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Estimating Interest Rate Setting Behavior in Korea: A Constrained Ordered Choices Model Approach

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Abstract

We study the Bank of Korea's interest rate setting behavior using an array of constrained ordered choices models, where the Monetary Policy Committee revises the target policy interest rate only when the current market interest rate deviates from the optimal rate by more than certain threshold values. Our models explain changes in the monetary policy stance well for the monthly frequency Korean data since January 2000. We find important roles for the output gap and the foreign exchange rate in understanding the Bank of Korea's rate decision-making process. We also implement out-of-sample forecast exercises with September 2008 (Lehman Brothers Bankruptcy) for a split point. We demonstrate that out-of-sample predictability improves greatly for the rate cut and the rate hike decisions using standard error adjusted inaction bands.

Keywords: Monetary Policy; Bank of Korea; Probit Model; Robit Model; Logit Model; Target RP Rate; Interbank Call Rate; Taylor Rule

JEL Classification: C51; C52; E52; E58

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1 Introduction

When and to what extent central banks revise their target interest rates draw substantial attention of the public. In Korea, the Monetary Policy Committee (MPC) of the Bank of Korea (BOK) meets every month to revise the target RP rate (policy interest rate) that plays a key role in determining the interbank overnight interest rate, which is a market interest rate.[1] The present paper employs a discrete choice model approach to study the interest rate setting behavior of the BOK.

There are quite a few papers that investigate the BOK's monetary policy decision-making process using linear or nonlinear Taylor rules that specifies the policy interest rate as a *continuous* variable on a non-negative support.[2] For example, Eichengreen (2004) and Park (2008) report statistically significant roles for the real exchange rate, inflation, and output gaps from their linear Taylor rule estimations for the BOK, while Aizenman, Hutchinson, and Noy (2008) report a weak role of the output from their panel estimations for 16 emerging market countries including Korea. On the other hand, Oh (2006), Kwon (2007), Kim and Seo (2008), and Koo, Paya, and Peel (2012) employed nonlinear Taylor rule type policy rules, finding somewhat mixed evidence of nonlinearity.

To the best of our knowledge, our paper is the first attempt that employs a discrete choice model to approximate the BOK's interest rate setting behavior. The motivation of this approach is the following. The MPC does not revise the target interest rate continuously. Historically, the MPC holds monthly meetings and revises the target RP rate in multiples of 25 basis points. For instance, they may cut the target rate by 0.50%, or they may give a 0.25% interest rate hike, or they may let it stay where it is. These discrete actions may be better investigated using qualitative response (discrete choices) models such as the ordered probit model.

In the case of the US, Dueker (1999) followed by Hamilton and Jordà (2002), initiated a seminal study on the Fed's rate decision process by employing discrete choice model

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[1] Since the BOK officially employed the inflation targeting system in 1998, they have been implementing monetary policies by setting policy interest rates such as the target RP rate.
[2] Nominal interest rates are bounded below by 0%.

frameworks, the ordered probit and the autoregressive conditional hazard models, respectively. Hu and Phillips (2004a) extended the work by Park and Phillips (2000) on the *nonstationary binary* choice model to a *nonstationary discrete choice* model, then estimated the Fed's policy decision-making process, allowing the covariates in their latent equation to be nonstationary.[3] Kim, Jackson, and Saba (2009) employed the method of Hu and Phillips (2004a, 2004b) to out-of-sample forecast the Fed's monetary policy actions. Xiong (2012) used the ordered probit model to investigate the monetary policy stance of the People's Bank of China.

We employ an array of (constrained) ordered choices models that include the probit model, the logit model, and the newly proposed robit model (Liu, 2005), for the period between January 2000 and September 2013.[4] Unlike Kim *et al*. (2009) and Hu and Phillips (2004a, 2004b), we don't correct for nonstationarity, because we did not find any strong evidence of nonstationarity in the covariates we consider in this paper. We obtain solid evidence of important roles for the output gap and the won-dollar depreciation rate in understanding the Bank of Korea's rate decision-making process.

We report good in-sample fit performance of our models in predicting changes in the monetary policy stance of the BOK. Also, we implement out-of-sample forecast exercises using September 2008 (Bankruptcy of Lehman Brothers) as a split point. We obtained empirical evidence that shows satisfactory out-of-sample predictability with the recursive and the fixed size rolling window methods. We also show prediction accuracy for the rate cut and the rate hike decisions can improve greatly by employing standard error adjusted inaction bands.

The organization of the paper is as follows. Section 2 describes the main econometric model used in the present paper. In Section 3, we provide a data description and preliminary

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[3] Hu and Phillips (2004b) also investigated the Bank of Canada's monetary policy behavior using a similar methodology. Phillips, Jin, and Hu (2005) corrected the errors in Hu and Phillips (2004b) with regard to the convergence rates of Maximum Likelihood estimates.

[4] A referee pointed out that forecasting *cut* or *hike* decisions might be more important than predicting *stay* decisions correctly. For this purpose, the referee suggested to use the robit model that may help improve the fit of tails.

statistical analysis including unit root test results and linear Taylor rule model estimates. Section 4 reports and interprets the coefficient estimates from the probit, the logit, and the robit model. In Section 5, we present our in-sample-fit performance analyses and discuss the results. Section 6 reports out-of-sample prediction results. Section 7 concludes.

2 The Econometric Model

We assume that policy makers at the BOK set their target interest rate i_t^* by the following linear function at time *t*.

$$i_t^* = x_t'\beta - \varepsilon_t, \tag{1}$$

where x_t is a $k \times 1$ vector of macroeconomic characteristics variables (covariates) of the economy. Note that the target optimal interest rate (i_t^*) is *not* directly observable, that is, it is a latent variable. As in Kim *et al*. (2009) and Hu and Phillips (2004a, 2004b), we define another latent variable as follows.

$$y_t^* = i_t^* - i_{t-1} = x_t'\beta - i_{t-1} - \varepsilon_t, \tag{2}$$

where i_{t-1} is the *market* interest rate (interbank call rate) in previous period. Note that y_t^* measures deviations of the new optimal interest rate from the previous period market interest rate. That is, the greater y_t^* is in absolute value, the stronger the incentive to revise the target interest rate is.

We assume that the MPC of the BOK makes policy decisions on the target interest rate (target RP rate) in the following manner. Since rate revisions have historically been made in multiples of 25 basis points during monthly regular meetings, it seems to be reasonable to expect minor divergence of i_t^* from i_{t-1} to elicit no policy action. Put it differently, the MPC might revise the target interest rate only when y_t^* exceeds some threshold values.

We assume that there are three policy actions: cut (*C*) the interest rate, let it stay (*S*) where it is, or hike (*H*) the interest rate, which implies three regimes for the support of y_t^*.

These three regimes suggest that there are two thresholds, τ_L and τ_U such that a difference, $y_t^* = i_t^* - i_{t-1}$, less than the lower threshold (τ_L) would indicate that the interest rate should be lowered, a difference greater than the upper threshold (τ_U) would indicate that the MPC should raise the target RP rate, and any difference between the two thresholds, say, an *inaction band*, would indicate that the target RP rate should not be changed.[5] Based on this trichotomous-choice model framework, we define the following policy index measure y_t and its associated indicator functions $\ell_{i,t}$.

$$y_t = \begin{Bmatrix} -1, & \text{if} & y_t^* \le \tau_L & : C \\ 0, & \text{if} & \tau_L \le y_t^* < \tau_U & : S \\ 1, & \text{if} & y_t^* \ge \tau_U & : H \end{Bmatrix} \tag{3}$$

and

$$\ell_{i,t} = \begin{Bmatrix} \frac{y_t(y_t-1)}{2}, & \text{if } i = C \\ 1 - y_t^2, & \text{if } i = S \\ \frac{y_t(y_t+1)}{2}, & \text{if } i = H \end{Bmatrix} \tag{4}$$

Unlike y_t^*, the policy variable y_t is observable. The log likelihood function for a sample of size T, $\{y_t\}_{t=1}^T$, is given as follows.

$$\mathcal{L} = \sum_{t=1}^T \{\ell_{C,t} lnP_C(x_t;\theta) + \ell_{S,t} lnP_S(x_t;\theta) + \ell_{H,t} lnP_H(x_t;\theta)\}, \tag{5}$$

where θ is the parameter vector $(\beta, \tau_L, \tau_U)'$ and the probability function $P_i, i \in \{C, S, H\}$ is defined as,

$$P_i = \begin{Bmatrix} 1 - F(x_t'\beta - i_{t-1} - \tau_L), & \text{if } i = C \\ F(x_t'\beta - i_{t-1} - \tau_L) - F(x_t'\beta - i_{t-1} - \tau_U), & \text{if } i = S \\ F(x_t'\beta - i_{t-1} - \tau_U), & \text{if } i = H \end{Bmatrix} \tag{6}$$

We consider the following three types of constrained ordered choices models. When $F(\cdot)$ is assumed to be the standard normal distribution function, the model becomes the constrained ordered probit model with a restriction on the coefficient of the previous period

