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The Determinants of the Benchmark Interest Rates in China: A Discrete Choice Model Approach

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The Determinants of the Benchmark Interest Rates in China: A Discrete Choice Model Approach*

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Abstract

This paper empirically investigates the determinants of key benchmark interest rates in China using an array of constrained ordered probit models for quarterly frequency data from 1987 to 2013. Specifically, we estimate the behavioral equation of the People's Bank of China that models their decision-making process for revisions of the benchmark deposit rate and the lending rate. Our findings imply that the PBC's policy decisions are better understood as responses to changes in inflation and money growth, while output gaps and the exchange rate play negligible roles. We also implement in-sample fit analyses and out-of-sample forecast exercises. These tests show robust and reasonably good performances of our models in understanding dynamics of these benchmark interest rates.

Keywords: Monetary Policy; People's Bank of China; Ordered Probit Model; Deposit Rate; Lending Rate; In-Sample Fit; Out-of-Sample Forecast

JEL Classification: E52; E58

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1 Introduction

China is one of the fastest growing economies and has been considered as a new engine of world growth for many years. Naturally, when and to what extent the central bank in China, People's Bank of China (PBC), revises their target benchmark interest rates draw substantial attention of the public. In the present paper, we attempt to estimate the behavioral equation of the PBC as to the determination of the two benchmark interest rates in China: the deposit rate and the lending rate.

As is well documented, the PBC appears to have employed combinations of multiple policy instruments that include both the quantitative and interest rate instruments (Xie, 2004; Peng, Chen and Fan, 2006; Geiger, 2008; Zhang, 2009; Zhang and Liu, 2010; Xiong, 2012; Giardin, Lunven, and Ma, 2013; Sun, 2013). We are particularly interested in the PBC's benchmark interest rates among these instruments, because those interest rates have been always employed as policy instruments with no break since 1986 (Xiong, 2012). Also, as shown by He and Wang (2012), market interest rates in China have been heavily influenced by these benchmark rates.[1]

We recognize that the PBC will soon allow a transition of these benchmark interest rates to deregulated interest rates. However, it is likely for the PBC to employ another interest rate targets, such as the target federal funds rate in the US, in a market oriented economic system. Therefore, studying the decision making process for revisions of these rates would provide useful information on how the PBC will determine their monetary policy stance in the future.

One natural approach to study the PBC's interest rate setting behavior would be estimating a Taylor Rule type equation with an assumption that revisions of the target interest rate take place *continuously.* Since the work of Xie and Luo (2004) who employed the Taylor Rule to study China's monetary policy, Zhao and Gao (2004), Bian (2006), Wang and Zou (2006), and more recently, Fan, Yu, and Zhang (2011) also implemented similar linear Taylor rule models, while Zhang and Zhang (2008), Ouyang and Wang (2009), Chen and Zhou (2009), Zheng, Wang and Guo (2012), and Jawadi, Mallick, and Sousa (2014) used nonlinear models for China's monetary policy.

It should be noted, however, that the Monetary Policy Committee (MPC) under the PBC normally meets every quarter to make decisions on monetary policy stance. Furthermore, it turns

[1] In addition to these instruments, the importance of so-called window guidance has been also noted. See, among others, Chen, Chen, and Gerlack (2011).

out that the PBC revised their benchmark interest rates with a less than 30% frequency in 106 quarterly observations since 1987. Such a high degree inertia in dynamics of the policy interest rates may call for an alternative approach in studying the monetary policy decision-making process in China.

Since the seminal work of Dueker (1999), an array of researches has employed a discrete choice model framework to study the monetary policy stance of the Federal Reserve System. For example, Hamilton and Jordà (2002) used the autoregressive conditional hazard (ACH) model in combination with the ordered probit model. Hu and Phillips (2004a,b) extended the work of Park and Phillips (2000) to a nonstationary discrete choice model and studied the monetary policy decision-making process in Canada and in the US. Kim, Jackson, and Saba (2009) used Hu and Phillips' models to implement out-of-sample forecast exercises for the Fed's interest rate setting behavior. Using a similar discrete choice model, Monokroussos (2011) reported structural changes in the US monetary policy reaction function estimates around the pre- and the post Volcker eras. Also, Gerlach (2007) employed a discrete choice model framework to study policy actions of the European Central Bank (ECB), while Kim (2014) investigated interest rate setting behavior of the Bank of Korea.

There are quite a few papers that study the monetary policy stance decision-making process of the PBC using qualitative response models. He and Pauwels (2008) constructed a monetary policy stance index using multiple policy instruments. Then they studied how macroeconomic and financial variables explain realized policy actions that are measured by changes in this policy stance variable.[2] Constructing a refined policy stance index variable for a longer sample period, Xiong (2012) investigated the PBC's decision making process using a similar discrete choice model.[3]

Unlike these work, we take a direct approach to study dynamics of specific policy instruments instead of monetary policy index variables that are constructed by authors. Put it differently, we study policy decision-marking processes of the PCB in revising the benchmark interest rates that are actually *observable* to the public. Therefore, our analysis could provide practically more useful information to the market participants. In contrast to He and Pauwels (2008) and Xiong (2011), we employ a constrained ordered probit model that allows policy makers to revise the interest rate

[2] Instead of using all data series, they used multiple *latent* common factor components estimated from a big set of macroeconomic and financial variables via the method proposed by Bai and Ng (2004).

[3] He and Pauwels (2008) use the ordered probit model that allows covariates to be nonstationary (Hu and Phillips, 2004a,b), while Xiong (2012) employs the conventional discrete choice model where all covariates are stationary.

only when the on-going interest rate deviates sufficiently from a newly calculated optimal interest rate.

Using quarterly frequency data from 1987 to 2013, we estimate an array of our discrete choice models. Our findings highlight important and statistically significant roles of inflation and money growth rate in determination of the benchmark interest rates in China, while output gaps and the foreign exchange rate play negligible roles. In-sample fit analyses and out-of-sample forecast exercises demonstrate quite robust and reasonably good performances of our models.

The rest of the paper is organized as follows. Section 2 describes the econometric model employed in the present paper. In Section 3, we provide a data description and preliminary test results that present empirical justification of using discrete choice models. Section 4 reports our probit model estimation results and in-sample fit analyses. In Section 5, we discuss our out-of-sample forecast exercise results. Section 6 concludes.

2 The Econometric Model

The People's Bank of China (PBC) is assumed to set an optimal interest rate (i_t^*), a latent variable, based on observed exogenous macroeconomic variables ($\mathbf{x}_t$) at time t. We model this by the following linear equation.

$$i_t^* = \mathbf{x}_t' \beta - \varepsilon_t, \tag{1}$$

where β is a $k \times 1$ vector of coefficient and ε_t denotes a scalar error term.

We assume that the PBC revises the benchmark interest rate (i_t) only when the newly calculated optimal interest rate i_t^* in (1) deviates sufficiently from the prevailing interest rate from the previous period (i_{t-1}). It is convenient to define the following deviation variable between i_t^* and i_{t-1}.

$$y_t^* = i_t^* - i_{t-1}, \tag{2}$$

where y_t^* is also a latent variable. Note that the greater y_t^* is (in absolute value), the stronger the incentive to revise i_t would be. This framework has been first employed by Dueker (1999), then by Hu and Phillips (2004a, 2004b) and Kim *et al.* (2009), while He and Pauwels (2008) and Xiong

(2012) use ordered probit models with no such concern. Xiong employed a lagged policy stance variable instead, however, he reported negligible and insignificant coefficient estimates.

