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Effectiveness of Monetary Policy in Korea Due to Time Varying Monetary Policy Stance

Tae Bong Kim
(Assistant Professor, Department of Economics, Ajou University)

거시경제 및 통화정책 기조 변화가 통화정책의 유효성에 미친 영향 분석

김 태 봉
(아주대학교 경제학과 조교수)

* 김태봉: (e-mail) tbk@ajou.ac.kr, (address) Department of Economics, Ajou University, 206, Worldcup-ro, Yeongtong-gu, Suwon-si, Gyeonggi-do, 443-749, Korea.

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ABSTRACT

This paper has studied the monetary policy in Korea with a time varying VAR model using four key macroeconomic variables. First, inclusion of the exchange rate was a crucial factor in evaluating Korean monetary policy since the monetary policy demonstrated sensitivity to exchange rate movements during the crisis periods of both the Asian financial crisis of 1997 and the global financial crisis of 2008. Second, a specification of the stochastic volatilities in TVP-VAR model is important in explaining excessive movements of all variables in the sample. The overall moderation of variables in 2000s was more or less due to a reduction of the stochastic volatilities but also somewhat due to the macroeconomic fundamental structures captured by impulse response functons. Third, the degree of the monetary policy effectiveness of inflation was mitigated in recent periods but with increased persistence. Lastly, the monetary policy stance towards inflation stabilization has advanced ever since the inflation targeting scheme was adopted. However, there still seems to be a room for improvement in this aspect since the degree of the monetary policy stance towards inflation stabilization was relatively weaker than to output stabilization.

본고는 4개의 거시변수들을 포함한 Time Varying VAR 모형을 통해 한국의 통화정책 변화를 평가하였다. 첫째, 외환위기나 금융위기 때와 같이 통화정책이 환율변동에 대해 민감하게 변화하는 시기가 존재하므로 위기를 포함한 긴 표본 안에서 한국의 통화정책을 평가할 때는 환율을 모형 안에 포함시키는 것이 필요하다. 둘째, 표본기간 내에서 이례적인 큰 변동성이 때때로 나타나는 한국 거시변수들을 설명하기 위해서는 stochastic volatilities를 TVP-VAR 모형 내에서 설정할 필요가 있다. 한편, 2000년대 거시변수들의 안정화는 stochastic volatilities의 감소에 의해 설명되며, 부분적으로는 거시경제의 구조를 반영하는 충격반응함수에 의해서도 설명된다. 셋째, 통화정책의 인플레이션에 대한 유효성의 크기는 예전에 비해 최근 약화된 편이나 유효성의 지속성은 비교적 높아진 것으로 나타났다. 마지막으로 인플레이션 안정화에 대한 통화정책의 기조는 물가안정목표제가 도입되기 전에 비해 그 후에 적극적인 방향으로 개선되어 왔음을 보이고 있다. 하지만 우리나라의 통화정책은 그 기조가 경기변동에 비해 인플레이션 안정화에 대하여 여전히 덜 적극적인 것을 감안할 때 개선될 여지가 있는 것으로 판단된다.

I. Introduction

Evaluating the monetary policy in Korea often poses challenges to researchers due to the existence of structural changes and excessive volatilities. Korean economy has experienced high growth until the mid 1990s thanks to export driven production. But Korea was not exempt from the Asian financial crisis in the late 1990s which resulted in unprecedented high interest rate and the concurrent event of adopting the inflation targeting scheme. This was followed by the stabilization of overall macroeconomic variables until the global financial crisis came to the fore. Hence, standard econometric approaches such as constant parameter VAR or Taylor rule, often fails to explain the possibly time varying economic structures in Korean monetary policy especially when brought in the context of long span of time series data due to the limitation of such methods to describe the overall macroeconomic variables and monetary policy

An empirical assessment of the monetary policy in Korea on the inflation targeting scheme was first conducted by Kim and Park (2006). They estimated the conventional Taylor Rule and concluded that the post-inflation targeting period demonstrated the aggressive monetary stance towards inflation stability. However, the fact that this paper only used the short span of sample of the early 2000s cast considerable doubt on whether the subsequent monetary policy stance was stable. There are numerous papers that objected to the conclusion of Kim and Park (2006) once consequent observations were collected. Kim and Lee (2011) conducted GMM estimation of Taylor rule that included the expected inflation following Clarida *et al*. (2000) and reached a conclusion that the estimates of Taylor rule parameters did not imply the aggressive policy stance towards inflation stabilization despite the maintenance of the positive sign. More recently, Park (2012) conducted an investigation on the implied monetary policy stance based on estimated structural VAR and drew similar conclusions. In addition, he also conducted subsample analysis to distinguish the policy shift when the inflation targeting scheme was adopted. He resorted to excluding of crisis periods in subsample periods due to the fact that parameter estimates often exhibited not only the counter intuitive results but also the switched sign of the monetary policy stance. Once the exclusion of the 1997 financial crisis during the pre-inflation targeting period and the curtailment of the 2008 financial crisis to current periods were incorporated in the first subsample analysis, the long run response of the monetary policy toward inflation gap demonstrated positive signs. However, it is quite surprising that the long-run monetary policy stance towards inflation gap during the pre-inflation targeting periods showed stronger signs than the post-inflation targeting periods despite the fact that they were still both less than one. This suggests that the application of subsample analysis in the context of Korean data with constant parameter VAR is still questionable. Moreover, exclusion of crisis periods can arbitrarily trim the possible information which results in relatively short sample to draw any meaningful long run dynamics of monetary policy. Hence, it is necessary to extend the length of sample including crisis periods. Given the longer sample of Korean data, time varying parameter VAR model can be a suitable alternative among the available econometric frameworks to incorporate the possibly time varying dynamics without dividing into subsample. Moreover, including stochastic volatilities can potentially minimize the biased results on coefficient parameters of VAR when adverse episodes such as crises are included as Sims noted in his comment on Cogley and Sargent (2002).