[5] We allow the inaction band $[\tau_L, \tau_U]$ to be asymmetric because we do not impose any restriction on the thresholds. We may assume $\tau_L = -\tau_U$ for symmetric bands when τ_L is restricted to be less than zero.

interbank call rate (i_{t-1}) that appears in y_t^*.[6] Similarly, we employ the logit model as well as the newly proposed robit model (Liu, 2005) that use the logistic and the t-distribution functions, respectively. Since the robit model approximates the probit model as the degree of freedom goes to infinity, we focus on cases when the degree of freedom is fairly small to ensure the distribution to have a fat tail property.[7]

3 Data Descriptions and Preliminary Estimation Results

3.1 Data Descriptions

We use monthly frequency observations that span from January 2000 to September 2013. The target RP rate (i_t^R) is used as the policy interest rate of the BOK, which directly influences the interbank overnight interest rate (call rate, i_t^C).[8] Inflation (π_t) is the monthly log difference of the Consumer Price Index (CPI). As to the output gap ($\tilde{y}_t$), we consider the following two conventional 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 ($\tilde{y}_t^H$).[9] M2 growth rate (Δm_t) is the monthly log difference of the M2, while the won depreciation rate (Δs_t) denotes the monthly log difference of the Korean won price of one US dollar. Long-short spread (ls_t) is the 3-year government bond yield minus the 3-month government bond interest rate. All interest rates were transformed to monthly interest rates by dividing them by 12. We obtained all data from the BOK.

We plot the target RP rate and the call rate on the first panel of Figure 1, which exhibit very persistent co-movement dynamics over time. It should be noted that there is a sharp

[6] Note that its coefficient is restricted to be -1, since we are interested in the divergence measure of newly set optimal interest rate from the current market interest rate.
[7] The robit model approximates the logit model when the degree of freedom is seven. See Liu (2005) for details.
[8] The target RP rate and the call rate correspond to the target federal funds rate and the effective federal funds rate in the US, respectively, prior to the recent US financial crisis.
[9] For the quadratically detrended gap, we demeaned and detrended the real industrial production using an intercept, linear trend, and quadratic trend. See Clarida, Galí, and Gertler (2000), among others, who employed the same method. We separated HP cyclical components of the monthly real industrial production using 125,000 for the smoothing parameter.

decline in these rates right after the recent financial crisis that began in September 2008. Changes in the target RP rate appear on the second panel, which clearly show that the MPC has revised the target rate infrequently in multiples of 25 basis points. More specifically, there were 16 cuts (C) and 15 hike (H) decisions, while the MPC chose not to revise (S) the rate in the remaining 131 meetings. Furthermore, only for 5 out of 31 non-Stay (C or H) decisions, the MPC changed the target rate by more than 25 basis points. These observations led us to simplify the model to a trichotomous discrete choices model that is graphically represented on the third panel of Figure 1, which renders -1, 0, and 1 for cases of C, S, and H, respectively.[10]

Figure 1 around here

We also provide graphs for the remaining macroeconomic variables in Figures 2 and 3. For the output deviations shown in Figure 2, we note virtually no meaningful differences between the quadratically detrended gap ($\tilde{y}_t^Q$) and the HP filtered gap ($\tilde{y}_t^H$). Hence, in what follows, we provide our major empirical findings with $\tilde{y}_t^H$ only.

As can be seen in Figures 1, 2, and 3, all variables other than policy-related interest rates in the present paper seem to exhibit low degree persistence, which is desirable for the maximum likelihood estimator (MLE), because the MLE may yield wrong standard errors when there are nonstationary covariates (Park and Phillips, 2000; Hu and Phillips, 2004a,b).[11] In what follows, we provide formal test results that imply stationarity of all covariates in our latent variable equation (1).

On the other hand, target RP rate (i_t^R) and call rate (i_t^C) exhibit very high degree persistence, which may have issues in statistical inferences when the Least Squares (LS) estimator is employed, because these data may contain a unit root. However, since we use

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[10] Adding additional thresholds, we may extend the model to incorporate these 50 and 100 basis points changes. Since these are quite rare events (5 out of 162 observations), a trichotomous specification seems to be a more efficient choice.

[11] However, this caveat does not apply to out-of-sample forecast when one uses point estimates to formulate the conditional expectation (see Kim *et al.*, 2009).

discrete choice models for the policy variable, this does not cause such a problem in our models, because we transform the target RP rate into policy actions that have integer values $\{-1,0,1\}$. The (lagged) call rate in (2) is still a continuous variable. This is not a problem again, because its coefficient is constrained to be -1, so we do not estimate it.

Figures 2 and 3 around here

3.2 *Unit Root Tests*

We first implement the augmented Dickey-Fuller (ADF) test for all variables used in the present paper. The current empirical literature on the monetary policy heavily relies on the LS estimator or the generalized method of moments (GMM) estimator. For instance, one may use the LS estimator for backward looking Taylor rules, while the GMM estimator may be used for forward-looking Taylor rules (see Clarida *et al*., 2000). Since the LS and the GMM estimators require stationary dependent and independent variables, we first implement the conventional ADF test and report results in Table 1.

The ADF test rejects the null hypothesis of nonstationarity at the 5% significance level for the inflation rate, both output gap measures, and the won depreciation rate against the US dollar when an intercept is included and when both an intercept and time trend are included in the regression. The test rejects the null at the 10% level for the long-short spread and the M2 growth rate when an intercept is included. In a nutshell, all candidate covariate variables seem to exhibit fairly low persistence over time. These results are also consistent with eyeball metrics from Figures 2 and 3.

On the contrary, the test fails to reject the null of nonstationarity for the target RP rate and the interbank call rate even at the 10% significance level. They also show highly persistent movements as we can see in Figure 1. Since these (nominal) interest rate variables are bounded below by 0%, it is not technically appropriate to claim that they are nonstationary. However, they may still exhibit locally nonstationary movements which may hinder proper statistical inferences when one implement estimations for Taylor rule type linear regression models.

Table 1 around here

3.3 *Linear Taylor Rule Estimations*

This subsection implements estimations for an array of Taylor rules using the LS method for the following equation.

$$i_t = \alpha + \beta\pi_{t-1} + \gamma\tilde{y}_{t-1} + \theta x_{t-1} + \varepsilon_t, \tag{7}$$

where x_{t-1} is either a scalar or a vector of additional explanatory variables. Note that we assume that policy makers can access information on the macroeconomic variables with one-month lag. We also implement estimations for Taylor rules with the interest rate smoothing consideration (see Clarida *et al*., 2000, for example),

$$i_t = \alpha_S + \beta_S\pi_{t-1} + \gamma_S\tilde{y}_{t-1} + \theta_S x_{t-1} + \rho i_{t-1} + \varepsilon_t, \tag{8}$$

where ρ measures the degree of interest rate inertia. Note also that the coefficient with a subscript S denotes the short-run coefficient. For example, $\beta = \beta_S/(1-\rho)$ is the long-run coefficient on the inflation rate. Put it differently, if $\rho = 0.75$ and $\beta = 1.5$, then the central bank responds to a 1% inflation gap by raising the nominal interest rate by 0.375% ($\beta_S = 1.5 \times 0.25 = 0.375$) contemporaneously but will continue to raise it by 1.5% in the long-run.

All estimation results for (7) and (8) are reported in Table 2. We note that the coefficient on the output gap is always significant at the 1% level, while the coefficient on inflation is mostly insignificant. All other explanatory variables seem overall highly significant.

However, the long-run coefficients for the won depreciation rate and the long-short spread have *incorrect* signs when the interest rate smoothing is not considered. For example, when the won depreciates against the US dollar, the BOK may raise the target interest rate because inflationary pressure tends to build up, which implies a positive sign for the won depreciation rate. The conventional expectation hypothesis of the term structure of interest rates implies that widening long-short spread reflects higher expected inflation in near future, which then implies a positive sign as well by the same token. The LS estimator yielded a correct sign for the coefficients of Δs_{t-1} and Δls_{t-1} only when the interest rate smoothing is incorporated.

Our overall findings from these estimations include: (i) coefficient estimates for ρ that are close to one; (ii) quantitatively smaller short-run coefficient estimates for most explanatory variables than those of (7); (iii) correct signs for the won depreciation rate and the long-short spread.

It should be noted that (i) and (iii) imply that the equation (7) may be mis-specified since it ignores very high degree persistence, possibly nonstationarity, in the policy interest rate. Hence, including the lagged dependent variable (i_{t-1}) as in (8) may yield better estimates as long as it is stationary. But if the interest rate obeys a nonstationary stochastic process, statistical inferences based on these linear models may not be valid. Further, the estimated long-run coefficients for inflation in either specification seem to violate the Taylor Principle that requires $\beta > 1$ for the determinacy of inflation. For example, the first model for (8) yields $\beta_S = 0.005$ and $\rho = 0.961$, thus the long-run coefficient becomes $\beta = 0.161$ that is strictly less than 1. Since $\beta < 1$, inflation may become indeterminate, which seems to be at odds with stable inflation dynamics in Korea since 2000.