We employ a trichotomous discrete choice model. That is, we assume that the PBC chooses one of the following three policy actions: cut the interest rate (C), let it stay where it is (S), or raise the interest rate (H), which implies a three-regime model that requires two threshold variables, τ_L and τ_U. When y_t^* is less than the lower threshold (τ_L), it would indicate that the PBC should cut the interest rate ($y_t = -1$). A difference greater than the upper threshold (τ_U) would require an interest rate hike ($y_t = 1$), and any minor deviation between τ_L and τ_U, an *inaction* band, would indicate that the PBC will choose S ($y_t = 0$). Formally,

$$y_t = \begin{cases} -1, & \text{if} \quad y_t^* < \tau_L \qquad : C \\ 0, & \text{if} \quad \tau_L \leq y_t^* \leq \tau_U \quad : S \\ 1, & \text{if} \quad y_t^* > \tau_U \qquad : H \end{cases} \tag{3}$$

and

$$I_{j,t} = \begin{cases} \frac{y_t(y_t-1)}{2}, & \text{if} \quad j = C \\ 1 - y_t^2, & \text{if} \quad j = S \\ \frac{y_t(y_t+1)}{2}, & \text{if} \quad j = H \end{cases} \tag{4}$$

where $I_{j,t}$ is the indicator function for each of the realized policy index variables (y_t).

The log likelihood function for a random sample of size T, $\{y_t\}_{t=1}^T$, is the following.

$$\mathcal{L} = \sum_{t=1}^{T} \left(I_{c,t} \ln P_c \left(\mathbf{x}_t : \theta \right) + I_{s,t} \ln P_s \left(\mathbf{x}_t : \theta \right) + I_{h,t} \ln P_h \left(\mathbf{x}_t : \theta \right) \right) \tag{5}$$

where θ is the parameter vector (β, τ). The probability function P_j is defined as follows.

$$P_j = \begin{cases} 1 - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right), & \text{if} \quad j = C \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right) - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = S \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = H \end{cases} \tag{6}$$

We assume that $F(\cdot)$ is the standard normal (or logistic) distribution function, that is, we employ the constrained trichotomous ordered probit (or logit) model where the coefficient on i_{t-1} is restricted to be -1.

3 Data and Preliminary Analysis

3.1 Data Description

We use quarterly frequency observations that span from 1987:I to 2013:IV. As Xiong (2012) pointed out, the PBC has been using a set of policy instruments that includes its refinancing to banks, benchmark interest rates, and the required reserve ratio. We focus on the determination of the two benchmark interest rates in China, the lending rate and the deposit rate, which have been continuously employed by the PBC for key instruments since 1986.[4]

We plot these interest rates in the first panel of Figure1. It should be noted that these interest rates are infrequently revised. Among 106 quarterly observations, there were 14 cuts and 14 hikes for the benchmark deposit rate (second panel), while 15 cuts and 16 hikes were observed for the lending rate (third panel). That is, the PBC chose "stay" decisions with a little over 70% frequency, which implies that the PBC revises the rates only when the differential between its perceived optimal interest rate and the prevailing rate becomes greater than certain threshold values. The ordered probit model described earlier thus seems to be appropriate to estimate such decision-making processes. Corresponding trichotomous discrete choice variables ($y_t = -1,\ 0,\ 1$) are reported in the last two panels.

We also note that these interest rates exhibit highly persistent dynamics. In response to the Asian financial crisis in 1997:IV, the deposit rate declined from 7.47% to 5.67% and the lending rate went down from 10.08% to 8.64%. The rates continued to decrease for about 8 years, then started to increase from 2004:IV until the beginning of the recent financial crisis in 2008. In what follows, we show that linear models such as the Taylor rule, which often rely on the ordinary least squares (OLS) estimator, may not be appropriate to study the interest rate setting behavior of the PBC under such circumstances, because the OLS estimator may not perform well in the presence of highly persistent (possibly nonstationary) data.

[4] The benchmark lending rate gives the commercial banks a certain degree flexibility in setting their interest rates based on their credit assessment of their customers. The deposit interest rate is the rate paid by commercial or similar banks for demand, time, or savings deposits.

Figure 1 around here

Inflation (π_t) is the quarterly log difference of the All Items Consumer Price Index (CPI). For the output gap ($\tilde{y}_t$), we consider the following two measures: the quadratically detrended real industrial production index ($\tilde{y}_t^Q$) and the Hodrick-Prescott (HP) filtered cyclical component of the real industrial production index ($\tilde{y}_t^H$) setting the smoothing parameter at 1,600 for quarterly data. Money growth rate (Δm_t) is the quarterly log difference of the M1. The appreciation rate of Chinese Yuan (Δs_t) is the quarterly log difference of the nominal effective exchange index. All interest rates are divided by 4 to make them conformable to these quarterly growth rates. The CPI data is from the Organization for Economic Cooperation and Development (OECD), and real industrial production index is from the Economist Intelligence Unit (EIU) and the National Bureau of Statistics in China. All other data are obtained from the International Financial Statistics (IFS). We report graphs of these macroeconomic covariates in Figure 2.

Figure 2 around here

3.2 Unit Root Tests

We implement the Augmented Dickey-Fuller (ADF) test for all variables used in the study. Results are reported in Table 1.

The test fails to reject the null of nonstationarity for the primary lending rate and the deposit rate even at the 10% significance level, which seems to be consistent with their highly persistent movements shown in Figure 1. Note that the OLS estimator is not appropriate when some variables in regression equations are nonstationary. The ordered probit model employed in this paper, however, can avoid such problems, since the trichotomous policy index variable $y_t = \{-1,\ 0,\ 1\}$ is used instead of potentially nonstationary interest rates.

It should be also noted that the MLE estimation for the ordered probit/logit model may yield wrong standard errors if covariates are nonstationary. The procedure proposed by Hu and Phillips (2004a,b) applies in such cases. Since the ADF test strongly rejects the null of nonstationarity for all covariates irrespective of the specification of deterministic components, we employ the conventional MLE instead of Hu and Phillips' method.

Table 1 around here

3.3 Linear Taylor Rule Model Estimations

For comparison, we first implement estimations for an array of Taylor rules using the OLS method as follows.

$$i_t = \alpha + \gamma_\pi \pi_{t-1} + \gamma_y \tilde{y}_{t-1} + \Theta x_{t-1} + \varepsilon_t \tag{7}$$

where x_{t-1} is either a scalar or a vector of additional explanatory variables. γ_π and γ_y denote the long-run coefficients that provide information on how the central bank responds to innovations in inflation and the output gap, respectively. Following Xiong (2012), we assume that policy makers can access information on the macroeconomic covariate variables with one quarter lag. We also implement estimations for Taylor rules with the interest rate smoothing consideration (see Clarida, Galí, and Gertler, 2000, for example).

$$i_t = \alpha + \gamma_\pi^s \pi_{t-1} + \gamma_y^s \tilde{y}_{t-1} + \Theta_s x_{t-1} + \rho i_{t-1} + \varepsilon_t \tag{8}$$

Note that the short-run coefficients γ_π^s and γ_y^s and the smoothing parameter ρ in (8) jointly imply that the long-run effects on the interest rate are $\gamma_\pi^s/(1-\rho)$ and $\gamma_y^s/(1-\rho)$, which correspond to γ_π and γ_y in (7), respectively.

