.47	1.97	5.10	0.000	1.4	-1.2
22-Mar-05	0.25	small hike	22-Mar-05	2.5000	0	0.62	2.15	7.20	0.000	2.1	-1.0
03-May-05	0.25	small hike	03-May-05	2.7500	0	0.38	2.02	6.30	0.000	1.9	-1.2
30-Jun-05	0.25	small hike	30-Jun-05	3.0000	0	0.26	2.00	5.60	0.000	2.2	-1.0
09-Aug-05	0.25	small hike	09-Aug-05	3.2500	0	0.40	2.01	5.90	0.000	1.9	-0.3
20-Sep-05	0.25	small hike	20-Sep-05	3.5000	0	0.21	2.00	5.80	0.015	1.4	-0.6
01-Nov-05	0.25	small hike	01-Nov-05	3.7500	0	0.36	2.10	6.60	0.000	2.2	-0.5
13-Dec-05	0.25	small hike	13-Dec-05	4.0000	0	0.17	2.00	5.60	0.000	2.1	-0.3
31-Jan-06	0.25	small hike	31-Jan-06	4.2500	1	0.13	2.10	6.30	0.000	2.0	-0.4
28-Mar-06	0.25	small hike	28-Mar-06	4.5000	1	0.08	2.10	8.20		1.9	-0.1
10-May-06	0.25	small hike	10-May-06	4.7500	1	0.17	2.00	7.00		2.5	0.2
29-Jun-06	0.25	small hike	29-Jun-06	5.0000	1	0.26	1.90	5.90		3.1	0.0
08-Aug-06	0	no change	08-Aug-06	5.2500	1	-0.15	1.80	5.30		2.5	0.5
20-Sep-06	0	no change	20-Sep-06	5.2500	1	-0.21	1.70	4.00		2.3	0.5
25-Oct-06	0	no change	25-Oct-06	5.2500	1	-0.16	1.60	4.00		2.4	0.1
12-Dec-06	0	no change	12-Dec-06	5.2500	1	-0.32	1.50	2.90		2.6	0.1
31-Jan-07	0	no change	31-Jan-07	5.2500	1	-0.13	1.50	5.70		2.2	0.3
21-Mar-07	0	no change	21-Mar-07	5.2500	1	-0.31	1.40	5.50		2.2	0.2
09-May-07	0	no change	09-May-07	5.2500	1	-0.32	1.40	5.50		2.2	0.4
28-Jun-07	0	no change	28-Jun-07	5.2500	1	-0.31	1.50	6.00		1.4	0.4
07-Aug-07	0	no change	07-Aug-07	5.2500	1	-0.46	1.30	3.60		2.0	0.6
18-Sep-07	-0.5	large cut	18-Sep-07	5.2500	1	-1.03	1.30	3.50		1.9	0.5
31-Oct-07	-0.25	small cut	31-Oct-07	4.7500	0	-0.83	1.20	2.30		2.0	0.5
11-Dec-07	-0.25	small cut	11-Dec-07	4.5000	0	-1.22	1.20	1.90		2.2	0.5
30-Jan-08	-0.5	large cut	30-Jan-08	3.5000	0	-1.20	1.00	3.30		2.4	-0.3
18-Mar-08	-0.75	large cut	18-Mar-08	3.0000	-1	-1.48	1.00	2.70		2.7	-0.4
30-Apr-08	-0.25	small cut	30-Apr-08	2.2500	-1	-0.31	0.90	-0.60		2.3	-1.2
25-Jun-08	0	no change	25-Jun-08	2.0000	0	0.56	1.00	1.90		2.0	-0.5
05-Aug-08	0	no change	05-Aug-08	2.0000	0	0.23	0.90	4.30		2.6	-0.7