Table 2 around here

These findings all together imply that linear Taylor rules may not be ideal to investigate monetary policy decision-making processes in Korea. We avoid these potential issues by employing a qualitative response model for the monetary policy decision-making process. We report our findings in the next section.

4 Constrained Ordered Choices Model Estimations

This section reports our estimation results for the latent equation (1) via the three ordered choices models, the probit model, the logit model, and the robit model that uses the t-distribution with 5 degrees of freedom. We implement an array of economic models with alternative sets of covariates. Our backward looking models assume that the MPC observes key macroeconomic variables with one month lag. For instance, we estimate the coefficients for the past inflation rate (π_{t-1}) and the output gap ($\tilde{y}_{t-1}$) in the latent equation (Model Taylor B). We also estimate extended version models with additional covariates, again with one month lag. Probit model estimates for these backward looking models are provided on the first panel of Table 3.

Major findings are as follows. First, all threshold estimates are highly significant at least at the 10% level, which support the conjecture that the MPC revises the target RP rate only when there's a substantial deviation from the optimal rate based on the state of the economy. Second, the coefficient estimates for the output gap are highly significant at the 1% for 3 out of 5 models. The coefficient is significant at the 5% and 10% levels for the remaining two models. Third, the inflation rate is significant at the 10% level for 3 out of 5 models, which is somewhat surprising because the BOK has employed the inflation targeting system since 1998.[12] However, this does not necessarily imply that the BOK has neglected the inflation targeting system, because output gaps provide information on accelerating inflationary pressure, which can be realized in near future. Highly significant coefficient estimates for $\tilde{y}_t$, therefore, implies that the BOK has responded to expected inflation instead of realized inflation. Fourth, the M2 growth rate, the won depreciation rate, and the long-short spread have overall correct signs, but none was significant at the conventional level.

We then implement estimations with alternative assumptions on the information set of the MPC. Results are reported on the second panel of Table 3. Taylor C model utilizes the *current* period Taylor Rule variables (π_t, $\tilde{y}_t$), assuming that the MPC can observe those

[12] The BOK switched from the total CPI inflation to the *core* CPI inflation for the period between 2000 and 2006. They returned to the total CPI inflation in 2007. Replacing π_t with the core inflation yields similar results, because these two inflation measures exhibit quite similar dynamics over time.

variables without delay. We obtained significant coefficients for $\tilde{y}_t$ and the threshold values, τ_L and τ_U, but not for π_t. Next, we try an array of hybrid models, recognizing that the MPC is able to observe the *current* period *financial* market variables such as the won depreciation rate (Δs_t) and the long-short spread (ls_t). Interestingly, the coefficient on Δs_t has a correct sign and significant at the 10% in Taylor H1 model, while the coefficient on Δs_{t-1} was insignificant in Taylor B2 and Taylor B4 models. The current period long-short spread (ls_t) has a correct sign but is not significant. In all cases, the inflation rate is insignificant, while the coefficient on the output gap is always significant. We again find strong evidence of nonlinear adjustments of the target RP rate, because all threshold estimates are significant.

Table 3 around here

Logit model coefficient estimates (Table 4) are overall larger than but qualitatively similar as those from the probit model. The coefficient on the output gap is highly significant at the 1% level in all models we consider, whereas the inflation rate coefficient estimates are insignificant at any conventional significance levels. The *current* won depreciation rate (Δs_t) and the long-short spread have the correct sign and are highly significant at the 1% level. All threshold estimates are highly significant at the 1% level. The coefficient estimate for the lagged M2 growth rate (Δm_{t-1}) was always insignificant.

Table 4 around here

We also implemented estimations with the robit model specification that uses the *t*-distribution. We experimented with 3, 5, 7, and 30 degrees of freedom and obtained qualitatively similar results.[13] Coefficient estimates with 5 degrees of freedom are reported in Table 5. Results are overall similar to those from the logit model, which makes sense

[13] Results with other specifications are available upon requests.

because the robit model approximates the logit model with 7 degrees of freedom (see Liu, 2005).

We again obtained highly significant coefficient estimates for the output gap, the *current* won deprecation rate, both the current and the lagged long-short spread, and the upper and lower threshold variables. Coefficients on the inflation rate and the money growth rate were again insignificant in all models. In comparison with the probit model estimates, the robit and the logit model specifications provided more efficient estimates with smaller p-values with an exception of the inflation rate coefficient.

Table 5 around here

In a nutshell, the output gap ($\tilde{y}_t$) plays a dominantly important role in understanding monetary policy decision-making processes in Korea, while we obtain a lot weaker evidence for the other Taylor rule variable, π_t. These findings imply that the BOK has responded to *expected* inflation rather than *realized* inflation, because output gap provides information on incoming inflationary pressure that may be realized in the near future. Also, the current period won depreciation rate seems to play a key role, which makes sense because Korea is a small open economy. Note that this result contrasts sharply with the work by Hu and Phillips (2004a) and Kim *et al*. (2009) who find a negligible role of the foreign exchange rate in the Fed's decision-making processes.

We then investigate the stability of our coefficient estimates over the entire sample period. For this purpose, we recursively estimated our models beginning with the first half observations, January 2000 to June 2006, adding one additional observation in each round of estimations, which gives 82 sets of coefficient estimates for each model. We report the results from the probit model specification in Figure 4 for Models Taylor B and Taylor H1.[14]

We note that our results are quite robust over time as to the statistical significance of the estimates. That is, $\tilde{y}_{t-1}$ is overall highly significant at the 5%, while π_{t-1} and Δs_t are

[14] Results from other models are qualitatively similar.

significant at the 10%. We also note that the coefficient estimates are mildly rising as the sample period expands. For example, the coefficient estimate on Δs_t was 0.022 when the first half observations are used, while it increased gradually to 0.060 when we used all available observations. That is, it seems that the BOK has gradually increased the weights on the won-dollar exchange rate in determining its optimal policy interest rate.

Figure 4 around here

5 In-Sample Fit Performance of the Discrete Choices Models

Next, we evaluate our ordered choices models for the MPC's decision-making process in terms of the in-sample fit performance. We report results based on the probit model specification that performs qualitatively similarly but slightly better than the logit and the robit models.[15]

We plot estimated probabilities of *C* and *H* predictions from Models Taylor B, Taylor C, and Taylor H1 along with actual policy decisions (bar graphs) over time in Figure 5. All models yield very similar probability estimates, implying that our results are robust to alternative assumptions on the BOK's information set. The figure shows that changes in the probabilities calculated with the model estimates are overall consistent with the occurrences of actual rate decision actions. The probability of each event tends to increase rapidly when corresponding actual rate revisions (*C* and *H*) are implemented. Note that the probability of a *C* goes up to almost 100% during the recent financial crisis. Also, the estimated probability of an *H* climbs up fast in 2011 when the MPC raised the target RP rate several times.

Figure 5 around here

We report correct prediction (success) rates to evaluate the in-sample fit performance of our models. Recall that our models predict a *C* decision when y_t^* falls below τ_L. Likewise,

[15] Results from other specifications are available upon requests.

when y_t^* rises above τ_U, our model predicts an H action. It should be noted, however, that these threshold estimates come with uncertainty. Since it is more important to correctly predict revision actions (C and H) than S decisions, we adjust the inaction band using the standard errors of these threshold variable estimates in order to catch tail events more often.

To see this, we plot the estimated latent variable y_t^* for Models Taylor B, Taylor C, and Taylor H1 in Figure 6 along with the point estimates for τ_L and τ_U and their one standard error confidence bands. It is clear that a more compact inaction band such as $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$ would yield C and H predictions more frequently with a cost of lower success rate for S decisions. Employing inaction bands based solely on point estimates, one may obtain a very high success rate for S decisions, while correct prediction rates for C and H actions tend to become low.[16] Since it is more important to predict C and H actions, our in-sample fit analyses are based on standard error adjusted inaction bands.

Figure 6 around here

We report correct prediction (success) rates based on the probit model estimations for four alternative models in Table 6. The first panel provides results with one standard error inaction bands, $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$. Taylor B4 model performed the best in predicting C and H decisions correctly, even though its performance is the worst for S decisions, predicting 94 out of 131 S actions (71.76%). The model correctly predicted 9 out of 16 cut decisions (56.25%) and 8 out of 15 hike decisions (53.33%). Models Taylor C and Taylor H1 performed similarly well for C actions, whereas their performance for H actions were less satisfactory.

As we discussed earlier, in-sample-fit performance improves for C and H actions when narrower inaction bands are employed. Success rates for C decisions with 1.5 standard error inaction bands, $[\tau_L + 1.5 \times std(\tau_L), \tau_U - 1.5 \times std(\tau_U)]$, reported on the second panel

[16] For example, correct prediction rates for C, S, and H actions from Taylor B model were 18.75%, 96.28%, and 6.67%, respectively, when we employed a point estimate-based inaction band. Model Taylor H1 performed similarly, yielding 31.25%, 99.24%, and 6.67%, respectively.

range from 62.60% to 87.50%, while hike decisions were predicted with 40% to 60% accuracy. It should be noted that such improvement in prediction of *C* and *H* actions come with poorer performance for *S* actions. However, if one is more interested in predicting changes in the monetary policy stance, narrower inaction bands would be a better choice for that purpose.