All estimation results for (7) and (8) are reported in Table 2 for the lending rate and in Table 3 for the deposit rate. We note that the coefficient on inflation is always significant at the 1% level, while that of the output gap is mostly insignificant. All other explanatory variables are insignificant as well. Further, $\tilde{y}_{t-1}$ and Δs_{t-1} often have incorrect signs.[5]

We also note that these estimates violate the Taylor principle ($\gamma_\pi > 1$) no matter what specifications are used. For example, the implied long-run inflation coefficient is about 0.40 and 0.60

[5]Depreciations (decreases in Δs_{t-1}) tend to make inflationary pressure build up, which implies a negative coefficient on Δs_{t-1}.

for the lending rate and the deposit rate, respectively. It should be also noted that the degree of interest rate inertia measured by ρ in (8) is close to one. If the interest rate obeys a nonstationary stochastic process, as is implied by the ADF test in the previous section, the OLS estimates presented in Tables 2 and 3 might not be appropriate. The probit model, however, does not have such a problem since we use the policy index variable which assumes discrete numbers.

Tables 2 and 3 around here

4 Probit Model Estimation and In-Sample Fit Analysis

This section reports our findings based on the probit model estimations described in Section 2. Our benchmark model (Model 1) is motivated by the Taylor Rule with an assumption that the policy-makers observe inflation and the output gap with one period lag. Extended models with additional covariates are also considered. That is, Models 2 and 3 include Δm_{t-1} and Δs_{t-1}, respectively, in addition to the Taylor Rule variables π_{t-1} and $\tilde{y}_{t-1}$. Model 4 is the full model that includes all key macroeconomics covariates. Results are provided in Table 4 and 5.

Major findings are roughly tri-fold. First, all threshold estimates are highly significant at any conventional levels, which imply that the PBC revises the benchmark lending and deposit rates only when there is a substantial deviation of the current rate from the optimal rate. Second, the coefficient estimate on inflation is always significant, while the output gap coefficient estimates are all insignificant. Third, Models 2 and 4 estimations show that money growth coefficient is significant at least at the 10% level, while the yuan appreciation rate (Δs_{t-1}) coefficient estimates are always insignificant.

These results suggest inflation and money growth rate play important roles in the PBC's interest rates decision-making process, which is consistent with findings by He and Pauwels (2008) and Xiong (2012) who also reported an important role of inflation in understanding the monetary policy stance in China.[6]

[6]Shu and Ng (2010) use a narrative approach by compiling indices of the PBC's policy stance on the basis of meeting notes and the policy statements. They also find that the money growth rate and inflation are key determinants of the monetary policy in China.

Tables 4 and 5 around here

We implement a robustness check analysis to see how stable these coefficient estimates are over our sample period. For this purpose, we repeatedly estimate our model beginning with the first half observations (1987:II to 2000:III) by adding one additional observation for each round of estimations, which gives 52 sets of coefficient estimates for each model. We report results in Figure 3 for the lending rate and in Figure 4 for the deposit rate, which confirms the robustness of our full-sample estimates. The inflation coefficient estimates are significant at the 5% level and the money growth rate coefficient estimates are mostly significant at the 10% level. The output gap coefficient estimates are negligible and always statistically insignificant.

Figures 3 and 4 around here

Next, we evaluate our ordered probit models for the PBC's decision-making process in terms of the in-sample fit performance analysis. For this purpose, we report correct prediction rates of our models in Tables 6 and 7. For the benchmark lending rate, Model 1 predicted 5 C decisions correctly out of 15 actual cut decisions, resulting in a 33% success rate. The model correctly predicted 85% of S decisions, while its prediction success rate for H decisions was 13%. Combining all results, Model 1's overall performance was 66%. Models 2, 3, and 4 performed similarly. The in-sample-fit performances for the deposit rate are also similar to those of the lending rate.

Tables 6 and 7 around here

It should be noted that the overall success rate is heavily influenced by high success rates for S decisions, which is about 70.75% for the lending rate and 73.58% for the deposit rate. On the other hand, we have very low success rates for C and H decisions that occur infrequently. Note that these results are obtained when predictions are formulated solely based on the point estimates. Given the uncertainty around the point estimates, one has to be more careful about making reliable statistical inferences. For this purpose, we calculate the probability of each policy intervention for all observation points using the estimated coefficients in Model 2. In Figures 5 and 6, the estimated probabilities are illustrated with actual decisions (bar graphs) over the full sample period. These figures show that our models explain changes in the probabilities fairly well. The probability of each event tends to rise rapidly when corresponding actions take place. For instance, the probability of a C goes up rapidly during the Asian financial crisis around in 1998. Also, the estimated probability of an H climbs up fast around 2007 and 2011 when the PBC raised the interest rates several times.

As to mismatches between the predicted possibilities and the actual decisions in these figures, we might rely on the following institutional features of the monetary decision-making process in China. Although the PBC might propose that it was time to take certain policy actions based on macroeconomic or financial market signals, the State Council might not be in a position to dispose in a timely manner because it makes decisions based on consensus. In other words, other ministries (e.g. the National Development and Reform Commission, the Ministry of Commerce, and the Ministry of Finance) will need to be on board with the proposed change in monetary policy stance before the State Council makes a decision. Therefore, there might be some time lags between PBC's proposals and the State Council's disposal.

Figures 5 and 6 around here

Recall that the our models predict C and H decisions less successfully when we use the point estimates for τ_L and τ_U. Recognizing the uncertainty around these point estimates for thresholds, we re-evaluate the in-sample performance of our models as follows. In Figure 7, we plot the estimated latent variable y_t^* from Models 2 for the lending rate and deposit rate along with the estimates for τ_L and τ_U and their 95% confidence bands. Obviously, a more compact inaction band such as $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$ will yield more C and H predictions with a cost of lower success rates for S decisions. With such a strategy, overall in-sample fit performance declines because of substantial decreases in the success rate for S decisions (see Tables 8 and 9). However, we observe significantly higher success rates for other decision choices.

Figure 7 around here

Tables 8 and 9 around here

5 Out-of-Sample Forecasting

This section evaluates the out-of-sample predictability of our ordered probit models for the interest rate setting behavior in China. Predicting the PBC's revision decisions on these rates provides crucially useful information not only to financial market participants but also entrepreneurs who make important investment decisions.

We first implement our exercises by a recursive method with the first half of the observations as the split point. The recursive forecasting approach begins with a memory window of 2000:III from the beginning point. That is, we start calculating one-period ahead forecast on the policy variable (C, S, and H) using first 53 observations. Then adding the 54th observation, we re-estimate and formulate the forecast of the next policy outcome with this expanded set of observations. We continue to do this until we forecast the last policy action in 2013:III using the full sample data from 1987:I to 2013:II.

As is well-known, the recursive forecasting strategy may not perform well if there are structural changes in the underlying data generating process. Put it differently, if regime changes occur some time during the early period of analysis, then including earlier data in the estimation could reduce the forecastability of our model. To address this possibility, we also employ a fixed rolling window approach described as follows.

Here we begin with the same initial 53 observations. After estimating and predicting the first policy action, we add the 54th observation, but drop the 1st observation, thereby retaining an updated 53-observation estimation window, which is used to produce the next policy outcome. We repeat this procedure until we forecast the last policy outcome variable using the last sample set of 53 observations.

We report calculated out-of-sample probabilities of cuts and hikes in Figures 8 and 9, for the lending rate and the deposit rate, respectively. Realized C and H policies are also reported in bar graph.

