Essays on Macroeconomic and Financial Stability

by

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Abstract

Assessing and Forecasting Financial Vulnerability in the U.S.: A Factor Model Approach

This paper presents a factor-based forecasting model for the financial market vulnerability in the U.S. We estimate latent common factors via the method of the principal components from 170 monthly frequency macroeconomic data to out-of-sample forecast the Cleveland Financial Stress Index. Our factor models outperform both the random walk and the autoregressive benchmark models in out-of-sample predictability for short-term forecast horizons, which is a desirable feature since financial crises often come to a surprise realization. Interestingly, the first common factor, which plays a key role in predicting the financial vulnerability index, seems to be more closely related with real activity variables rather than nominal variables. The recursive and the rolling window approaches with a 50% split point perform similarly well.

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

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

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

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.

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Chapter 1

Forecasting Financial Market Vulnerability in the U.S.:

A Factor Model Approach

1.1 Introduction

Financial market crises often occur abruptly and quickly spread to other sectors of the economy, which often results in prolonged economic downturns. The recent global financial crisis triggered by the collapse of Lehman Brothers in September 2008 provides one of the most recent and relevant examples. The economics profession has failed to anticipate this financial crisis, and greatly underestimated severity of the spillover of the crisis to real activity that resulted in the Great Recession. Since these crises often come to a surprise realization with no systemic warnings, and because they create long-lasting harmful effects on real sectors even when turbulent periods are over, it would be useful to have an instrument that predicts the vulnerability of financial markets in the near future.

For this purpose, it is crucially important to find appropriate measures of the financial market vulnerability, which quantifies the potential risk that prevails in financial markets. Since the seminal work of Girton and Roper (1977), the Exchange Market Pressure (EMP) index has been frequently employed by researchers in this literature. See Tanner (2002) for a review.

One alternative measure that is rapidly gaining popularity since the crisis is the financial stress index (FSI). Unlike the EMP index that is based on exchange rate depreciation and reserves changes, the FSI index is constructed using a broad range of financial market key variables. In the case of the U.S., 12 financial stress indices has become available (Oet et al., 2011) including three FSIs contributed by regional Federal Reserve banks. See, among others, Hakkio and Keep (2009), Kliesen and Smith (2010), Oet et al. (2011), and Brave and Butters (2012). For other recent research contribution to financial stress, see also Hatzius et al. (2010) and Carlson, Lewis, and Nelson (2014).[1]

Conventional approaches to predict financial crises include the following. Eichengreen et al. (1995) and Sachs et al. (1996) use linear regressions to test the statistical significance of various economic variables on the occurrence of crises. Other group of researches employs discrete choice model approaches, either parametric probit or logit regressions (Frankel and Rose,1996; Cipollini and Kapetanios, 2009) or non-parametric signals approach (Kaminsky et al., 1998; Brüggemann and Linne, 1999; Edison, 2003; Berg and Pattillo, 1999; Bussiere and Mulder,1999; Berg et al. 2005; M.Ei-Shang, Tendlik and Schweinitz, 2013; Christensen and Li, 2014).

Some of recent studies started to investigate what economic variables help predict financial market vulnerability proxied by newly developed FSIs. For instance, Christensen and Li (2014) propose a model to forecast the FSIs developed by IMF for

[1] There's also an array of work that provides regional financial stress indices such as Grimaldi (2010, 2011), Hollo, Kremer, and Lo Duca (2012), and Islami and Kurz-Kim (2013) for the Euro area as well as for individual countries such as Greece (Louzis and Vouldis, 2011), Sweden (Sandhal *et al.*, 2011), Canada (Illing and Liu, 2006), Denmark (Hansen, 2006), Switzerland (Hanschel and Monnin, 2005), Germany (van Roye, 2011), Turkey(Cevik, Diboglu and Kenc, 2013), Colombia (Morales and Estrada, 2010), and Hong Kong (Yiu, Ho, and Lin, 2010).

13 OECD countries, utilizing 12 economics leading indicators and three composite indicators. They used the signal extraction approach proposed by Kaminsky et al. (1998). Slinenberg and de Haan (2011) constructed their own FSIs for 13 OECD countries and investigated what economic variables have predictive contents for the FSIs via linear regression models, finding no clear linkages between economic variables and the FSIs. Misina and Tkacz (2009) investigated the predictability of credit and asset price movements for financial market stress in Canada.

This paper presents a factor-based prediction model in a data-rich environment to out-of-sample forecast the Financial Stress Index (FSI) developed by the Federal Reserve Bank of Cleveland. We extract multiple latent common factors using the method of the principal components (Stock and Watson, 2002) for a large panel of 170 time series macroeconomic data that include nominal and real activity variables from October 1991 to October 2014. To avoid complications from nonstationarity issues, we apply the principle component analysis (PCA) to differenced data then recover *level* factors from estimated factors (Bai and Ng, 2004). We implement an array of out-of-sample forecast exercises with the random walk as well as a stationary autoregressive model as the benchmark model. We evaluate the predictive accuracy of our models relative to these benchmark models using the ratio of the root mean squared prediction errors ($RRMSPE$) and the Diebold-Mariano-West (DMW) test statistics.

Our major findings are as follows. First, our models outperform the benchmark models in out-of-sample predictability for short-term ($1-$ to $6-$month) forecast horizons. It should be noted that this is a desirable feature since financial crises often occur abruptly with no prior warnings. Second, parsimonious models with just one or two factors perform as well as bigger models that use up to 8 factors. Third, the first common factor that plays a key role in our forecast exercises seems to be more closely related with real sector variables rather than nominal sector variables. Lastly, we employ the recursive scheme as well as the fixed rolling window approach with the 50% split point. Our factor models perform similarly well under these two schemes.

The rest of the paper is organized as follows. Section 2 describes the econometric model and the out-of-sample forecasts schemes. We also explain our evaluation methods as to the out-of-sample prediction accuracy of our models. In Section 3, we provide a data description and preliminary analyses for estimated latent common factors. Section 4 reports our major findings from in-sample fit analyses and out-of-sample forecast exercises. Section 5 concludes.

1.2 The Econometric Model

Let $x_{i,t}$ be a macroeconomic variable $i \in \{1, 2, .., N\}$ at time $t \in \{1, 2, .., T\}$.

$$x_{i,t} = c_i + \lambda_i^{'} \mathbf{F}_t + e_{i,t}, \tag{1.1}$$

where c_i is a fixed effect intercept, $\mathbf{F}_t = [F_{1,t} \ \cdots \ F_{r,t}]^{'}$ is an $r \times 1$ vector of *latent* common factors, and $\lambda_i = [\lambda_{i,1} \ \cdots \ \lambda_{i,r}]^{'}$ denotes an $r \times 1$ vector of factor loading coefficients for $x_{i,t}$. $e_{i,t}$ is the idiosyncratic error term. All variables other than those that are represented as a percentage term (interest rates, unemployment rates, etc.) are log-transformed.

Estimation is carried out via the method of the principal components for the first-differenced data. As Bai and Ng (2004) show, the principal component estimators for $\mathbf{F}_t$ and λ_i are consistent irrespective of the order of $\mathbf{F}_t$ as long as $e_{i,t}$ is stationary. However, if $e_{i,t}$ is an integrated process, a regression of $x_{i,t}$ on $\mathbf{F}_t$ is spurious. To avoid this problem, we apply the method of the principal components to the first-differenced data. That is, we rewrite (**??**) by the following.

$$\Delta x_{i,t} = \lambda_i^{'} \Delta \mathbf{F}_t + \Delta e_{i,t} \tag{1.2}$$

for $t = 2, \cdots, T$. Let $\Delta \mathbf{x}_i = [\Delta x_{i,1} \ \cdots \ \Delta x_{i,T}]^{'}$ and $\Delta \mathbf{x} = [\Delta \mathbf{x}_1 \ \cdots \ \Delta \mathbf{x}_N]$. We first normalize the data before the estimations, since the method of the principal components is not scale invariant. Taking the principal components method for $\Delta \mathbf{x} \Delta \mathbf{x}^{'}$ yields factor estimates $\Delta \hat{\mathbf{F}}_t$ along with their associated factor loading coefficients $\hat{\lambda}_i$. Estimates for the idiosyncratic components are naturally given by the residuals $\Delta \hat{e}_{i,t} = \Delta x_{i,t} - \hat{\lambda}_i^{'} \Delta \hat{\mathbf{F}}_t$. Level variables are recovered by re-integrating these estimates,

$$\hat{e}_{i,t} = \sum_{s=2}^{t} \Delta \hat{e}_{i,s} \tag{1.3}$$

for $i = 1, 2, ..., N$. Similarly,

$$\hat{\mathbf{F}}_t = \sum_{s=2}^{t} \Delta \hat{\mathbf{F}}_s \tag{1.4}$$

After obtaining latent factor estimates, we employ the following regression model. Abstracting from deterministic terms,

$$fsi_{t+j} = \beta^{'} \Delta \hat{\mathbf{F}}_t + \alpha fsi_t + u_{t+j}, \; j = 1, 2, .., k \tag{1.5}$$

That is, we implement direct forecasting regressions for the j-period ahead financial stress index (fsi_{t+j}) on (differenced) common factor estimates ($\Delta \hat{\mathbf{F}}_t$) and the current value of the index (fsi_t), which belong to the information set (Ω_t) at time t. Note that (**??**) is an AR(1) process for $j = 1$ extended by exogenous common factors. This formulation is based on our preliminary unit-root test results for the FSI that show strong evidence of stationarity.[2] Applying the ordinary least squares (OLS) estimator for (**??**) yields the following j-period ahead forecast for the financial stress index.

$$\widehat{fsi}^{F}_{t+j|t} = \hat{\beta}^{'} \Delta \hat{\mathbf{F}}_t + \hat{\alpha} fsi_t \tag{1.6}$$

To statistically evaluate our factor models, we employ the following nonstationary random walk model as the (no change) benchmark model.

$$fsi_{t+1} = fsi_t + \varepsilon_{t+1} \tag{1.7}$$

It is straightforward to show that (**??**) yields the following j-period ahead forecast.

$$\widehat{fsi}^{R}_{t+j|t} = fsi_t, \tag{1.8}$$

[2]Results are available upon request.

where fsi_t is the current value of the financial stress index.

We also employ the following stationary AR(1)-*type* model as an alternative benchmark model.

$$fsi_{t+j} = \alpha_j fsi_t + \varepsilon_{t+1}, \tag{1.9}$$

where α_j is the coefficient on the current FSI in the direct regression for the j-period ahead FSI variable, which yields the following j-period ahead forecast.

$$\widehat{fsi}^{AR}_{t+j|t} = \hat{\alpha}_j fsi_t, \tag{1.10}$$

For evaluation of the prediction accuracy, we use the ratio of the root mean square prediction error ($RRMSPE$), $RMSPE$ from the benchmark model divided by $RMSPE$ from the factor model. Note that our factor model performs better than the benchmark model when $RRMSPE$ is greater than 1.

Also, we employ the Diebold-Mariano-West (DMW) test in order to statistically evaluate the out-of-sample predictability of our factor model. For the DMW test, we define the following function.

$$d_t = L(\varepsilon^A_{t+j|t}) - L(\varepsilon^F_{t+j|t}), \tag{1.11}$$

where $L(\cdot)$ is a loss function from forecast errors under each model, that is,

$$\varepsilon^A_{t+j|t} = fsi_{t+j} - \widehat{fsi}^{A}_{t+j|t} \ (A = R, AR), \ \varepsilon^F_{t+j|t} = fsi_{t+j} - \widehat{fsi}^{F}_{t+j|t} \tag{1.12}$$

One may use either the squared error loss function, $(\varepsilon^j_{t+j|t})^2$, or the absolute loss function, $|\varepsilon^j_{t+j|t}|$.

The DMW statistic can be used to test the null of equal predictive accuracy, $H_0 : Ed_t = 0$,

$$DMW = \frac{\bar{d}}{\sqrt{\widehat{Avar}(\bar{d})}}, \tag{1.13}$$

where $\bar{d}$ is the sample mean loss differential, $\bar{d} = \frac{1}{T-T_0}\sum_{t=T_0+1}^{T} d_t$, and $\widehat{Avar}(\bar{d})$ denotes the asymptotic variance of $\bar{d}$,

$$\widehat{Avar}(\bar{d}) = \frac{1}{T-T_0}\sum_{i=-q}^{q} k(i,q)\hat{\mathbf{\Gamma}}_i \tag{1.14}$$

$k(\cdot)$ is a kernel function where T_0/T is the split point in percent, $k(\cdot) = 0,\ j > q$, and $\hat{\Gamma}_j$ is j^{th} autocovariance function estimate.[3] Note that our factor model (**??**) nests the stationary benchmark model in (**??**). Therefore, we use critical values proposed by McCracken (2008) for this case. For the DMW statistic with the random walk benchmark (**??**), which is not nested by (**??**), we use the asymptotic critical values, which are obtained from the standard normal distribution.

1.3 Data Descriptions and Factor Estimations

1.3.1 Data Descriptions

We use the Cleveland Financial Stress Index (CFSI), obtained from the FRED, to measure the financial market vulnerability. The index integrates 11 daily financial

[3]Following Andrews and Monahan (1992), we use the quadratic spectral kernel with automatic bandwidth selection for our analysis.

market indicators which are grouped into four sectors: debt, equity, foreign exchange, and banking. See Oet et al. (2011) for details. As we can see in Figure 1, the CFSI tracks recent financial crises reasonably well. For example, the index shows elevated level of risk during the recent major crises such as the U.S. subprime mortgage crisis that started around 2006, global financial market meltdown triggered by the failure of Lehman Brothers in September 2008, and the European sovereign debt crisis that started at the end of 2009. That is, the CFSI seems to be an appropriate measure of the financial market vulnerability. The data is monthly frequency and is traced back to October 1991.

Figure 1 around here

We obtained 170 monthly frequency macroeconomic time series data from the FRED and the Conference Boards Indicators Database. Observations span from October 1991 to October 2014 to match the availability of the CFSI. We organized these 170 time series data into 9 small groups as summarized in Table 1. Groups #1 through #5 (Data ID #1 to #103) are variables that are closely related with real activity, while groups #6 to #9 (Data ID #104 to #170) are mostly nominal variables. Detailed explanations on individual time series are reported in the appendix.

Table 1 around here

1.3.2 Latent Factors and their Characteristics

We estimated up to 8 latent common factors via the method of the principal components for the first-differenced data. In Figure 2, we report estimated first four (differenced) common factors, $\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_4$ and their level counterparts F_1, F_2, F_3, F_4, obtained by re-integrating these differenced factors. One notable observation is that the first common factor F_1 exhibits rapid declines around 2001 and 2008, which correspond to a recession after the burst of the U.S. IT bubble (a.k.a. the dot-com bubble) and the Great Recession, respectively. In what follows, we demonstrate that F_1 is more closely related with real activity variables, though it also represent a group of nominal variables as well.