Table 6 around here

6 Evaluating Out-of-Sample Predictability of the Models

This section evaluates the out-of-sample predictability of our ordered choices models for the interest setting behavior in Korea. Predicting the monetary policy stance is crucially important not only to financial market participants but also to entrepreneurs who make investment decisions that are heavily influenced by their prospect on interest rate dynamics in near future. We implement an array of out-of-sample forecast exercises to see if our model helps predict the BOK's monetary policy decisions in the future.

We implement our exercises using the following two forecast strategies: the recursive method and the fixed-size rolling window method, both beginning with the initial 104 observations for the sub-sample period between January 2000 and September 2008. We choose this split point because this initial set of observations corresponds to the pre-Lehman Brothers Bankruptcy period, which may help evaluate how well our models out-of-sample predict the BOK's responses to the recent financial crisis.

The recursive forecasting approach begins with a memory window of the pre-Lehman Brothers Failure period and ends with a window of the entire sample period, January 2000 to September 2013. That is, we start calculating a one-period ahead forecast on the policy action (*C*, *S*, *H*) using the initial 104 observations. Then, we add the 105th observation and predict the next policy outcome with this expanded set of observations. We continue to do this until we forecast the last policy action in September 2013 using the data from January 2000 to August 2013.

As is well-known, the recursive forecasting strategy may not perform well in the presence of a structural change in the data generating process (DGP). If regime changes occur sometime during the early period of the analysis, inclusion of earlier data in the estimation could worsen the forecastability of our model. To address this possibility, we also employ a fixed-size rolling window scheme described as follows.

Here we begin with the same initial 104 observations for the pre-Lehman Brothers Failure period. After estimating the model, we forecast the next month (105th) policy outcome. Then, we add the 105th actual observation, but drop the 1st observation, thereby retaining an updated 104-observation estimation window, which is used to produce the 106th policy outcome. We repeat this process until we forecast the last policy outcome using the most recent 104 observations from December 2004 to August 2013.

Note that our out-of-sample forecast exercises are naturally based only on backward looking Taylor Rule type models. Since we are doing out-of-sample forecast, we assume that econometricians utilize currently available information set (Ω_t) to predict the policy action in the next period. We employ two conditional expectation models for $E(y_{t+1}|\Omega_t) = \{-1,0,1\}$, where the information set is either $\Omega_t = \{\pi_t, \tilde{y}_t\}$ or $\Omega_t = \{\pi_t, \tilde{y}_t, \Delta s_t\}$.

Again, we report probit model estimation results only in Table 7. "*Taylor Recursive*" denotes the forecast results using the recursive method with $\{\pi_t, \tilde{y}_t\}$ for covariates in the latent equation, whereas "*Taylor Extended Rolling*" is the results with the rolling window method using $\{\pi_t, \tilde{y}_t, \Delta s_t\}$. Again, results on the top panel are based one standard error bands and results with 1.5 standard error bands are reported on the second panel.

During the *post*-Lehman Brothers Bankruptcy period, there were 8 cut decisions, 47 stay decisions, and 5 hike decisions. With one standard error bands, extended version Taylor Rule model out-of-sample forecasts 7 out of 8 cut decisions correctly (87.5%) when the rolling window scheme is employed. Also, the model predicted 3 out of 5 hike decisions correctly (60%). Overall, out-of-sample forecasts with the rolling window forecast scheme performed slightly better than those with the recursive scheme, implying a possible structural change in the DGP.

When we use the 1.5 standard error bands, we observe a further improvement in out-of-sample forecast performance for *C* decisions for the models with the rolling window method. That is, extended version Taylor Rule model out-of-sample forecasts all 8 cut decisions, while Taylor Rule model forecasts 7 out of 8 cut decisions. Again, we observed better out-of-sample forecast performance from the rolling window method compared with those from the recursive scheme. Note also that we enhanced the out-of-sample forecastability for *C* and *H* decisions with a cost of lower success rate for *S* decisions by adopting standard error adjusted inaction bands.

Table 7 around here

Market participants (say, Fed watchers) who are particularly interested in changes in the monetary policy stance would be eager to learn how likely the central bank would be to *revise* the target policy rate. So, we report estimated probabilities of a *C* and an *H* from our out-of-sample forecast exercises in Figure 7. Results from our extended version Taylor Rule model are reported because we obtain qualitatively similar estimates from other models. We also show actual occurrences of realized *C* and *H* decisions on the same graphs.

We observe rapidly escalating probability of a cut decision right after the Lehman Brothers Failure episode in both models, matching with multiple cut decisions during that period. We also see the probability of a *C* action to climb up in 2012 and 2013 after a long period of virtually 0% probability of a *C*, which coincide with three actual cut decisions. The probability of an *H* action goes up rapidly in late 2009 until 2011 that are encountered with 5 interest rate hike decisions.

It is interesting to see that the predicted probability of an *H* action has stayed quite high before actual *H* actions occurred, which might have happened that the MPC delayed their actions facing political pressure against contractionary policy actions. Or they might wanted to decide on their interest rate revision more carefully probably due to sluggish recovery in other economies outside Korea or possibly some other non-macroeconomics issues.

Figure 7 around here

Lastly, we report estimates for y_t^* (solid lines), τ_L and τ_U (dashed lines), and one standard error inaction bands (dotted lines) in Figure 8. This is to demonstrate how forecast performances can improve for C and H actions by employing a standard error adjusted (narrower) inaction band. For example, when the rolling window method is used for our models, y_t^* falls below the inaction band but stays above the τ_L estimate at the end of the sample. That is, our model cannot out-of-sample forecast the last cut decision that occurred at the end of the sample if one uses the point estimate based criteria instead of using standard error adjusted inaction bands. Similarly, standard error unadjusted inaction bands would not be able to predict H actions in 2010 to 2011, whereas our models correctly predict 60% such actions using 1.5 standard error inaction bands.

Figure 8 around here

6 Concluding Remarks

This paper investigates the BOK's monetary policy decision making process using ordered discrete choice models. Historically, the MPC has revised the target policy interest rate in multiples of 25 basis points during their monthly meetings. This convention leads us to use ordered choices models where the MPC changes the policy rate only when there is substantial divergence of the current interest rate from the optimal interest rate based on key macroeconomic variables.

Using monthly frequency data for an array of alternative model specifications, we report empirical evidence of good in-sample fit performance. Our latent equation estimates from the probit, the logit, and the newly suggested robit models imply important roles for the output gap and the won depreciation rate in describing the BOK's interest rate setting behavior. These findings imply that the BOK has responded to expected inflation instead of realized inflation utilizing information on future inflation through changes in the output gap. Significant coefficient estimates for the won exchange rate indicate that the BOK has paid close attention to it because Korea is a small open economy.

We also evaluate out-of-sample prediction performance of our approach using September 2008 as a split point for the recursive and the fixed size rolling window forecast schemes. Again, our models perform well for out-of-sample predictions. For instance, our Taylor rule type models in combination with the fixed size rolling window scheme predicted most rate cut decisions as well as the majority hike decisions since the Lehman Brothers Bankruptcy episode. We also show that forecast performance for tail actions (*C* and *H*) can improve greatly with a cost of lower success rates for *S* actions by employing standard error adjusted inaction bands, which is a desirable feature for market participants who are particularly interested in changes in the monetary policy stance.

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Table 1. Augmented Dickey-Fuller Unit Root Test Results

	ADF$_c$	*ADF*$_t$
RP Rate (i_t^R)	-1.956	-2.952
Call Rate (i_t^C)	-2.262	-2.881
Inflation Rate (π_t)	-3.216†	-3.478†
Quad Detrended ($\tilde{y}_t^Q$)	-3.909‡	-3.940†
HP Detrended ($\tilde{y}_t^H$)	-4.014‡	-4.027‡
M2 Growth Rate (Δm_t)	-2.548*	-2.679
Won Dep Rate (Δs_t)	-4.238‡	-4.271‡
Long-Short Spread (ls_t)	-2.601*	-2.628

Note: *ADF*$_c$ and *ADF*$_t$ denote the augmented Dickey-Fuller unit root test when an intercept is included and when both an intercept and linear time trend are present. We select the number of lags by the general-to-specific rule with a maximum 12 lags and the 10% significance level criteria. $*$, $\dagger$, and $\ddagger$ denote rejections of the unit-root null hypothesis at the 10%, 5%, and 1% significance level, respectively.