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$	
16-Sep-08	0	no change	16-Sep-08	2.0000	0	-0.35	0.90	5.50	2.9	-0.9
29-Oct-08	-0.5	large cut	29-Oct-08	1.5000	0	0.72	0.80	2.90	2.3	-2.3
16-Dec-08	-0.75	large cut	16-Dec-08	1.0000	-1	0.35	0.70	-2.40	1.2	-3.1
28-Jan-09	0	no change	28-Jan-09	0.1250	-1	0.28	0.50	-4.30	0.8	-5.1
18-Mar-09	0	no change	18-Mar-09	0.1250	-1	0.50	0.40	-3.30	0.9	-5.7
29-Apr-09	0	no change	29-Apr-09	0.1250	-1	0.34	0.50	-1.00	1.7	-6.4
24-Jun-09	0	no change	24-Jun-09	0.1250	-1	0.26	0.50	-1.60	2.3	-6.1
12-Aug-09	0	no change	12-Aug-09	0.1250	-1	0.33	0.60	1.60	1.2	-7.7
23-Sep-09	0	no change	23-Sep-09	0.1250	-1	0.26	0.60	3.10	1.5	-7.2
04-Nov-09	0	no change	04-Nov-09	0.1250	-1	0.26	0.70	3.10	1.2	-7.6
16-Dec-09	0	no change	16-Dec-09	0.1250	-1	0.25	0.60	4.60	1.6	-7.6
27-Jan-10	0	no change	27-Jan-10	0.1250	-1	0.19	0.60	4.70	1.2	-7.2
16-Mar-10	0	no change	16-Mar-10	0.1250	-1	0.23	0.60	4.20	0.8	-7.3
28-Apr-10	0	no change	28-Apr-10	0.1250	-1	0.25	0.60	4.60	0.9	-6.9
23-Jun-10	0	no change	23-Jun-10	0.1250	-1	0.12	0.60	4.80	0.9	-6.8
10-Aug-10	0	no change	10-Aug-10	0.1250	-1	0.08	0.60	3.80	0.9	-7.7
21-Sep-10	0	no change	21-Sep-10	0.1250	-1	0.05	0.60	3.60	1.1	-7.2
03-Nov-10	0	no change	03-Nov-10	0.1250	-1	0.02	0.60	2.80	1.1	-6.8
14-Dec-10	0	no change	14-Dec-10	0.1250	-1	0.13	0.50	2.80	0.6	-6.6
26-Jan-11	0	no change	26-Jan-11	0.1250	-1	0.10	0.60	5.70	0.9	-6.0
15-Mar-11	0	no change	15-Mar-11	0.1250	-1	0.10	0.60	4.80	1.1	-5.8
27-Apr-11	0	no change	27-Apr-11	0.1250	-1	0.13	0.60	6.10	1.5	-5.8
22-Jun-11	0	no change	22-Jun-11	0.1250	-1	0.08	0.50	5.80	2.2	-5.8
09-Aug-11	0	no change	09-Aug-11	0.1250	-1	0.02	0.60	5.10	1.9	-6.0
21-Sep-11	0	no change	21-Sep-11	0.1250	-1	0.00	0.60	5.30	2.1	-6.2
02-Nov-11	0	no change	02-Nov-11	0.1250	-1	0.05	0.60	3.90	1.5	-6.0
13-Dec-11	0	no change	13-Dec-11	0.1250	-1	0.03	0.60	4.30	1.1	-5.5
25-Jan-12	0	no change	25-Jan-12	0.1250	-1	0.03	0.70	3.30	1.5	-5.6
13-Mar-12	0	no change	13-Mar-12	0.1250	-1	0.06	0.70	3.40	1.8	-5.0
25-Apr-12	0	no change	25-Apr-12	0.1250	-1	0.05	0.70	3.50	1.8	-4.7
20-Jun-12	0	no change	20-Jun-12	0.1250	-1	0.01	0.70	2.80	1.7	-4.5
01-Aug-12	0	no change	01-Aug-12	0.1250	-1	0.03	0.80	3.80	1.6	-4.8
13-Sep-12	0	no change	13-Sep-12	0.1250	-1	0.03	0.80	4.30	1.3	-4.5
24-Oct-12	0	no change	24-Oct-12	0.1250	-1	0.03	0.90	4.30	1.4	-4.0

