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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 the two 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 its 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. Our empirical findings 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, the People's Bank of China (PBC) has received great attention from the public regarding when and to how it would revise the target benchmark interest rates. In the present paper, we attempt to estimate the behavioral function of the PBC. To put it differently, we attempt to understand how they determine the two policy interest rates: the benchmark 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 monetary and interest rate instruments (Xie, 2004; Peng, Chen, and Fan, 2006; Geiger, 2008; Zhang, 2009; Liu and Zhang, 2010; Xiong, 2012; Giardin, Lunven, and Ma, 2014; Sun, 2013). Among others, we pay a special attention on the PBC's benchmark interest rates, because those interest rates have been consistently 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.

We acknowledge that the PBC will eventually allow these regulated interest rates to be determined mainly by market forces. However, it is highly likely that the PBC would employ another interest rate targets, such as the target (range) federal funds rate in the US, in a more market oriented economic system in the future. Therefore, studying the decision making process for revisions of these interest rates would provide useful information on how the PBC will determine their monetary policy stance in the future.

One popular approach to study the PBC's interest rate setting behavior is based on a Taylor rule-type model that assumes the PBC revises the target interest rate *continuously*. Since the work of Xie and Luo (2002) 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) estimated similar versions of *linear* Taylor rule models, while Zhang and Zhang (2008), Ouyang and Wang (2009), Chen and Hou (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, 4 times a year, to make decisions on the monetary policy stance. Further, it turns out that the PBC revised their benchmark interest rates with a less than 30% frequency based on 106 quarterly observations since 1987. Such a high degree inertia in dynamics of the policy interest rates calls for an alternative approach in studying the monetary policy decision-making process in China.

Since the seminal work of Dueker (1999), many researchers have employed a discrete choice model framework to study the monetary policy stance of the Federal Reserve System in the US. 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 the US, respectively. On the other hand, 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 U.S. 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, Shi, and Hwang (2016) investigated interest rate setting behavior of the Bank of Korea.

There are 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.[1] 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.[2]

Unlike these researches, 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 (2012), we employ a constrained ordered probit model that allows policy makers to revise the interest rate only when the 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 discrete choice models for China's monetary policy decision making process. 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 examines advantages and disadvantages of using other policy instruments to identify the monetary policy stance in China. In Section 3, we describe the econometric model employed in the present paper. Section 4 provides a data description and preliminary test results that highlight empirical justification of using discrete choice models. Section 5 reports our probit model estimation results and in-sample fit analyses. In Section 6, we discuss our out-of-sample forecast exercise results. Section 7 concludes.

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

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

2 Policy Instruments of Monetary Policy in China

As we mentioned briefly in the previous section, the PBC has employed an array of policy instruments. This section provides short descriptions on those instruments, then discusses the merits of investigating the policy decision-making process on the target benchmark interest rates in comparison with alternative instruments.

PBC's major policy instruments include the required reserve ratio (RRR), the benchmark deposit and lending rates, and central bank bills (short-term bonds) that the PBC has used for open market operations (OMO) since 2002. Changes in the monetary policy stance via these instruments are normally observable because the PBC announces their actions to the public, sometimes prior to effective dates. The PBC also adopts policy instruments that may not be readily observable such as foreign exchange interventions, window guidance, and administrative measures.[3]

The RRR is a quantity-based instrument that helps manage banking system liquidity introduced in 1998 (He and Pauwels, 2008; Xiong, 2012). RRR is not a popularly employed instrument in advanced economies, because its effect on the money supply is too strong for small-scale adjustments. Interestingly, the PBC made a lot more frequent changes in RRR than in the commercial bank benchmark deposit and lending rates during times of financial market turmoil.

That is, as we can see in Table 1, the PBC made 20 revisions in RRR after the recent financial crisis in September 2008, while they revised the benchmark rates only 8 times. These actions sharply contrast with their earlier behavior prior to the Asian financial crisis in 1998. As we can see in Figure 1, RRR virtually stays constant until around 1998. That is, they used the benchmark lending and deposit rates more frequently than RRR during tranquil periods of time. This probably reflects the severity of the Great Recession triggered by the recent financial crisis. To put it differently, it might be the case that the PBC had to rely heavily on RRR which generates more powerful impacts on credit markets than the benchmark interest rates. However, revisions in RRR are normally consistent with those in the benchmark interest rates as they exhibit comovements (see Figure 1) over time, which implies that the PBC has combined these policy instruments.

Table 1 and Figure 1 around here

The PBC started conducting OMO on a regular basis in 2002, which helped reducing the stock of outstanding central bank bills that has increased substantially due to PBC's sterilization of heavy inflows of the foreign exchanges into China (He and Pauwels, 2008). Also, the PBC often used OMO in combination with RRR by absorbing excess market liquidity from maturing central bank bills into required reserves by raising RRR.

[3] Foreign exchange interventions are often used to control movements of yuan in the forex market. Window guidance normally gives nonbinding advices to financial institutions regarding their target credit growth and desirable financial resource allocations. Administrative measures are often used to control the speed of commercial loan growth.(He and Pauwels,2008)

Notwithstanding the significantly important roles of RRR and OMO in understanding the monetary policy decision-making process in China, we are particular interested in the PBC's commercial bank benchmark deposit and lending rates because they have been consistently employed as policy instruments with no break since 1986 compared with RRR and OMO.

We also acknowledge that various kinds of monetary aggregate variables are used in the literature to measure the monetary policy stance in China (Xie, 2004; Burdekin and Siklos, 2008; Koivu, 2008). However, changes in the monetary base, M1, or M2 reflect money demand shocks as well as the monetary policy shock. Furthermore, changes in monetary aggregates are greatly influenced by foreign factors or export revenues. The PBC typically attempts to sterilize these changes, but their sterilization procedures may not be entirely successful, which means measuring the policy stance via innovations in monetary aggregates could be a challenge.