We note that the rolling window method performs better than the recursive method in our experiment. The probability of a cut increases faster with the rolling window scheme. Similarly, the probability of a hike rises rapidly reaching almost 100% with the rolling window, while the highest probability with the recursive method was below 50%. We observed similar out-of-sample forecast performances for the deposit rate. These findings suggest that some changes, either gradual or abrupt, have occurred to the PBC's interest rate setting behavior. In Figures 3 and 4, we noted that inflation and money growth coefficients decreased steadily, which might have been caused by relatively moderate movements of macroeconomic variables including inflation (see Figure 2). Also, as we can see in Figure 1, revisions to the benchmark interest rates have been quite modest in absolute sizes compared with earlier adjustments. All these observations imply that the PBC is moving toward the direction of fine-tuning the interest rate.

Figures 8 and 9 around here

6 Concluding Remarks

This paper estimates the response function of the PBC to changes in macroeconomic variables as to revisions of their benchmark interest rates: the deposit rate and the lending rate. We employ an array of constrained ordered probit models for quarterly frequency data from 1987 to 2013, because the conventional least squares estimator for Taylor rule type models seems inappropriate given inertial movements of these policy interest rates. Our preliminary analysis also justifies the use of qualitative response models.

We find that the PBC's interest rate setting behavior could be well-explained by discrete responses to changes in inflation and in money growth rate. Output gaps and the yuan appreciation rate seem to play negligible and insignificant roles in determining revision decisions on these benchmark interest rates. We evaluated our models using an in-sample fit criteria, which demonstrated fairly good performances. We also implemented out-of-sample prediction exercises, employing both the recursive and the fixed rolling window schemes with initial 50% observations as a split point. Our model performed fairly well especially when the fixed rolling window method is used.

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Table 1. Augmented Dickey-Fuller Test Results

	ADF_c	ADF_t
i_t^L	-1.308	-2.721
i_t^D	-1.162	-1.974
π_t	$-3.845^{\ddagger}$	$-4.170^{\ddagger}$
$\tilde{y}_t^Q$	$-3.366^{\dagger}$	-3.363^{*}
$\tilde{y}_t^H$	$-4.313^{\ddagger}$	$-4.305^{\ddagger}$
Δm_t	$-4.149^{\ddagger}$	$-4.459^{\ddagger}$
Δs_t	$-9.404^{\ddagger}$	$-9.594^{\ddagger}$

Note: ADF_c and ADF_t denote the augmented Dickey-Fuller unit root test statistics when an intercept is included and when both an intercept and time trend are present, respectively. We select the number of lags by the general-to-specific rule with a maximum 12 lags and the 10% significance level. *, †, and ‡ denote rejections of the unit root null hypothesis at the 10%, 5%, and 1% significance level, respectively.

Table 2. Linear Taylor Rule Coefficient Estimations: Lending Rates

	Long-Run Coefficients			
π_{t-1}	0.166(0.024)	0.165(0.025)	0.171(0.027)	0.171(0.028)
$\tilde{y}_{t-1}$	−0.004(0.026)	−0.003(0.027)	−0.008(0.028)	−0.008(0.029)
Δm_{t-1}	*n.a.*	0.002(0.016)	*n.a.*	0.002(0.016)
Δs_{t-1}	*n.a.*	*n.a.*	0.004(0.009)	0.004(0.009)
	Short-Run Coefficients with Interest Rate Smoothing			
π_{t-1}	0.037(0.007)	0.036(0.007)	−0.038(0.008)	−0.037(0.008)
$\tilde{y}_{t-1}$	−0.002(0.007)	−0.001(0.007)	−0.003(0.007)	−0.002(0.007)
Δm_{t-1}	*n.a.*	0.001(0.004)	*n.a.*	0.001(0.004)
Δs_{t-1}	*n.a.*	*n.a.*	0.001(0.002)	0.001(0.002)
i_{t-1}	0.904(0.023)	0.903(0.023)	0.903(0.023)	0.903(0.023)

Note: Standard errors are in parenthesis. Output gap is the HP cyclical component. Using the quadratically detrended gap yields qualitatively similar results. All results are available upon request.

Table 3. Linear Taylor Rule Coefficient Estimations: Deposit Rates

	Long-Run Coefficients			
π_{t-1}	0.268(0.033)	0.264(0.043)	0.265(0.035)	0.262(0.036)
$\tilde{y}_{t-1}$	0.009(0.018)	0.011(0.018)	0.001(0.018)	0.011(0.019)
Δm_{t-1}	*n.a.*	0.015(0.023)	*n.a.*	0.015(0.023)
Δs_{t-1}	*n.a.*	*n.a.*	−0.002(0.013)	−0.002(0.013)
	Short-Run Coefficients with Interest Rate Smoothing			
π_{t-1}	0.046(0.008)	0.045(0.008)	0.049(0.009)	0.048(0.009)
$\tilde{y}_{t-1}$	−0.004(0.004)	−0.004(0.004)	−0.006(0.004)	−0.005(0.004)
Δm_{t-1}	*n.a.*	0.007(0.005)	*n.a.*	0.008(0.005)
Δs_{t-1}	*n.a.*	*n.a.*	0.004(0.003)	0.004(0.003)
i_{t-1}	0.923(0.020)	0.922(0.019)	0.924(0.019)	0.923(0.019)

Note: Standard errors are in parenthesis. Output gap is the HP cyclical component. Using the quadratically detrended gap yields qualitatively similar results. All results are available upon request.

Table 4. Probit Model Estimations: Lending Rates

	Model 1	*Model 2*	*Model 3*	*Model 4*
π_{t-1}	0.289(0.077)	0.263(0.073)	0.290(0.090)	0.262(0.084)
$\tilde{y}_{t-1}$	-0.006(0.060)	0.023(0.059)	-0.006(0.071)	0.024(0.066)
Δm_{t-1}	*n.a.*	0.063(0.034)	*n.a.*	0.063(0.034)
Δs_{t-1}	*n.a.*	*n.a.*	0.000(0.029)	-0.001(0.027)
τ_L	-0.793(0.145)	-0.843(0.144)	-0.793(0.145)	-0.844(0.144)
τ_U	0.757(0.124)	0.797(0.139)	0.757(0.124)	0.797(0.139)

Note: Standard errors are in parenthesis. Output gap is the HP cyclical component. Using the quadratically detrended gap yields qualitatively similar results. All results are available upon request.

Table 5. Probit Model Estimations: Deposit Rates

	Model 1	*Model 2*	*Model 3*	*Model 4*
π_{t-1}	0.442(0.103)	0.399(0.096)	0.462(0.126)	0.418(0.118)
$\tilde{y}_{t-1}$	-0.003(0.083)	0.049(0.086)	-0.022(0.087)	0.031(0.095)
Δm_{t-1}	*n.a.*	0.113(0.055)	*n.a.*	0.113(0.055)
Δs_{t-1}	*n.a.*	*n.a.*	0.015(0.034)	0.016(0.032)
τ_L	-1.206(0.207)	-1.321(0.229)	-1.207(0.212)	-1.320(0.232)
τ_U	1.208(0.184)	1.311(0.230)	1.207(0.186)	1.308(0.230)

Note: Standard errors are in parenthesis. Output gap is the HP cyclical component. Using the quadratically detrended gap yields qualitatively similar results. All results are available upon request.