Table 2. Taylor Rule Type Linear Model Coefficient Estimations

	Long-Run Coefficients				
Inflation Rate	0.034	0.028	0.033	0.042*	0.035
(π_{t-1})	(0.023)	(0.023)	(0.023)	(0.022)	(0.022)
Output Gap	0.006‡	0.006‡	0.007‡	0.005‡	0.006‡
($\tilde{y}_{t-1}$)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
M2 Growth Rate	-	0.035†	-	-	0.039‡
(Δm_{t-1})		(0.013)			(0.013)
Won Dep Rate	-	-	-0.006†	-	-0.003
(Δs_{t-1})			(0.003)		(0.003)
Long-Short Spread	-	-	-	-0.544‡	-0.536‡
(ls_{t-1})				(0.123)	(0.125)
	Short-Run Coefficients with Interest Rate Smoothing				
Inflation Rate	0.005	0.005	0.005	0.004	0.004
(π_{t-1})	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Output Gap	0.002‡	0.002‡	0.001‡	0.002‡	0.001‡
($\tilde{y}_{t-1}$)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
M2 Growth Rate	-	0.000	-	-	-0.001
(Δm_{t-1})		(0.002)			(0.002)
Won Dep Rate	-	-	0.001†	-	0.001
(Δs_{t-1})			(0.000)		(0.000)
Long-Short Spread	-	-	-	0.054†	0.049*
(ls_{t-1})				(0.021)	(0.022)
Smoothing Parm	0.961‡	0.960‡	0.965‡	0.972‡	0.976‡
(i_{t-1})	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)

Note: The policy interest rate is the target RP rate. Taylor rule reference variables are lagged by one-period. Output gap is the HP cyclical component of the real industrial production index. Quadratically detrended index yielded qualitatively similar results, thus are not reported. All results are available upon request. ∗, †, and ‡ denote significance at the 10%, 5%, and 1% significance level, respectively.

Table 3. Probit Model Coefficient Estimation Results

	Backward Looking Models				
	Taylor B	Taylor B1	Taylor B2	Taylor B3	Taylor B4
Inflation Rate	0.217*	0.189*	0.220*	0.283	0.240
(π_{t-1})	(0.131)	(0.115)	(0.133)	(0.240)	(0.193)
Output Gap	0.043‡	0.040‡	0.043‡	0.074*	0.066†
($\tilde{y}_{t-1}$)	(0.014)	(0.011)	(0.014)	(0.043)	(0.033)
M2 Growth Rate	-	0.068	-	-	0.057
(Δm_{t-1})		(0.062)			(0.097)
Won Dep Rate	-	-	0.002	-	-0.012
(Δs_{t-1})			(0.017)		(0.023)
Long-Short Spread	-	-	-	3.197	2.776
(ls_{t-1})				(2.459)	(1.908)
Lower Threshold	-0.342‡	-0.320‡	-0.347‡	-0.636*	-0.556*
(τ_L)	(0.108)	(0.090)	(0.112)	(0.378)	(0.285)
Upper Threshold	0.347‡	0.325‡	0.353‡	0.641*	0.559*
(τ_U)	(0.107)	(0.087)	(0.114)	(0.379)	(0.288)

	Alternative Models			
	Taylor C	Taylor H1	Taylor H2	Taylor H3
Inflation Rate	-	0.215	0.292	0.255
(π_{t-1})		(0.154)	(0.226)	(0.230)
Output Gap	-	0.058‡	0.072*	0.085†
($\tilde{y}_{t-1}$)		(0.021)	(0.038)	(0.044)
Inflation Rate	0.077	-	-	-
(π_t)	(0.158)			
Output Gap	0.064‡	-	-	-
($\tilde{y}_t$)	(0.027)			
Won Dep Rate	-	0.060*	-	0.078
(Δs_t)		(0.031)		(0.050)
Long-Short Spread	-	-	2.766	2.443
(ls_t)			(2.008)	(1.884)
Lower Threshold	-0.490‡	-0.462‡	-0.586*	-0.699*
(τ_L)	(0.193)	(0.168)	(0.308)	(0.366)
Upper Threshold	0.493‡	0.471‡	0.586*	0.701*
(τ_U)	(0.188)	(0.167)	(0.311)	(0.368)

Note: The policy interest rate is the target RP rate. Output gap is the HP cyclical component of the real industrial production index. Quadratically detrended index yielded qualitatively similar results, thus are not reported. All results are available upon request. $*$, †, and ‡ denote significance at the 10%, 5%, and 1% significance level, respectively.

Table 4. Logit Model Coefficient Estimation Results

	Backward Looking Models				
	Taylor B	Taylor B1	Taylor B2	Taylor B3	Taylor B4
Inflation Rate	1.183	1.154	1.179	1.002	0.991
(π_{t-1})	(0.773)	(0.774)	(0.787)	(0.752)	(0.752)
Output Gap	0.221‡	0.222‡	0.216‡	0.278‡	0.281†
($\tilde{y}_{t-1}$)	(0.043)	(0.042)	(0.04)	(0.052)	(0.05)
M2 Growth Rate	-	0.154	-	-	0.031
(Δm_{t-1})		(0.469)			(0.378)
Won Dep Rate	-	-	0.076	-	-0.022
(Δs_{t-1})			(0.092)		(0.092)
Long-Short Spread	-	-	-	15.831‡	16.128‡
(ls_{t-1})				(4.228)	(4.235)
Lower Threshold	-2.579‡	-2.581‡	-2.584‡	-2.805‡	-2.810‡
(τ_L)	(0.303)	(0.301)	(0.304)	(0.297)	(0.294)
Upper Threshold	2.617‡	2.623‡	2.636‡	2.932‡	2.936‡
(τ_U)	(0.293)	(0.294)	(0.302)	(0.394)	(0.393)

	Alternative Models			
	Taylor C	Taylor H1	Taylor H2	Taylor H3
Inflation Rate	-	1.112	1.076	0.981
(π_{t-1})		(0.831)	(0.732)	(0.794)
Output Gap	-	0.293‡	0.288‡	0.354†
($\tilde{y}_{t-1}$)		(0.045)	(0.053)	(0.053)
Inflation Rate	0.288	-	-	-
(π_t)	(0.913)			
Output Gap	0.301‡	-	-	-
($\tilde{y}_t$)	(0.052)			
Won Dep Rate	-	0.361‡	-	0.333‡
(Δs_t)		(0.110)		(0.119)
Long-Short Spread	-	-	15.551‡	13.640‡
(ls_t)			(4.679)	(5.032)
Lower Threshold	-2.726‡	-2.772‡	-2.791‡	-2.978‡
(τ_L)	(0.300)	(0.320)	(0.290)	(0.298)
Upper Threshold	2.768‡	2.827‡	2.912‡	3.075‡
(τ_U)	(0.322)	(0.318)	(0.401)	(0.395)

Note: The policy interest rate is the target RP rate. Output gap is the HP cyclical component of the real industrial production index. Quadratically detrended index yielded qualitatively similar results, thus are not reported. All results are available upon request. $*$, †, and ‡ denote significance at the 10%, 5%, and 1% significance level, respectively.

Table 5. Robit Model Coefficient Estimation Results

Backward Looking Models	Taylor B	Taylor B1	Taylor B2	Taylor B3	Taylor B4
Inflation Rate	0.839	0.818	0.830	0.715	0.709
(π_{t-1})	(0.543)	(0.544)	(0.561)	(0.535)	(0.534)
Output Gap	0.151‡	0.152‡	0.148‡	0.195‡	0.196‡
($\tilde{y}_{t-1}$)	(0.029)	(0.028)	(0.026)	(0.036)	(0.035)
M2 Growth Rate	-	0.108	-	-	0.023
(Δm_{t-1})		(0.322)			(0.168)
Won Dep Rate	-	-	0.056	-	-0.011
(Δs_{t-1})			(0.063)		(0.068)
Long-Short Spread	-	-	-	10.96‡	11.08‡
(ls_{t-1})				(3.032)	(3.066)
Lower Threshold	-1.744‡	-1.743‡	-1.748‡	-1.902‡	-1.904‡
(τ_L)	(0.216)	(0.215)	(0.218)	(0.210)	(0.21)
Upper Threshold	1.771‡	1.775‡	1.791‡	2.032‡	2.034‡
(τ_U)	(0.204)	(0.205)	(0.212)	(0.292)	(0.292)

Alternative Models	Taylor C	Taylor H1	Taylor H2	Taylor H3
Inflation Rate	-	0.787	0.761	0.685
(π_{t-1})		(0.589)	(0.520)	(0.562)
Output Gap	-	0.199‡	0.202‡	0.243 ‡
($\tilde{y}_{t-1}$)		(0.031)	(0.037)	(0.038)
Inflation Rate	0.214	-	-	-
(π_t)	(0.649)			
Output Gap	0.205‡	-	-	-
($\tilde{y}_t$)	(0.036)			
Won Dep Rate	-	0.248‡	-	0.225 ‡
(Δs_t)		(0.078)		(0.084)
Long-Short Spread	-	-	10.93‡	9.288 ‡
(ls_t)			(3.368)	(3.696)
Lower Threshold	-1.836‡	-1.877 ‡	-1.893 ‡	-2.011 ‡
(τ_L)	(0.211)	(0.229)	(0.204)	(0.211)
Upper Threshold	1.876‡	1.920‡	2.025 ‡	2.111 ‡
(τ_U)	(0.229)	(0.227)	(0.301)	(0.297)

Note: We use the robit model with 5 degrees of freedom for estimations. Results with 3, 7, and 30 degrees of freedom are qualitatively similar. The policy interest rate is the target RP rate. Output gap is the HP cyclical component of the real industrial production index. Quadratically detrended index yielded qualitatively similar results, thus are not reported. All results are available upon request. $*$, †, and ‡ denote significance at the 10%, 5%, and 1% significance level, respectively.