In addition, the monetary targets announced by the PBC may not serve an appropriate proxy of the monetary policy stance, because, as He and Pauwels (2008) point out, these targets are announced at an annual frequency with no frequent revisions. Further, Liao and Tapsoba (2014) report the stable relationship between the money demand, output, and interest rates disappears after 2008 due to rapid financial innovation and liberalization, which implies a more important role of price-based monetary targets such as interest rates in conducting monetary policy.

We recognize that PBC has carried out interest rate reforms toward a more market-orientated system. This does not necessarily mean that the PBC will never attempt to influence market interest rates. Since January 2013, the PBC started using new policy tools such as short-term liquidity operations (SLO), standing lending facility (SLF), the medium-term lending facility (MLF), and pledged supplementary lending (PSL).

Under a more market-oriented financial system, we believe that the PBC will target short-run interest rates, paying attention on interest rates in the medium to the long-term, which is in line with the federal reserve system's strategy. Therefore, the present paper that investigates the behavioral function of the PBC regarding its determination of optimal interest rates would provide useful information in predicting the PBC's actions in the future.

3 The Econometric Model

The People's Bank of China (PBC) is assumed to set an optimal interest rate (i_t^*) based on exogenous macroeconomic variables ($\mathbf{x}_t$) that are observed at time t. i_t^* is not directly observable to the public. That is, it is a *latent* variable. 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 in the previous period (i_{t-1}). For this, we define the following deviation variable of i_t^* from 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, Jackson and Saba (2009), whereas He and Pauwels (2008) and Xiong (2012) used conventional ordered probit models with no such mechanism. Xiong employed a lagged policy stance variable instead, even though he failed to find significant coefficient estimates for that variable.

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.

For this, let's denote y_t the observable policy varible that takes discrete values. 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,

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

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.

4 Data and Preliminary Analysis

4.1 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 marginal refinancing facility, 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 two interest rates in the first panel of Figure 2. It should be noted that these 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 over 70% frequency, which implies that the PBC revises the rates only when its perceived optimal interest rate deviates sufficiently from the prevailing rate. The ordered probit model described earlier thus seems to be appropriate for estimating such discrete actions. 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.

Figure 2 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

[4] Given the benchmark lending rate, commercial banks set their interest rates based on their credit assessment of their customers. The deposit interest rate is the rate paid by banks on demand, time, or savings accounts.

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 3.

Figure 3 around here

4.2 Unit Root Tests

We implement the augmented Dickey-Fuller (ADF) test for all variables used in the study. Results are reported in Table 2.

The test fails to reject the null hypothesis 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 2. 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 2 around here

4.3 Linear Taylor Rule Model Estimations

We perform another preliminary analysis by estimating 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 help infer 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) as follows.

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

Note that the short-run coefficients γ_π^s and γ_y^s and the smoothing parameter ρ in (8) jointly imply $\gamma_\pi = \gamma_\pi^s/(1-\rho)$ and $\gamma_y = \gamma_y^s/(1-\rho)$ in (7).

All estimation results for (7) and (8) are reported in Table 3. We note that the coefficient on inflation is always highly significant at the 1% level, while that of the output gap is mostly insignificant. All other explanatory variables are also insignificant. 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 for the lending rate and the deposit rate, respectively. Furthermore, we noticed that the degree of interest rate inertia, measured by ρ in (8), is close to one, which implies that the interest rates obey a near unit root process. If the interest rates are nonstationary as is implied by the ADF test in the previous section, the OLS estimates presented in Table 3 might not be appropriate. The probit model estimates in the following section, however, does not have such a problem since we use the policy index variable which assumes discrete numbers.

Table 3 around here

5 Probit Model Estimation and In-Sample Fit Analysis

This section reports our estimates for the probit model described earlier. 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.

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 are substantial deviations 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

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

(2012) who also reported an important role of inflation in understanding the monetary policy stance in China.[6]

Table 4 around here

We implement a robustness check analysis to see how stable these coefficient estimates are over the sample period. For this purpose, we recursively estimate our models beginning with the first half observations (1987:II to 2000:III), then repeat estimations by adding one observation in each round until all observations are used. That is, we obtain 52 sets of coefficient estimates for each model. We report the coefficient estimates along with their 95% confidence bands in Figure 4 for the models 1 and 2.

The coefficient estimates from our recursive estimations are overall stable over time, 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.

Figure 4 around here

Next, we evaluate our ordered probit models for the PBC's decision-making process in terms of in-sample fit performance. For this purpose, we report correct prediction rates of our models in Table 5. 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. Overall success rates for the deposit rate were slightly higher for the deposit rate than those for the lending rate, though success rates for C and H decisions were roughly similar.

Table 5 around here

Overall success rates are heavily influenced by high success rates for S decisions, which is about 85% for the lending rate and 92% for the deposit rate. On the other hand, 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.

[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.

Figure 5 plots the estimated latent variable y_t^* from Models 2 for the lending rate and the 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 $[\tau_L + 2 \times std(\tau_L), \tau_U - 2 \times std(\tau_U)]$ will yield more C and H predictions with a cost of lower success rates for S decisions. Such schemes would be desirable when market participants are vigilant for possible changes in the monetary policy stance. Model evaluation results with this alternative scheme are reported in Table 6.

We observe roughly similar in-sample fit performance. Even though the success rate for S decisions declines in all models, our models perform much better for C and H decisions. For instance, the success rate for C decisions improves to 53% for the lending rate, while the success rate for H decisions goes up as high as 38%.

Figure 5 around here

Table 6 around here

Even though our alternative scheme improves the success rates for C and H decisions considerably, the performance of our models still may not be considered satisfactory. Note that our models predict C and H decisions only when y_t^* deviates from the inaction band. In other words, our models may fail to produce a warning signal even when y_t^* approaches rapidly toward the threshold values.

Recognizing this, we calculate and report the probability estimate of each policy intervention using the coefficient estimates from Model 2. In Figure 6, the estimated probabilities are illustrated with actual decisions (bar graphs) over the full sample period. These figures show that our models trace 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.