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
12-Dec-12	0	no change	12-Dec-12	0.1250	-1	0.01	0.90	2.60		1.2	-4.1
30-Jan-13	0	no change	30-Jan-13	0.1250	-1	0.02	0.90	3.70		1.6	-3.8
20-Mar-13	0	no change	20-Mar-13	0.1250	-1	-0.01	0.90	4.20		1.4	-3.7
01-May-13	0	no change	01-May-13	0.1250	-1	-0.02	1.00	2.20		1.4	-3.5
19-Jun-13	0	no change	19-Jun-13	0.1250	-1	0.02	1.00	2.10		0.8	-3.9
31-Jul-13	0	no change	31-Jul-13	0.1250	-1	0.02	1.00	4.30		1.5	-4.1
18-Sep-13	0	no change	18-Sep-13	0.1250	-1	0.05	0.90	4.20		1.5	-3.5
30-Oct-13	0	no change	30-Oct-13	0.1250	-1	0.03	1.00	3.30		1.4	-3.6
18-Dec-13	0	no change	18-Dec-13	0.1250	-1	0.05	1.00	2.80		1.1	-3.4
29-Jan-14	0	no change	29-Jan-14	0.1250	-1	0.04	1.00	4.18		1.7	-4.3
19-Mar-14	0	no change	19-Mar-14	0.1250	-1	0.05	0.91	3.47		1.5	-3.8
30-Apr-14	0	no change	30-Apr-14	0.1250	-1	0.01	0.95	4.43		1.5	-3.5
18-Jun-14	0	no change	18-Jun-14	0.1250	-1	0.01	1.00	4.73		1.5	-4.0
30-Jul-14	0	no change	30-Jul-14	0.1250	-1	0.02	0.89	4.75		1.5	-3.7
17-Sep-14	0	no change	17-Sep-14	0.1250	-1	0.03	1.09	4.68		1.8	-3.8
29-Oct-14	0	no change	29-Oct-14	0.1250	-1	0.02	1.02	4.92		1.9	-3.4
17-Dec-14	0	no change	17-Dec-14	0.1250	0	0.09	1.03	4.32		1.6	-3.3
28-Jan-15	0	no change	28-Jan-15	0.1250	0	0.06	1.09	4.68		1.7	-1.9
18-Mar-15	0	no change	18-Mar-15	0.1250	0	0.14	0.90	1.56		1.2	-1.6
29-Apr-15	0	no change	29-Apr-15	0.1250	0	0.11	0.93	1.09		1.4	-1.3
17-Jun-15	0	no change	17-Jun-15	0.1250	0	0.15	1.04	2.80		1.5	-2.1
29-Jul-15	0	no change	29-Jul-15	0.1250	0	0.18	1.17	3.39		1.5	-1.8
17-Sep-15	0	no change	17-Sep-15	0.1250	0	0.30	1.13	2.37		1.6	-3.2
28-Oct-15	0	no change	28-Oct-15	0.1250	0	0.14	1.21	1.65		1.6	-3.0
16-Dec-15	0.25	small hike	16-Dec-15	0.1250	0	0.54	1.17	2.88		1.5	-2.9
27-Jan-16	0	no change	27-Jan-16	0.3750	1	0.09	1.15	1.98		1.5	-1.6
16-Mar-16	0	no change	16-Mar-16	0.3750	1	0.34	1.18	3.06		1.4	-2.1
27-Apr-16	0	no change	27-Apr-16	0.3750	1	0.21	1.09	1.65		1.5	-1.9
16-Jun-16	0	no change	16-Jun-16	0.3750	1	0.19	1.17	4.02		1.6	-2.1
27-Jul-16	0	no change	27-Jul-16	0.3750	1	0.15	1.19	3.60		1.7	-1.9
21-Sep-16	0	no change	21-Sep-16	0.3750	1	0.21	1.14	4.16		1.6	-1.6
02-Nov-16	0	no change	02-Nov-16	0.3750	1	0.28	1.05	3.60		1.6	-1.5
14-Dec-16	0.25	small hike	14-Dec-16	0.3750	1	0.45	1.32	3.83		1.7	-1.4
01-Feb-17	0	no change	01-Feb-17	0.6250	1	0.20	1.23	3.91		1.8	-0.8

Table 14 (contd). Data used in estimations

Date of FOMC decision	Target change	Dependent variable y_t	Effective date of FOMC action		$pbias_{t-1}$	$spread_t$	$house_t$	gdp_t	$surprise_t$		
15-Mar-17	0.25	small hike	15-Mar-17	0.6250	1	0.39	1.29	2.79		1.8	-0.8
03-May-17	0	no change	03-May-17	0.8750	1	0.20	1.22	6.28		1.9	-0.6
14-Jun-17	0.25	small hike	14-Jun-17	0.8750	1	0.29	1.17	4.99		1.7	-0.5
26-Jul-17	0	no change	26-Jul-17	1.1250	1	0.07	1.22	4.14		1.9	-0.3
20-Sep-17	0	no change	20-Sep-17	1.1250	1	0.14	1.18	3.79		1.6	0.0
01-Nov-17	0	no change	01-Nov-17	1.1250	1	0.29	1.13	4.73		1.8	0.2
13-Dec-17	0.25	small hike	13-Dec-17	1.1250	1	0.52	1.29	4.67		1.6	0.4
31-Jan-18	0	no change	31-Jan-18	1.3750	1	0.41	1.19	6.02		1.7	0.6
21-Mar-18	0.25	small hike	21-Mar-18	1.3750	1	0.65	1.24	3.66		1.8	0.8
02-May-18	0	no change	02-May-18	1.6250	1	0.55	1.32	5.99		1.9	0.2
13-Jun-18	0.25	small hike	13-Jun-18	1.6250	1	0.61	1.35	6.40		2.0	0.1
01-Aug-18	0	no change	01-Aug-18	1.8750	1	0.52	1.17	6.30		2.1	0.3
26-Sep-18	0.25	small hike	26-Sep-18	1.8750	1	0.66	1.28	6.94		2.0	6.1
08-Nov-18	0	no change	08-Nov-18	2.1250	1	0.52	1.20	5.26		2.0	6.2
19-Dec-18	0.25	small hike	19-Dec-18	2.1250	1	0.46	1.26	5.28		2.0	6.3
30-Jan-19	0	no change	30-Jan-19	2.3750	0	0.20	1.26	5.11		2.1	0.8
20-Mar-19	0	no change	20-Mar-19	2.3750	0	0.11	1.23	2.58		2.0	0.5
01-May-19	0	no change	01-May-19	2.3750	0	-0.04	1.14	3.08		2.0	0.6
19-Jun-19	0	no change	19-Jun-19	2.3750	0	-0.35	1.27	3.83		1.7	0.8