This paper estimates the relationships between key macroeconomic variables of Korea and time varying VAR model (TVP-VAR henceforth) with stochastic volatilities. Given this estimated model, time varying monetary policy for Korea can be recovered for conventional evaluations, i.e. how the monetary policy stance towards inflation stabilization has evolved over time. This paper is not alone to apply TVP-VAR as the literature on this topic has been growing. Cogley and Sargent (2002) is one of the early researchers to apply TVP-VAR in macroeconomic context for U.S. economy and Cogley and Sargent (2005) has augmented this application with stochastic volatilities in response to Sims's comment. The spirit of this model and estimation method has been applied to several economies. Primiceri (2005) used this application to assess the time varying behaviors of U.S. monetary policy and witnessed the evolving trend towards more aggressive stance in spite of the negligible change in effectiveness. Benati and Mumtaz (2005) applied this framework on U.K. economy and Baumeister *et al*. (2008) on Euro economy. Nakajima *et al*. (2011) applied on Japanese economy and modified its framework to explain the lost decade of Japanese growth when the monetary policy and interest rate tool was tied due to zero lower bound. To author's knowledge, this paper is the first to apply this framework on the Korean monetary policy.[1] In addition, exchange rate which were generally used for analyzing developing countries, has been added to the vector of macroeconomic variables in order to evaluate the Korean monetary policy which faces the trinity problem due to its susceptibility from large swings of

1 Choi and Son (2013) is the first paper which employed the time varying VAR but have focused on the time varying effectiveness of government expenditures on Korean economy's growth.

international capital flows. The paper proceeds as follows. Section 2 illustrates the econometric methodology for estimating time varying parameter VAR. Section 3 presents the estimation results and their implications for the monetary policy in Korea. Section 4 concludes.

II. Econometric Methodology

1. Time Varying Parameter VAR with Stochastic Volatilities

TVP-VAR model illustrated in this section is a basic structural VAR model with all the parameters time varying including volatilities of the shocks following Cogley and Sargent (2005) and Primiceri (2005). Alternatively, one could specify the time varying structure by regime switch as in Sims and Zha (2006). Although regime switch models can as well capture discrete breaks of policy changes, they are considered less suitable for reflecting gradual changes in private agents' behavior where aggregation mostly smoothes away discrete breaks as argued by Primiceri (2005). Thus, this paper chooses to specify drifting coefficients and stochastic volatilities as opposed to regime switch.

To identify the structural shocks, the coefficient matrix that represents contemporaneous relationship between variables assumes lower triangular. The macro variables of interest for analysis is

$$\mathbf{y}_t = \begin{bmatrix} y_{1,t} \\ y_{2,t} \\ \vdots \\ y_{n,t} \end{bmatrix}$$

Then, the model is

$$A_t\mathbf{y}_t = c_t + \Phi_{1,t}\mathbf{y}_{t-1} + \Phi_{2,t}\mathbf{y}_{t-2} + ... + \Phi_{k,t}\mathbf{y}_{t-k} + \Sigma_t\varepsilon_t \qquad t = k+1, ..., T \tag{1}$$

where A_t is the contemporaneous coefficient matrix

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{n1,t} & \cdots & a_{nn-1,t} & 1 \end{bmatrix} \tag{2}$$

The stochastic volatilities are also time varying denoted by

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{n,t} \end{bmatrix} \tag{3}$$

also note that the coefficient matrices, $\Phi_{i,t,}$ including constant terms, c_t, are time varying.

Converting the structural representation equation (1) into a reduced form VAR,

$$\mathbf{y}_t = c_t + B_{1,t}\mathbf{y}_{t-1} + B_{2,t}\mathbf{y}_{t-2} + ... + B_{k,t}\mathbf{y}_{t-k} + A_t^{-1}\Sigma_t\varepsilon_t \tag{4}$$

For ease of notation,

$$\mathbf{y}_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t$$

where

$$X_t = I_n \otimes \left[1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-k}\right]$$

and β_t is a stacked vector of B_t's for t in equation (4). Similarly, define $\mathbf{a}_t$ and σ_t as stacked vector of $a_{ij,t}$'s and $\sigma_{i,t}$'s in matrix equations (2) and (3). This paper assumes the evolution processes of these time varying parameters are random walk as in equations (5).

$$\begin{aligned} \beta_{t+1} &= \beta_t + u_{\beta t} \\ \mathbf{a}_{t+1} &= \mathbf{a}_t + u_{at} \\ \log\sigma_{t+1} &= \log\sigma_t + u_{\sigma t} \end{aligned} \qquad \begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{\alpha t} \\ u_{\sigma t} \end{pmatrix} \sim N\left(0, \begin{bmatrix} I_n & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_\sigma \end{bmatrix}\right) \tag{5}$$

The other alternative would be autoregressive process as AR(1) for coefficients or GARCH for time varying volatilities. However, it is well known in this literature that the random walk specification has few advantages in this class of model. First, the number of parameters to estimate is reduced, a significant advantage as the number of time varying parameters are large. Second, although random walk in general hits the upper and lower bounds easily, the assumption is innocuous as long as the sample data for estimation is finite. Moreover, random walk specification makes it easier to identify the potential permanent shifts such as monetary policy's regime shift than AR and GARCH models which requires identification of the long run means which normally require longer span of sample data. This is desirable since this paper applies the time varying model onto Korean data which is believed to contain relatively many structural changes within a short span of time.

2. Estimation Methodology

The model proposed in the previous subsection does not require a unique estimation method. However, it has been widely accepted in the literature that Bayesian inference is a practical and efficient approach to handle models such as TVP-VAR. A class of model like TVP-VAR has unobservable components such as time varying parameters which are hardly distinguished from the shock processes. Thus, Bayesian inference which treats the parameters of a model as random variables is deemed natural in dealing with such situations. Additionally, Markov Chain Monte Carlo method which numerically maximizes the posterior distributions of parameters of interest is proven to be quite efficient when the model contains a high dimensional parameter space. This subsection outlines Gibbs sampler which divides the high dimensional parameter joint distributions into lower dimensional joint distributions with multi-steps. Gibbs sampler in general allows to maximize the posterior distributions of a subset of parameters of interest in each step conditional on remaining parameters fixed onto previously drawn values. The theoretical background for justification of Gibbs sampler is *Hammersley-Clifford Thoerem* in which conditional distributions of parameters contain enough information to constitute the full joint distribution of parameters.