Figure 6 around here

It should be noted that estimated probabilities tend to be higher in the pre-2000 period compared with those in the latter period. As can be seen in Figure 3, output gaps exhibit a big swing in the pre-2000 period. Inflation was also extremely high and volatile in the pre-2000 period, which required substantially bigger revisions of the benchmark interest rates as can be seen in Figure 2. Since our model does not distinguish quantitative differences in the size of revisions, our models tend to generate lower probabilities in the post-2000 period samples. However, our models are able to pick up rapidly rising probabilities for hikes and cut decisions.

Our models generated very high probabilities of a hike decision in around 1994 for both benchmark interest rates. It turns out that the PBC used alternative instruments during that time.

That is, the growth rate of central bank refinancing to commercial banks decreased from 44.19% in 1993:III to 6.4% in 1994:IV. This implies that our models correctly predicted the monetary policy stance during this period.

As to other possible mismatches between the predicted possibilities (probabilities) and the actual decisions in these figures, we suggest an explanation based on the following institutional features about the actual monetary policy 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 substantial time lags between PBC's proposals and the State Council's disposal, which may explain why actual decisions tend to lag our model predictions.

6 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 50% observations as the split point. The recursive forecasting approach begins with a memory window from the beginning of the sample to 2000:III. 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. To 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 54^{th} policy action, we add the 54^{th} actual observation, but drop the 1st observation from the sample, thereby retaining an updated 53-observation estimation window, which is used to produce the next policy outcome, the 55^{th} action. 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 7 and 8, 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 (C) increases faster with the rolling window scheme. Similarly, the probability of a hike (H) 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 performance 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 Figure 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 3). Also, as we can see in Figure 2, 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 7 and 8 around here

7 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 may be inappropriate when the policy interest rates show substantial degree inertia. 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-size rolling window schemes with initial 50% observations as a split point. Our model performed fairly well especially when the rolling window method is used.

References

Bai, J., and S. Ng (2004): "A panic attack on unit roots and cointegration," *Econometrica*, 72(4), 1127–77.

Bian, Z. (2006): "A review of empirical issues of Taylor rule and its applicability in China," *Journal of Finance Research*, 08, 56–69.

Burdekin, R. C., and P. L. Siklosb (2008): "What has driven Chinese monetary policy since 1990s? Investigating the People's Bank' s policy rule," *Journal of International Money and Finance*, 27(5), 847– 859.

Chen, H., Q. Chen, and S. Gerlach (2011): "The implementation of monetary policy in China:The internal market and bank lending," *HKIMR Working Paper*, 26.

Chen, Y., and Z. Huo (2009): "A conjecture of Chinese monetary policy rule: Evidence from survey data, Markov regime switching, and drifting coefficients," *Annals of Economics and Finance*, 10(1), 111–153.

Clarida, R., J. Galí, and M. Gertler (2000): "Monetary policy rules and macroeconomic stability: Evidence and some theory," *The Quarterly Journal of Economics*, 115(1), 147–180.

Dueker, M. (1999): "Measuring monetary policy inertia in target federal funds rate changes," *Federal Reserve Bank of St Louis Review*, 81(3-9).

Fan, L., Y. Yu, and C. Zhang (2011): "An empirical evaluation of China's monetary policies," *Journal of Macroeconomics*, 33(2), 358–371.

Geiger, M. (2008): "Instruments of monetary policy in China and their effectiveness: 1994-2006," United Nations Conference on Trade and Development, No. 187.

Gerlach, S. (2007): "Interest rate setting by the ECB: Words and deeds," *International Journal of Central Banking*, 3(3), 1–46.

Girardin, E., S. Lunven, and G. Ma (2014): "Inflation and China's monetary policy reaction function: 2002-2013," BIS Papers No. 77.

Hamilton, J. D., and Òscar Jordà (2002): "A model for the federal funds target rate," *Journal of Political Economy*, 110, 1135–1167.

He, D., and L. L. Pauwels (2008): "What prompts the people's bank of china to change its monetary policy stance? Evidence from a discrete choice model," *China & World Economy*, 16(6), 1–21.

He, D., and H. Wang (2012): "Dual-track interest rates and the conduct of monetary policy in China," *China Economic Review*, 23(4), 928–47.

Hu, L., and P. C. B. Phillips (2004a): "Dynamics of the federal funds target rate: A nonstationary discrete choice approach," *Journal of Applied Econometrics*, 19, 851–867.

——— (2004b): "Nonstationary discrete choice," *Journal of Econometrics*, 120, 103–138.

Jawadi, F., S. K. Mallick, and R. M. Sousa (2014): "Nonlinear monetary policy reaction functions in large emerging economies: The case of Brazil and China," *Applied Economics*, 46(9), 973–984.

Kim, H., J. Jackson, and R. Saba (2009): "Forecasting the FOMC's interest rate setting behavior: A further analysis," *Journal of Forecasting*, 28(2), 145–165.

Kim, H., W. Shi, and K.-M. Hwang (2016): "Estimating interest rate setting behavior in Korea: A constrained ordered choices model approach," *Applied Economics*, 48, 2199–2214.

Koivu, T. (2009): "Has the Chinese economy become more sensitive to interest rates? Studying credit demand in China," *China Economic Review*, 20(3), 455–470.

Liao, W., and S. J.-A. Tapsoba (2014): "China's Monetary Policy and Interest Rate Liberalization: Lessons from International Experiences," IMF Working Paper 14/75.

Liu, L., and W. Zhang (2010): "A new Keynesian model for analysing monetary policy in mainland China," *China Journal of Asian Economics*, 21(6), 540–551.

Monokroussos, G. (2011): "Dynamic limited dependent variable modeling and US monetary policy," *Journal of Money, Credit and Banking*, 43(2-3), 519–534.