Figure 2 around here

We report the factor loading coefficient (λ_i) estimates and marginal R^2 of each variable in Figures 3 to 7 to study how each of these factors is associated with the macroeconomic variables in groups #1 to #9. The marginal R^2 is an in-sample fit statistic obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis and the descriptions are reported in the Data Appendix.

We investigate the nature of the first common factor using the factor loading coefficients for F_1. It should be noted that loading coefficients of most variables in the groups #1 (output and income) and #2 (orders) are positive. Among the group

#3 variables, the loading coefficients are negative for the unemployment-related variables (IDs $41-50$), whereas they are positive for employment or labor participation variables (IDs $51-74$) and earnings related data (IDs $75-80$). Positive coefficients were also found from the group #3 (housing) and #4 (stock price) variables. Also within the group #8, interest rates have positive loading coefficients, while interest rate spreads including risk premium variables have negative signs. Price level variables in the group #9 have positive loadings, which are consistent with negative loading coefficients of foreign exchange rates measured as the price of domestic currency (US dollars) relative to the foreign currencies. Overall, these observations imply that the first common factor represent the business cycle of the US economy.

When it comes to the marginal R^2 estimation, F_1 explains a substantial portion of variations in measures of production and the employment part in the labor market, even though it also explain non-negligible portions of variations in price variables as well. Overall, F_1 seems to better represent real activity performance.

Figure 3 around here

As we can see in Figure 4, the second common factor F_2 loads heavily on the group #9 (price variables) as well as the group #5 (exchange rates). The marginal R^2 estimates of these variables are far greater than those of other variables. Factor loading coefficients of these variables are similar to those in Figure 3 and tend to be bigger in absolute terms than other coefficients. Therefore, F_2 seems to be more closely associated with the two groups of nominal variables, domestic prices and foreign exchange rates.

Figure 4 around here

F_3 captures mainly the information on the group #5 stock price variables. As we can see in the marginal R^2 analysis, it explains over 60% of variations in these variables. The loading coefficient estimates are mostly negative except the first one in this group, the price-earning ratio (earnings/price), which should be the case. Note that the sign itself does not matter because the method of the principle components estimates the loadings and factors jointly.[4] Similar reasoning implies that the group #8 variables (interest rates) are well explained by F_4.

Figures 5 and 6 around here

1.4 Forecasting Exercises

1.4.1 In-Sample Fit Analysis

We implement an array of least squares estimations for the CFSI with alternative sets of explanatory variables from $\{\Delta F_1, \Delta F_2, ..., \Delta F_8\}$. Results are reported in Table 2 for the $1-, 2-, 3-, 6-$, and $12-$month ahead values of the CFSI.

We employ an R^2-based selection method for one-factor model to the 8-factor full model to find good combinations of explanatory variables. The first common factor ΔF_1 seems to play the most important role in explaining variations in the CFSI for all forecasting time horizons we consider.

[4]One may multiply both the loadings and the factor by -1 without affecting any stastistical inferences.

We note that adding more factors after the first common factor does not substantially increase the fit. That is, it seems that one or two factor models are sufficient for a good in-sample fit. It should be also noted that factor estimates help explain CFSIs for relatively short time horizons. For example, factors explain 20 to 30% variations in 1−month ahead CFSIs, while they explain less than 10% of variations in 1−year ahead CFSIs even with full 8 factor models.[5]

Table 2 around here

In Table 3, we also report the least squares estimates of the coefficients in the regression model of the 1−period ahead CFSI index ($cfsi_{t+1}$). We note that the first common factor is highly significant whether one period lagged CFSI ($cfsi_t$) is included in the regression or not. The second common factor also plays an important role when pure factor models without $cfsi_t$ are employed. Our models are good as to the In-sample fit especially when $cfsi_t$ is included, which should be the case because the CFSI is highly persistent. Our factor models without lagged CFSI index still exhibit fairly high in-sample fit. The 8 factor full model explains roughly 30% of variation of the one-month ahead CFSI.

Table 3 around here

[5]We also considered alternative factor selection methods. For instance, the adjusted R^2 selection method usually chose the 5− or 6−factor model, while a stepwise selection method (Specific-to-General rule) selected the 4− or 5−factor model for the FSI. However, added gains are still fairly small.

1.4.2 Out-of-Sample Forecast Exercises and Evaluations of Models

We implement out-of-sample forecast exercises using two methods. First, we use a recursive forecast scheme. That is, we begin with an out-of-sample forecast of the $j-$period ahead CFSI index ($fsi_{\frac{T}{2}+j}$) using the 50% initial observations ($t = 1, 2, ..., \frac{T}{2}$). Then, we add one additional observation to the sample ($t = 1, 2, ..., \frac{T}{2}, \frac{T}{2} + 1$) and implement another forecast ($fsi_{\frac{T}{2}+j+1}$) using this expanded set of observations. We repeat this until we forecast the last observations. We implement this scheme for up to 12 month forecast horizons, $j = 1, 2, 3, 6, 12$.

The second scheme is a fixed rolling window method that repeats forecasting by adding one additional observation with the same split point but dropping one earliest observation in order to maintain the identical sample size. That is, after the initial forecast described earlier, we forecast $fsi_{\frac{T}{2}+j+1}$ using an updated (shifted to the right) data set ($t = 2, 3, ..., \frac{T}{2}, \frac{T}{2} + 1$) maintaining the same number of observations.

We employ two benchmark models for the evaluations of our factor-based forecast models: the nonstationary random walk model and a stationary autoregressive model. Out-of-sample forecast performance is evaluated using the ratio of the root mean square prediction error, $RRMSPE$, of the benchmark model to that of the factor model. When the $RRMSPE$ is greater than one, the factor model outperforms the benchmark model. Also, we implement the DMW test to statistically evaluate prediction accuracy of our models.

$RRMSPE$ estimates of our factor models relative to the random walk benchmark are reported in Table 4. We note that our factor models outperform the benchmark model for all forecast horizons from 1 month to 1 year. The $RRMSPE$

estimates are greater than one for all cases both with the recursive and the rolling window schemes. Similarly as in the in-sample fit analyses reported earlier, one factor model with the first common factor ΔF_1 performs as well as bigger models with more factor estimates.

The DMW statistics are reported in Table 4. Using the asymptotic critical values from the standard normal distribution, the test rejects the null hypothesis of equal predictive accuracy at the 10% significance level in majority cases when the forecast horizon is 3 month or longer. For shorter forecast time horizon (1 and 2 month), the test rejects the null for just one case even though the test statistic is all positive meaning that the test favors the factor models.

Tables 4 and 5 around here

We report $RRMSPE$ estimates and the DMW statistics of our factor model with a stationary autoregressive competing model in Tables 6 and 7. We note that most $RRMSPE$ estimates are greater than one when the forecast horizon is between $1-$ and $6-$month. The $RRMSPE$ estimates were all less than one for $12-$month ahead out-of-sample forecast. It should be noted, however, that short-term forecast accuracy is more desirable feature for predicting the financial market vulnerability, because financial crises often occur abruptly.

Note that our factor models nest the benchmark AR model, which results in size distortion when the asymptotic critical values are used. Therefore, we use the critical values from McCracken (2008). The DMW test rejects the null hypothesis for most cases at the 10% significance level when the forecast horizon is shorter than 12−month, which is consistent with the results in Table 6.

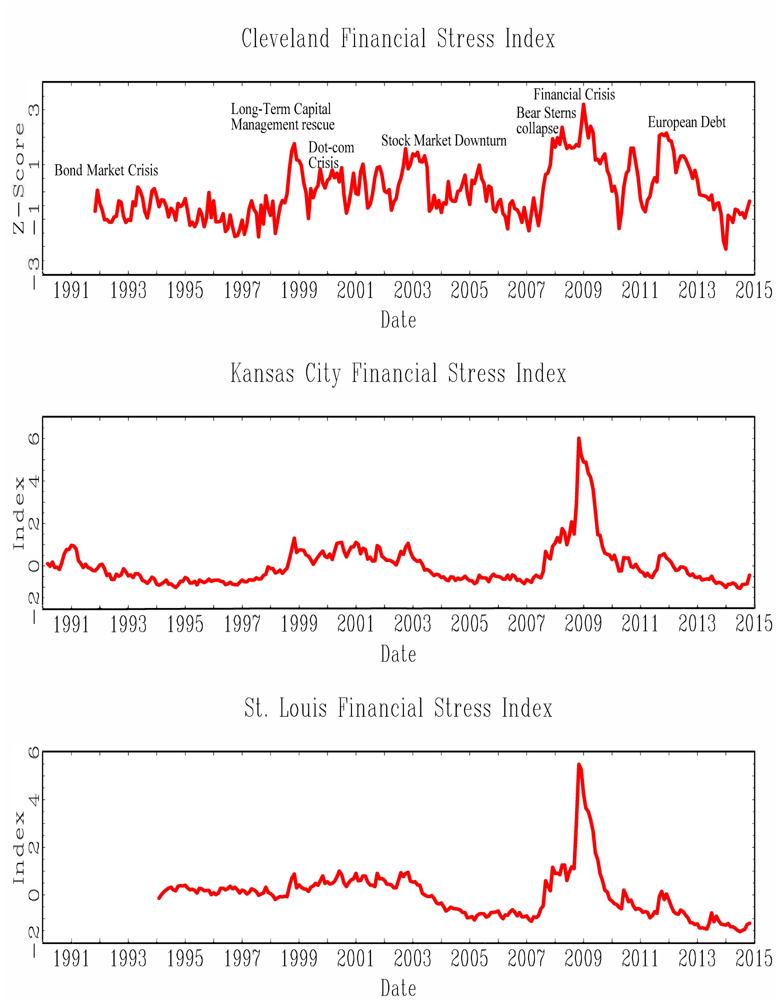
Tables 6 and 7 around here

1.5 Concluding Remarks

This paper proposes a forecast model for systemic risk in the U.S. financial market in a data-rich environment. We use the latest financial stress index developed by Federal Reserve Bank of Cleveland as a proxy variable of the financial market vulnerability. We employ a parsimonious method to extract latent common factors from a panel of 170 monthly frequency time series macroeconomic variables from October 1991 to October 2014. In presence of nonstationarity in the data, we apply the method of the principle components (Stock and Watson, 2002) to differenced data (Bai and Ng, 2004) to estimate the latent factors consistently.

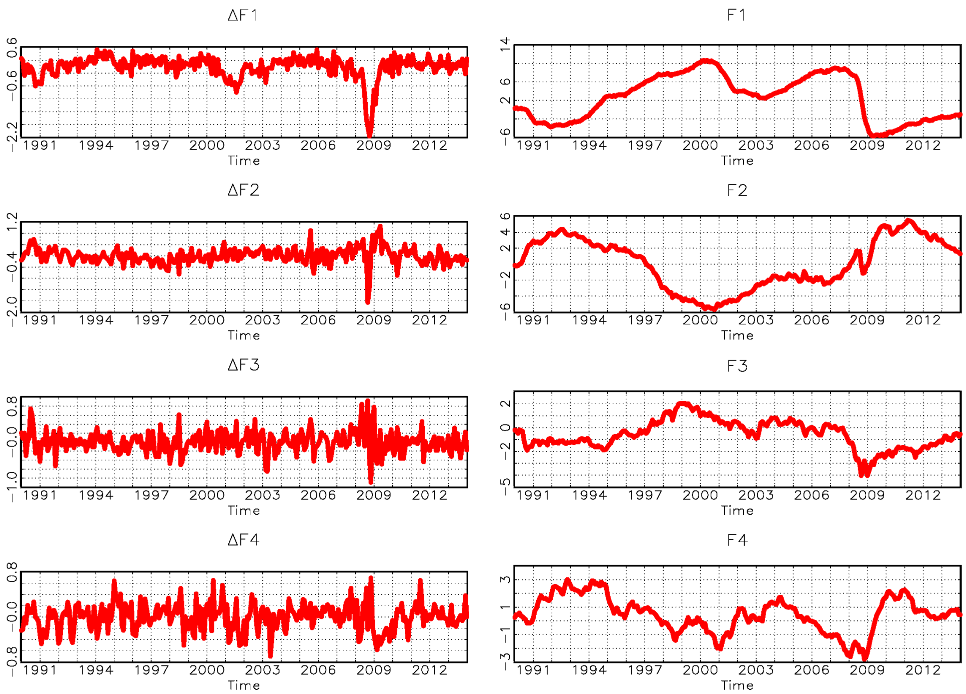
We implement an array of out-of-sample prediction exercises using the recursive and the fixed rolling window schemes for 1-month to 1-year forecast horizons. Based on the $RRMSPE$ estimates and the DMW statistics, our factor-based forecast models overall outperform the nonstationary random walk benchmark model as well as the stationary autoregressive model especially for short-horizon predictions, which is a desirable feature because financial crises often come to a surprise realization. The parsimonious models with one or two factors perform as well as bigger models in providing potentially useful information to policy makers and financial market participants. Interestingly, real activity variables represented by the first common factor are shown to have substantial predictive contents for the financial market vulnerability even in the short-run.

Figure 1. Financial Stress Indices



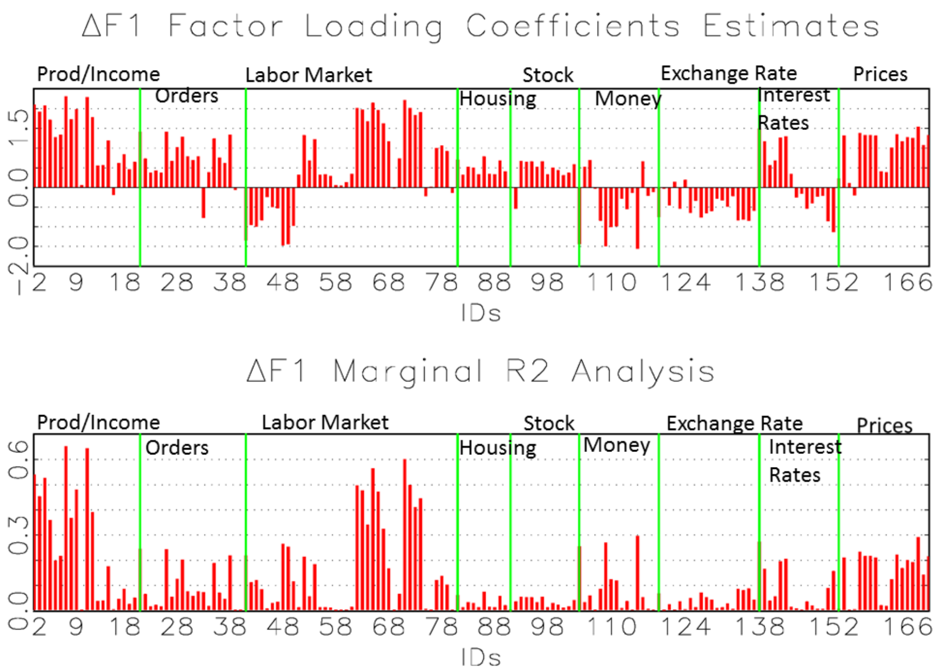
Note: The Cleveland Financial Stress Index is obtained from the FRED. The index is a z-score monthly frequency data constructed by the Cleveland Fed. The other two indices are also obtained from the FRED.