Notes. For the definitions of the variables see Section 4. The reported original values of $surprise_t$ are multiplied by 10 in all estimations.

Table B2. Sample descriptive statistics

Variable	Mean	Median	Standard deviation	Minimum	Maximum	First-order autocorrelation coefficient
Δy_t	0.02	0.00	0.81	-0.50	0.50	0.43
$pbias_{t-1}$	-0.01	0.00	0.74	-1.00	1.00	0.68
$spread_t$	0.08	0.12	0.51	-1.48	1.71	0.75
$house_t$	1.52	1.49	0.25	0.95	2.15	0.97
gdp_t	4.96	4.90	1.72	-2.00	9.40	0.72
$target_t$	4.80	5.25	2.23	1.00	9.81	0.99
$target_t$	4.80	5.25	2.23	1.00	9.75	0.99
$infl_t$	2.88	2.70	1.22	0.70	7.00	0.88
gap_t	-0.41	-0.30	1.88	-4.50	3.20	0.98
$surprise_t$	-0.01	0.00	0.07	-0.36	0.15	0.15

Notes. Sample period: 7/1987–1/2006 (150 observations). For the definitions of the variables see Section 4. The original values of $surprise_t$ are multiplied by 10.

Table B3. Tests for unit roots

	The Augmented Dickey-Fuller (ADF) unit root tests					
Variable	Sample period (and size)	Data frequency	Deterministic terms*	Lag length	t-statistic	P-value**
Δy_t	12/1987-7/2019 (254 obs.)	FOMC decisions	C	3	-4.24	0.0007
$pbias_{t-1}$	9/1987-7/2019 (256 obs.)	FOMC decisions	C	1	-4.07	0.0013
$spread_t$	8/1987-7/2019 (257 obs.)	FOMC decisions	C	0	-5.85	0.0000
$house_t$	1/1959-1/2017 (680 obs.)	monthly	C, LT	16	-4.23	0.0043
gdp_t	8/1987-7/2019 (257 obs.)	FOMC decisions	C	0	-6.25	0.0000
$surprise_t$	8/1987-1/2014 (213 obs.)	FOMC decisions	C	0	-16.54	0.0000

Notes. * C - constant, LT - linear trend; ** MacKinnon (1996) one-sided p-values. For the definitions of the variables see Section 4. 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. The estimated scaled parameters from the second step of the CF Swopit model with controls for endogeneity

Variables	Regime equation	Output equations	
		Loose regime	Tight regime
$pbias_{t-1}$	2.00 (0.43)***		
$spread_t$	2.40 (0.73)***	1.75 (0.43)***	2.79 (1.21)*
$house_t$	8.45 (1.91)***		
gdp_t		0.65 (0.13)***	1.38 (0.53)**
$v_{s,t}$	-6.16 (2.64)*	-1.11 (0.29)***	-2.41 (1.06)*
$threshold_1$	13.22 (3.19)***	0.27 (0.48)	7.03 (2.88)*
$threshold_2$	15.18 (3.28)***	1.83 (0.55)***	12.13 (4.16)**

Notes. Sample period: 7/1987–1/2006 (150 observations). ***/**/* denote the statistical significance at the 0.1/1/5 percent level. The asymptotic standard errors are shown in parentheses. The explanatory variables are defined in Section 4.2. The dependent variable is defined in Section 4.1