Table 6. In-sample Fit evaluations Base on Point Estimates: Lending Rate

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	5	6	0	4	4	0
Stay predicted	10	63	14	11	67	13
Hike predicted	0	5	2	0	4	3
Correct Prediction (%)	33%	85%	13%	27%	89%	19%
Overall Performance (%)		66%			70%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	5	6	0	5	6	0
Stay predicted	10	63	14	10	63	14
Hike predicted	0	5	2	0	5	2
Correct Prediction (%)	33%	85%	13%	33%	85%	13%
Overall Performance (%)		66%			66%	

Note: In-sample fit results are based on the point estimates for the latent equation coefficients and the threshold values.

Table 7. In-sample Fit evaluations Base on Point Estimates: Deposit Rate

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	3	3	0	3	3	0
Stay predicted	11	71	12	11	71	12
Hike predicted	0	3	2	0	3	2
Correct Prediction (%)	21%	92%	14%	21%	92%	14%
Overall Performance (%)		72%			72%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	3	3	0	3	2	0
Stay predicted	11	71	12	11	73	12
Hike predicted	0	3	2	0	2	2
Correct Prediction (%)	21%	92%	14%	21%	95%	14%
Overall Performance (%)		72%			74%	

Note: In-sample fit results are based on the point estimates for the latent equation coefficients and the threshold values.

Table 8. In-sample Fit evaluations with Point Estimates and Standard Errors: Lending Rate

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	6	8	0	6	9	0
Stay predicted	9	61	13	9	60	12
Hike predicted	0	5	3	0	5	4
Correct Prediction (%)	40%	82%	19%	40%	81%	25%
Overall Performance (%)		67%			67%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	6	8	0	6	9	0
Stay predicted	9	61	13	9	60	12
Hike predicted	0	5	3	0	5	4
Correct Prediction (%)	40%	82%	19%	40%	81%	25%
Overall Performance (%)		67%			67%	

Note: In-sample fit evaluations are based on the point estimates for the latent equation coefficients and the threshold values adjusted by their standard errors. The inaction band for this table is $[\tau_L + std(\tau_L), \tau_L - std(\tau_L)]$.

Table 9. In-sample Fit evaluations with Point Estimates and Standard Errors: Deposit Rate

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	4	5	0	5	7	0
Stay predicted	10	67	12	9	66	10
Hike predicted	0	5	2	0	4	4
Correct Prediction (%)	29%	87%	14%	36%	86%	29%
Overall Performance (%)		70%			71%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	5	6	0	5	8	0
Stay predicted	9	66	12	9	65	10
Hike predicted	0	5	2	0	4	4
Correct Prediction (%)	36%	86%	14%	36%	84%	29%
Overall Performance (%)		70%			70%	

Note: In-sample fit evaluations are based on the point estimates for the latent equation coefficients and the threshold values adjusted by their standard errors. The inaction band for this table is $[\tau_L + std(\tau_L), \tau_L - std(\tau_L)]$.