Figure 2. Factor Estimates: Differenced and Level Factors



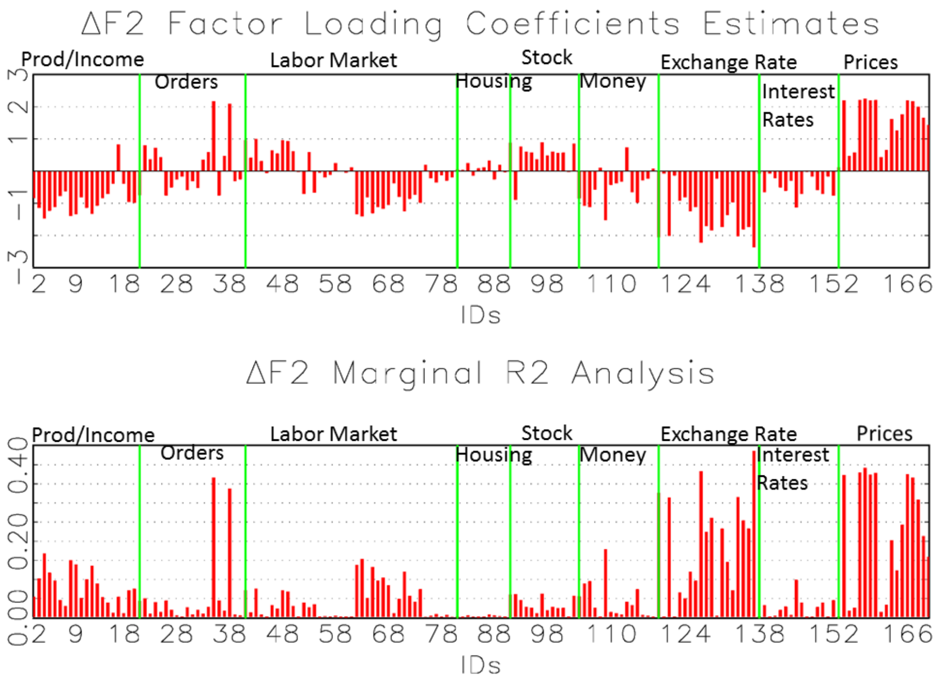
Note: We obtained up to 8 factors by applying the method of the principal components to 170 monthly frequency macroeconomic time series variables. Level factors (second column) are obtained by re-integrating estimated common factors (first column).

Figure 3. Common Factor #1



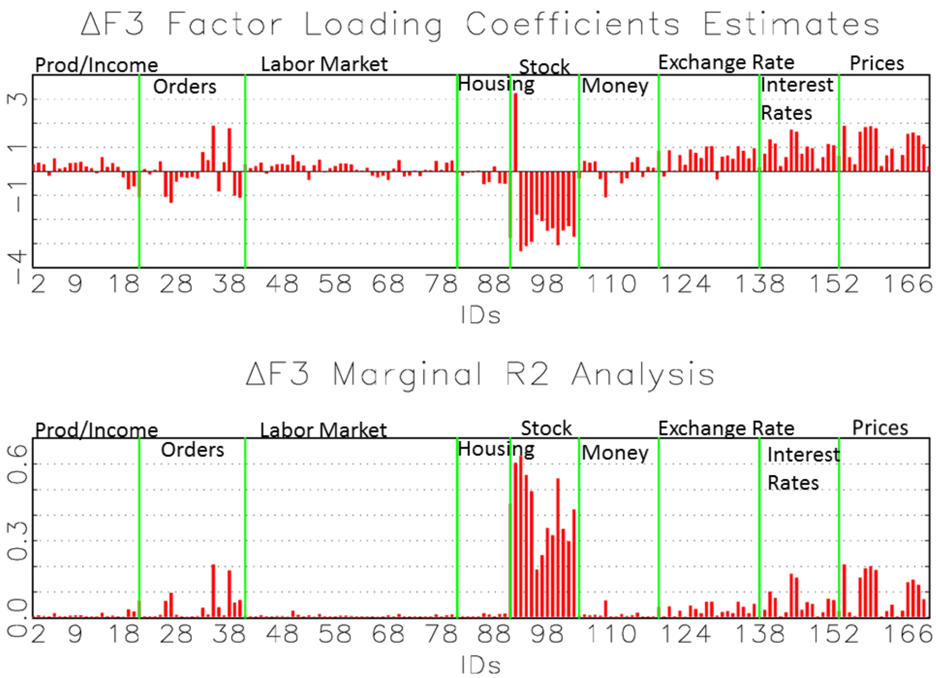
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 4. Common Factor #2



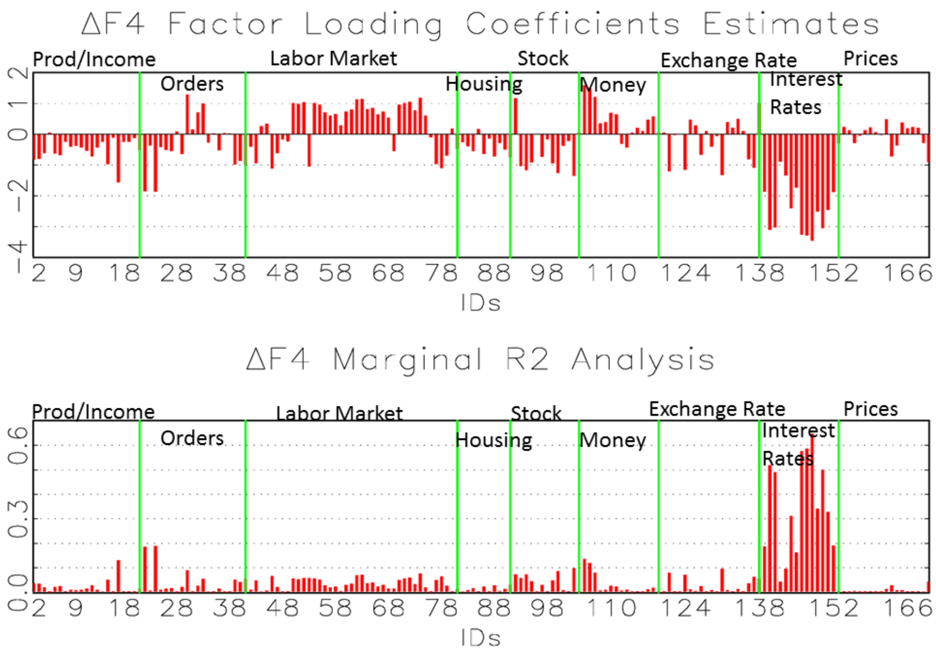
Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 5. Common Factor #3



Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Figure 6. Common Factor #4



Note: Factor loading coefficients (λ_i) for each common factor estimate are reported. The marginal R^2 is obtained by regressing each of the individual time series variables onto each estimated factor, one at a time, using the full sample of data. The individual series in each group are separated by vertical lines and labeled by group IDs. The data IDs are on the x-axis.

Table 1. Macroeconomic Data Descriptions

Group ID	Data ID	Data Descriptions
#1	$1-21$	Output and Income
#2	$22-40$	Consumption, Orders and Inventories
#3	$41-80$	Labor Market
#4	$81-90$	Housing
#5	$91-103$	Stock Market
#6	$104-118$	Money and Credit
#7	$119-137$	Exchange Rate
#8	$138-152$	Interest Rate
#9	$153-170$	Prices

Note: See the data appendix for descriptions of individual data series.

Table 2. j-Period Ahead In-Sample R^2 Fit Analysis

	Factors	R^2
$j = 1$	ΔF_1	0.211
	$\Delta F_1, \Delta F_5$	0.251
	$\Delta F_1, \Delta F_2, \Delta F_5$	0.270
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.283
$j = 2$	ΔF_1	0.194
	$\Delta F_1, \Delta F_5$	0.224
	$\Delta F_1, \Delta F_2, \Delta F_5$	0.255
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.267
$j = 3$	ΔF_1	0.183
	$\Delta F_1, \Delta F_3$	0.209
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.228
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_5$	0.247
$j = 6$	ΔF_1	0.103
	$\Delta F_1, \Delta F_3$	0.124
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.137
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_7$	0.147
$j = 12$	ΔF_1	0.020
	$\Delta F_1, \Delta F_2$	0.034
	$\Delta F_1, \Delta F_2, \Delta F_3$	0.047
	$\Delta F_1, \Delta F_2, \Delta F_3, \Delta F_7$	0.061

Note: We regress each set of estimated factors to j-period (month) ahead financial stress index, then report the R^2 value from each regression.

Table 3. OLS Estimations for the 1-Period Ahead Index ($cfsi_{t+1}$)

	OLS Coefficient Estimates							
$cfsi_t$	**0.848** (26.599)	*n.a.*	**0.857** (26.161)	*n.a.*	**0.855** (25.973)	*n.a.*	**0.851** (24.523)	*n.a.*
$\Delta F_{1,t}$	**−0.205** (−2.301)	**−1.288** (−8.605)	**−0.194** (−2.166)	**−1.288** (−8.703)	**−0.196** (−2.189)	**−1.288** (−8.727)	**−0.202** (−2.222)	**−1.288** (−9.014)
$\Delta F_{2,t}$	*n.a.*	*n.a.*	−0.118 (−1.143)	**0.503** (2.677)	−0.116 (−1.126)	**0.504** (2.689)	−0.112 (−1.079)	**0.507** (2.793)
$\Delta F_{3,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	0.077 (0.653)	0.349 (1.589)	0.080 (0.674)	0.352 (1.655)
$\Delta F_{4,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	−0.003 (−0.022)	0.274 (1.262)
$\Delta F_{5,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	0.042 (0.296)	**1.050** (4.282)
$\Delta F_{6,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	0.104 (0.694)	−0.108 (−0.399)
$\Delta F_{7,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	−0.289 (−1.843)	−0.452 (−1.602)
$\Delta F_{8,t}$	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	*n.a.*	0.055 (0.328)	0.187 (0.616)
c	0.003 (0.109)	0.028 (0.532)	0.003 (0.104)	0.028 (0.528)	0.003 (0.104)	0.027 (0.525)	0.003 (0.096)	0.027 (0.526)
R^2	0.782	0.213	0.783	0.234	0.783	0.241	0.786	0.301
$\tilde{R}^2$	0.779	0.208	0.779	0.225	0.779	0.229	0.778	0.277

Note: We regress 1-period (month) ahead financial stress index onto a set of explanatory variables that include factor estimates and lagged financial stress index. Coefficient estimates that are significant at the 5% are in bold. R^2 and adjusted R^2 ($\tilde{R}^2$) are also reported. t-statistics are reported in the brackets.

Table 4. j**-Period Ahead Out-of-Sample Forecast: ARF vs. RW**

RRMSPE: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	1.021	1.040	1.057	1.099	1.120
$\Delta F_1, \Delta F_2$	1.019	1.030	1.039	1.082	1.098
$\Delta F_1, \Delta F_3$	1.018	1.059	1.064	1.112	1.126
$\Delta F_1, \Delta F_4$	1.018	1.039	1.060	1.091	1.113
$\Delta F_1, \Delta F_2, \Delta F_3$	1.015	1.048	1.045	1.094	1.108

RRMSPE: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	1.025	1.044	1.060	1.102	1.129
$\Delta F_1, \Delta F_2$	1.023	1.032	1.036	1.085	1.113
$\Delta F_1, \Delta F_3$	1.033	1.072	1.068	1.110	1.126
$\Delta F_1, \Delta F_4$	1.012	1.042	1.067	1.092	1.126
$\Delta F_1, \Delta F_2, \Delta F_3$	1.029	1.059	1.043	1.091	1.114

Note: *RRMSPE* denotes the mean square error from the random walk (RW) model relative to the mean square error from our factor model (ARF). Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Table 5. j-Period Ahead Out-of-Sample Forecast: ARF vs. RW

DMW: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	0.735	1.262	1.847^*	$2.892^{\ddagger}$	$3.502^{\ddagger}$
$\Delta F_1, \Delta F_2$	0.667	0.974	1.235	$2.397^{\dagger}$	$2.651^{\ddagger}$
$\Delta F_1, \Delta F_3$	0.639	1.572	1.844^*	$3.006^{\ddagger}$	$3.268^{\ddagger}$
$\Delta F_1, \Delta F_4$	0.661	1.228	1.899^*	$2.693^{\ddagger}$	$3.412^{\ddagger}$
$\Delta F_1, \Delta F_2, \Delta F_3$	0.552	1.291	1.293	$2.527^{\dagger}$	$2.679^{\ddagger}$

DMW: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	0.833	1.271	1.835^*	$2.519^{\ddagger}$	$2.905^{\ddagger}$
$\Delta F_1, \Delta F_2$	0.783	0.978	1.078	$2.176^{\dagger}$	$2.545^{\dagger}$
$\Delta F_1, \Delta F_3$	1.110	1.721^*	1.829^*	$2.501^{\dagger}$	$2.753^{\ddagger}$
$\Delta F_1, \Delta F_4$	0.429	1.181	$1.995^{\dagger}$	$2.259^{\dagger}$	$2.791^{\ddagger}$
$\Delta F_1, \Delta F_2, \Delta F_3$	0.988	1.485	1.148	$2.100^{\dagger}$	$2.467^{\dagger}$

Note: *DMW* denotes the Diebold-Mariano-West statistic. ‡, †, and $*$ indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively. Critical values were obtained from the standard normal distribution, which is the asymptotic distribution of the *DMW* test statistic.

Table 6. j-Period Ahead Out-of-Sample Forecast: ARF vs. AR

RRMSPE: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	1.013	1.013	1.019	1.008	0.973
$\Delta F_1, \Delta F_2$	1.011	1.004	1.001	0.992	0.953
$\Delta F_1, \Delta F_3$	1.010	1.032	1.025	1.020	0.978
$\Delta F_1, \Delta F_4$	1.010	1.013	1.021	1.001	0.967
$\Delta F_1, \Delta F_2, \Delta F_3$	1.008	1.021	1.006	1.003	0.962

RRMSPE: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	1.016	1.018	1.023	1.023	0.996
$\Delta F_1, \Delta F_2$	1.014	1.006	1.000	1.007	0.981
$\Delta F_1, \Delta F_3$	1.024	1.045	1.030	1.030	0.993
$\Delta F_1, \Delta F_4$	1.004	1.016	1.030	1.013	0.993
$\Delta F_1, \Delta F_2, \Delta F_3$	1.020	1.033	1.006	1.012	0.983

Note: *RRMSPE* denotes the mean square error from the autoregressive (AR) model relative to the mean square error from our factor model (ARF). Therefore, when *RRMSPE* is greater than one, our factor models perform better than the benchmark model.