Ouyang, Z., and S. Wang (2009): "The asymmetric reaction of monetary policy to inflation and real GDP in China," *Economic Research Journal*, 9, 27–38.

Park, J. Y., and P. C. B. Phillips (2000): "Nonstationary binary choice," *Econometrica*, 68(1429-1482).

Peng, W., H. Chen, and W. Fan (2006): "Interest rate structure and monetary policy implementation in mainland China," *China Economic Issues*, 1-06.

Shu, C., and B. Ng (2011): "Monetary Stance and Policy Objectives in China: A Narrative Approach," *HKMA China Economic Issues*, 1/10.

Sun, R. (2013): "Does monetary policy matter in China? A narrative approach.," *China Economic Review*, 23, 56–74.

Wang, S., and H. Zou (2006): "Taylor's rule in the condition of opening economy: To test the monetary policy of China," *Statistical Research*, 23, 42–47.

Xie, P. (2004): "China's monetary policy:1998-2002," Stanford Center for International Development Working paper 217.

Xie, P., and X. Luo (2002): "Taylor rule and its empirical test in China's monetary policy," *Economic Research Journal*, 3, 2–13.

Xiong, W. (2012): "Measuring the monetary policy stance of the People's Bank of China: An ordered probit analysis," *China Economic Review*, 23, 512–533.

Zhang, W. (2009): "China's monetary policy: Quantity versus price rules," *Journal of Macroeconomics*, 31(3), 473–84.

Zhang, Y., and D. Zhang (2008): "Interest rate rule with a role of money and its empirical test in China," *Economic Research Journal*, 12, 65–74.

Zhao, J., and H. Gao (2004): "Robust monetary policy rules in an environment of interest rate liberalization in China," *China Economic Quarterly*, 3, 41–64.

Zheng, T., X. Wang, and H. Guo (2012): "Estimating forward-looking rules for China'smonetary policy: A regime-switching perspective," *China Economic Review*, 23(2), 47–59.

Table 1. Timeline of Monetary Policy Changes

Announced Date	Effective Date	Lending	Deposit	RRR
	1 September 1988	1.08	1.44	1
	1 February 1989	2.34	2.70	
	15 April 1990		−1.26	
	21 August 1990	−0.72	−1.44	
	21 April 1991	−0.72	−1.08	
	1 May 1993	0.72	1.62	
	1 July 1993	1.62	1.8	
	1 January 1995	1.08		
	1 May 1996	−1.08	−1.8	
	23 August 1996	−0.9	−1.71	
23 October 1997	23 October 1997	−1.44	−1.8	
21 March 1998	23 March 1998			−5
	25 March 1998	−0.72	−0.45	
	1 July 1998	−0.99	−0.45	
	7 December 1998	−0.54	−0.45	
	10 June 1999	−0.54	−0.45	
21 November 1999	21 November 1999			−2
20 February 2002	21 February 2002	−0.54	−0.27	
23 August 2003	21 September 2003			1
11 April 2004	25 April 2004			0.5
28 October 2004	29 October 2004	0.27	0.27	
24 April 2006	28 April 2006	0.27		
16 June 2006	5 July 2006			0.5
21 July 2006	15 August 2006			0.5
18 August 2006	19 August 2006	0.27	0.27	
3 November 2006	15 November 2006			0.5
5 January 2007	15 January 2007			0.5
16 February 2007	25 February 2007			0.5
17 March 2007	18 March 2007	0.27	0.27	
5 April 2007	16 April 2007			0.5
29 April 2007	15 May 2007			0.5
18 May 2007	5 June 2007			0.5
	19 May 2007	0.18	0.27	
20 July 2007	21 July 2007	0.27	0.27	
30 July 2007	15 August 2007			0.5
21 August 2007	22 August 2007	0.18	0.27	
6 September 2007	25 September 2007			0.5
14 September 2007	15 September 2007	0.27	0.27	

Table 1. Continued

Announced	Effective	Lending	Deposit	RRR
13 October 2007	25 October 2007			0.5
10 November 2007	26 November 2007			0.5
20 December 2007	20 December 2007	0.18	0.27	
16 January 2008	25 January 2008			0.5
18 March 2008	25 March 2008			0.5
16 April 2008	25 April 2008			0.5
12 May 2008	20 May 2008			0.5
7 June 2008	25 June 2008			1
15 September 2008	16 September 2008	−0.27		
15 September 2008	25 September 2008			-1^{*}
8 October 2008	9 October 2008	−0.27	−0.27	
8 October 2008	15 October 2008			−0.5
29 October 2008	30 October 2008	−0.27	−0.27	
27 November 2008	27 November 2008	−1.08	−1.08	
	5 December 2008			$-1^{\dagger}$
				-2^{*}
	25 December 2008			−0.5
	18 January 2010			$0.5^{\dagger}$
18 January 2010	25 February 2010			$0.5^{\dagger}$
25 February 2010	10 May 2010			$0.5^{\dagger}$
19 October 2010	20 October 2010	0.25	0.25	
	16 November 2010			0.5
	29 November 2010			0.5
	20 December 2010			0.5
	20 January 2011			0.5
	24 February 2011			0.5
	25 March 2011			0.5
5 April 2011	6 April 2011	0.25	0.25	
	21 April 2011			0.5
	19 May 2011			0.5
	20 June 2011			0.5
6 July 2011	7 July 2011	0.25	0.25	
	5 December 2011			−0.5
	24 February 2012			−0.5
	18 May 2012			−0.5
7 June 2012	8 June 2012	−0.25	−0.25	
5 July 2012	6 July 2012	−0.25	−0.31	

Note: Authors expanded a similar timeline table in He and Pawels (2008) based on published documents of the PBC. Superscripts † and ∗denote changes in RRR in big banks and in small banks, respectively.

Table 2. 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_tdenote 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 3. Linear Taylor Rule Coefficient Estimations

(a) 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)

(b) 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

(a) 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)

(b) 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 5. In-sample Fit evaluations with Point Estimates

(a) Lending Rates

	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%	

(b) Deposit Rates

	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 estimates.

