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Are Structural Parameters of DSGE Models Stable in Korea?

This paper investigates whether the structural parameters of dynamic stochastic general equilibrium (DSGE) models are stable over time in an emerging country with Korean data. To answer this question, this paper estimates a baseline DSGE model by maximum likelihood method in the Kalman filtering algorithm. We find that the Korean financial crisis in the late 1997 did not change the structural parameters in the DSGE model in spite of significant policy changes and institutional reforms. This empirical finding is very important because it reinforces the validity of DSGE modeling strategy by confirming the fundamental assumption in DSGE models, which states the structural parameters should be stable over different policy regimes. Moreover, this paper shows that the current micro-founded DSGE model is superior to the pure time series models in forecasting key macroeconomic variables in most cases. Finally, the current DSGE model seems to successfully reproduces the relative volatilities of consumption, investment and hours worked with respect to output as well as the pattern of contemporaneous correlations of output with other variables.

Key words: Structural parameter stability, dynamic stochastic general equilibrium model, Kalman filter
JEL Classification: C51, C52, E32, E37

1 Introduction

Since the large-scale system-of-equation models in Cowles Commission tradition were severely criticized by not only Lucas critique (1976) and but also Sims critique (1980), dynamic stochastic general equilibrium (henceforth, DSGE) models and vector autoregression (henceforth, VAR) models have become two standard building blocks of modern macroeconomists.

First, a DSGE model, firstly presented by Kydland and Prescott (1982), attempts to explain the movements and co-movements of many of central macroeconomic variables within the laboratories they created, firmly based on microeconomic foundations. Work following this tradition usually has relied on simulation approach based on the *calibrated* values of parameters. Then, by comparing moments of the artificial data from simulations in DSGE models with those of the actual data, a researcher is able to answer a variety of "what if?" questions in the laboratory, which is usually impossible in the traditional empirical work (see, for example, King et al., 1988; Cooley, 1995). Moreover, contrary to the empirical work based on the reduced form estimation, the micro-founded DSGE models are transparent enough that researchers can clearly understand the relationship of key macroeconomic variables. From the theoretical perspective, however, the most important benefit of DSGE models is that they are free from Lucas critique (1976) and they thus meet modern standards of conceptual rigor (Woodford, 2007).

However, DSGE models are often criticized because they are not rich enough to match the data in multi-dimensions by ignoring some features of the economy for the idealization and imposing strong restrictions on the actual data. Furthermore, when one attempts to deal with the actual data in a DSGE model, it is hard to apply traditional econometric methods for estimation, hypothesis testing, and forecasting to DSGE models.

Second, a VAR model, pioneered by Sims (1980), is proposed as an alternative to Cowles Commission's large-scale macroeconometric system. The main rationale behind VAR models is that no variables can be treated as being a priori exogenous in the economy populated with forward-looking rational agents whose behaviors are subject to the solution of an intertemporal optimization model (Cooley and LeRoy, 1985; Favero, 2001). In addition, the specification of VAR models does not require detailed prior knowledge about the economic system. Therefore, one can easily estimate parameters of interest, test the statistical hypotheses and generate out-of-sample forecasts using VAR models.

However, because they are not firmly founded in economy theory, VAR models are often criticized to fail to uncover structural relationships among variables. Hence, even though VAR models are able to fit the data, the parameters they give are not easily interpretable (Hartley et al., 1997). In addition, from the practical points, VAR models often require large samples of observations to estimate the coefficients of interests.

With this background in mind, this paper estimates a small-scale DSGE model for Korean economy by applying the maximum likelihood (ML) estimation methodology developed by Ireland (2004) in which a micro-founded DSGE model is augmented with VAR-structured measurement errors. Thus this approach attempts to couple the flexibility of VAR methodology with the theoretical rigor of DSGE models. More specifically, this joint approach seeks to take advantage of VAR models to capture movements in the data which are not explained by real business cycle theory. Then, contrary to the calibration method, the maximum likelihood estimation of model parameters allows us to exploit the standard econometric tools within the DSGE framework (Ruge-Murcia, 2007). For example, we can assess the adequacy of a DSGE model by comparing its performance for forecasting with those of pure time series models.

As acknowledged by Watson (1994), two important questions must be answered in any business cycle research. First, how do the variables respond to exogenous shocks and how long? Second, are the business cycles largely the result of supply shocks like productivity shocks? In other words, what are the important sources of economic fluctuations? This paper also attempts to answer these questions by taking advantage of the impulse response function and the variance decomposition analysis.