Table 7. j-Period Ahead Out-of-Sample Forecast: ARF vs. AR

DMW: Recursive Method

Factors/j	1	2	3	6	12
ΔF_1	0.550^*	0.531^*	$1.067^\dagger$	0.594^*	-1.947
$\Delta F_1, \Delta F_2$	0.484^*	0.181	0.060	-0.581	-2.586
$\Delta F_1, \Delta F_3$	0.436^*	$1.079^\dagger$	$1.219^\dagger$	$1.215^\dagger$	-1.672
$\Delta F_1, \Delta F_4$	0.450^*	0.512^*	$1.363^\ddagger$	0.053	-2.246
$\Delta F_1, \Delta F_2, \Delta F_3$	0.351^*	$0.803^\dagger$	0.313^*	0.194^*	-2.071

DMW: Rolling Window Method

Factors/j	1	2	3	6	12
ΔF_1	$0.571^\dagger$	$0.611^\dagger$	$1.296^\ddagger$	$1.766^\ddagger$	-0.344
$\Delta F_1, \Delta F_2$	$0.543^\dagger$	0.246^*	0.010	$0.583^\dagger$	-1.209
$\Delta F_1, \Delta F_3$	$0.861^\dagger$	$1.335^\ddagger$	$1.430^\ddagger$	$1.859^\ddagger$	-0.558
$\Delta F_1, \Delta F_4$	0.133^*	$0.527^\dagger$	$1.618^\ddagger$	$1.031^\ddagger$	-0.576
$\Delta F_1, \Delta F_2, \Delta F_3$	$0.757^\dagger$	$1.080^\ddagger$	$0.295^\dagger$	$0.770^\dagger$	-1.134

Note: *DMW* denotes the Diebold-Mariano-West statistic. ‡, †, and $*$ indicate rejection of the null hypothesis at the 1%, 5%, and 10% significance level, respectively. Critical values were obtained from McCracken (2008) since the factor model nests the benchmark AR model.

Data Appnnedix

Data ID	Series ID	Descriptions
1 (Group #1)	CUMFNS	Capacity Utilization: Manufacturing (SIC), Percent of Capacity, Monthly, S.A.
2	TCU	Capacity Utilization: Total Industry, Percent of Capacity, Monthly, S.A.
3	INDPRO	Industrial Production Index, Index 2007=100, Monthly, S.A.
4	IPBUSEQ	Industrial Production: Business Equipment, Index 2007=100, Monthly, S.A.
5	IPCONGD	Industrial Production: Consumer Goods, Index 2007=100, Monthly, S.A.
6	IPDCONGD	Industrial Production: Durable Consumer Goods, Index 2007=100, Monthly, S.A.
7	IPDMAT	Industrial Production: Durable Materials
8	IPFINAL	Industrial Production: Final Products (Market Group), Index 2007=100, Monthly, S.A.
9	IPFPNSS	Industrial Production: Final Products and Nonindustrial Supplies
10	IPFUELS	Industrial Production: Fuels
11	IPMANSICS	Industrial Production: Manufacturing (SIC), Index 2007=100, Monthly, S.A.
12	IPMAT	Industrial Production: Materials
13	IPMINE	Industrial Production: Mining, Index 2007=100, Monthly, S.A.
14	IPNCONGD	Industrial Production: Nondurable Consumer Goods
15	IPNMAT	Industrial Production: nondurable Materials
16	IPUTIL	Industrial Production: Electric and Gas Utilities, Index 2007=100, Monthly, S.A.
17	NAPMPI	ISM Manufacturing: Production Index
18	PI	Personal Income
19	RPI	Real Personal Income,S.A. Annual Rate,Billions of Chained 2009 Dollars
20	W875RX1	Real personal income excluding current transfer receipts
21 (Group #2)	CMRMTSPL	Real Manufacturing and Trade Industries Sales
22	NAPM	ISM Manufacturing: PMI Composite Index,S.A.
23	NAPMII	ISM Manufacturing: Inventories Index
24	NAPMNOI	ISM Manufacturing: New Orders Index;S.A.
25	NAPMSDI	ISM Manufacturing: Supplier Deliveries Index, S.A.
26	A0M057	Manufacturing and trade sales (mil. chain 2009 $)
27	A0M059	Sales of retail stores (mil. Chain 2009$)

36	DPCERA3M086SBEA	Real personal consumption expenditures (chain-type quantity index)
37	DSERRG3M086SBEA	Personal consumption expenditures: Services (chain-type price index)
38	PCEPI	Personal Consumption Expenditures: Chain-type Price Index
39	U0M083	Consumer expectations NSA (Copyright, University of Michigan)
40	UMCSENT	University of Michigan: Consumer Sentiment
41 (Group #3)	UEMP15OV	Number of Civilians Unemployed for 15 Weeks Over (Thousands of Persons)
42	UEMP15T26	Number of Civilians Unemployed for 15 to 26 Weeks
43	UEMP27OV	Number of Civilians Unemployed for 27 Weeks and Over
44	UEMP5TO14	Number of Civilians Unemployed for 5 to 14 Weeks
45	UEMPLT5	Number of Civilians Unemployed - Less Than 5 Weeks
46	UEMPMEAN	Average (Mean) Duration of Unemployment, S.A.
47	UEMPMED	Median Duration of Unemployment
48	UNEMPLOY	Civilian Unemployment Thousands of Persons, Monthly, S.A.,
49	UNRATE	Civilian Unemployment Rate, Percent, Monthly, S.A.
50	A0M005	Average weekly initial claims unemploy
51	A0M441	Civilian Labor Force
52	CE16OV	Civilian Employment, Thousands of Persons, Monthly, S.A.
53	NAPMEI	ISM Manufacturing: Employment Index©
54	A0M090	Ratio civilian employment to working-age population (pct.)
55	CIVPART	Civilian Labor Force Participation Rate, Percent, Monthly, S.A.
56	LNS11300012	Civilian Labor Force Participation Rate - 16 to 19 years
57	LNS11300036	Civilian Labor Force Participation Rate - 20 to 24 years
58	LNS11300060	Civilian Labor Force Participation Rate - 25 to 54 years, Percent, Monthly, S.A.
59	LNS11324230	Civilian Labor Force Participation Rate - 55 years and over, Percent, Monthly, S.A.
60	LNS11300002	Civilian Labor Force Participation Rate - Women, Percent, Monthly, S.A.
61	LNU01300001	Civilian Labor Force Participation Rate - Men, Percent, Monthly, Not S.A.
62	MANEMP	All Employees: Manufacturing
63	DMANEMP	All Employees: Durable goods

71	USPRIV	All Employees: Total Private Industries
72	USTPU	All Employees: Trade, Transportation Utilities
73	USTRADE	All Employees: Retail Trade
74	USWTRADE	All Employees: Wholesale Trade
75	AHECONS	Average Hourly Earnings Of Production And Nonsupervisory Employees:Construction
76	AHEMAN	Average Hourly Earnings Of Production And Nonsupervisory Employees:Manufacturing
77	A0M001	Average Weekly Hours: Manufacturing
78	AWOTMAN	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing
79	CES0600000007	Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing
80	CES0600000008	Average Hourly Earnings Of Production And Nonsupervisory Employees:Goods-Producing
81 (Group #4)	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started
82	HOUSTMW	Housing Starts in Midwest Census Region
83	HOUSTNE	Housing Starts in Northeast Census Region
84	HOUSTS	Housing Starts in South Census Region
85	HOUSTW	Housing Starts in West Census Region
86	PERMIT	New Private Housing Units Authorized by Building Permits
87	PERMITMW	New Private Housing Units Authorized by Building Permits in the Midwest
88	PERMITNE	New Private Housing Units Authorized by Building Permits in the North
89	PERMITS	New Private Housing Units Authorized by Building Permits in the South
90	PERMITW	New Private Housing Units Authorized by Building Permits in the West
91 (Group #5)	P/E	S&P'S COMPOSITE COMMON STOCK: PRICE-EARNINGS RATIO (%,NSA)
92	Dvd 12M Yld - Gross	S&P'S COMPOSITE COMMON STOCK: DIVIDEND YIELD (% PER ANNUM)
93	SP500	S&P'S COMMON STOCK PRICE INDEX: COMPOSITE
94	S5INDU	S&P'S COMMON STOCK PRICE INDEX: INDUSTRIALS
95	SPF	S&P'S COMMON STOCK PRICE INDEX: Financials
96	S5UTIL	S&P'S COMMON STOCK PRICE INDEX:Utilities
97	S5ENRS	S&P'S COMMON STOCK PRICE INDEX: Energy
98	S5HLTH	S&P'S COMMON STOCK PRICE INDEX: Health Care
99	S5INFT	S&P'S COMMON STOCK PRICE INDEX: Information Technology

106	CILDCBM027SBOG	Commercial and Industrial Loans, Domestically Chartered Commercial Banks
107	CILFRIM027SBOG	Commercial and Industrial Loans, Foreign-Related Institutions
108	M1SL	M1 Money Stock
109	M2REAL	Real M2 Money Stock(Billions of 1982-83 Dollars)
110	M2SL	M2 Money Stock
111	MABMM301USM189S	M3 for the United States©
112	MBCURRCIR	Monetary Base; Currency In Circulation
113	NONBORRES	Reserves Of Depository Institutions, Nonborrowed
114	REALLNNSA	Real Estate Loans, All Commercial Banks
115	TOTRESNS	Total Reserves of Depository Institutions
116	NONREVSL	Total Nonrevolving Credit Owned and Securitized, Outstanding
117	NREVNSEC	Securitized Consumer Nonrevolving Credit, Outstanding(Billions of Dollars);Not S.A.
118	A0M095	Ratio consumer installment credit to personal income (pct.)
119 (Group #7)	EXCAUS	Canada / U.S. Foreign Exchange Rate
120	EXCHUS	China / U.S. Foreign Exchange Rate
121	EXDNUS	Denmark / U.S. Foreign Exchange Rate
122	EXHKUS	Hong Kong / U.S. Foreign Exchange Rate
123	EXINUS	India / U.S. Foreign Exchange Rate
124	EXJPUS	Japan / U.S. Foreign Exchange Rate
125	EXKOUS	South Korea / U.S. Foreign Exchange Rate
126	EXMAUS	Malaysia / U.S. Foreign Exchange Rate
127	EXNOUS	Norway / U.S. Foreign Exchange Rate
128	EXSFUS	South Africa / U.S. Foreign Exchange Rate
129	EXSIUS	Singapore / U.S. Foreign Exchange Rate
130	EXSLUS	Sri Lanka / U.S. Foreign Exchange Rate
131	EXSZUS	Switzerland / U.S. Foreign Exchange Rate
132	EXTAUS	Taiwan / U.S. Foreign Exchange Rate
133	EXTHUS	Thailand / U.S. Foreign Exchange Rate
134	EXALUS	Australia/U.S. Foreign Exchange Rate

141	GS5	5-Year Treasury Constant Maturity Rate
142	TB3MS	3-Month Treasury Bill: Secondary Market Rate
143	TB6MS	6-Month Treasury Bill: Secondary Market Rate
144	AAA	Bond Yield: Moody's Aaa Corporate(% Per Annum)
145	BAA	Bond Yield: Moody's Baa Corporate(% Per Annum)
146	sfyGS1	GS1-FEDFUNDS
147	sfyGS10	GS10-FEDFUNDS
148	sfyGS5	GS5-FEDFUNDS
149	sfy3mo	TB3MS-FEDFUNDS
150	sfy6mo	TB6MS-FEDFUNDS
151	sfyAAA	BAA-FEDFUNDS
152	sfyBAA	AAA-FEDFUNDS
153 (Group #9)	CPIAPPSL	Consumer Price Index for All Urban Consumers: Apparel(Index 1982-84=100)
154	CPIAUCSL	Consumer Price Index for All Urban Consumers: All Items
155	CPILFESL	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy
156	CPIMEDSL	Consumer Price Index for All Urban Consumers: Medical Care
157	CPITRNSL	Consumer Price Index for All Urban Consumers: Transportation
158	CUSR0000SA0L2	Consumer Price Index for All Urban Consumers: All items less shelter
159	CUSR0000SA0L5	Consumer Price Index for All Urban Consumers: All items less medical
160	CUSR0000SAC	Consumer Price Index for All Urban Consumers: Commodities
161	CUSR0000SAD	Consumer Price Index for All Urban Consumers: Durables
162	CUSR0000SAS	Consumer Price Index for All Urban Consumers: Services
163	NAPMPRI	ISM Manufacturing: Prices Index©
164	PPICMM	Producer Price Index: Commodities: Metals and metal products: Primary nonferrous metals
165	PPICRM	Producer Price Index: Crude Materials for Further Processing
166	PPIFCG	Producer Price Index: Finished Consumer Goods
167	PPIFGS	Producer Price Index: Finished Goods
168	PPIITM	Producer Price Index: Intermediate Materials: Supplies Components
169	DCOILWTICO	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma

Chapter 2

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

2.1 Introduction

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

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

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

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

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

It should be noted, however, that the Monetary Policy Committee (MPC) under the PBC normally meets every quarter to make decisions on monetary policy stance. Furthermore, it turns out that the PBC revised their benchmark interest rates with a less than 30% frequency in 106 quarterly observations since 1987. Such a high degree inertia in dynamics of the policy interest rates may call for an alternative approach in studying the monetary policy decision-making process in China.

Since the seminal work of Dueker (1999), an array of researches has employed a discrete choice model framework to study the monetary policy stance of the Federal

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

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

Unlike these work, we take a direct approach to study dynamics of specific policy instruments instead of monetary policy index variables that are constructed

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

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

by authors. Put it differently, we study policy decision-marking processes of the PCB in revising the benchmark interest rates that are actually *observable* to the public. Therefore, our analysis could provide practically more useful information to the market participants. In contrast to He and Pauwels (2008) and Xiong (2011), we employ a constrained ordered probit model that allows policy makers to revise the interest rate only when the on-going interest rate deviates sufficiently from a newly calculated optimal interest rate.

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

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

2.2 The Econometric Model

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

$$i_t^* = \mathbf{x}_t'\beta - \varepsilon_t, \tag{2.1}$$

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

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

$$y_t^* = i_t^* - i_{t-1}, \tag{2.2}$$

where y_t^* is also a latent variable. Note that the greater y_t^* is (in absolute value), the stronger the incentive to revise i_t would be. This framework has been first employed by Dueker (1999), then by Hu and Phillips (2004a, 2004b) and Kim *et al.* (2009), while He and Pauwels (2008) and Xiong (2012) use ordered probit models with no such concern. Xiong employed a lagged policy stance variable instead, however, he reported negligible and insignificant coefficient estimates.