Table 6. In-sample Fit evaluations with Two Standard Error

(a) Lending Rates

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	8	12	1	8	11	1
Stay predicted	7	56	11	7	56	9
Hike predicted	0	6	4	0	7	6
Correct Prediction (%)	53%	76%	25%	53%	76%	38%
Overall Performance (%)		65%			67%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	8	12	1	8	11	1
Stay predicted	7	56	11	7	56	9
Hike predicted	0	6	4	0	7	6
Correct Prediction (%)	53%	76%	25%	53%	76%	38%
Overall Performance (%)		65%			67%	

(b) Deposit Rates

	Model 1			*Model 2*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	6	13	0	5	10	0
Stay predicted	8	58	10	9	61	9
Hike predicted	0	6	4	0	6	5
Correct Prediction (%)	43%	75%	29%	36%	79%	36%
Overall Performance (%)		65%			68%	
	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	6	12	0	6	10	0
Stay predicted	8	59	10	8	61	9
Hike predicted	0	6	4	0	6	5
Correct Prediction (%)	43%	77%	29%	43%	79%	36%
Overall Performance (%)		66%			69%	

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 [τ_L+2×std(τ_L),τ_L-2×std(τ_L)].

Figure 1. Policy-Related Interest Rates in China

Note: RRR (big banks) and RRR (small banks) are on the right-side axis.

Figure 2. Interest Rates and Policy Actions

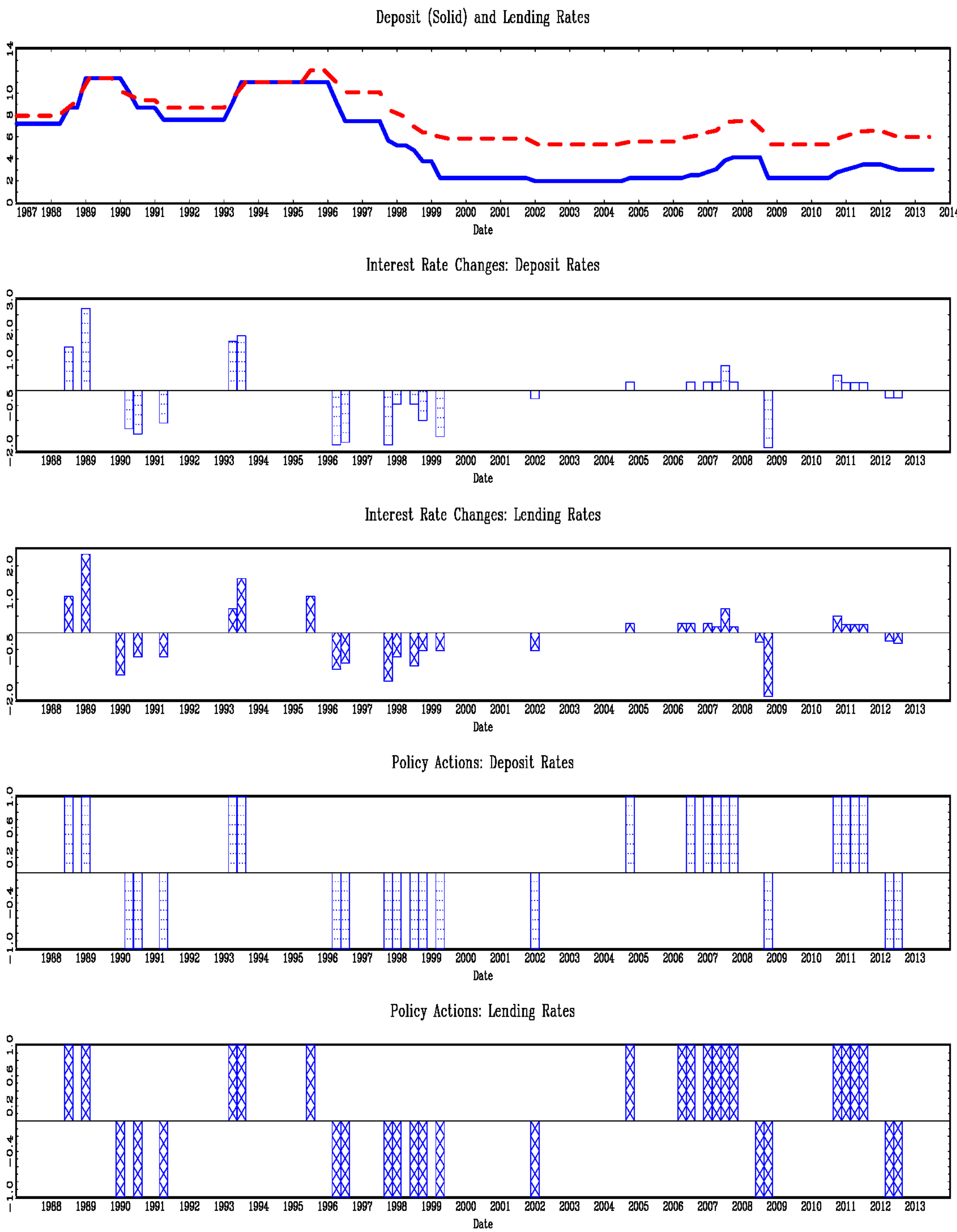
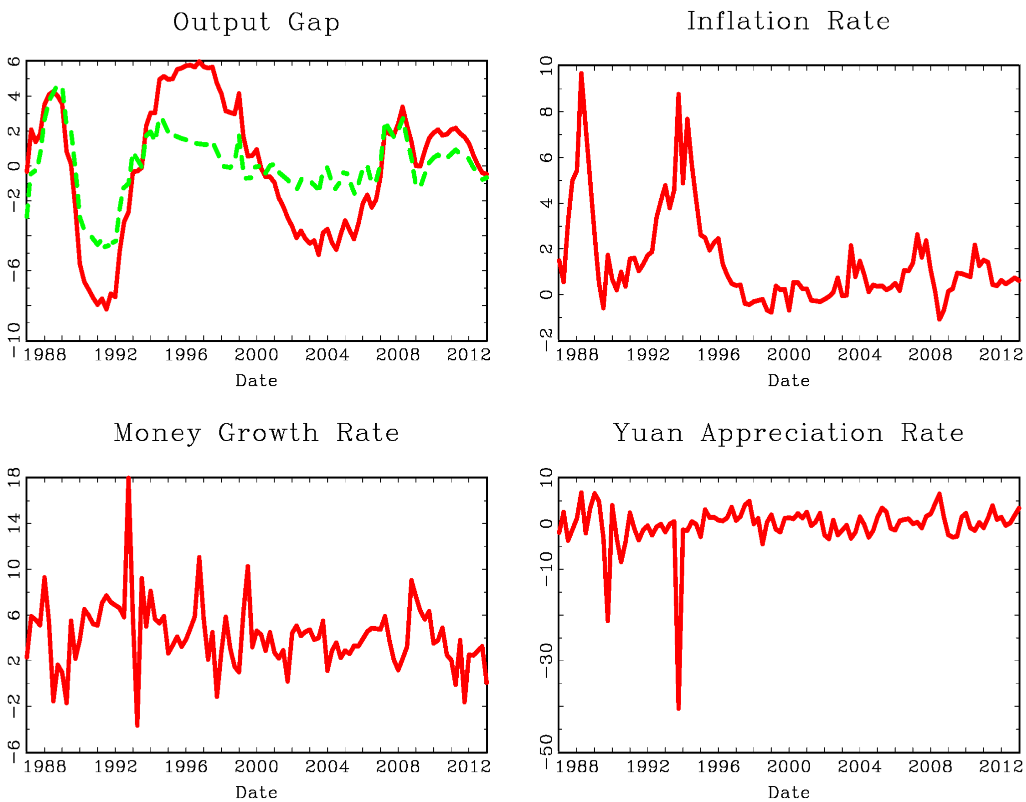