For this purpose, the rest of the paper is structured as follows. Section 2 introduces a baseline DSGE model which is in the line of Hansen's (1985) one-sector growth model with indivisible labor. Section 3 solves this model by applying Blanchard and Kahn's (1980). Section 4 accounts for how the solved system in Section 3 can be used to estimate a DSGE model. In this section, the baseline DSGE model is augmented with VAR structured measurement errors to obtain an econometrically conformable DSGE model. The motivation of including measurement errors will become clear after the stochastic singularity problem is discussed. Section 5 presents main empirical findings of this chapter. In this section, estimated deep parameters are presented with their standard errors. Then, based on these estimates, the responses of endogenous variables to an external shock and variance decomposition analysis are provided. Most importantly, we examine the structural parameter stability by comparing the estimated parameters from the pre-financial crisis period with those from the post-crisis period. This section closes by comparing the forecast performance of the current DSGE model with those of pure time series models and by comparing the second moments for the data and the simulation. Finally, Section 6 concludes.

2 Setting up a Baseline DSGE Model

This paper employs Hansen's (1985) one-sector stochastic growth model with indivisible labor. The reason is that, in the academic literature, this DSGE model is regarded as a superior one in accounting for the stylized facts of the business cycle than Kydland and Prescott's (1982) divisible labor model because most of the variation in total hours worked is mainly due to variations in the number of people employed (extensive margin) rather than those in the number of hours worked per worker (intensive margin). In this model, since the allocation of a competitive equilibrium is equivalent to the solution of a social planner's problem, one can solve a simpler social planner's problem without taking into account the prices for labor and capital.

Herein, a benevolent social planner chooses aggregate per capita consumption C_t and aggregate per capita hours worked H_t in order to maximize the following expected utility function of a representative household in each period $t = 0, 1, 2, \cdots$,

$$E_0 \sum_{t=0}^{\infty} \beta^t [\ln(C_t) - \gamma H_t], \tag{2.1}$$

where β, the subjective discount factor, is positive and less than unity reflecting a preference for current consumption, $-\gamma < 0$ is disutility weight of labor, and E_0 is the expectations operator conditional on information available at time 0. Then, since the utility function is linear in labor across time, the intertemporal elasticity of substitution on labor is infinite (Hansen, 1985; Rogerson, 1988).

One type of aggregate per capita output Y_t is produced with capital K_t and labor supply H_t according to the Cobb-Douglas production function described by

$$Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}, \tag{2.2}$$

where $0 < \alpha < 1$ represents capital's share in output.

The total factor productivity of the economy A_t, which is assumed to be temporary, follows the first-order autoregressive process:

$$\ln A_t = (1-\rho)\ln \bar{A} + \rho \ln A_{t-1} + \varepsilon_t, \tag{2.3}$$

where $\bar{A} > 0$ and $0 < \rho < 1$. The innovation ε_t, the only shock in this artificial economy, is identically, independently and normally distributed with zero mean and standard deviation σ. It is also assumed that A_t is known at the beginning of period t before the social planner makes a decision. The choice of AR(1) specification for the shock follows the standard practice in the DSGE literature.

During each period, output Y_t can either be consumed or invested, subject to the aggregate resource constraint of the economy

$$Y_t = C_t + I_t. \tag{2.4}$$

The capital stock available for production in period $t+1$, K_{t+1}, is determined at the end of period t according to the following accumulation equation

$$K_{t+1} = (1-\delta)K_t + I_t, \tag{2.5}$$

where the rate of capital depreciation satisfies $0 < \delta < 1$.

The resource constraint and capital accumulation equation can be combined as,

$$K_{t+1} = (1-\delta)K_t + Y_t - C_t.$$

In the current system, the social planner chooses the infinite sequences of controls $\{Y_t, C_t, I_t, H_t, K_{t+1}\}_{t=0}^{\infty}$ to maximize the utility function (2.1) subject to constraints (2.2)–(2.5) and K_0. Thus, when K_t is given from the previous period $t-1$ and A_t is observed at time t, the social planner determines Y_t by making decision on H_t and divides Y_t between C_t and I_t. Then, next period capital stock K_{t+1} is automatically determined.

3 Solving the Model

To find a solution to the dynamic model is to write the non-predetermined endogenous variables in terms of the predetermined variables and the exogenous variables. However, since most DSGE models do not have a known analytical solution, one has to approximate the solutions to these non-linear models. Among the approximation solution methods, in the literature log-linear approximation method has been extensively used following Blanchard and Kahn (1980), King et al. (1988), and Campbell (1994).[1]

Although there has been some criticism on this method, this paper chooses to solve the current DSGE model using the log-linear approximation method for facilitating the implementation of the likelihood-based estimations.[2] As clearly noted in An and Schorfheide (2007), this method is still popular in the literature on the likelihood-based DSGE model estimations at least for two reasons. First, it can be easily linked to a state-space model and thus can be analyzed with the Kalman filtering algorithm. Another reason for its popularity seems to be the computational burden which researchers often encounter when evaluating the likelihood for non-linear solution of a DSGE model.