Figure 1. Interest Rates and Policy Actions

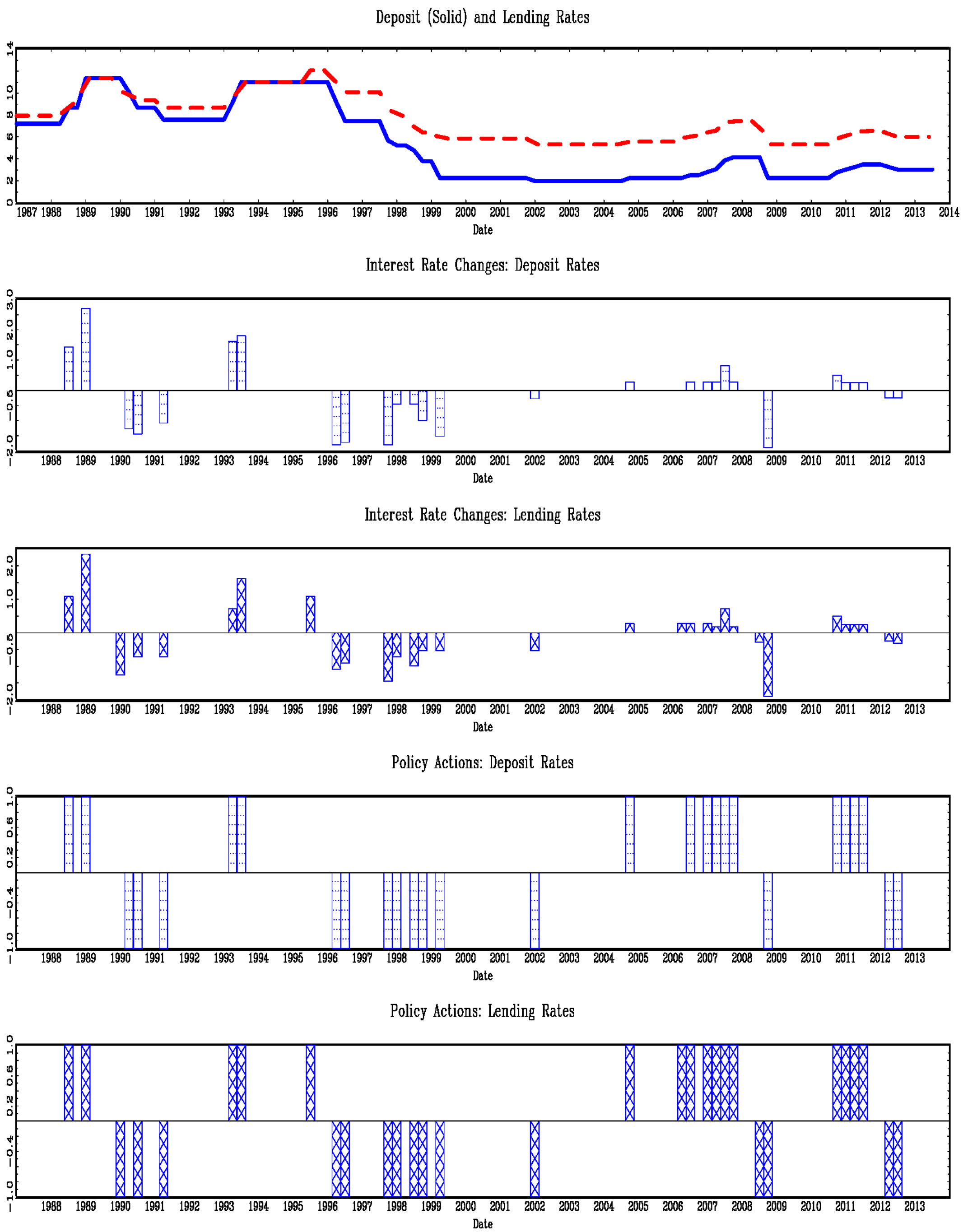
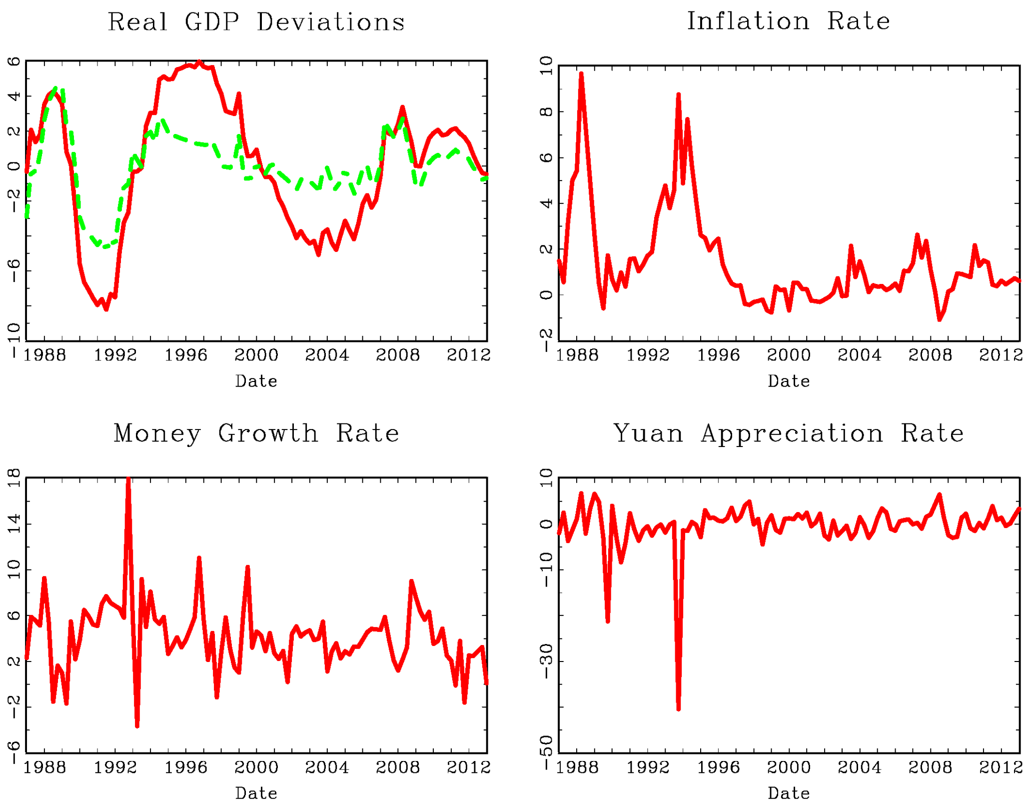
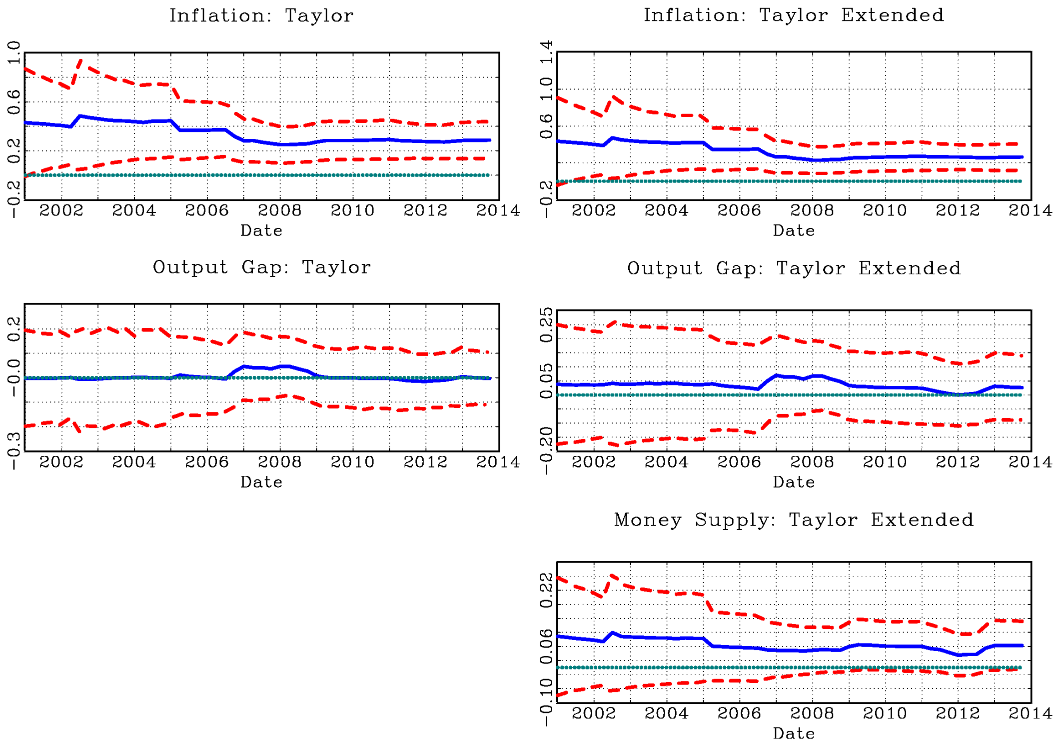


Figure 2. Key Macroeconomic Covariates



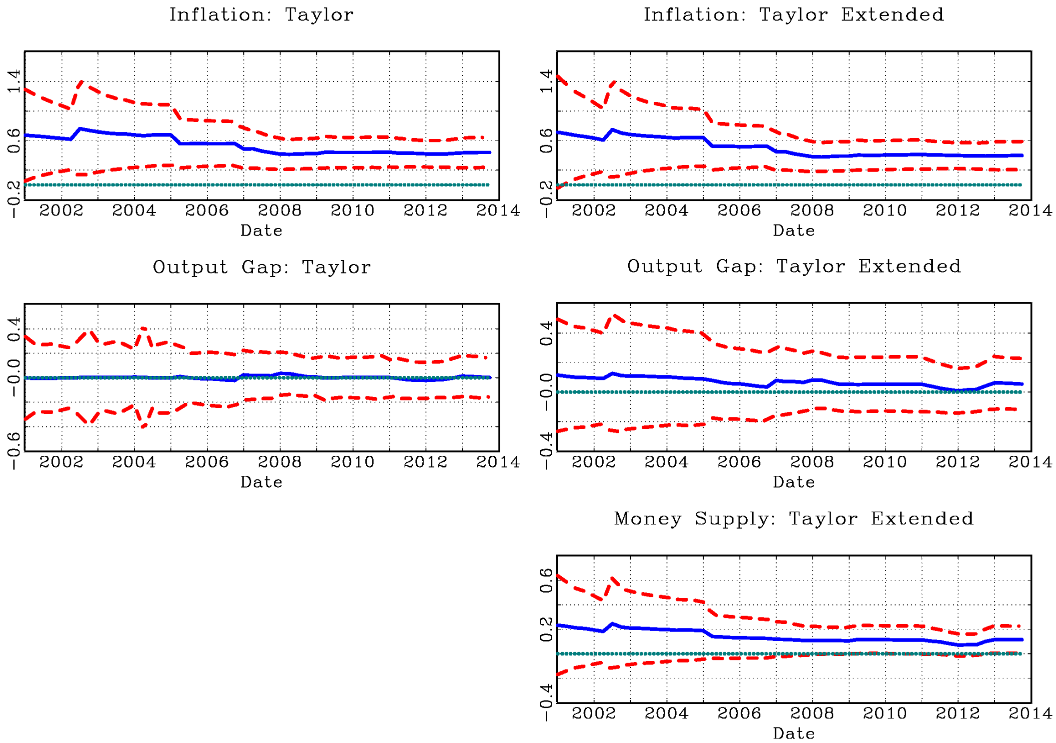
Note: We use two measures of the output gap: quadratically detrended real industrial production (solid) and the cyclical component of real industrial production(dashed) by the Hodrick-Prescott filter. Two detrending methods produce similar output gaps. Inflation is the quarterly change in the log CPI. The money growth rate denotes the quarterly change in the log M1. The yuan appreciation rate is the quarterly change in the log nominal effective exchange rate, which is a trade weighted average of the nominal exchange rates of renminbi relative to a set of foreign currencies.

