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AUWP 2014-02

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ESTIMATING INTEREST RATE SETTING BEHAVIOR IN KOREA: AN ORDERED PROBIT MODEL APPROACH

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February 2014

Abstract

We investigate the Bank of Korea's interest rate setting behavior using a discrete choice model, where the Monetary Policy Committee revises the target policy interest rate only when the gap between the current market interest rate and the optimal rate exceeds a certain threshold value. Using monthly frequency data since 2000, we evaluate an array of ordered probit models in terms of the in-sample fit. We find important roles for the output gap, inflation, and the won depreciation rate against the US dollar. We also implement out-of-sample forecast exercises with September 2008 (Lehman Brothers Bankruptcy) for a split point, finding good out-of-sample predictability of our models.

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

JEL Classification: 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 general public. In Korea, the Monetary Policy Committee (MPC) of the Bank of Korea meets every month to revise the target RP rate that plays a key role in determining the interbank overnight interest rate, which is a market interest rate. The present paper employs a discrete choice model approach to study the interest setting behavior of the Bank of Korea.

There are quite a few papers that have investigated the Bank of Korea'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.¹ 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 Bank of Korea, while Aizenman, Hutchinson, and Noy (2008) report a weak role of the output from their panel estimation for 16 emerging market countries that include Korea. On the other hand, Oh (2006), Kwon (2007), Kim and Seo (2008), and Koo, Paya, and Peel (2012) employed nonlinear Taylor rule type monetary policy rules, finding somewhat mixed evidence of nonlinearity.

To the best of our knowledge, this paper is the first one that employs a discrete choice model to approximate the Bank of Korea'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 choice) models such as the ordered probit model.

¹ Nominal interest rates are bounded from below by 0%.

In case of the US, Dueker (1999), and later Hamilton and Jordà (2002), initiated the study by employing discrete choice modeling frameworks, the ordered probit and the autoregressive conditional hazard models, respectively, for the Federal Reserve's interest rate setting behavior. Hu and Phillips (2004a) employed an extended model of the work by Park and Phillips (2000) on nonstationary binary choice model to a nonstationary discrete choice model, then estimated the Fed's policy decision making process when policy makers evaluate the state of the economy using potentially nonstationary macroeconomic variables.² Kim, Jackson, and Saba (2009) employed the method of Hu and Phillips (2004a) 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 discrete choice models for the data between January 2000 and September 2013. Unlike Kim et al. (2009) and Hu and Phillips (2004a,b), 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 evaluate our models in terms of the insample fit, finding overall good performance of our models. We obtain solid evidence of important roles for the output gap, inflation, and the won-dollar depreciation rate in explaining the Bank of Korea's rate decision making processes. Also, we implement outof-sample forecast experiments using the Lehman Brothers Failure (September 2008) as a split point. We report satisfactory evidence of the out-of-sample predictability with the recursive and the fixed rolling window methods.

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 statistical analysis including unit root test results and linear Taylor rule model estimates. Section 4 reports our major empirical findings and in-sample-fit performance. In Section 5, we report out-of-sample prediction results. Section 6 concludes.

² Hu and Phillips (2004b) investigated the Bank of Canada's monetary policy behavior. Phillips, Jin, and Hu (2005) corrected the errors in Hu and Phillips (2004b) with regard to the convergence rates of ML estimates.

2 The Econometric Model

We assume that policy makers at the Bank of Korea set an optimal 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. Following Kim *et al.* (2009) and Hu and Phillips (2004*a*,*b*), we define the following another latent variable.

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

where i_{t-1} is the actual *market* interest rate (interbank call rate) in previous period. Note that y_t^* measures the deviation 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 Monetary Policy Committee (MPC) of the Bank of Korea 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.³ Based on this trichotomous choice model, we define the following policy index measure y_t and its associated indicator functions $\ell_{i,t}$.

$$y_{t} = \begin{cases} -1, \text{ if } y_{t}^{*} \leq \tau_{L} & : C \\ 0, \text{ if } \tau_{L} \leq y_{t}^{*} < \tau_{U} : S \\ 1, \text{ if } y_{t}^{*} \geq \tau_{U} & : H \end{cases}$$
(3)

and

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

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

$$\mathcal{L} = \sum_{t=1}^{T} \{ \ell_{C,t} ln P_C(x_t; \theta) + \ell_{S,t} ln P_S(x_t; \theta) + \ell_{H,t} ln P_H(x_t; \theta) \},$$
(5)

where θ is the parameter vector $(\beta, \tau_L, \tau_U)'$ and the probability mass function P_i is defined as follows.