Gibbs sampler algorithm is briefly illustrated below and more details can be found in Primiceri (2005) and Nakajima *et al*. (2011). Define $\mathbf{Y} \equiv \{\mathbf{y}_t\}_{t=1}^{T}$, $\mathbf{a} \equiv \{\mathbf{a}_t\}_{t=1}^{T}$, $\beta \equiv \{\beta_t\}_{t=1}^{T}$, $\sigma \equiv \{\sigma_t\}_{t=1}^{T}$ and $\omega \equiv \{\Sigma_\beta, \Sigma_a, \Sigma_\sigma\}$. The objective is to maximize the joint posterior distribution, $p(\beta, \mathbf{a}, \sigma, \omega|\mathbf{Y})$. This can be decomposed into conditional posterior distributions,

$$p(\beta, \mathbf{a}, \sigma, \omega|\mathbf{Y}) \propto p(\beta|\mathbf{a}, \sigma, \Sigma_\beta, \mathbf{Y})\, p(\Sigma_\beta|\beta)\, p(\mathbf{a}|\beta, \sigma, \Sigma_a, \mathbf{Y})\, p(\Sigma_a|\mathbf{a})\, p(\sigma|\beta, \mathbf{a}, \Sigma_\sigma, \mathbf{Y})\, p(\Sigma_\sigma|\sigma)$$

The sampling algorithm naturally follows from those conditional posterior distributions

1. Initialize $\beta^{(0)}, \mathbf{a}^{(0)}, \sigma^{(0)}, \omega^{(0)}$
2. Draw $\beta^{(k)}$ from $p\left(\beta|\mathbf{a}^{(k-1)}, \sigma^{(k-1)}, \Sigma_\beta^{(k-1)}, \mathbf{Y}\right)$
3. Draw $\Sigma_\beta^{(k)}$ from $p\left(\Sigma_\beta|\beta^{(k)}\right)$
4. Draw $\mathbf{a}^{(k)}$ from $p\left(\mathbf{a}|\beta^{(k)}, \sigma^{(k-1)}, \Sigma_a^{(k-1)}, \mathbf{Y}\right)$
5. Draw $\Sigma_a^{(k)}$ from $p\left(\Sigma_a|\mathbf{a}^{(k)}\right)$
6. Draw $\sigma^{(k)}$ from $p\left(\sigma|\beta^{(k)}, \mathbf{a}^{(k)}, \Sigma_\sigma^{(k-1)}, \mathbf{Y}\right)$
7. Draw $\Sigma_\sigma^{(k)}$ from $p\left(\Sigma_\sigma|\sigma^{(k)}\right)$
8. Go back to step 2 until $k = \max\ number\ of\ iterations$

In order to implement this algorithm, there are a few things that need to be specified. First, the initial draw $\beta^{(0)}, \mathbf{a}^{(0)}, \sigma^{(0)}, \omega^{(0)}$ should be chosen which is normally set by the standard OLS estimates from time invariant VAR with pre-sample period. Second, the posterior distributions are constructed not only by the likelihood of the model which is often referred to "data telling" element but also by prior distributions. Thus, the prior distributions need to be set in order to avoid the implausible space of parameters such as violating invertibility of certain matrices and explosive roots. Third, sampling from the posterior distributions can vary depending on the analytical form of the distributions. Lastly, 10, 000 MCMC draws are used for the main results after initial 1000 burn-in draws.

A. Prior Distributions

The prior distributions of parameters, {$\mathbf{a}$, β, σ}, are set by OLS estimates of time invariant VAR with pre-sample periods and those of hyperparameters such as {Σ_β , Σ_a, Σ_σ } are set with inverse gamma distributions that are conjugate distributions. For the main results presented below, the OLS estimates for {$\mathbf{a}$, β, σ} on initial nine years of the sample has been used. The variances of those parameters have been set as wide as possible. For the sensitivity analysis mentioned later, various choices of subsample periods have been tested. As for the priors of hyperparameters, they are in general set as diffuse and uninformative. The prior distribution for {Σ_β} is the most tight among other hyperparameters. This is necessary in order to avoid implausible behaviors of time varying coefficients as discussed by Primiceri (2005). The tightness of prior distributions for {Σ_σ} is disparate among the parameters associated with macroeconomic variables. For example, time series data for exchange rate of Korean Won shows highly volatile movements in events such as financial crisis and required slightly tighter prior distribution to obtain reasonable estimates of stochastic volatilities for the whole sample periods.

Initial draws in step 1 of Gibbs sampler is $\beta^{(0)} = \widehat{\beta}_{OLS}$, $\mathbf{a}^{(0)} = \widehat{\mathbf{a}}_{OLS}$, $\log \sigma^{(0)} = \log \widehat{\sigma}_{OLS}$, $\Sigma_\beta = \Sigma_a = \Sigma_\sigma = 4 \times I$.

<Table 1> Prior Distributions

Parameters	Distribution	a	b
β	Normal	$\widehat{\beta}_{OLS}$	$4 \cdot V\left(\widehat{\beta}_{OLS}\right)$
a	Normal	$\widehat{\mathbf{a}}_{OLS}$	$10 \cdot I_n$
$\log \sigma$	Normal	$\log \widehat{\sigma}_{OLS}$	$50 \cdot I_n$
Σ_β^{-2}	Gamma	10	0.001
Σ_a^{-2}	Gamma	4	0.0001
$\Sigma_{\sigma_p}^{-2}$	Gamma	4	0.01
$\Sigma_{\sigma_x}^{-2}$	Gamma	4	0.01
$\Sigma_{\sigma_{ex}}^{-2}$	Gamma	4	0.0001
$\Sigma_{\sigma_r}^{-2}$	Gamma	4	0.04

B. Sampling Method

Sampling β can be done with simulation smoother developed by De Jong and Shephard (1995). TVP-VAR can be rewritten in a form of linear Gaussian State Space where β is the latent variable. Once a linear Gaussian state space is written, the initial period of β can be drawn from the prior distribution while the following periods are drawn from the posterior distributions, $p\ (\beta|\mathbf{a}^{(k-1)},\ \sigma^{(k-1)},\ \Sigma_{\beta}^{(k-1)},\ \mathbf{Y})$, constructed by Kalman Filter (or forward filter) and smooth filter(or backward filter). Sampling **a** is analogous to sampling β except the latent variable process is now written in terms of **a**.

Sampling σ is rather more involved than β or **a** since the state space in terms of state variable, σ, becomes non-Gaussian. One method to draw from non-Gaussian state space model is a mixture sampler proposed by Kim *et al*. (1998) and this was applied to TVP-VAR framework by Primiceri (2005). The other method is the multi move sampler of Shephard and Pitt (1997) which was applied by Nakajima *et al*. (2011). In this paper, we choose the latter method which draws the σ from the exact posterior distribution rather than the former method in which σ are drawn from approximated posterior distribution.