Figure 3. Constancy of the Latent Coefficient Estimates: Lending Rate



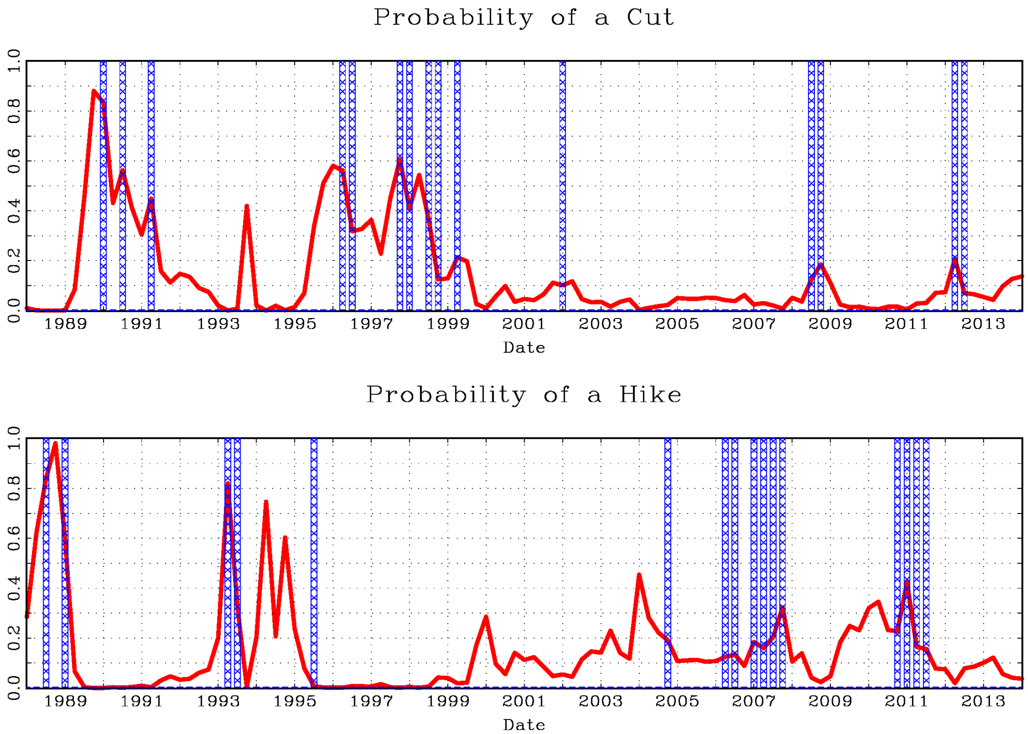
Note: We recursively estimate the latent equation coefficients repeatedly beginning with the initial half of the sample period, 1987:I to 2000:II, adding one more observation in each round of estimations. Dashed lines are corresponding 95% confidence bands.

Figure 4. Constancy of the Latent Coefficient Estimates: Deposit Rate



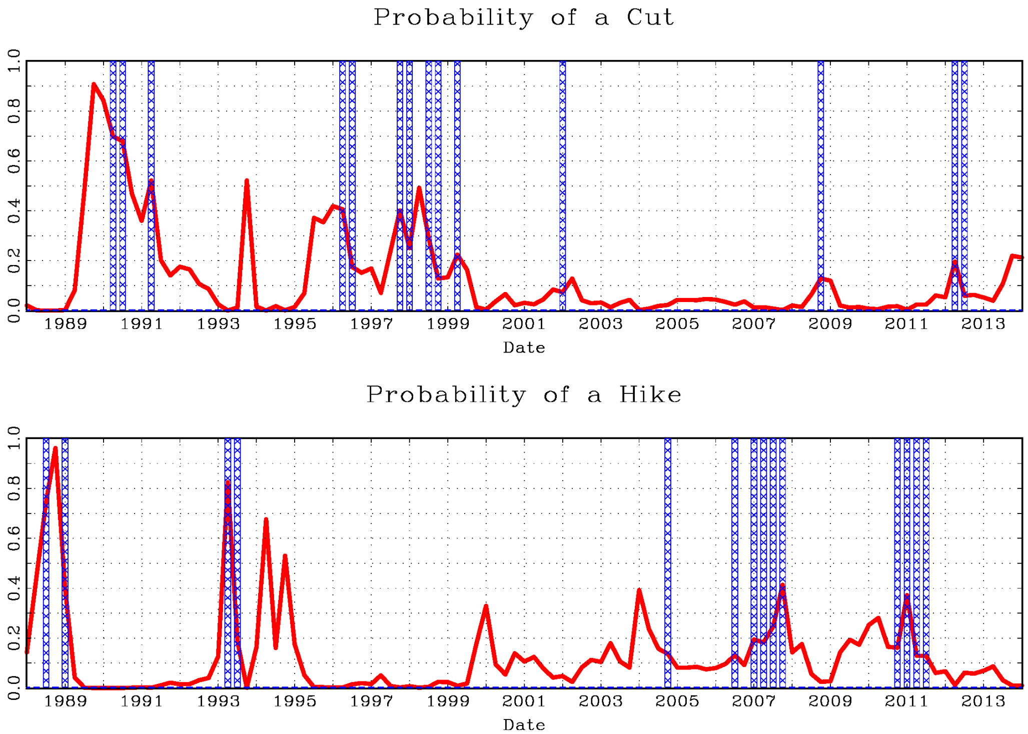
Note: We recursively estimate the latent equation coefficients repeatedly beginning with the initial half of the sample period, 1987:I to 2000:II, adding one more observation in each round of estimations. Dashed lines are corresponding 95% confidence bands.

Figure 5. In-Sample Fit Performance of Probit Models: Lending Rate



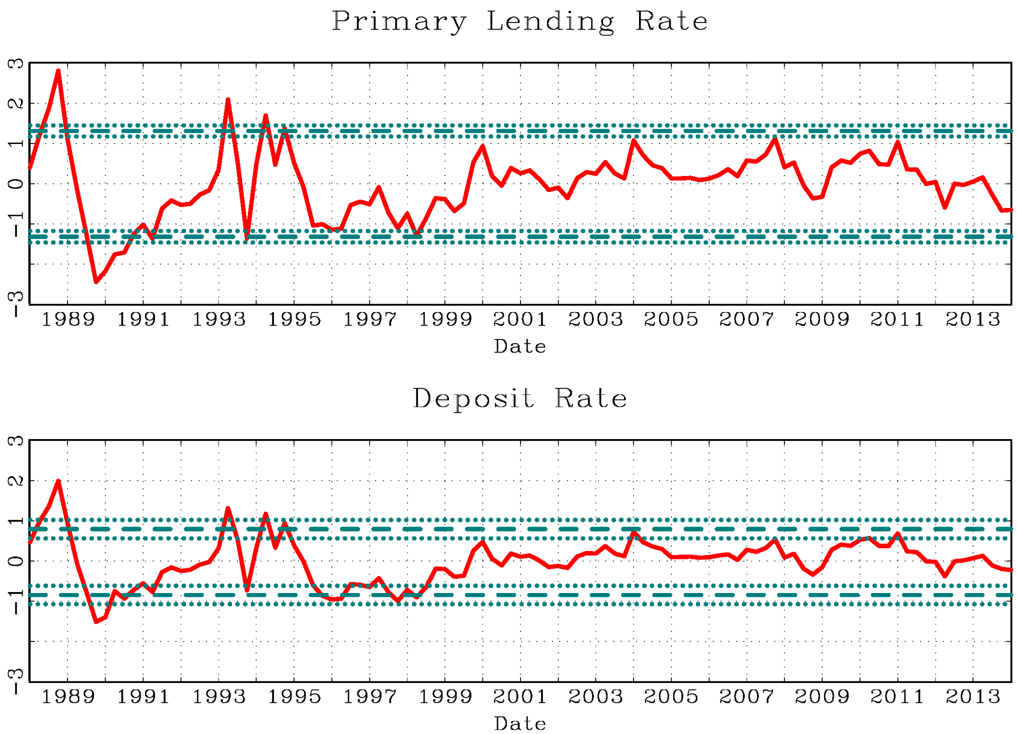
Note: We calculate estimated in-sample probabilities for each policy action from the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized policy actions.