$$P_{i} = \begin{cases} 1 - F(x_{t}'\beta - i_{t-1} - \tau_{L}), & \text{if } i = C \\ F(x_{t}'\beta - i_{t-1} - \tau_{L}) - F(x_{t}'\beta - i_{t-1} - \tau_{U}), & \text{if } i = S \\ F(x_{t}'\beta - i_{t-1} - \tau_{U}), & \text{if } i = H \end{cases}$$
(6)

³ 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.

We assume that $F(\cdot)$ is the standard normal distribution function, that is, the model is the conventional ordered probit model with a restriction on the coefficient of the previous period interbank call rate (i_{t-1}) that appears in y_t^* .^{4,5}

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 Bank of Korea, which directly influences the interbank overnight interest rate (call rate, i_t^C).⁶ Inflation (π_t) is the monthly log difference of the Consumer Price Index. As to the output gap (\tilde{y}_t), we consider the following two popular 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).⁷ M2 growth rate (Δm_t) is 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 are divided by 12 to make monthly interest rates. We obtain all data from the Bank of Korea.

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 also noted that there is a sharp decline right after the recent financial crisis starting in 2008. On the second

⁴ 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.

⁵ Alternatively, one may use the logistic regression, which results in an ordered logistic model.

⁶ 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.

⁷ 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 (1999), 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.

panel, we represent changes in the target RP rate, which clearly show that the MPC have revised the target rate infrequently in multiples of 25 basis points. That is, there were 16 cuts and 15 hike decisions, while the MPC chose not to revise 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 choice model that can be graphically represented in the third panel in Figure 1, which renders -1, 0, and 1 for cases of *C*, *S*, and *H*, respectively.⁸

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 and the HP filtered gap. Hence, in what follows, we provide our major empirical findings with the HP filtered gap only.

As we can see in Figures 1, 2, and 3, it seems that all variables other than policyrelated interest rates in the present paper exhibit low degree persistence, which is desirable for the maximum likelihood estimator (MLE). Target RP Rate and Call Rate exhibit very high degree persistence, which may have problems in statistical inference using LS type regressions because the data series may have a unit root. However, since we use a discrete choice model for the policy variable, this is not a problem in our models.

It should be noted that the MLE may yield wrong standard errors when there are nonstationary covariates (Park and Phillips, 2000; Hu and Phillips, 2004b). In what follows, we show that the long-short spread and the M2 growth rate have relatively more persistent movements than other covariates, which may create potential problems in

⁸ 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.

statistical inferences. 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)

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 least squares (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. 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 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. These results are also consistent with eyeball metrics from Figures 2 and 3. In a nutshell, all candidate covariate variables seem to exhibit fairly low persistence over time.

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 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

Next, we implement estimations for an array of Taylor rules using the LS method as follows.

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

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 period lag. We also implement estimations for Taylor rules with the interest rate smoothing consideration (Clarida, Galí, and Gertler, 2000, for example),

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

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 inflation rate 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 Bank of Korea 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.

Our findings from estimations for (8) include: (i) coefficient estimates for ρ 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. Note that (i) and (iii) imply that the equation (7) may be mis-specified since it ignores very high degree persistence 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 ($\beta > 1$). 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 might not have happened in Korea since 2000.

Table 2 around here

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

4 Ordered Probit Model Estimations and In-Sample Fit Performance

This section reports our findings based on the probit model estimation for the latent equation (1). We implement an array of economic models with alternative sets of

covariates. Our benchmark model assumes that the MPC observes key macroeconomic variables with one month lag. For instance, we start estimating the coefficients for the past inflation rate (π_{t-1}) and the output gap (\tilde{y}_{t-1}), Model Taylor B, then estimate four similar models adding extra covariates, again with one month lag, Models Taylor B1 to Taylor B4. Results are provided in Table 3.

Major findings are as follows. First, all threshold estimates are highly significant at least at the 10% level, which imply 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 also 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 seems to be fairly important, because it is significant at the 10% level for 3 out of 5 models. 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.