III. Empirical Analysis

1. Data

Estimating TVP-VAR for Korean economy involves four variables, namely, nominal interest rate, inflation rate, output growth and exchange rate. Although the current policy rate of Korean monetary authority is the overnight call rate whose series only began in 1991:Q1, this paper chose the Monetary Stabilization Bond rate with 1 year maturity which began in 1987:Q1 since the longer sample period was available. The inflation rate is the growth rate of Consumer Price Index which is the also the target rate for the Bank of Korea. The output is the real GDP growth. The exchange rate is Won/Dollar exchange rate. The sample starts from 1987:Q1 to 2013:Q1. The ordering of the times series is inflation rate, GDP growth, exchange rate growth and the interest rate, respectively, following the convention of VAR literature. This implies that the financial variables of exchange rate and interest rate could react contemporaneously to changes in economic fundamentals such as inflation and GDP.

When data are brought to the estimation, the interest rate in difference was selected over the interest rate level as the main result.. The first reason is that augmented Dickey-Fuller test was not able to reject the null hypothesis of existence of unit root in the interest rate.[2] A similar finding with unit root in the overnight call rate of Korea is documented in Park (2012). Nakajima *et al*. (2011) also used this specification as well. Second, the estimation with difference in the interest rate demonstrated more stability and less sensitivity to prior distributions. The lag structure is set as two quarters. This was chosen because two lags with a quarterly model in general is widely accepted considering many documents related to monetary policy in both U.S. and Korea. Additionally, a lag of four in TVP-VAR instead contains too many parameters to estimate given that short span of time series data for Korea.

2. Empirical Results

A common practice for checking whether the estimation is valid in the Bayesian inference is to examine the mixing property and convergence statistics. [Figure 1] and <Table 2> together summarize the mixing property and convergence statistics of some selected hyperparameters. In [Figure 1], the first row shows the sample autocorrelation of MCMC chains. Second row of [Figure 1] is the sample paths of those hyperparameters, and the last row is the posterior distributions. As can be seen from the sample autocorrelations and the sample paths, the bulk of hyperparameters show a good mixing property since they approach zero quickly. <Table 2> confirms these observations by presenting formal test statistics. Convergence diagnostics[3] of selected parameters imply that the null hypothesis of convergence to the stationary distribution is not rejected at 5% significance level. The last column in <Table 2> is the inefficiency factor[4] which shows very low numbers indicating a good mixing property. Lastly, the posterior distributions with smooth unimodal shape indicate well identified estimates of hyperparameters.

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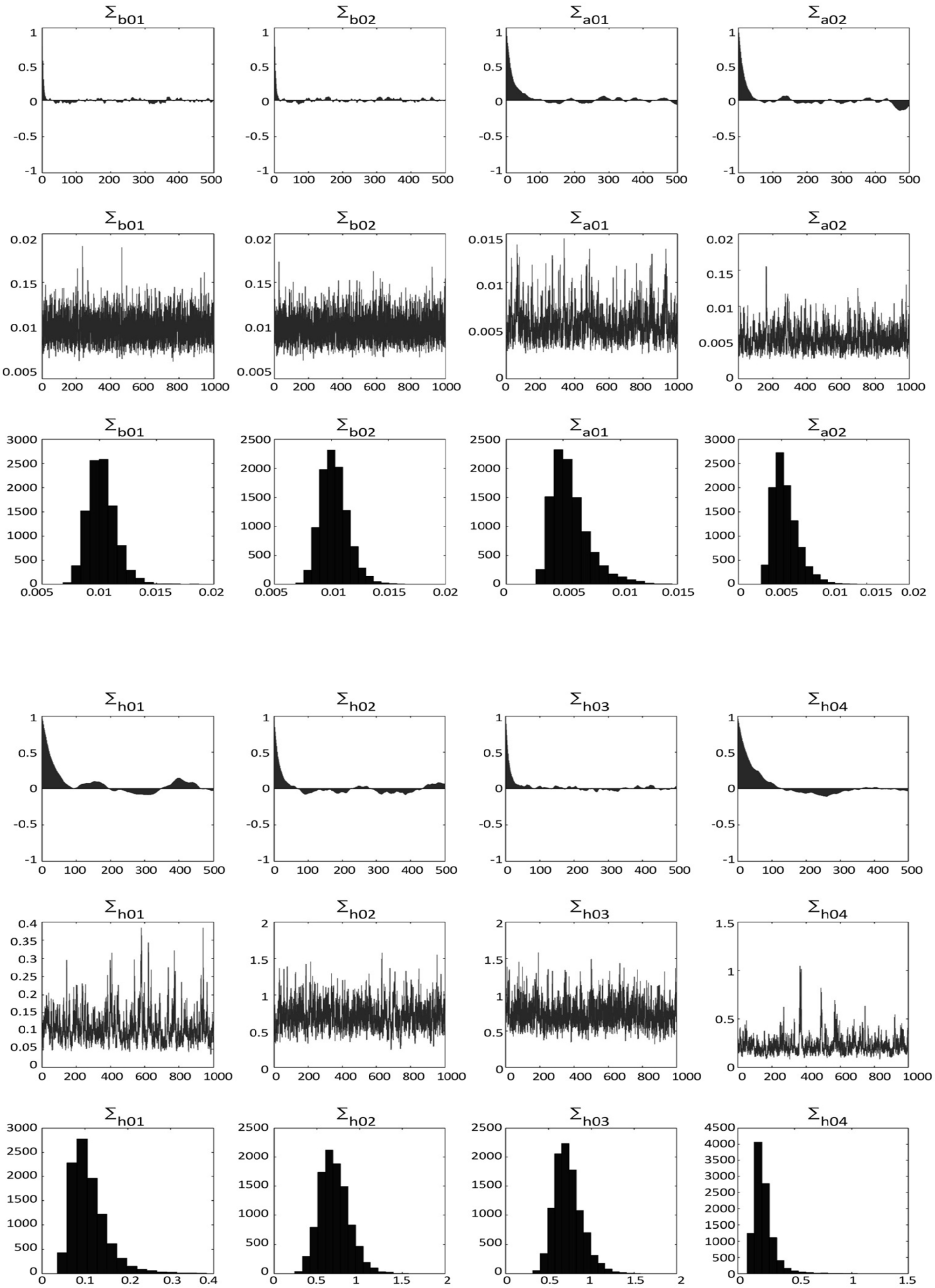
2 t-statistics was -1.244 without drift, -0.6620 with drift and -2.8567 with time trend all of which are accepted at 1% critical value.