Table 6. In-Sample Fit Evaluations

(A) Inaction Band: $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$

	Taylor B			*Taylor B4*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	5	8	1	9	10	1
Stay Predicted	11	114	11	7	94	6
Hike Predicted	0	9	3	0	27	8
Correct Prediction (%)	31.25	87.02	20.00	56.25	71.76	53.33
Overall Prediction (%)		75.31			68.52	

	Taylor C			*Taylor H1*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	8	7	0	7	5	0
Stay Predicted	8	111	10	9	113	11
Hike Predicted	0	13	5	0	13	4
Correct Prediction (%)	50.00	84.73	33.33	43.75	85.50	26.67
Overall Prediction (%)		76.54			75.93	

(B) Inaction Band: $[\tau_L + 1.5 \times std(\tau_L), \tau_U - 1.5 \times std(\tau_U)]$

	Taylor B			*Taylor B4*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	10	14	1	14	37	1
Stay Predicted	6	99	8	2	50	5
Hike Predicted	0	18	6	0	44	9
Correct Prediction (%)	62.50	75.57	40.00	87.50	38.17	60.00
Overall Prediction (%)		59.26			45.06	

	Taylor C			*Taylor H1*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	11	12	0	10	11	0
Stay Predicted	5	91	9	6	95	9
Hike Predicted	0	28	6	0	25	6
Correct Prediction (%)	68.75	69.47	40.00	62.50	72.52	40.00
Overall Prediction (%)		66.67			68.52	

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

Table 7. Out-of-Sample Forecasts

(A) Inaction Band: $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$

	Taylor Recursive			*Taylor Rolling*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	5	2	0	6	7	0
Stay Predicted	3	28	3	2	23	2
Hike Predicted	0	17	2	0	17	3
Correct Prediction (%)	62.50	59.57	40.00	75.00	48.94	60.00
Overall Prediction (%)		58.33			54.33	

	Taylor Extended Recursive			*Taylor Extended Rolling*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	5	3	0	7	9	0
Stay Predicted	3	28	2	1	21	2
Hike Predicted	0	16	3	0	17	3
Correct Prediction (%)	62.50	59.57	60.00	87.50	44.68	60.00
Overall Prediction (%)		60.00			51.67	

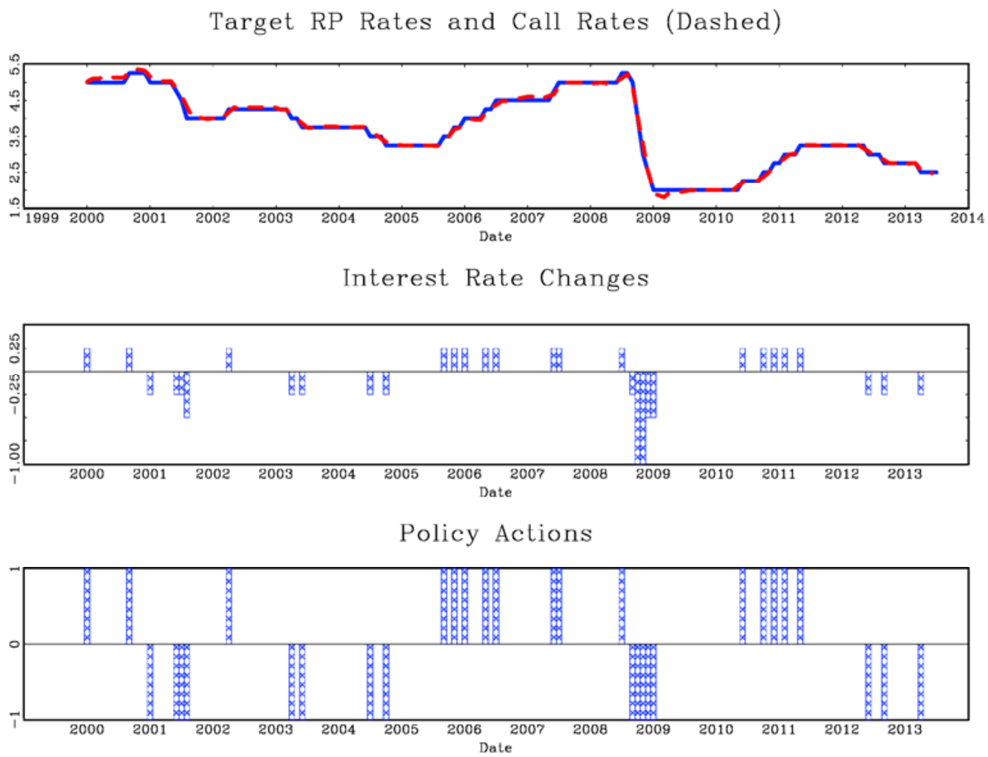
(B) Inaction Band: $[\tau_L + 1.5 \times std(\tau_L), \tau_U - 1.5 \times std(\tau_U)]$

	Taylor Recursive			*Taylor Rolling*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	5	6	0	7	10	0
Stay Predicted	3	23	2	1	19	2
Hike Predicted	0	18	3	0	18	3
Correct Prediction (%)	62.50	48.94	60.00	87.50	40.43	60.00
Overall Prediction (%)		51.67			48.33	

	Taylor Extended Recursive			*Taylor Extended Rolling*		
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	5	6	0	8	13	0
Stay Predicted	3	23	2	0	16	2
Hike Predicted	0	18	3	0	18	3
Correct Prediction (%)	62.50	48.94	60.00	100.00	34.04	60.00
Overall Prediction (%)		51.67			45.00	

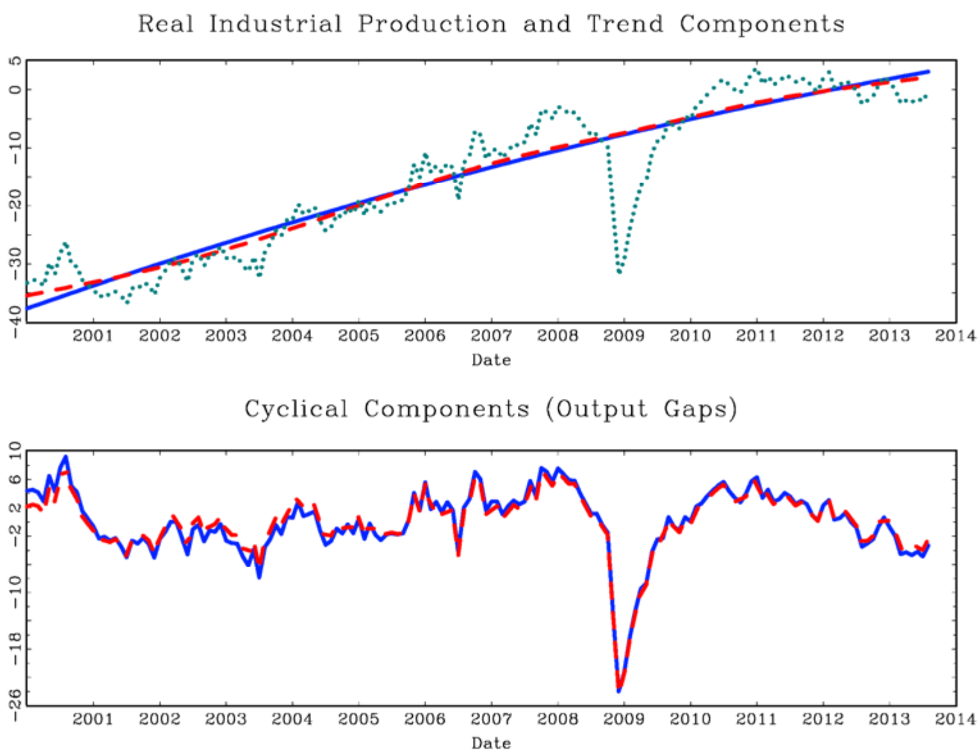
Note: Out-of-sample forecast results are based on the ordered probit model estimates with the recursive method and the fixed size rolling window method, both beginning with the pre-Lehman Brothers Bankruptcy period data (104 initial observations), September 2008.