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

$$y_t = \begin{cases} -1, & \text{if} \quad y_t^* < \tau_L \quad : C \\ 0, & \text{if} \quad \tau_L \leq y_t^* \leq \tau_U \quad : S \\ 1, & \text{if} \quad y_t^* > \tau_U \quad : H \end{cases} \tag{2.3}$$

and

$$I_{j,t} = \begin{cases} \frac{y_t(y_t-1)}{2}, & \text{if} \quad j = C \\ 1 - y_t^2, & \text{if} \quad j = S \\ \frac{y_t(y_t+1)}{2}, & \text{if} \quad j = H \end{cases} \tag{2.4}$$

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

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

$$\mathcal{L} = \sum_{t=1}^{T} \left(I_{c,t} \ln P_c \left(\mathbf{x}_t : \theta \right) + I_{s,t} \ln P_s \left(\mathbf{x}_t : \theta \right) + I_{h,t} \ln P_h \left(\mathbf{x}_t : \theta \right) \right) \tag{2.5}$$

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

$$P_j = \begin{cases} 1 - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right), & \text{if} \quad j = C \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right) - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = S \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = H \end{cases} \tag{2.6}$$

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

2.3 Data and Preliminary Analysis

2.3.1 Data Descriptions

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

Figure 1 around here

We plot these interest rates in the first panel of Figure1. It should be noted that these interest rates are infrequently revised. Among 106 quarterly observations, there were 14 cuts and 14 hikes for the benchmark deposit rate (second panel), while 15 cuts and 16 hikes were observed for the lending rate (third panel). That is, the PBC chose "stay" decisions with a little over 70% frequency, which implies that the PBC revises the rates only when the differential between its perceived optimal

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

interest rate and the prevailing rate becomes greater than certain threshold values. The ordered probit model described earlier thus seems to be appropriate to estimate such decision-making processes. Corresponding trichotomous discrete choice variables ($y_t = -1,\ 0,\ 1$) are reported in the last two panels.

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

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

Intelligence Unit (EIU) and the National Bureau of Statistics in China. All other data are obtained from the International Financial Statistics (IFS). We report graphs of these macroeconomic covariates in Figure 2.

Figure 2 around here

2.3.2 Unit Root Tests

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

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

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

Table 1 around here

2.3.3 Linear Taylor Rule Model Estimations

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

$$i_t = \alpha + \gamma_\pi \pi_{t-1} + \gamma_y \tilde{y}_{t-1} + \Theta x_{t-1} + \varepsilon_t \tag{2.7}$$

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

$$i_t = \alpha + \gamma_\pi^s \pi_{t-1} + \gamma_y^s \tilde{y}_{t-1} + \Theta_s x_{t-1} + \rho i_{t-1} + \varepsilon_t \tag{2.8}$$

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

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

We also note that these estimates violate the Taylor principle ($\gamma_\pi > 1$) no matter what specifications are used. For example, the implied long-run inflation coefficient is about 0.40 and 0.60 for the lending rate and the deposit rate, respectively. It should be also noted that the degree of interest rate inertia measured by ρ in (**??**) is close to one. If the interest rate obeys a nonstationary stochastic process, as is implied by the ADF test in the previous section, the OLS estimates presented in Tables 2 and 3 might not be appropriate. The probit model, however, does not have such a problem since we use the policy index variable which assumes discrete numbers.

Tables 2 and 3 around here

2.4 Probit Model Estimation and In-Sample Fit Analysis

This section reports our findings based on the probit model estimations described in Section 2. Our benchmark model (Model 1) is motivated by the Taylor Rule with an assumption that the policy-makers observe inflation and the output gap with one period lag. Extended models with additional covariates are also considered. That is, Models 2 and 3 include Δm_{t-1} and Δs_{t-1}, respectively, in addition to the

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

Taylor Rule variables π_{t-1} and $\tilde{y}_{t-1}$. Model 4 is the full model that includes all key macroeconomics covariates. Results are provided in Table 4 and 5.

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

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

Tables 4 and 5 around here

We implement a robustness check analysis to see how stable these coefficient estimates are over our sample period. For this purpose, we repeatedly estimate our model beginning with the first half observations (1987:II to 2000:III) by adding one additional observation for each round of estimations, which gives 52 sets of coefficient estimates for each model. We report results in Figure 3 for the lending rate and

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

in Figure 4 for the deposit rate, which confirms the robustness of our full-sample estimates. The inflation coefficient estimates are significant at the 5% level and the money growth rate coefficient estimates are mostly significant at the 10% level. The output gap coefficient estimates are negligible and always statistically insignificant.

Figures 3 and 4 around here

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

Tables 6 and 7 around here

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

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

Figures 5 and 6 around here

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

Figure 7 around here

Tables 8 and 9 around here

2.5 Out-of-Sample Forecasting

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

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

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

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

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

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

Figures 8 and 9 around here

2.6 Concluding Remarks

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

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

Table 1. Augmented Dickey-Fuller Test Results

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

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

Table 2. Linear Taylor Rule Coefficient Estimations: Lending Rates

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

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

Table 3. Linear Taylor Rule Coefficient Estimations: Deposit Rates

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

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

Table 4. Probit Model Estimations: Lending Rates

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

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

Table 5. Probit Model Estimations: Deposit Rates

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

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

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

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

	Model 3			*Model 4*		
	Cut	*Stay*	*Hike*	*Cut*	*Stay*	*Hike*
Cut predicted	5	6	0	5	6	0
Stay predicted	10	63	14	10	63	14
Hike predicted	0	5	2	0	5	2
Correct Prediction (%)	33%	85%	13%	33%	85%	13%
Overall Performance (%)		66%			66%	

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

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

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

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

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

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

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

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

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

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

Figure 1. Interest Rates and Policy Actions

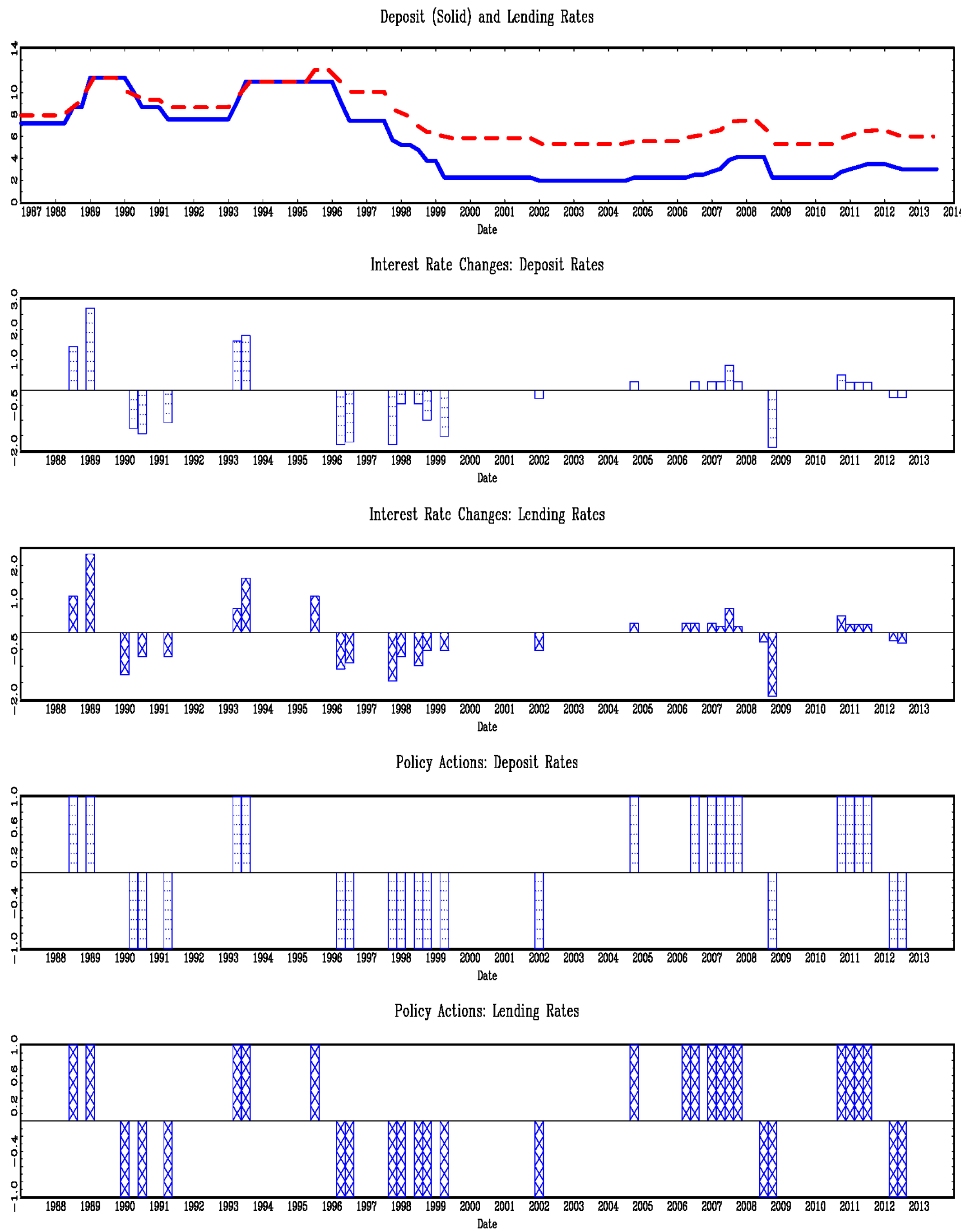
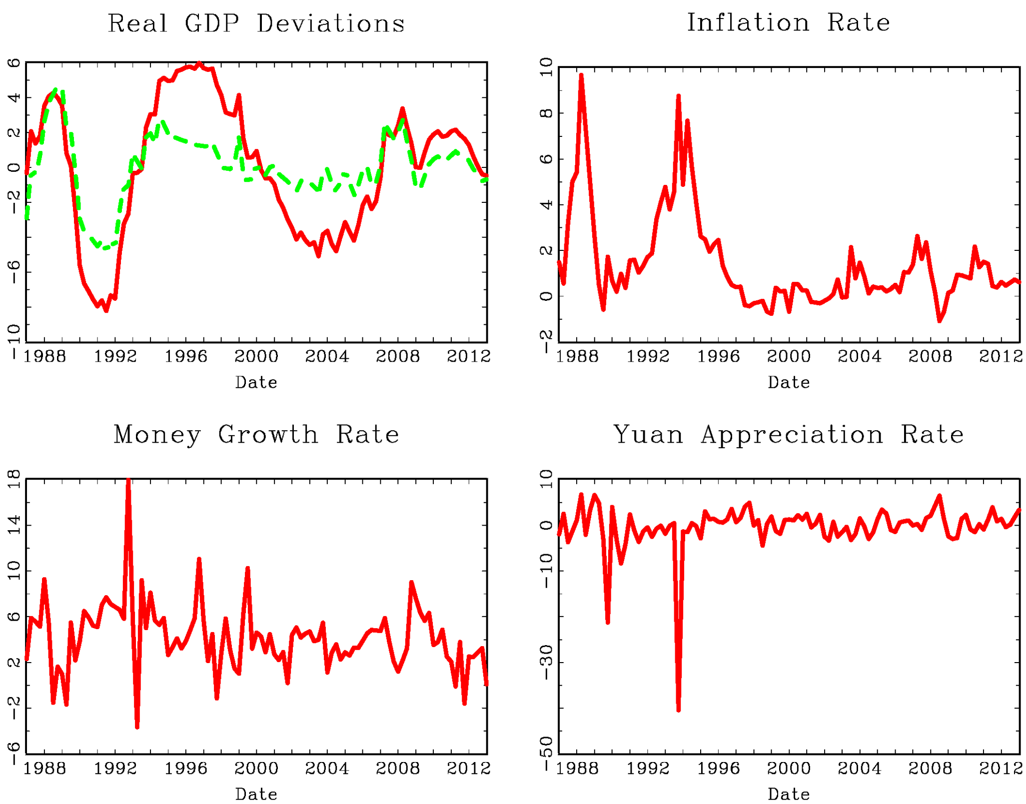
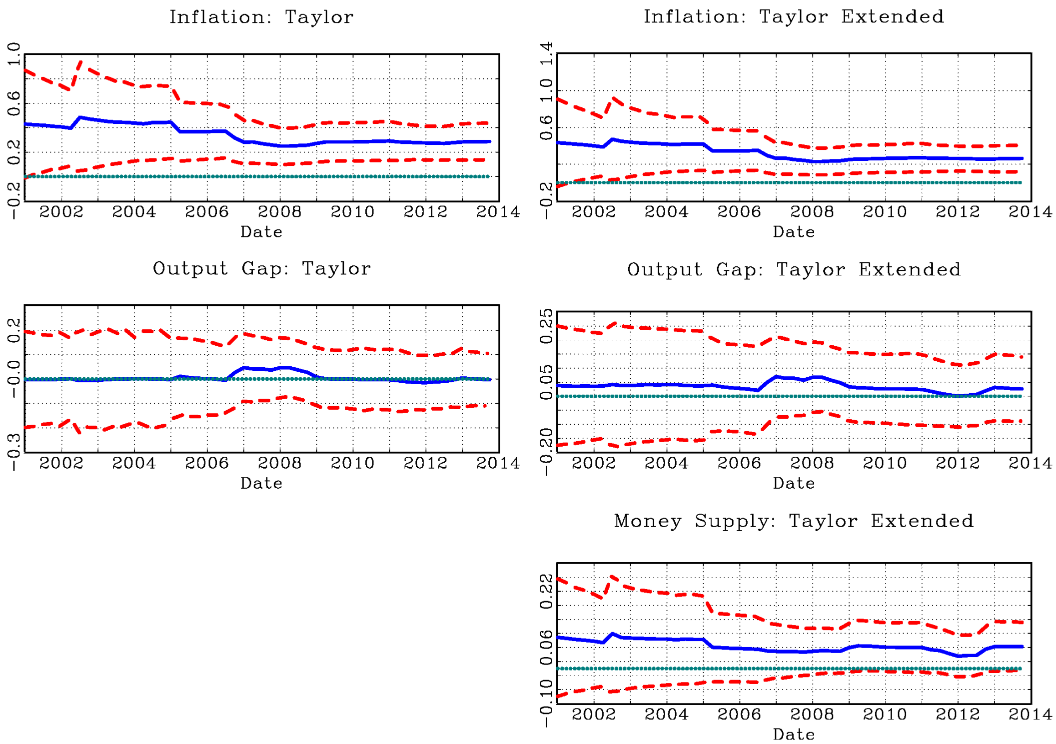