Table 3 around here

We then implement similar estimations with alternative models. Results are provided in Table 4. We first experiment with the current period Taylor Rule variables (π_t , \tilde{y}_t), finding 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 *current* period macroeconomic variables for the won depreciation rate (Δs_t) and the longshort spread (ls_t). We note that the coefficient on Δs_t has a correct sign and significant at the 10%, while the coefficient on Δs_{t-1} was insignificant in Taylor B2 and Taylor B4. 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 4 around here

In a nutshell, the Taylor Rule variables, the inflation rate and especially the output gap, play important roles in understanding monetary policy decision making processes in Korea. Even though Korea has employed inflation targeting since 1998, coefficient estimates on the output gap were always highly significant, while it wasn't the case for inflation. Also, the current period won depreciation rate seems to play a key role, which make sense because Korea is a small open economy, which provides a sharp contrast with the work by Hu and Phillips (2004a) and Kim et a. (2009) for the Fed's response function estimates.⁹

Next, we evaluate our ordered probit model for the MPC's decision making process in terms of the in-sample fit performance. For this purpose, we report correct prediction rates of our models in Table 5.¹⁰ When we use π_{t-1} and \tilde{y}_{t-1} for covariates (Taylor B), the overall success rate based on the point estimates is 80.25%, while correct prediction rates for *C*, *S*, and *H* are 18.75%, 96.28%, and 6.67%, respectively. For Taylor H1, the success rates for *C*, *S*, and *H* are 31.25%, 99.24%, and 6.67%, respectively, resulting in the overall prediction rate of 83.95%. It should be noted that the overall success rate is heavily influenced by very high success rates for *S*, which takes up about 81% of actual decisions.¹¹ On the contrary, we have very low success rates for other decisions when our predictions are based on the point estimates.

⁹ Their work implies that the foreign exchange rate was not a major factor for the Federal Reserve's decision making process.

¹⁰ Results from Taylor B, Taylor B4, Taylor C, and Taylor H1 are reported for simplicity.

¹¹ There were 16 cuts, 131 stays, and 15 hike decisions.

Table 5 around here

In Figure 4, we report estimated probabilities of *C* and *H* along with actual decisions (bar graphs) over time. The figures show that our model explains the changes in the probabilities fairly well, because the probability of each event tends to increase rapidly when corresponding actual actions are made. Note that the probability of a *C* goes up to almost 100% during the recent financial crisis. The estimated probability of an *H* climbs up fast in 2011 when the MPC raised the target RP rate several times. We also note that our results are quite robust because Models Taylor B, Taylor C, and Taylor H1 all yield similar probability estimates.

Figure 4 around here

Recall that our models predict *C* and *H* decisions less successfully when we use the point estimates for τ_L and τ_U . However, it should be noted that these threshold estimates come with uncertainty, that is, we may have to consider using the standard errors of these estimates. To see this, we plot the estimated latent variable y_t^* for Models Taylor B, Taylor C, and Taylor H1 in Figure 5. We also plot point estimates for τ_L and τ_U along with their one standard deviation confidence bands. Obviously, a more compact inaction band such as $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$ will yield more *C* and *H* predictions with a cost of lower success rate for *S* decisions. With such a strategy, we re-evaluate and report the in-sample fit performance in Table 6. Overall performance declines because of substantial decreases in the success rate for *S* decisions. However, we observe significantly higher success rates for other decision choices.

Figure 5 and Table 6 around here

5 Out-of-Sample Predictability

This section evaluates the out-of-sample predictability of our ordered probit 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 important 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 experiments to see if our model helps predicting changes in the monetary policy stance in the future.

We implement our exercises using two forecast strategies: the recursive method and the fixed 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 see how well our model out-of-sample predicts the Bank of Korea'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 memory window of the entire sample period, January 2000 to September 2013. That is, we start calculating one-period ahead forecast on the policy variable (C, S, H) using the initial 104 observations. Then, we add 105th observations and predict the next policy outcome with this expanded set of observations. We continue to do this until we forecast the last policy variables in September 2013 using the data from January 2000 to July 2013.

As is well-known, the recursive forecasting strategy may not perform well if there was some structural change in the model underlying the data. If regime changes occur some time during the early period of the analysis, then including earlier data in the estimation could reduce the forecastability of our model. To address this possibility, we also employ the Rolling Window Scenario 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 observation, but drop the 1st observation, thereby retaining an updated 104-observation estimation window, which is used to produce the 106th policy outcome. We iterate on this process until we forecast the last policy variable using the last sample set of 104 observations, December 2004 to July 2013.