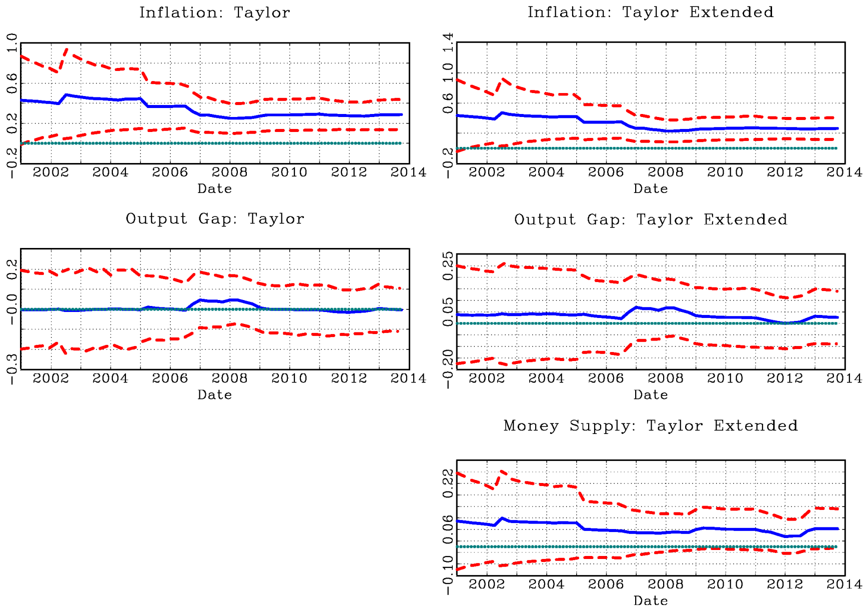
Figure 3. Key Macroeconomic Covariates



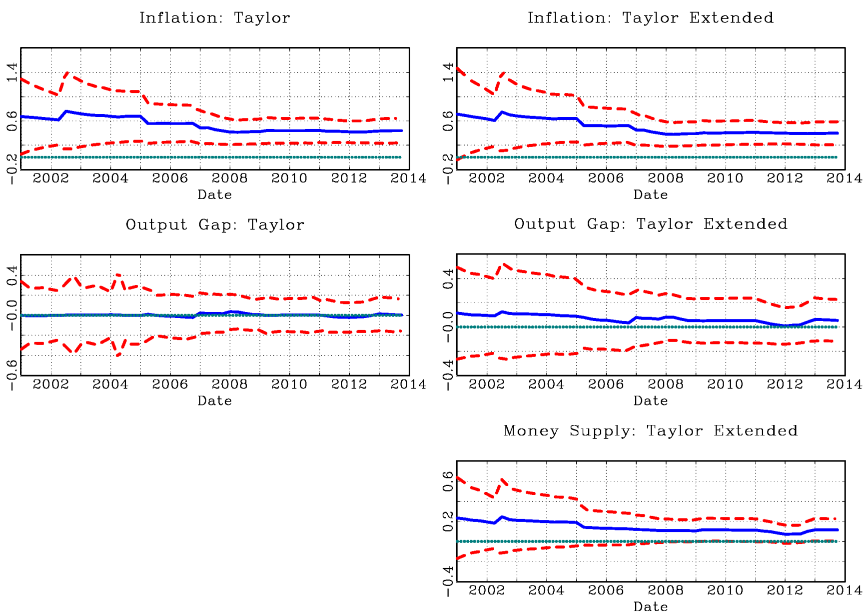
Note: We use two measures of the output gap: quadratically detrended real industrial production (solid) and the cyclical component of real industrial production(dashed) by the Hodrick-Prescott filter. Two detrending methods produce similar output gaps. Inflation is the quarterly change in the log CPI. 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 4. Constancy of the Latent Coefficient Estimates