The log-linear approximation method involves several steps. First, we need to establish the expectational nonlinear system by deriving optimality conditions. Next, this nonlinear system must be linearized around the steady state. Then, applying Blanchard and Kahn's (1980) solution method yields the solution of the linearized system of difference equations.

First of all, we can derive two optimality conditions for this problem: the intratemporal optimality condition (3.1) and the intertemporal optimality condition (3.2).

$$\gamma = \frac{(1-\alpha)Y_t}{H_t} \cdot \frac{1}{C_t}. \tag{3.1}$$

[1]Uhlig (1999), Klein (2000) and Sims (2002) provide solution algorithms for the linearized approximate models.

[2]In particular, the linear approximation method has been criticized as it suppresses higher moments which may be important in certain circumstances. For example, Kim and Kim (2003) demonstrate how linearization can generate approximation errors that can yield a reversal of welfare ordering in international business cycle models.

$$1/C_t = \beta E_t(1/C_{t+1})[\alpha(Y_{t+1}/K_{t+1}) + 1 - \delta] \tag{3.2}$$

for all $t = 0, 1, 2, \cdots$.

Now we attain a non-linear expectational system with 6 equations for 6 variables: (2.2)–(3.2) for $Y_t, C_t, I_t, H_t, K_t, A_t$. Then, the next step is to construct a linear approximation to the original non-linear expectational system by log-linearizing 6 equations around the steady state after removing trends in the variables (Campbell, 1994). The outcome of this second step is summarized as the following six equations,[3]

$$\hat{y}_t = \hat{a}_t + \alpha\hat{k}_t + (1-\alpha)\hat{h}_t, \tag{3.3}$$

$$\hat{a}_t = \rho\hat{a}_{t-1} + \varepsilon_t, \tag{3.4}$$

$$(1/\beta - 1 + \delta)\hat{y}_t = [(1/\beta - 1 + \delta) - \alpha\delta]\hat{c}_t + \alpha\delta)\hat{i}_t, \tag{3.5}$$

$$\hat{k}_{t+1} = (1-\delta)\hat{k}_t + \delta\hat{i}_t, \tag{3.6}$$

$$\hat{c}_t + \hat{h}_t = \hat{y}_t, \tag{3.7}$$

$$0 = (1/\beta)\hat{c}_t - (1/\beta)E_t\hat{c}_{t+1} + (1/\beta - 1 + \delta)E_t\hat{y}_{t+1} - (1/\beta - 1 + \delta)\hat{k}_{t+1}, \tag{3.8}$$

where we denote the detrended stationary variables with lower letters. Then, we denote a hat over a variable as representing a percentage deviation of that variable from its steady state level, for instance, $\hat{c}_t = \ln(c_t/c)$, etc.

Given the above linearized expectational system of 6 difference equations, we can solve the current system through Blanchard and Kahn's (1980) method. However, Blanchard and Kahn's solution method can be applied when the models are written

[3]The detailed procedure is available upon request to the author.

as the form of (3.9),

$$\begin{bmatrix} x_{1,t+1} \\ E_t(x_{2,t+1}) \end{bmatrix} = K \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} + Lz_t, \tag{3.9}$$

where $x_{1,t}$ signifies a vector of predetermined variables (i.e., $E_t(x_{1,t+1}) = x_{1,t+1}$), $x_{2,t}$ is a vector of control variables (i.e., $E_t(x_{2,t+1}) + \zeta_{t+1} = x_{2,t+1}$ with ζ_{t+1} denoting an expectation error), and z_t is a vector of exogenous forcing variables.

Therefore, as a preliminary step, we need to convert the above system into the form of (3.9). This step requires a system reduction, which involves expressing the model in terms of uniquely determined variables such as $\hat{a}_t$, $\hat{c}_t$, and $\hat{k}_t$ (King and Watson, 2002).[4] It can be shown that the conformable difference system is

$$\begin{bmatrix} \hat{k}_{t+1} \\ E_t(\hat{c}_{t+1}) \end{bmatrix} = K \begin{bmatrix} \hat{k}_t \\ \hat{c}_t \end{bmatrix} + L\hat{a}_t, \tag{3.10}$$

where K is a 2×2 matrix and L is a 2×1 vector.