We do not distinguish backward Taylor Rule type models from either the current or hybrid models any more. Since we are doing out-of-sample forecast, we assume that econometricians utilize currently available information set (Ω_t) to predict the policy variable in the next period. For example, we obtain $E(y_{t+1}|\Omega_t) = \{-1,0,1\}$, where the information set is $\Omega_t = \{\pi_t, \tilde{y}_t\}$ or $\Omega_t = \{\pi_t, \tilde{y}_t, \Delta s_t\}$. Results are reported in Table 7. For example, "*Taylor Recursive*" is the forecast results using the recursive method using $\{\pi_t, \tilde{y}_t\}$ for covariates in the latent equation, while "*Taylor Extended Rolling*" is the results with the rolling window method using $\{\pi_t, \tilde{y}_t, \Delta s_t\}$.

During the *post*-Lehman Brothers Bankruptcy period, there were 8 cut decisions, 47 stay decisions, and 5 hike decisions. All four models in Table 7 predicted 5 out of 8 cut decisions correctly (62.5% success) when we use point estimates, while they did relatively poorly in predicting hike decisions correctly. Overall success rates range from 73.33% to 76.67%, which show that our model exhibit fairly good out-of-sample forecasting performance. We do not find any substantial differences in the prediction performance between the recursive method and the fixed rolling window method.

Table 7 around here

Since *C* and *H* decisions occur quite *infrequently* compared with *S* decisions, it wouldn't be easy to predict these events based solely on the point estimates. Instead, one might pay more attention to the changes in the (out-of-sample) probability of each event,

calculated from the past history. We plot and report calculated (out-of-sample) probabilities of cuts and hikes in Figure 6, which is done by the recursive and the rolling window methods when econometrician's information set is $\Omega_t = {\pi_t, \tilde{y}_t, \Delta s_t}$. We also show actual occurrences of realized *C*s and *H*s on the same graphs.

Note that both models correctly out-of-sample forecast multiple cut decisions right after the Lehman Brothers Failure with very high accuracy. We also see the probability of a *C* to climb up in 2012 and 2013 after a long period of virtually 0% probability of a Cut, which coincide with three cut decisions. The probability of an *H* goes up rapidly in late 2009 until 2011 that are encountered with 5 interest rate hike decisions. It seems interesting to see that the predicted probability of an *H* has been quite high before actual actions were made, which might have happened that the MPC delayed their 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 some other political concerns.

Figure 6 around here

6 Concluding Remarks

This paper investigates the Bank of Korea's monetary policy decision making process using discrete choice models. Historically, the Monetary Policy Committee has made the target policy rate revisions in multiples of 25 basis points during their monthly meetings. This convention leads us to use an ordered probit model where the MPC make revisions only when there are 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 that shows good in-sample fit and find important roles for the output gap, inflation, and the won depreciation rate in describing the Bank of Korea's interest rate setting behavior. We also evaluate out-of-sample prediction performance of our approach using September 2008 as a split point for the recursive and the fixed rolling window forecast schemes. Our model accurately out-of-sample predicted rate cuts that occurred right after the Lehman Brothers Bankruptcy.

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	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 Detreded (\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 (<i>ls_t</i>)	-2.601 [*]	-2.628

Table 1. Augmented Dickey-Fuller Unit Root Test Results

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. *, †, and ‡ denote rejections of the unit-root null hypothesis at the 10%, 5%, and 1% significance level, respectively.

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)				

Table 2. Taylor Rule Type Linear Models Coefficient Estimations

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.

	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*
(au_L)	(0.108)	(0.090)	(0.112)	(0.378)	(0.285)
Upper Threshold	0.347‡	0.325‡	0.353‡	0.641^{*}	0.559*
(au_U)	(0.107)	(0.087)	(0.114)	(0.379)	(0.288)

Table 3. Probit Model Coefficient Estimation Results: Backward Looking Models

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.

	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)			
M2 Growth Rate	-	-	-	0.067
(Δm_{t-1})				(0.111)
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*
(au_L)	(0.193)	(0.168)	(0.308)	(0.366)
Upper Threshold	0.493‡	0.471‡	0.586^{*}	0.701^{*}
(au_U)	(0.188)	(0.167)	(0.311)	(0.368)

Table 4. Probit Model Coefficient Estimation Results: Alternative Models

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.