Figure 6. In-Sample Fit Performance of Probit Models: Deposit Rate



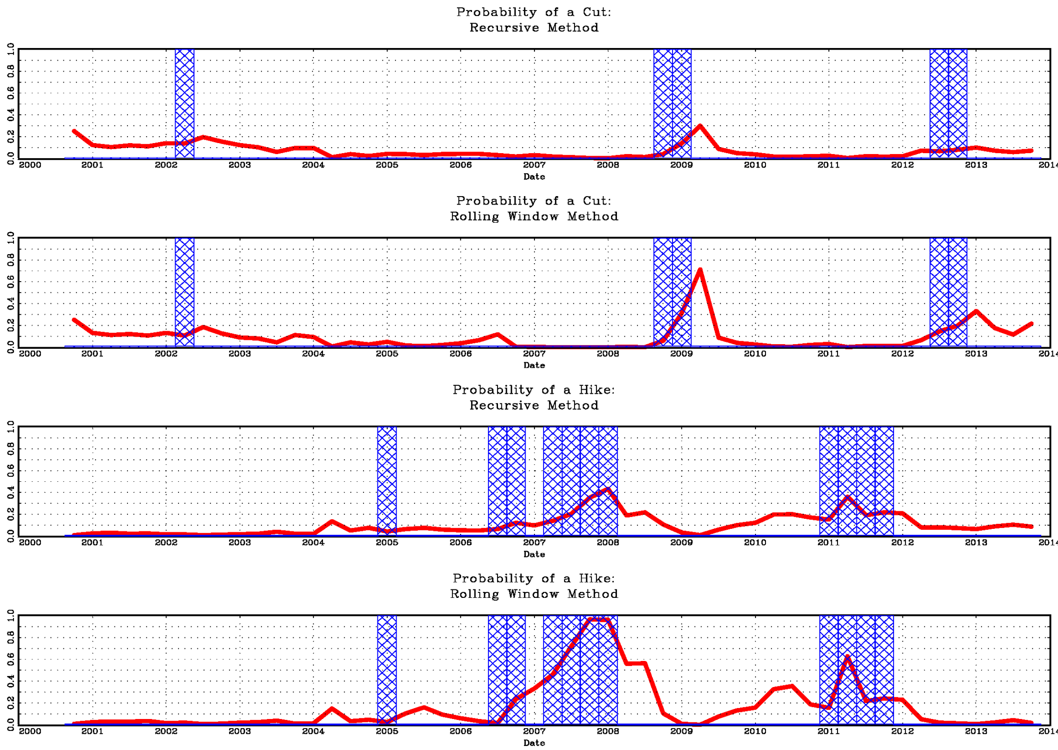
Note: We calculate estimated in-sample probabilities for each policy action from the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized policy actions.

Figure 7. Deviations from the Optimal Rate and Thresholds: Lending Rate



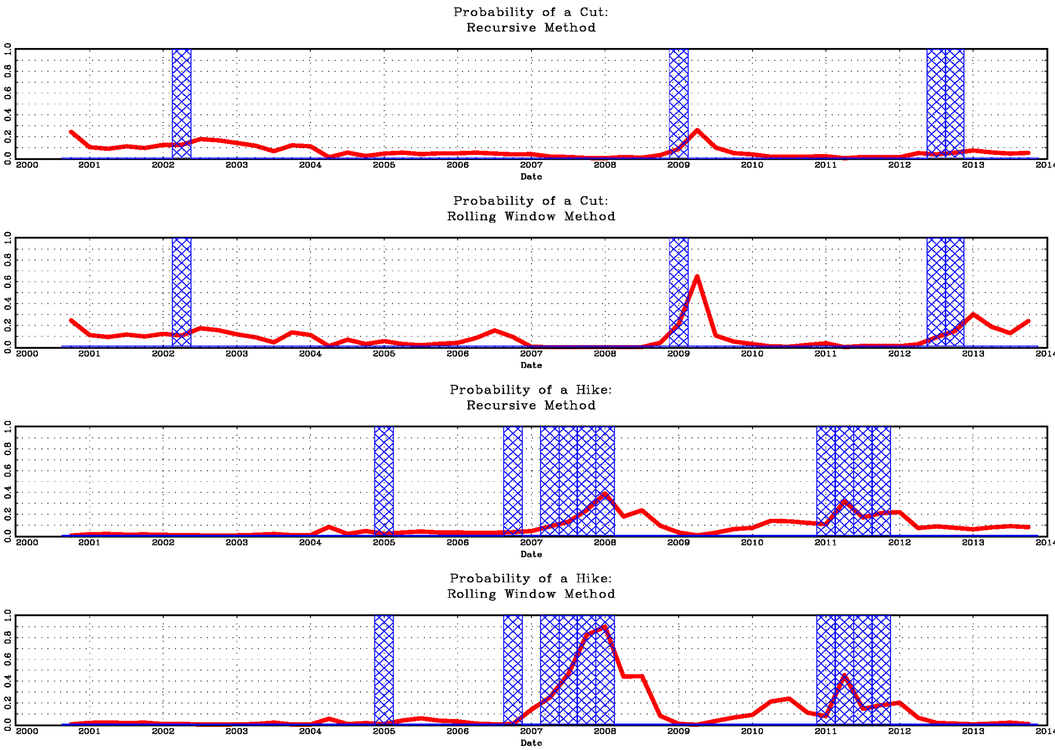
Note: We calculate deviations from the optimal interest rate ($y_t^* = i_t^* - i_{t-1}$) along with the upper and lower threshold values (τ_U, τ_L) from the model with the covariates ($\pi_{t-1}, \tilde{y}_{t-1}^H, \Delta m_{t-1}$). Dashed lines are τ_U and τ_L point estimates and dotted lines are their associated one standard deviation confidence bands.

Figure 8. Out-of-Sample Forecast Performance: Lending Rate



Note: We calculate the one-period ahead out-of-sample forecast probability of each policy action using the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized events for each action. Out-of-sample forecasting is done with the recursive method and the fixed rolling window method, both beginning with the first half observations (53 initial observations).

Figure 9. Out-of-Sample Forecast Performance: Deposit Rate



Note: We calculate the one-period ahead out-of-sample forecast probability of each policy action using the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized events for each action. Out-of-sample forecasting is done with the recursive method and the fixed rolling window method, both beginning with the first half observations (53 initial observations).