Figure 2. Key Macroeconomic Covariates



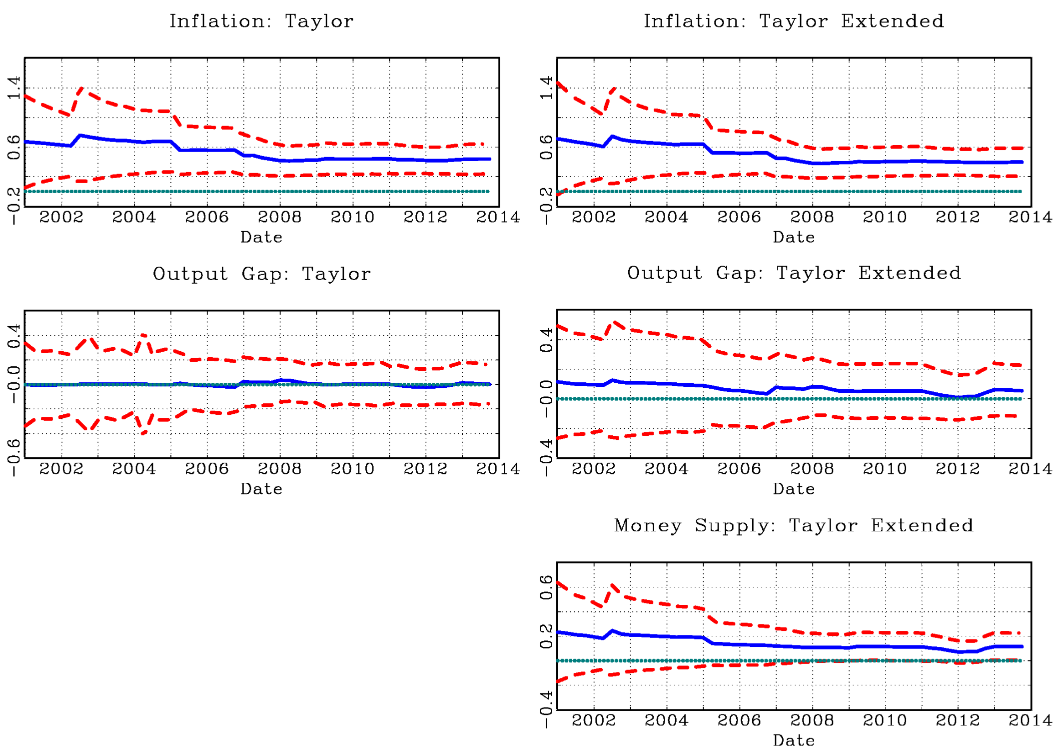
Note: We use two measures of the output gap: quadratically detrended real industrial production (solid) and the cyclical component of real industrial production(dashed) by the Hodrick-Prescott filter. Two detrending methods produce similar output gaps. Inflation is the quarterly change in the log CPI.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

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



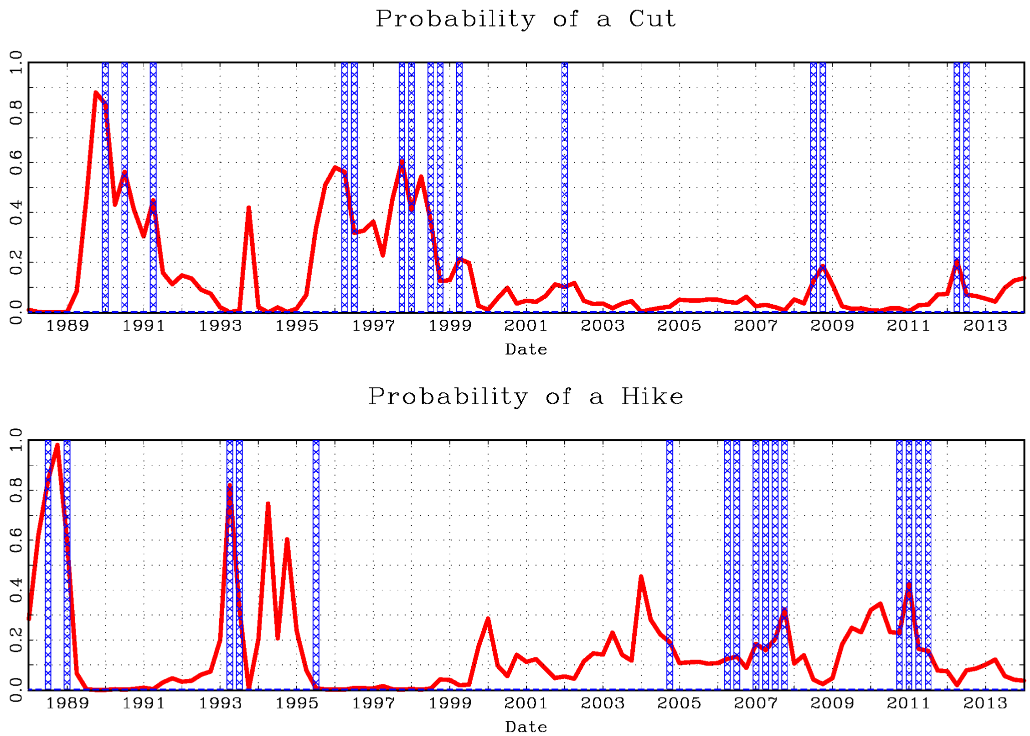
Note: We recursively estimate the latent equation coefficients repeatedly beginning with the initial half of the sample period, 1987:I to 2000:II, adding one more observation in each round of estimations. Dashed lines are corresponding 95% confidence bands.

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



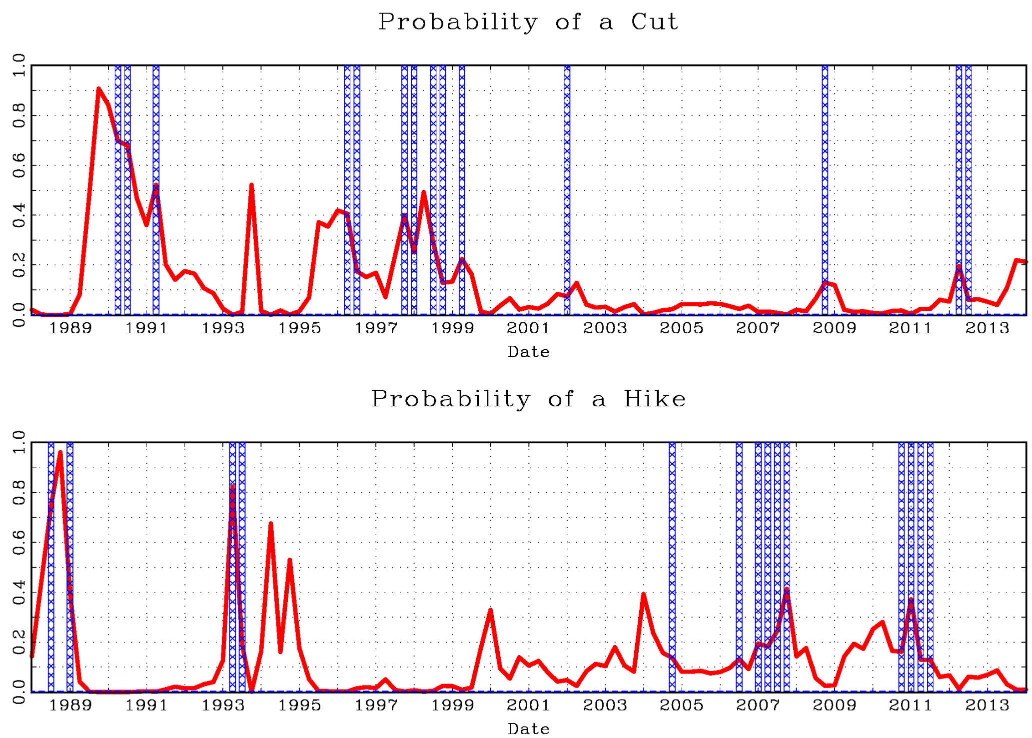
Note: We recursively estimate the latent equation coefficients repeatedly beginning with the initial half of the sample period, 1987:I to 2000:II, adding one more observation in each round of estimations. Dashed lines are corresponding 95% confidence bands.

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



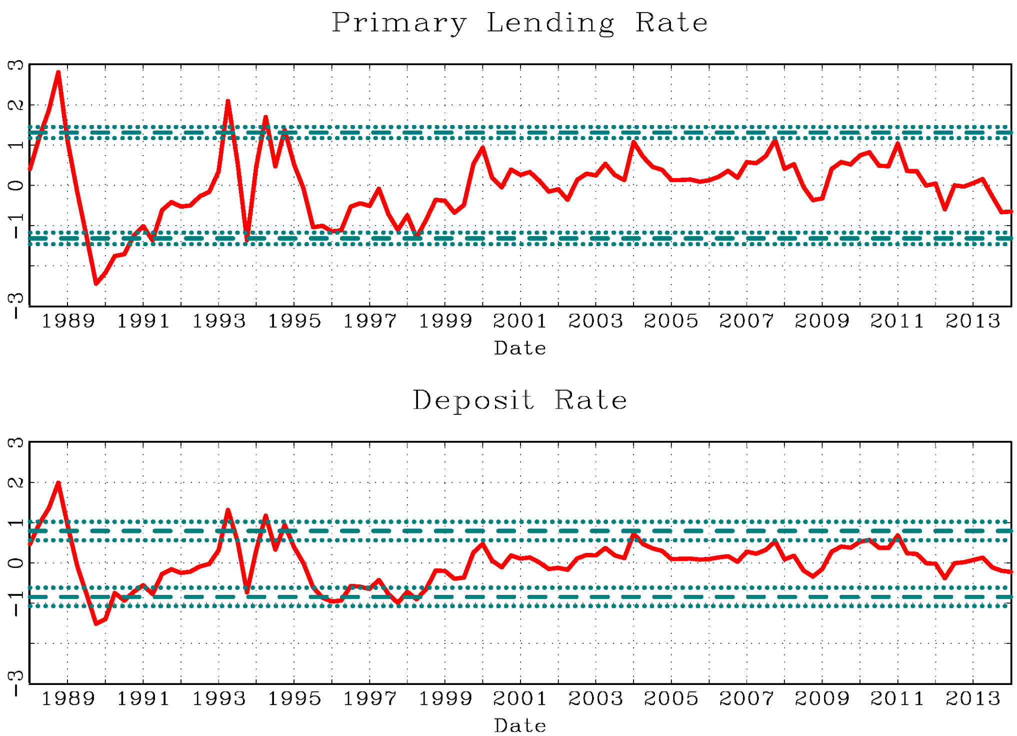
Note: We calculate estimated in-sample probabilities for each policy action from the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized policy actions.

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



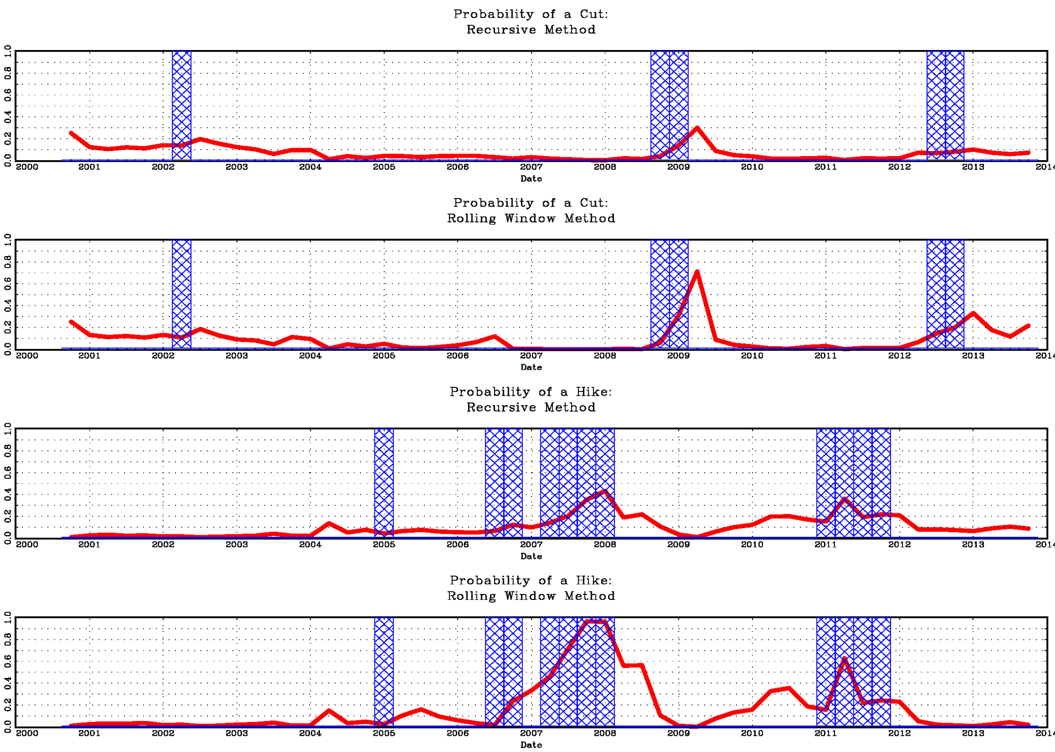
Note: We calculate estimated in-sample probabilities for each policy action from the model with the covariates $(\pi_{t-1}, \tilde{y}^H_{t-1}, \Delta m_{t-1})$. Bar graphs indicate realized policy actions.

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



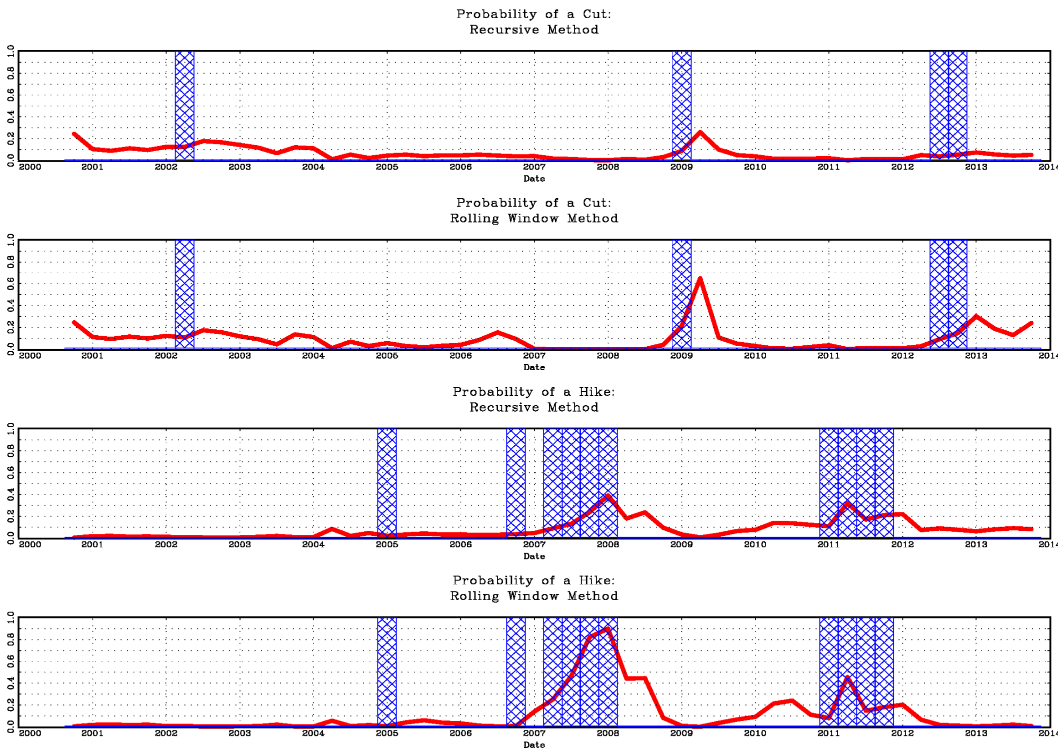
Note: We calculate deviations from the optimal interest rate ($y_t^* = i_t^* - i_{t-1}$) along with the upper and lower threshold values (τ_U, τ_L) from the model with the covariates ($\pi_{t-1}, \tilde{y}_{t-1}^H, \Delta m_{t-1}$). Dashed lines are τ_U and τ_L point estimates and dotted lines are their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

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



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

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



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

Chapter 3

Estimating Interest Rate Setting Behavior in Korea:

A Constrained Ordered Choices Model Approach

3.1 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 BOKs 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,

[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%.