		Taylor B			Taylor B4	
	Cut	Stay	Hike	Cut	Stay	Hike
Cut Predicted	3	3	0	 3	2	0
Stay Predicted	13	126	14	13	125	14
Hike Predicted	0	2	1	 0	4	1
Correct Prediction (%)	18.75	96.18	6.67	18.75	95.42	6.67
Overall Prediction (%)		80.25			79.63	
	Taylor C			Taylor H1		
	Cut	Stay	Hike	 Cut	Stay	Hike
Cut Predicted	4	1	0	5	1	0
Stay Predicted	12	130	14	11	130	14
Hike Predicted	0	0	1	 0	0	1
Correct Prediction (%)	25.00	99.24	6.67	 31.25	99.24	6.67
Overall Prediction (%)		83.33			83.95	

Table 5. In-Sample Fit Evaluations Based on Point Estimates

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

		Taylor B			Taylor B4	
	Cut	Stay	Hike	 Cut	Stay	Hike
Cut Predicted	5	8	1	9	9	1
Stay Predicted	11	114	11	7	95	6
Hike Predicted	0	9	3	 0	27	8
Correct Prediction (%)	31.25	87.02	20.00	56.25	72.52	53.33
Overall Prediction (%)		75.31			69.14	
	Taylor C			Taylor H1		
_	Cut	Stay	Hike	 Cut	Stay	Hike
Cut Predicted	8	7	0	7	5	0
Stay Predicted	8	112	10	9	112	11
Hike Predicted	0	12	5	 0	14	4
Correct Prediction (%)	50.00	85.50	33.33	 43.75	85.50	26.67

Table 6. In-Sample Fit Evaluations with Point Estimates and Standard Errors

Note: In-sample fit results 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 defined by $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$.

75.93

77.16

Overall Prediction (%)

	Taylor Recursive				Τı	aylor Rolli	ng
	Cut	Stay	Hike	_	Cut	Stay	Hike
Cut Predicted	5	1	0		5	1	0
Stay Predicted	3	40	4		3	40	5
Hike Predicted	0	6	1	_	0	6	0
Correct Prediction (%)	62.50	85.11	20.00		62.50	85.11	0.00
Overall Prediction (%)		76.67				75.00	
	Taylor Extended Recursive				Taylor Extended Rolling		
	Cut	Stay	Hike	_	Cut	Stay	Hike
Cut Predicted	5	1	0	-	5	1	0
Stay Predicted	3	40	4		3	39	5
Hike Predicted	0	6	1		0	7	0
Correct Prediction (%)	62.50	85.11	20.00	-	62.50	82.98	0.00
Overall Prediction (%)		76.67				73.33	

Table 7. Out-of-Sample Forecasts with Point Estimates

Note: Out-of-sample forecasting is done with the recursive method and the rolling window method, both beginning with the pre-Lehman Brothers Bankruptcy period data (104 initial observations), September 2008. The latter strategy forecasts the 105th policy variable using the initial 104 observations. Then, adding 105th observation but dropping the first observation so that we maintain 104 observations, we forecast the 106th policy variable, and so on. The former strategy is implemented similarly but without dropping any previous observations.



Figure 1. Interest Rates and Monetary Policy Actions

Note: The target RP rate (solid) and the market call interest rate (dashed) appear in the first panel. Revisions of the target RP rate have historically 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). See the last panel.





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 Macro 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. 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: (π_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 events for each action.



Figure 5. Deviations from the Optimal Rate and Thresholds

Note: We calculate deviations from the optimal interest rate $(y_t^* = i_t^* - i_{t-1})$ and upper and lower threshold values (τ_U, τ_L) for the models with the following three sets of covariates in the latent equation: $(\pi_{t-1}, \tilde{y}_{t-1})$, (π_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 6. Out-of-Sample Forecast Performance

Note: We calculate the one-period ahead out-of-sample forecast probability of each action in the next period using (π_t , \tilde{y}_t , Δs_t). Bar graphs indicate realized events for each action. 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. The latter strategy forecasts the 105th policy variable using the initial 104 observations. Then, adding 105th observation but dropping the first observation so that we maintain 104 observations, we forecast the 106th policy variable, and so on. The former strategy is implemented similarly but without dropping any previous observations.