Figure 1. Interest Rates and Monetary Policy Actions



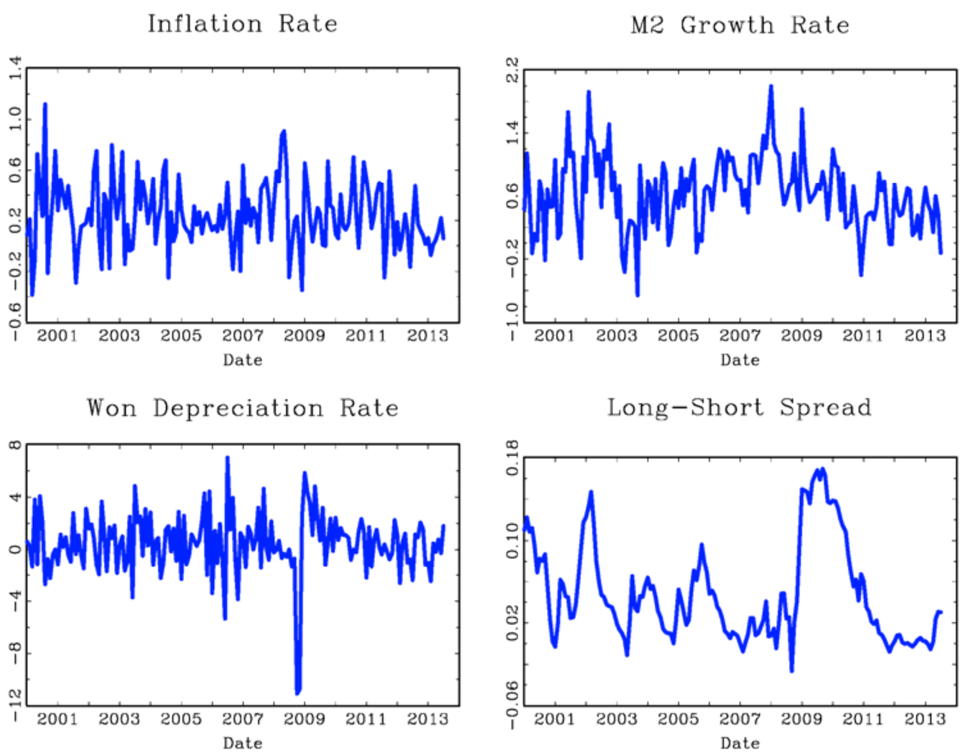
Note: The target RP rate (solid) and the market call interest rate (dashed) appear on the first panel. Revisions of the target RP rate have been made in multiples of 25 basis points as we can see in the second panel. We model policy actions to include three possible choices for the Bank of Korea as to the interest rate settings: Cut (-1), Hike (1), and Stay (0) as can be seen in the last panel.

Figure 2. Real Industrial Production: Trend and Cyclical Components



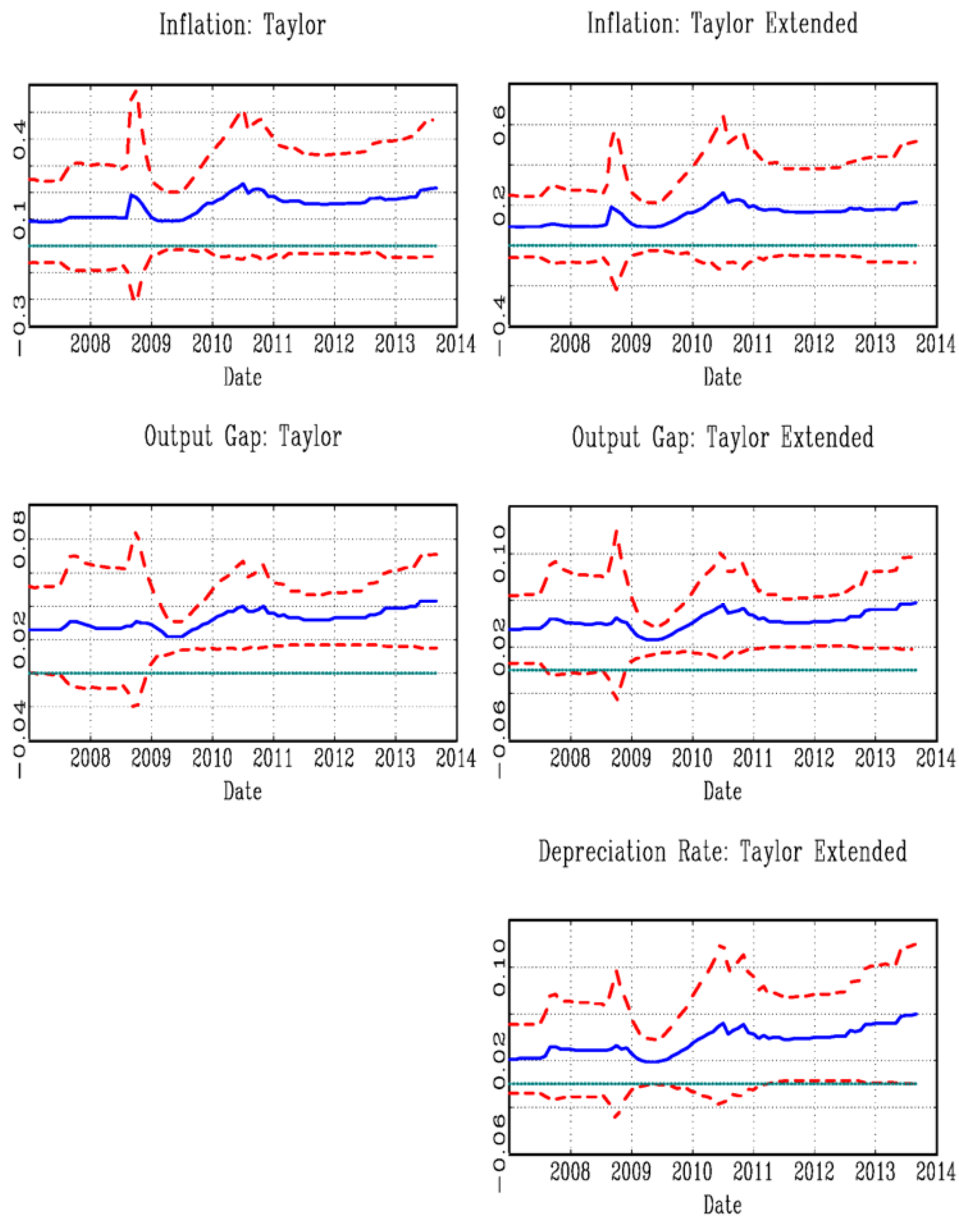
Note: We use two measures of the output gap: quadratically detrended real industrial production (solid) and the cyclical component of real industrial production (dashed) by the Hodrick-Prescott filter. Two detrending methods produce very similar output gaps.

Figure 3. Inflation Rate and Other Key Macroeconomic Data



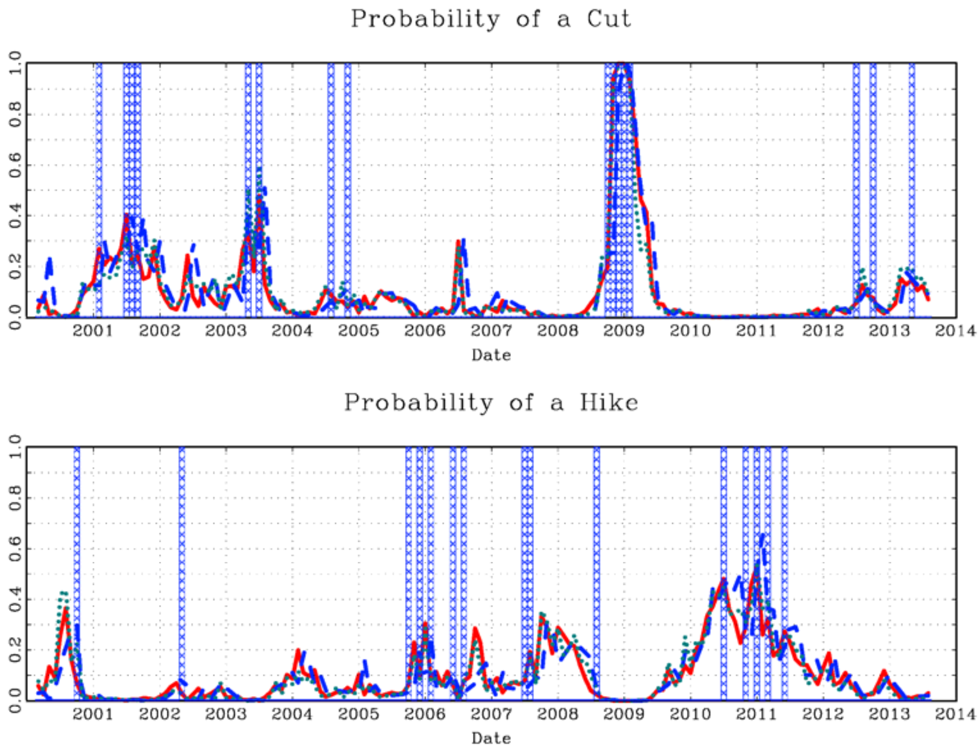
Note: The inflation rate is the monthly change in log CPI. The M2 growth rate denotes the monthly change in the log M2. We use the won-dollar exchange rate, which is the unit price of the US dollar in terms of Korean won. The won depreciation rate is the monthly change in the log exchange rate. The long-short spread is the 3-year government bond (monthly) yield minus the (monthly) yield of the 91-day government bond.