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 BOKs 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 Jord (2002), initiated a seminal study on the Feds rate decision process by employing discrete choice model 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 Feds 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 Feds monetary policy actions. Xiong (2012) used the ordered probit model to investigate the monetary policy stance of the Peoples Bank of China.

[3]Hu and Phillips (2004b) also investigated the Bank of Canadas 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

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 dont 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 Koreas 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 statistical analysis including unit root test results and linear Taylor rule model estimates. Section 4 reports and interprets the coefficient estimates from

[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.

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.

3.2 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.

$$i_t^* = \mathbf{x}_t'\beta - \varepsilon_t, \tag{3.1}$$

where $\mathrm{x}_t isak?1vectorofmacroeconomiccharacteristicsvariables(covariates)oftheeconomy.Notethatt$
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.

$$y_t^* = i_t^* - i_{t-1} = \mathbf{x}_t'\beta - i_{t-1} - \varepsilon_t, \tag{3.2}$$

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 $\tau_L$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]We allow the inaction band [τ_L,τ_U] to be asymmetric because we do not impose any restriction on the thresholds. We may assume τ_L=-τ_U for symmetric bands when τ_L is restricted to be less than zero.. Based on this trichotomous-choice model framework, we define the following policy index measure y_t and its associated indicator functions $I_{j,t}$.

$$y_t = \begin{cases} -1, & \text{if} \quad y_t^* < \tau_L \qquad : C \\ 0, & \text{if} \quad \tau_L \leq y_t^* \leq \tau_U \quad : S \\ 1, & \text{if} \quad y_t^* > \tau_U \qquad : H \end{cases} \tag{3.3}$$

and

$$I_{j,t} = \begin{cases} \frac{y_t(y_t-1)}{2}, & \text{if} \quad j = C \\ 1 - y_t^2, & \text{if} \quad j = S \\ \frac{y_t(y_t+1)}{2}, & \text{if} \quad j = H \end{cases} \tag{3.4}$$

[5]We allow the inaction band $[?_L, ?_U] tobeasymmetricbecausewedonotimposeanyrestrictionnonthethresholds.Wemaya$
$-?_U forsymmetricbandswhen?_L isrestrictedtobelessthanzero.$

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

$$\mathcal{L} = \sum_{t=1}^{T} \left(I_{c,t} \ln P_c \left(\mathbf{x}_t : \theta \right) + I_{s,t} \ln P_s \left(\mathbf{x}_t : \theta \right) + I_{h,t} \ln P_h \left(\mathbf{x}_t : \theta \right) \right) \tag{3.5}$$

where θ is the parameter vector $(\beta,\ \tau)$. The probability function P_j is defined as follows.

$$P_j = \begin{cases} 1 - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right), & \text{if} \quad j = C \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_L\right) - F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = S \\ F\left(\mathbf{x}_t'\beta - i_{t-1} - \tau_U\right), & \text{if} \quad j = H \end{cases} \tag{3.6}$$

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 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]

[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.

3.3 Data Descriptions and Preliminary Estimation Results

3.3.1 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 (Δs_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 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

[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, Gal, 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.

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).

[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).

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 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

3.3.2 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.

3.3.3 Linear Taylor Rule Estimations

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

$$i_t = \alpha + \gamma_\pi \pi_{t-1} + \gamma_y \tilde{y}_{t-1} + \Theta_s x_{t-1} + \varepsilon_t \tag{3.7}$$

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),

$$i_t = \alpha + \gamma_\pi^s \pi_{t-1} + \gamma_y^s \tilde{y}_{t-1} + \Theta_s x_{t-1} + \rho i_{t-1} + \varepsilon_t \tag{3.8}$$

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, γ_π=$\gamma_\pi^s/(1-\rho)$ is the long-run coefficient on the inflation rate. Put it differently, if ρ=0.75 and γ_π=1.5, then the central bank responds to a 1% inflation gap by raising the nominal interest rate by 0.375% ($\gamma_\pi^s = 1.5?0.25 = 0.375) contemporaneously but will continue to raise it by 1.5\% in the long-run.$

All estimation results for (**??**) and (**??**) 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 ? that are close to one; (ii) quantitatively smaller short-run coefficient estimates for most explanatory variables than those of (**??**); (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 (**??**) 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 (**??**) 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 γ_π¿1 for the determinacy of inflation. For example, the first model for (**??**) yields γ_π^s=0.005 and ρ=0.961, thus the long-run coefficient becomes γ_π=0.161 that is strictly less than 1. Since γ_π¡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.

3.4 Constrained Ordered Choices Model Estimations

This section reports our estimation results for the latent equation (**??**) 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 theres 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

[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.

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 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 (Δls_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 (Δls_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) 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 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.

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

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 Feds 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 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

[14] Results from other models are qualitatively similar.

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

3.5 In-Sample Fit Performance of the Discrete Choices Models

Next, we evaluate our ordered choices models for the MPCs 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 BOKs 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.

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

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 $\tilde{y}_t$ falls below τ_L. Likewise, when $\tilde{y}_t$ 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 $\tilde{y}_t$ 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 $[\tau_L+\text{std}(\tau_L),\tau_U\text{-std}(\tau_U)]$ 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

[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.

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, [τ_L+std(τ_L),τ_U-std(τ_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, [τ_L+1.5?std(τ_L),τ_U-1.5?std(τ_U)], reported on the second panel 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

3.6 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 BOKs 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 BOKs 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($\tilde{y}_{t+1}$ —Ω_t)=-1,0,1, where the information set is either Ω_t=π_t,$\tilde{y}_t$ or Ω_t=π_t,$\tilde{y}_t$,Δs_t.

Again, we report probit model estimation results only in Table 7. Taylor Recursive denotes the forecast results using the recursive method with π_t,$\tilde{y}_t$ for covariates in the latent equation, whereas Taylor Extended Rolling is the results with the rolling window method using π_t,$\tilde{y}_t$,Δs_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 $\tilde{y}_t$(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, $\tilde{y}_t$ 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.

Figures 8 around here

3.7 Concluding Remarks

This paper investigates the BOKs 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 BOKs 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. $*$, †, and ‡ 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	

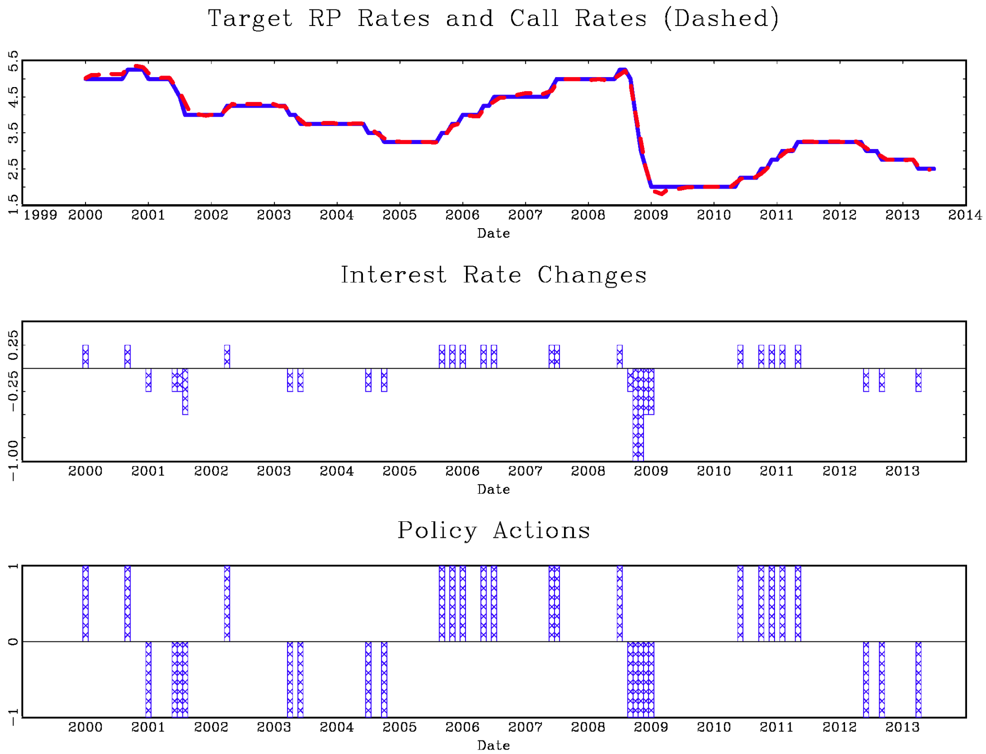
(B) Inaction Band: $[\tau_L + 1.5 \times std(\tau_L), \tau_U - 1.5 \times std(\tau_U)]$

	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	

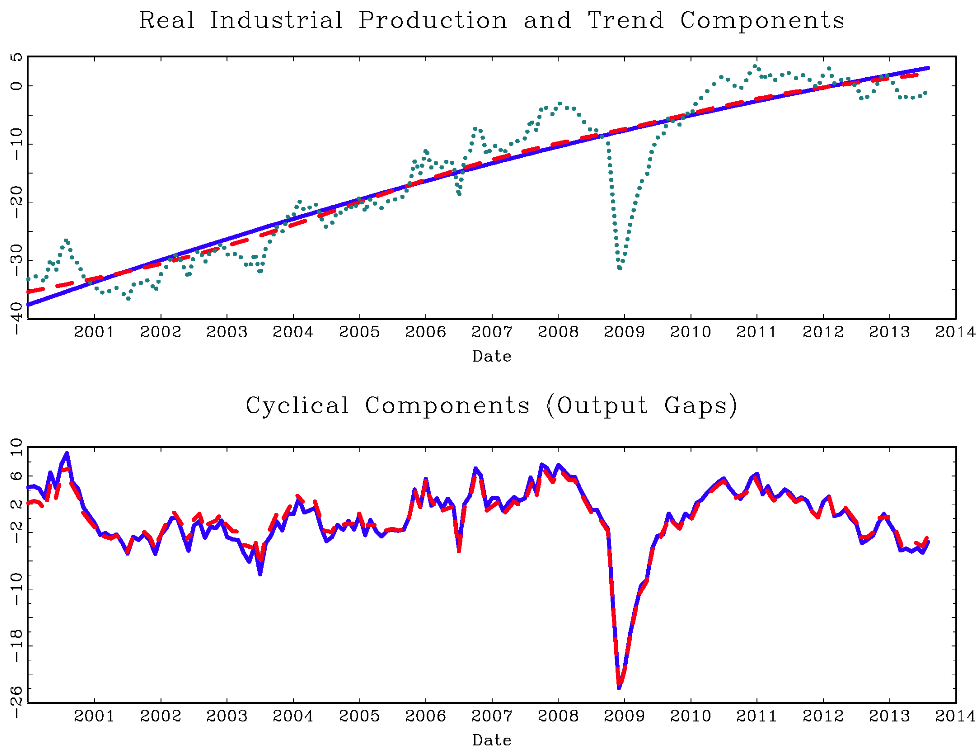
Note: Out-of-sample forecast results are based on the ordered probit model estimates with the recursive method and the fixed size rolling window method, both beginning with the pre-Lehman Brothers Bankruptcy period data (104 initial observations), September 2008.

Figure 1. Interest Rates and Monetary Policy Actions



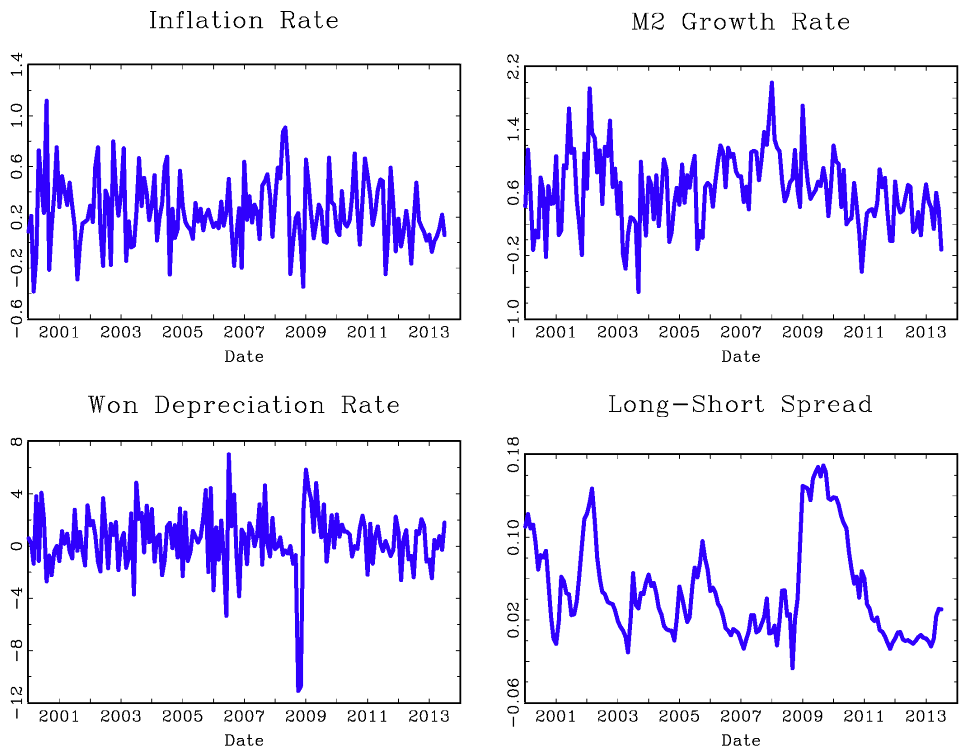
Note: The target RP rate (solid) and the market call interest rate (dashed) appear on the first panel. Revisions of the target RP rate have been made in multiples of 25 basis points as we can see in the second panel. We model policy actions to include three possible choices for the Bank of Korea as to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