3 See Geweke *et al*. (1991). This test statistics follow the standard Z-score table.

4 See Chib (2001).

[Figure 1] Sample Autocorrelation, MCMC Chains and Posterior Distributions



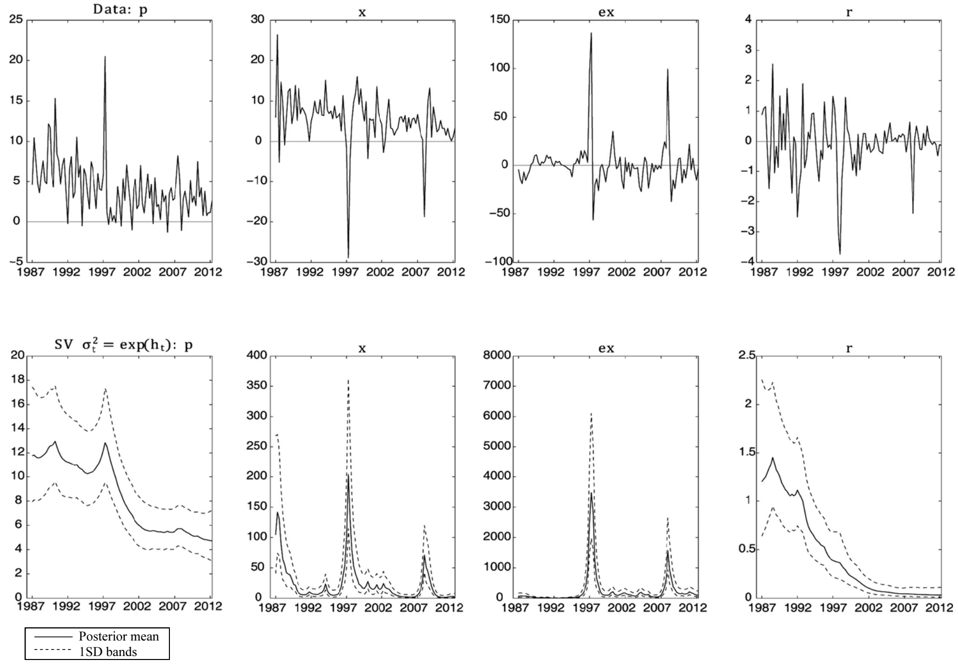
<Table 2> Estimates and Statistics for Selected Hyperparameters

Parameters	Mean	St.Dev.	5%	95%	Geweke	Inef.Factor
$\Sigma_{\beta 1}$	0.0102	0.0012	0.0082	0.0129	0.704	3.49
$\Sigma_{\beta 2}$	0.0103	0.0012	0.0083	0.0129	0.760	5.93
Σ_{a1}	0.0056	0.0016	0.0034	0.0100	0.233	34.40
Σ_{a2}	0.0055	0.0015	0.0034	0.0091	0.522	26.88
$\Sigma_{\sigma 1}$	0.1098	0.0429	0.0556	0.2204	0.550	59.63
$\Sigma_{\sigma 2}$	0.7043	0.1718	0.4061	1.0788	0.801	19.94
$\Sigma_{\sigma 3}$	0.7280	0.1597	0.4666	1.0953	0.082	23.99
$\Sigma_{\sigma 4}$	0.2267	0.0899	0.1214	0.4545	0.513	60.82

[Figure 2] shows times series data of four variables and evolving stochastic volatilities associated with those variables. It is evident that Inflation rate before 2000 had both higher trend and volatilities compared to that of post-2000 at first glance at data. The evolution of stochastic volatility of inflation rate supports this moderation of inflation rate since it shows significant decrease since 2000. Accordingly, the overall reduction of the interest rate volatility has been substantial during the sample period. As for the GDP and the exchange rate, those variables show excessive movements during crisis periods such as the financial crisis of 1997 and the global financial crisis of 2008. Such conspicuous episodes are captured by large sized shocks of stochastic volatilities.

Assessing the simulation results such as impulse response functions with TVP-VAR models can be presented in various ways. First, time varying impulse response functions on sample periods can be drawn by fixing the time horizon of simulations to a certain period. On the other hand, standard impulse response functions can be derived by fixing parameters on a certain period of sample. The former is on the left panels of [Figure 3] while the latter is on the right panels. [Figure 3] shows impulse response functions of three variables to interest rate one standard deviation shock and thus this implies the time varying effectiveness of monetary policy in Korea. For a sensible comparison on simulations, the standard deviation of shocks for each sample period is fixed to a constant which is the mean of stochastic volatilities of interest rate. The first row of [Figure 3] is the impulse response function of inflation rate. The overall magnitude of impulse response of inflation has been reduced after