(a) Lending Rates

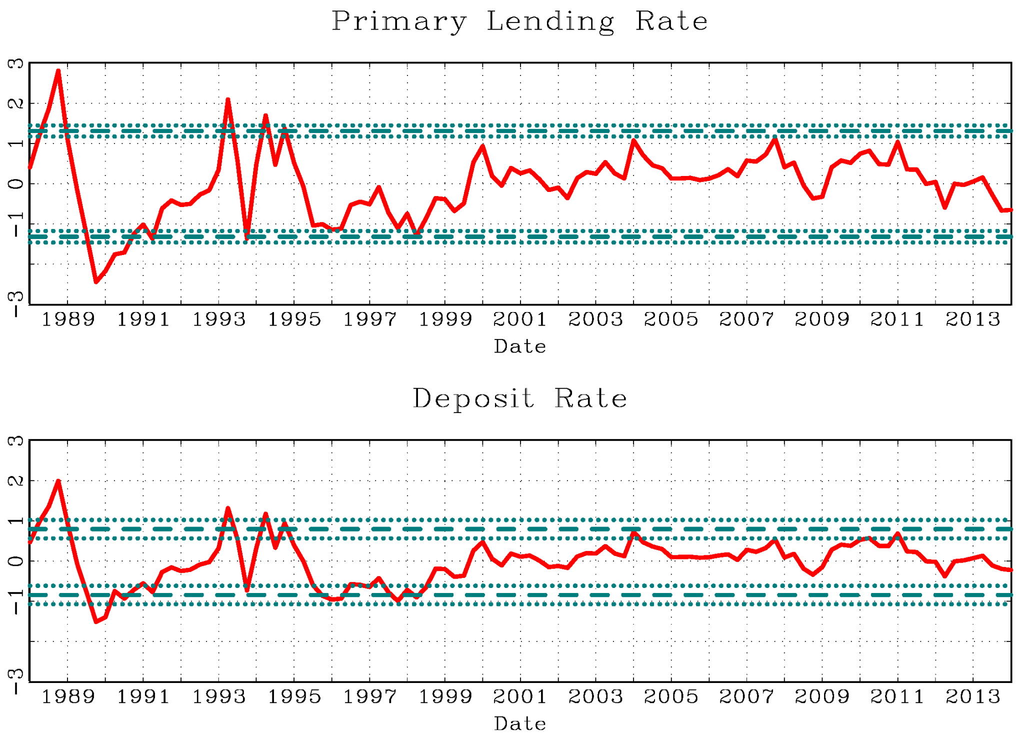


(b) Deposit Rates



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.

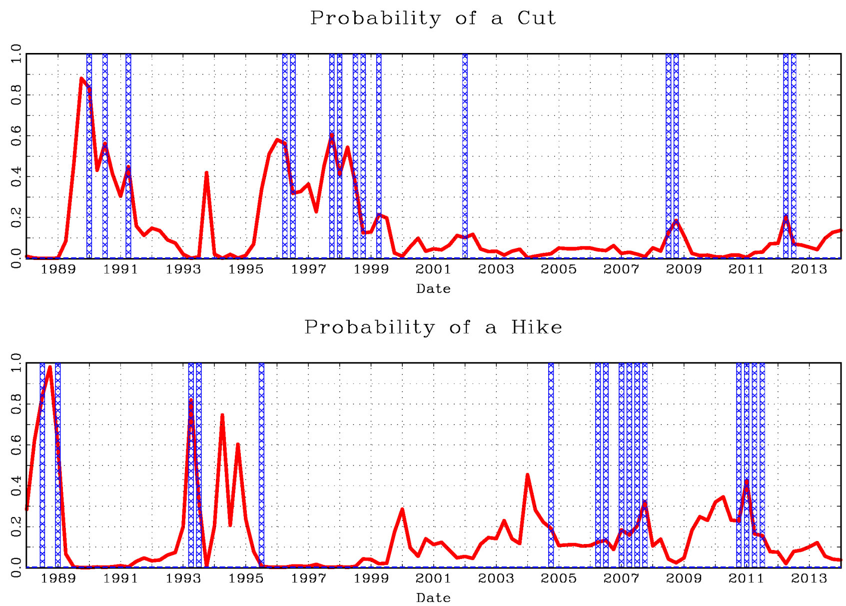
Figure 5. Deviations from the Optimal Rate and Thresholds



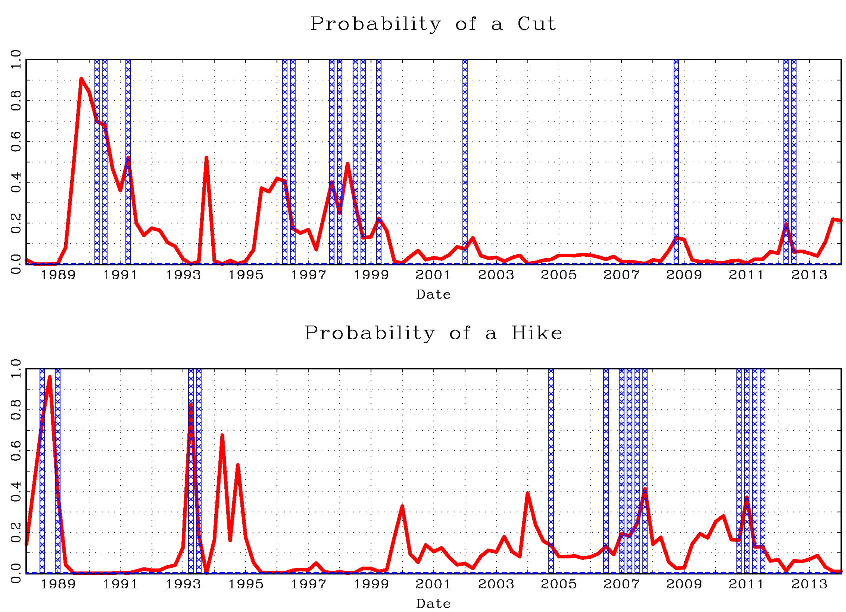
Note: We calculate deviations from the optimal interest rate $(y_t^* = i_t^* - i_{t-1})$along with the upper and lower threshold values $(\tau_U, \tau_L)$from the model with the covariates $(\pi_{t-1}, \tilde{y}_{t-1}^H, \Delta m_{t-1})$. Dashed lines are $\tau_U$and $\tau_L$point estimates and dotted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