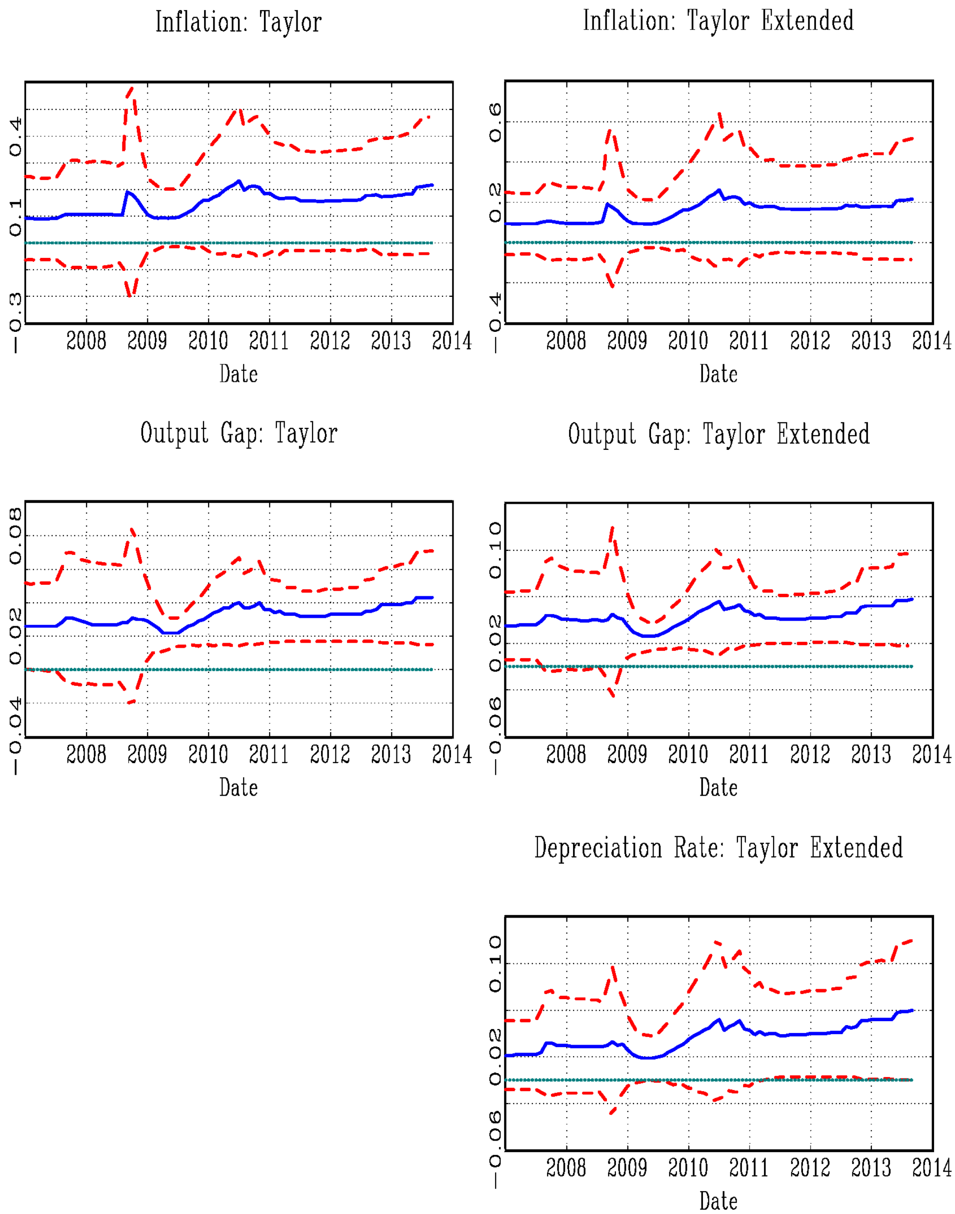
Note: We use two measures of the output gap: quadratically detrended real industrial production (solid) and the cyclical component of real industrial production (dashed) by the Hodrick-Prescott filter. Two detrending methods produce very similar output gaps.

Figure 3. Inflation Rate and Other Key Macroeconomic Data



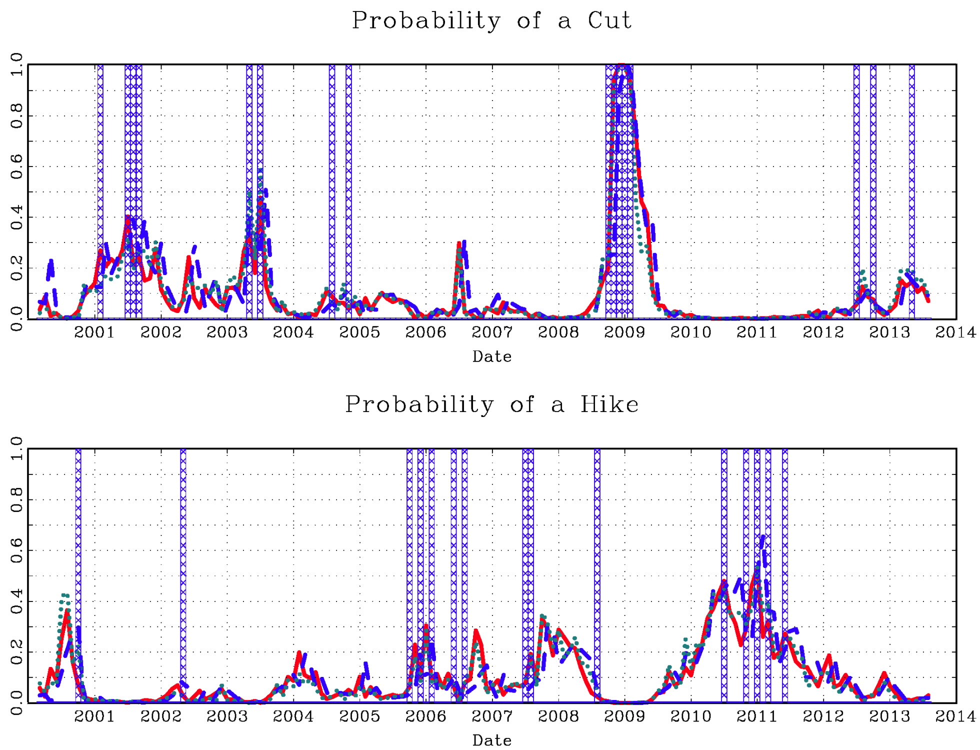
Note: The inflation rate is the monthly change in log CPI. The M2 growth rate denotes the monthly change in the log M2. We use the won-dollar exchange rate, which is the unit price of the US dollar in terms of Korean won. The won depreciation rate is the monthly change in the log exchange rate. The long-short 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



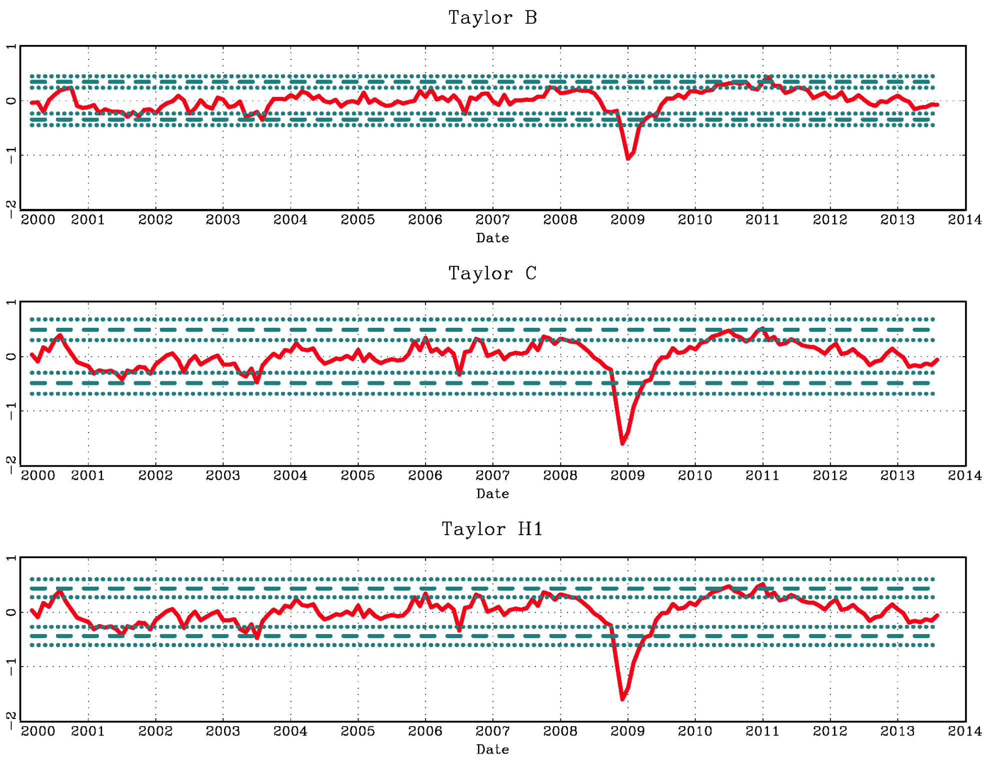
Note: We estimated the latent equation coefficients repeatedly beginning with the initial half of the sample period, 2000M1 to 2006M10, adding one more observation in each round of estimations. Inflation and output gap are lagged once, while the appreciation rate is the contemporaneous one. Dashed lines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

Figure 5. In-Sample Fit Performance of Probit Models



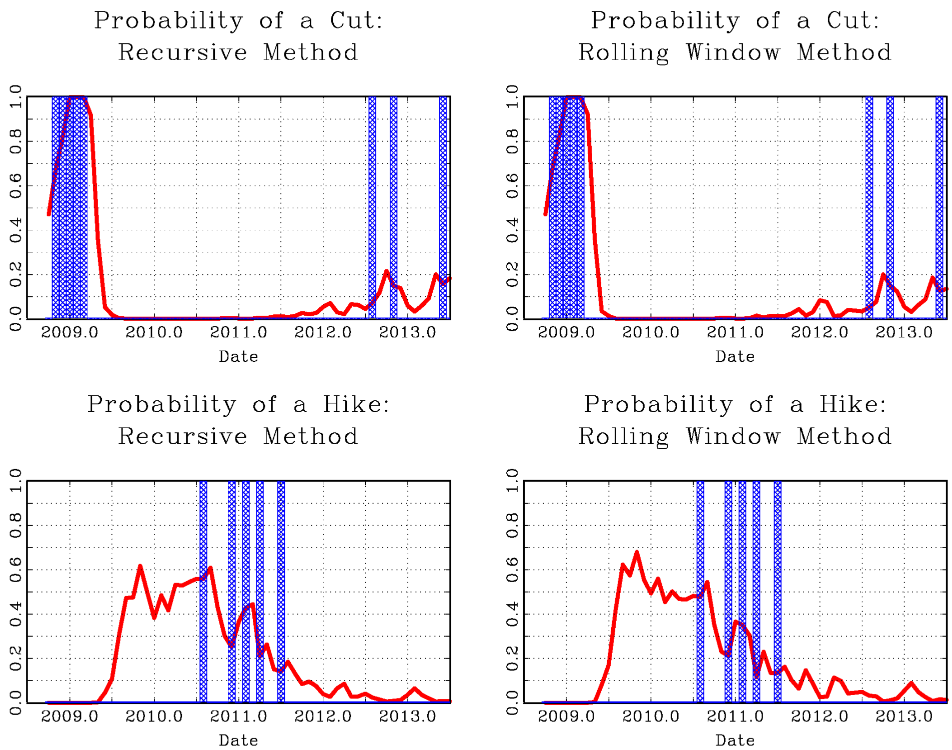
Note: We calculate in-sample probability of each action for the models with the following three sets of covariates in the latent equation and plotted in solid, dashed, and dotted lines, respectively: $(\pi_t, \tilde{y}_t)$, $(\pi_{t-1}, \tilde{y}_{t-1})$, $(\pi_{t-1}, \tilde{y}_{t-1}, \Delta s_t)$. Bar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

Figure 6. Deviations from the Optimal Rate and Thresholds



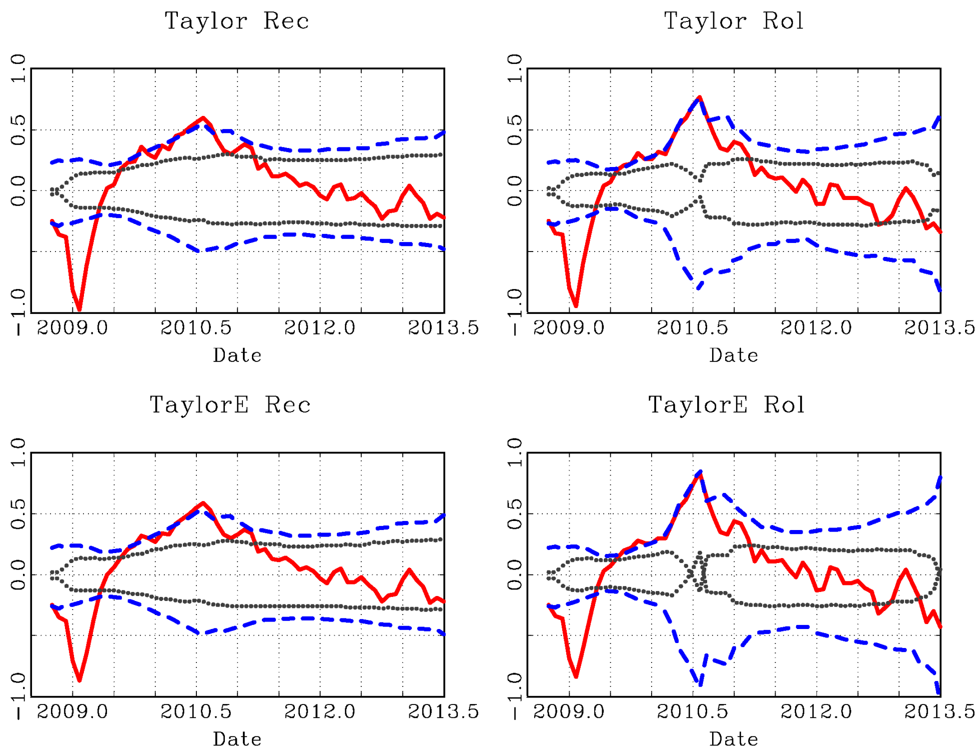
Note: We calculate deviations from the optimal interest rate ($y_t^* = i_t^* - i_{t-1}$) and upper and lower threshold values (τ_U, τ_L) for the models with the following three sets of covariates in the latent equation: $(\pi_{t-1}, \tilde{y}_{t-1})$, $(\pi_t, \tilde{y}_t)$, $(\pi_{t-1}, \tilde{y}_{t-1}, \Delta s_t)$. 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, $[\tau_L + std(\tau_L), \tau_U - std(\tau_U)]$.