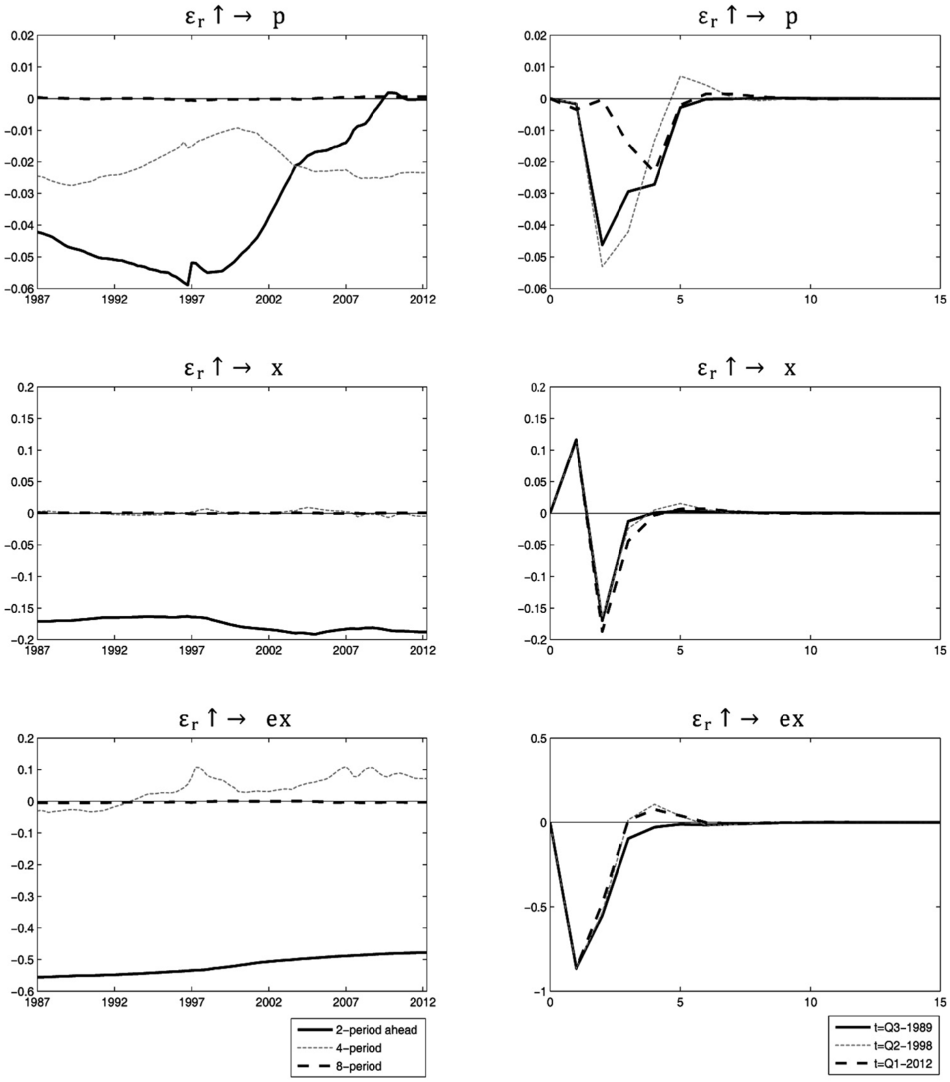
[Figure 2] Data and Stochastic Volatilities



2000. The reduction largely comes from response after two quarters. But the recent inflation response, for example, 2012:Q2, peaks four quarters after the shock compared to that of the past when the response peaked after two quarters and returned to zero. The inflation response during the financial crisis in 1998:Q2 was the largest which is closely followed by the initial sample period which is 1989:Q3. Second and third row of [Figure 3] are the responses of GDP and exchange rate. In contrast to inflation's response, time varying responses of those variables across the sample period show less dramatic changes.

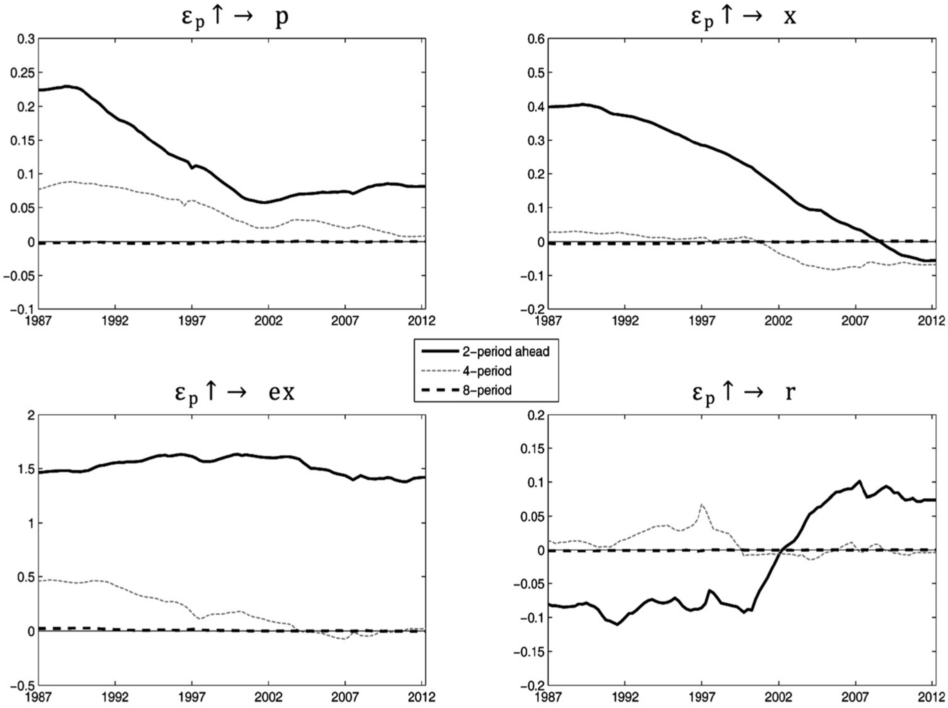
Next three figures show time varying impulse responses of four variables to shocks other than interest rate shock. In Figure 4, the inflation rate responds more sensitively to its own shock in the earlier periods while less in the latter periods. Hence, this evidence together with the stochastic volatilities evolution in [Figure 2] implies that the moderation of inflation rate volatilities did not solely come from the reduction of stochastic volatilities but also from the time varying coefficients of VAR that reflect the economic structures. With respect to GDP growth, the inflation shock has contributed positively until mid 2000s but it has had more negative effects on GDP growth more recently. Exchange rate response did not significantly change over time but has slightly been mitigated towards later sample. The most important

[Figure 3] Impulse Response Functions of Four Variables to Interest Rate shock



impulse response function in this paper is the interest rate response to inflation shock which is at the right hand bottom panel of [Figure 4]. This is related to the monetary policy stance towards the inflation stabilization. The increase in interest rate response to a positive inflation shock would imply more aggressive stance towards inflation stabilization. This impulse response function evidently shows the positive growth of the interest rate response after two quarters since 2002, which