Figure 4. Constancy of the Latent Coefficient Estimates



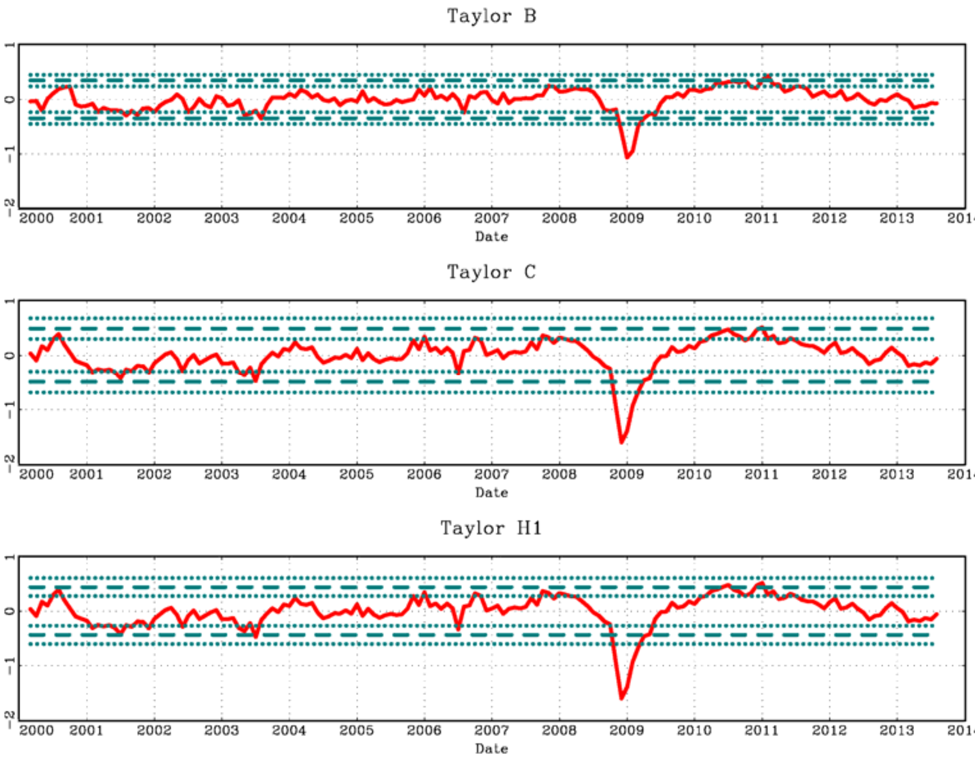
Note: We estimated the latent equation coefficients repeatedly beginning with the initial half of the sample period, 2000M1 to 2006M10, adding one more observation in each round of estimations. Inflation and output gap are lagged once, while the appreciation rate is the contemporaneous one. Dashed lines are 95% confidence bands. Reported graphs are based on the probit model specification.

Figure 5. In-Sample Fit Performance of Probit Models



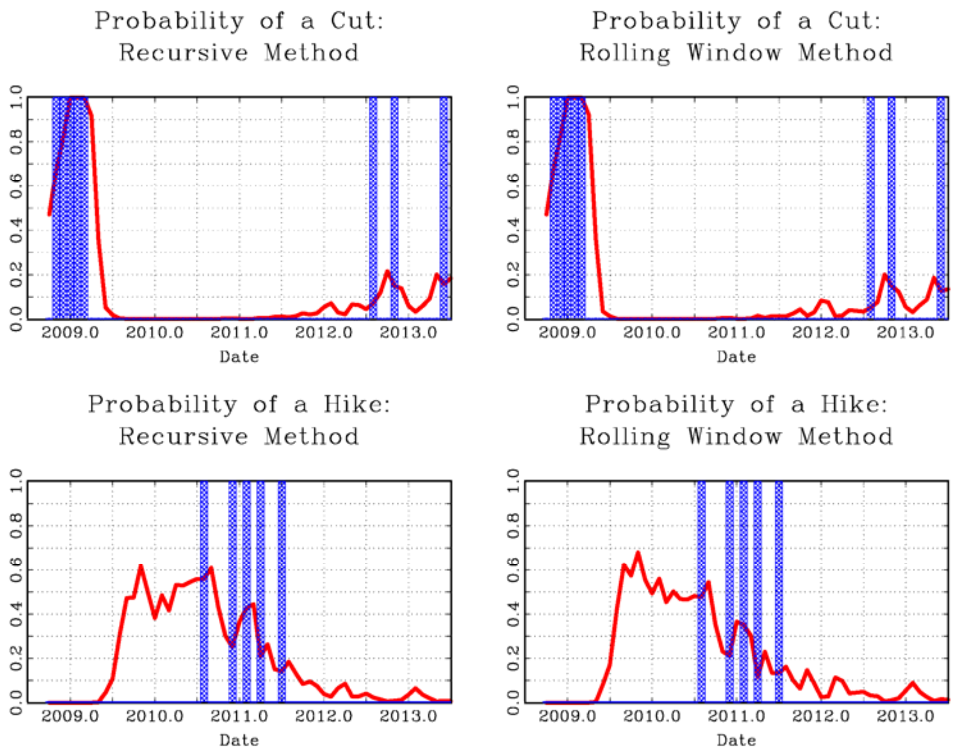
Note: We calculate in-sample probability of each action for the models with the following three sets of covariates in the latent equation and plotted in solid, dashed, and dotted lines, respectively: $(\pi_t, \tilde{y}_t)$, $(\pi_{t-1}, \tilde{y}_{t-1})$, $(\pi_{t-1}, \tilde{y}_{t-1}, \Delta s_t)$. Bar graphs indicate realized policy actions.

Figure 6. Deviations from the Optimal Rate and Thresholds



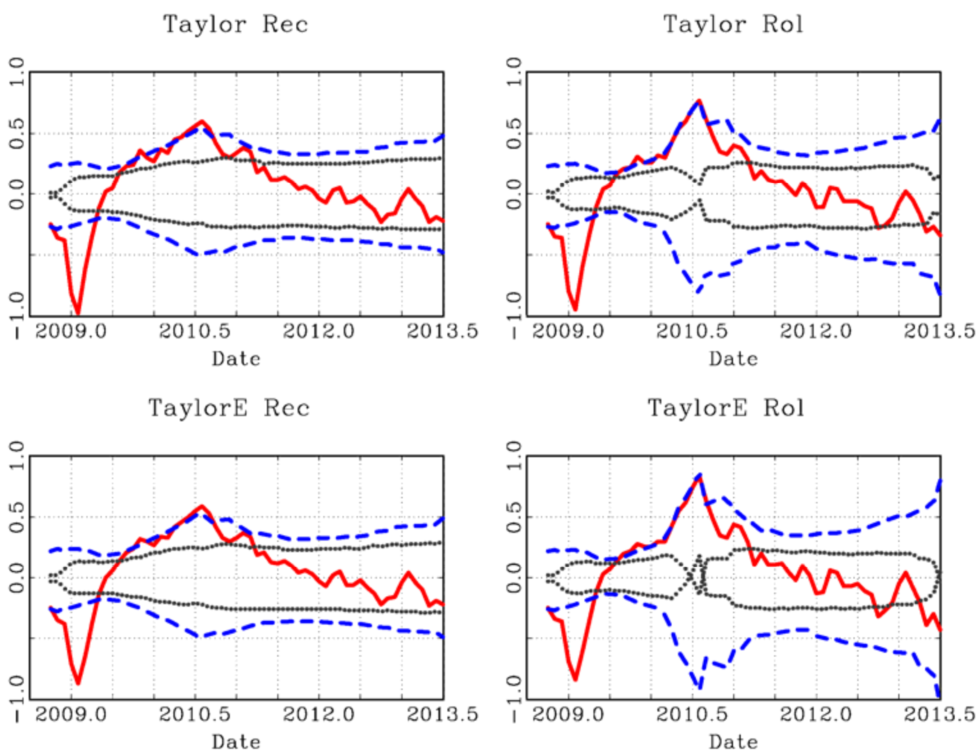
Note: We calculate deviations from the optimal interest rate ($y_t^* = i_t^* - i_{t-1}$) and upper and lower threshold values (τ_U, τ_L) for the models with the following three sets of covariates in the latent equation: ($\pi_{t-1}, \tilde{y}_{t-1}$), ($\pi_t, \tilde{y}_t$), ($\pi_{t-1}, \tilde{y}_{t-1}, \Delta s_t$). Sold lines are y_t^* estimates, dashed lines are estimated τ_U and τ_L point estimates, and dotted lines are one standard deviation confidence bands of threshold estimates.

Figure 7. Out-of-Sample Forecast: Probability Estimates



Note: We calculate the one-period ahead out-of-sample forecast probability of each action in the next period using $(\pi_t, \tilde{y}_t, \Delta s_t)$. Bar graphs indicate realized actions. Out-of-sample forecasting is done with the recursive method and the rolling window method, both beginning with the pre-Lehman Brothers Bankruptcy data (104 initial observations), September 2008.

Figure 8. Out-of-Sample Forecast: y_t^* and Inaction Band Estimates



Note: The solid line represents y_t^* estimates, the dashed lines are τ_L and τ_U estimates, and the dotted lines are $\tau_L + std(\tau_L)$ and $\tau_U - std(\tau_U)$ estimates. The area between the dotted lines indicates the one standard error inaction band, $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$.