Figure 6. In-Sample Fit Performance of Probit Models

(a) Lending Rates

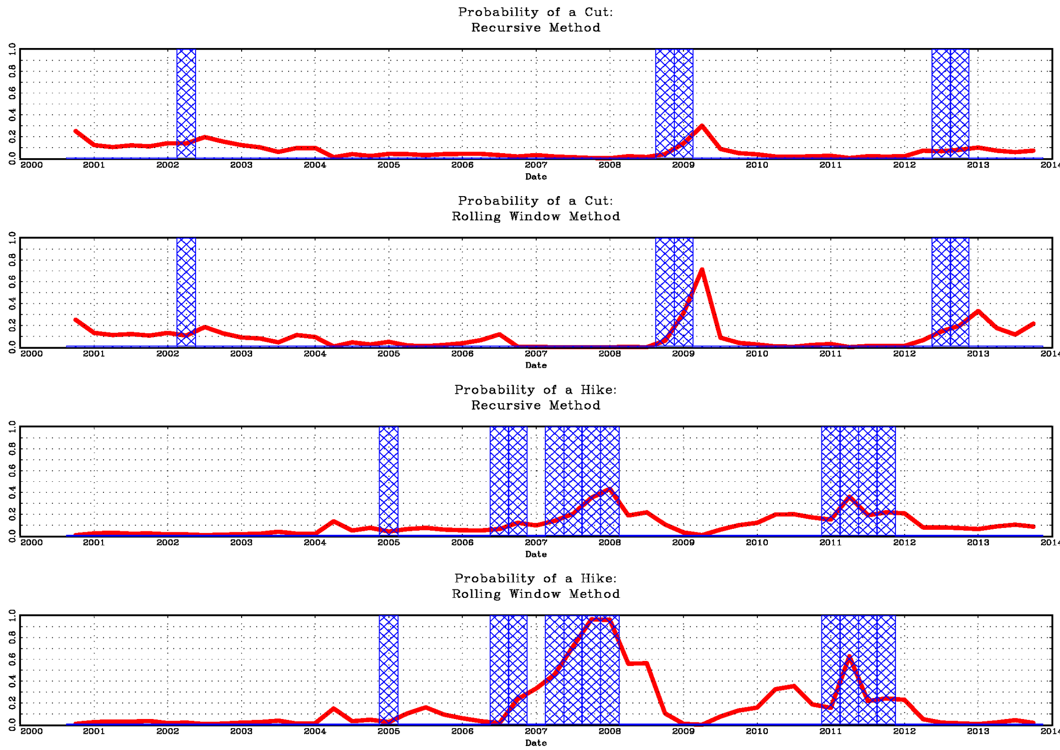


(b) Deposit Rates



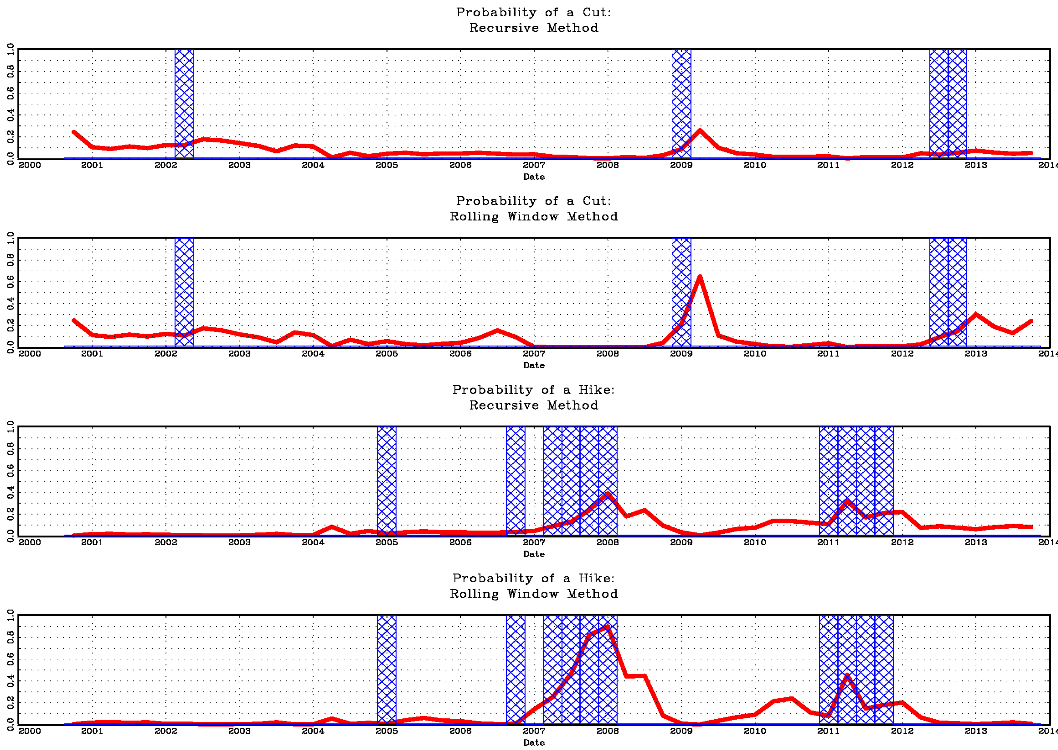
Note: We calculate estimated in-sample probabilities for each policy action from the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized policy actions.

Figure 7. Out-of-Sample Forecast Performance: Lending Rates



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 8. Out-of-Sample Forecast Performance: Deposit Rates



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).