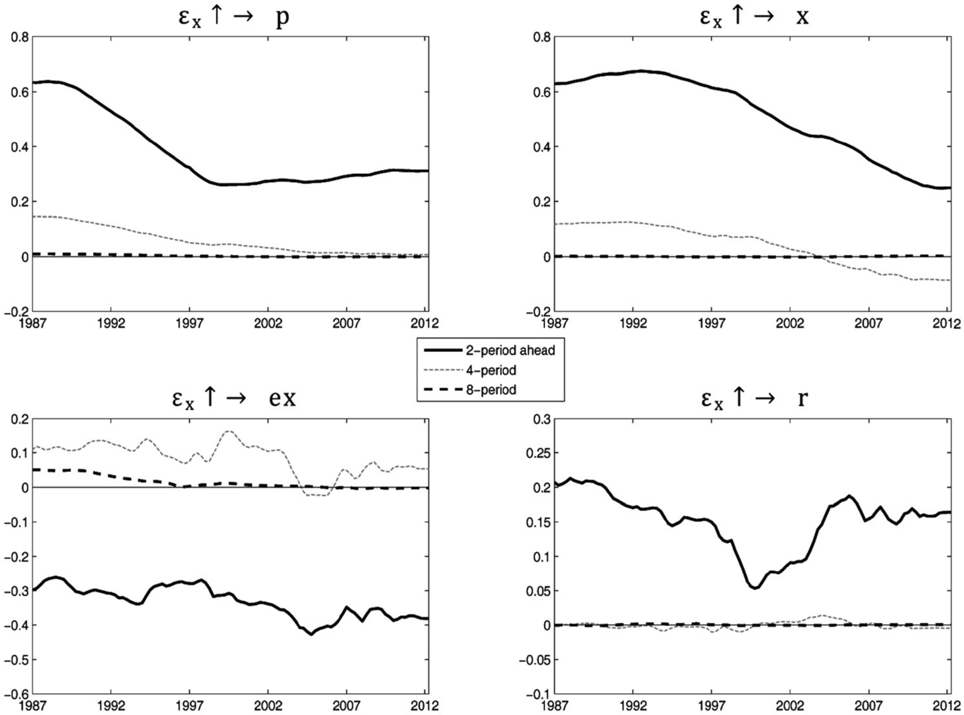
[Figure 4] Impulse Response Functions to Inflation shock



took a turn around 2000 with the advent of the inflation targeting scheme. However, this response, i.e. monetary policy stance, has been more or less stagnant after 2007. At any rate, this suggests that the monetary policy stance on inflation stabilization has indeed improved once the inflation targeting scheme was introduced.

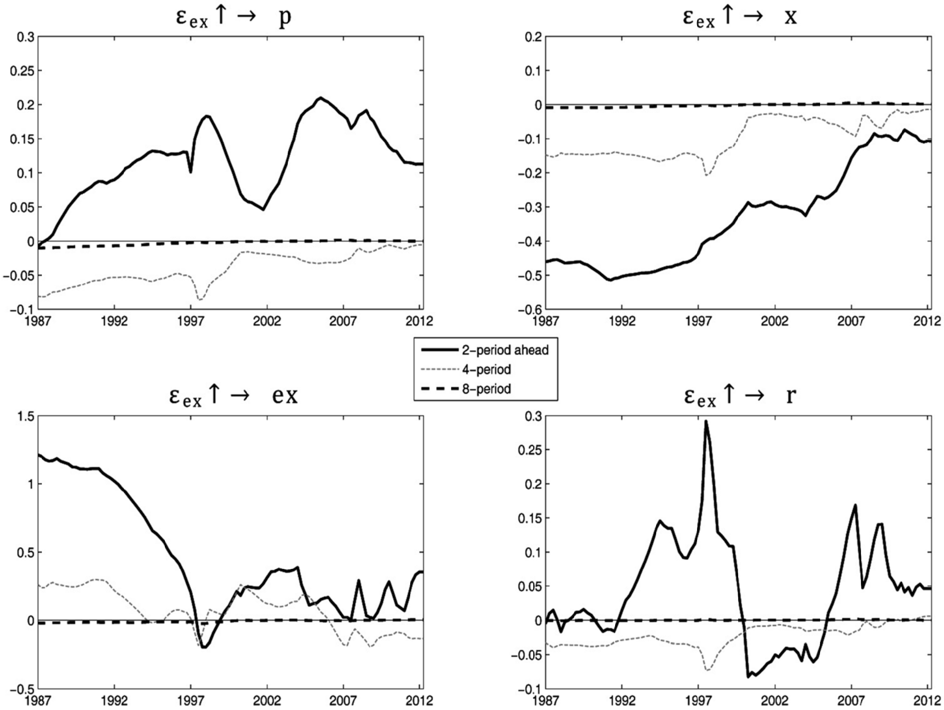
[Figure 5] is impulse response functions to GDP growth shock. The overall moderation of both inflation and GDP growth to GDP growth shock is apparent in the graphs while that of the exchange rate response is less clear. The interest rate response experienced a considerable drop during the 1997 financial crisis which can be explained by IMF's prescription of imposing a very high interest rate on sovereign bonds on Korean economy in spite of the drastic drop in output With the exception of this episode, the output stabilization stance has been stable.

[Figure 5] Impulse Response Functions to GDP growth shock



[Figure 6] is the impulse response functions to the exchange rate shock. First, the exchange rate response to its own shock has been moderated after 1997 which is in line with the overall moderation of other variables. However, the exchange rate shock to inflation rate has been somewhat strong not only during the 1997 crisis but also in mid 2000s. The initial GDP growth response was negative to the exchange rate shock but has been mitigated recently. The monetary policy towards exchange rate shocks shows disparate responses from time to time. In the earlier sample periods, ranging from the beginning to the early 1990s, the interest rate does not respond until four quarters after the exchange rate shock with slightly negative sign. This situation changes in the mid 1990s. It is clear that the interest rate has shown strong response within shorter time horizon. This change can be interpreted as the increased sensitivity of the monetary policy to external conditions. Moreover, the strong response after two quarters imply the relatively immediate monetary policy response compared to the past but such phenomena can also be interpreted as "overreacting" as the change in response was slightly more negative after four

[Figure 6] Impulse Response Functions to Exchange rate shock

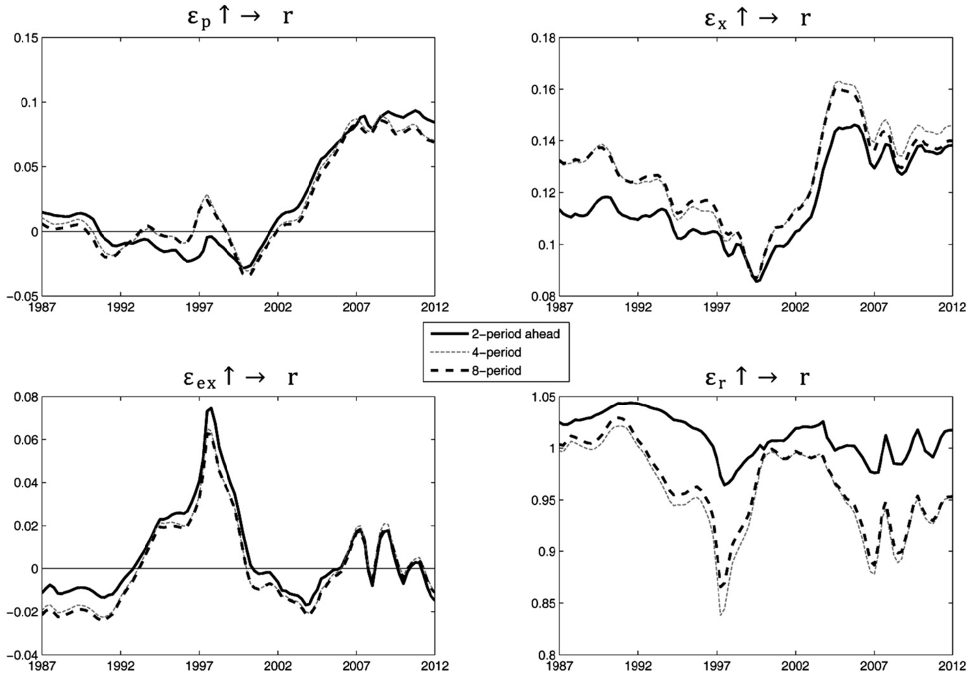


quarters. It can be further deduced that the high level of interest rate set during the crisis was in fact not due to the inflation or output but to massive depreciation of Korean Won. This can only be captured when exchange rate is included in the system, otherwise the monetary policy during this period would have been overly contractionary despite the economy was in recession. The second largest interest rate response to exchange rate shock was in 2007 and in the global financial crisis of 2008. In contrast to 1997 crisis, these periods show that the negative response virtually vanishes in four quarters and thus do not demonstrate “overreaction” of the monetary policy in response to exchange rate shocks. In 2007, the spike in oil price has deteriorated terms of trade for Korea. Although oil price or terms of trade was not brought to the estimation, the interest rate response to exchange rate shock in 2007 seems to somewhat reflect this episode. During the global financial crisis, it is quite clear that the monetary policy was sensitive to exchange rate movements.

Although the results above show that the monetary policy has been improving in the sense of the inflation stabilization policy, it is still not clear whether its stance was ”strong enough”. Taylor principle is a considered as a norm that the interest rate responds to the inflation one to one in the long-run in order to stabilize inflation. And confirming whether the data supports this Taylor principle in the empirical studies is the key point to evaluate the monetary policy stance towards inflation stabilization. For example, Clarida *et al*. (2000) has evaluated the monetary policy stance of the U.S. with an estimated Taylor rule. The long-run coefficient to inflation gap is the key parameter to assess the degree of the monetary policy stance. Clarida *et al*. (2000) has documented that this stance was above one for the U.S. economy and thus concluded that the monetary policy was aggressive to inflation stabilization. However, in our context, this stance parameter could not be derived since the interest rate in difference was entered into the system for the estimation stability.[5] Hence, the model is not able to evaluate whether the monetary policy was stabilizing or destabilizing the inflation in the long run. Instead one can indirectly infer a short run stance toward inflation stabilization relative to output stabilization. [Figure 7] shows the cumulative impulse response to all four shocks in the system and it is thus the interest rate level response to shocks. The shocks in the initial period are all normalized by 1 % increase of the corresponding variable. For example, the top-left panel of [Figure 7] shows the cumulative impulse response of interest rate in difference to 1% increase of the inflation rate from its own shock. The response of the interest rate level is slightly less than 0.1 after two years in recent periods. The response to GDP growth is around 0.15. It seems quite obvious that the monetary policy in Korea still had more weight on output stabilization as opposed to inflation stabilization at least in the short run. In order to consolidate this finding, a sensitivity analysis has been performed by varying the prior distributions of coefficient parameters. Particularly, prior distributions for {a, β, σ} in the benchmark estimations were set by OLS estimates of time invariant VAR with initial subsample. Instead of initial subsample, different subsamples such as more recent periods, periods after 2000 and the whole sample periods were investigated for OLS estimates and used as prior distributions. But the estimations consistently gave qualitatively similar results that the monetary policy's weight on output stabilization was relatively stronger than that on inflation stabilization.

5 To see this point, suppose the interest rate equation from VAR system is the following. For simplicity, $\Delta R_t = \beta_t^{rr} \Delta R_{t-1} + \beta_t^{r\pi} \pi_{t-1} + u_t^r$. Then, the interest rate level equation can be converted with lag operators as $\phi(L) R_t = \beta_t^{r\pi} \pi_{t-1} + u_t^r$ where $\phi(L) = \left(1 - (1 + \beta_t^{rr}) L + \beta_t^{rr} L^2\right)$. The long run inflation stabilization stance parameter, γ_π, can be derived with $\frac{\beta_t^{r\pi}}{\phi(1)}$ but $\phi(1)$ is zero.

[Figure 7] Cumulative Impulse Response Function of Interest Rate in Difference



IV. Conclusion

This paper has studied the monetary policy in Korea with a time varying VAR model using four key macroeconomic variables. First, inclusion of the exchange rate was a crucial factor in evaluating Korean monetary policy since the monetary policy demonstrated sensitivity to exchange rate movements during the crisis periods of both the Asian financial crisis of 1997 and the global financial crisis of 2008. Second, a specification of the stochastic volatilities in TVP-VAR model is important in explaining excessive movements of all variables in the sample. The overall moderation of variables in 2000s was more or less due to a reduction of the stochastic volatilities but also somewhat due to the macroeconomic fundamental structures captured by impulse response functions. Third, the degree of the monetary policy effectiveness on inflation was mitigated in recent periods but with increased persistence. Lastly, the monetary policy stance towards inflation stabilization has advanced ever since the inflation targeting scheme was adopted. However, there still seems to be a room for improvement in this aspect since the degree of the monetary policy stance towards inflation stabilization was relatively weaker than to output stabilization.

The advantage of TVP-VAR framework is its continuous update of estimation when time series data is in the process of being collected as time passes. Therefore, timely assessments of economic implications for the policy circle can be provided. In this sense, this paper can be one of pioneering research in the overall evaluation of the Korean monetary policy in the future.

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