Now, we can apply Blanchard and Kahn (1980)'s procedure to (3.10). This procedure begins with a Jordan decomposition of matrix K and then transforms the system with the diagonal matrix, which is composed of eigenvalues of K. Next, in the transformed system, the explosive part is solved forward and the stable part is solved backward. Based on these solutions, we can not only recover the solutions for $\hat{k}_t$ and $\hat{c}_t$, but also find the solutions for $\hat{y}_t$, $\hat{i}_t$ and $\hat{h}_t$.

Lastly, we can summarize the solutions to the current linear system as transition equations of state variables (3.11) and optimal policy functions (3.12),

$$\boldsymbol{s}_{t+1} = \Xi \boldsymbol{s}_t + \Phi \varepsilon_{t+1}, \tag{3.11}$$

and

$$\boldsymbol{f}_t = \Psi \boldsymbol{s}_t, \tag{3.12}$$

where $\boldsymbol{s}_t = \begin{bmatrix} \hat{k}_t & \hat{a}_t \end{bmatrix}'$ and $\boldsymbol{f}_t = \begin{bmatrix} \hat{y}_t & \hat{c}_t & \hat{i}_t & \hat{h}_t \end{bmatrix}'$. Then, given the state of the

[4] That is, we can rewrite the whole linear system into the reduced system only using $\hat{a}_t$, $\hat{c}_t$, and $\hat{k}_t$. Note that, (i) observations on $\hat{a}_t$, $\hat{c}_t$, and $\hat{k}_t$ are sufficient for determining $\hat{y}_t$ jointly from (3.3) through (3.8), (ii) given $\hat{y}_t$, both $\hat{i}_t$ and $\hat{h}_t$ are superfluous. Hence, all information we need to solve the problem are contained in $\hat{a}_t$, $\hat{c}_t$, and $\hat{k}_t$.

economy $\boldsymbol{s}_t$, which traces percentage deviations of two state variables from their steady-state levels, the policy functions (3.12) give us the optimal policy to follow. Thus, these are the solutions to the standard linear optimal control problem.

4 Model Estimation Methodology

4.1 Reinterpreting (3.11) and (3.12) for Estimation

For the purpose of estimation, notice first that we can observe only three independent endogenous variables due to the aggregate resource constraint (2.4) in the model. Thus, this paper uses just three observable variables Y_t, C_t and H_t in estimating the baseline DSGE model. Then, the theoretical linear system in the previous section, composed of transition equations (3.11) and policy functions (3.12), should be reinterpreted as a state space econometric model, composed of transition equations of hidden state vector (4.1) and observation (or measurement) equations (4.2)

$$\boldsymbol{s}_{t+1} = A\boldsymbol{s}_t + B\varepsilon_{t+1} \quad \Leftrightarrow \quad \begin{bmatrix} \hat{k}_{t+1} \\ \hat{a}_{t+1} \end{bmatrix} = \begin{bmatrix} A_{kk} & A_{ka} \\ 0 & \rho \end{bmatrix} \begin{bmatrix} \hat{k}_t \\ \hat{a}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \varepsilon_{t+1}, \tag{4.1}$$

and

$$\boldsymbol{d}_t = C\boldsymbol{s}_t \quad \Leftrightarrow \quad \begin{bmatrix} \hat{y}_t \\ \hat{c}_t \\ \hat{h}_t \end{bmatrix} = \begin{bmatrix} C_{yk} & C_{ya} \\ C_{ck} & C_{ca} \\ C_{hk} & C_{ha} \end{bmatrix} \begin{bmatrix} \hat{k}_t \\ \hat{a}_t \end{bmatrix}, \tag{4.2}$$

for all $t = 0, 1, 2, \cdots$.

There is a duality between two systems. However, there is a slight but important difference between (3.11) and (3.12) in the previous section and (4.1) and (4.2) in the current section. In (3.11) and (3.12), with $\hat{k}_t$ given from the previous period and $\hat{a}_t$ observed at the current period, the problem is to choose the optimal response of $\boldsymbol{f}_t$. On the other hand, in (4.1) and (4.2), the problem is to compute the expected values of a hidden state vector $\boldsymbol{s}_t$ conditional on the observation vector $\boldsymbol{d}_t$. Now, therefore, matrices A and C are the objects to be estimated using the observations on $\hat{y}_t$, $\hat{c}_t$, and $\hat{h}_t$.

4.2 Stochastic Singularity Problem

Notice that, in observation equations (4.2), the number of driving forces is smaller than that of observable variables. Namely, the model has only one shock – the aggregate technology shock – driving all business cycle fluctuations, but there are three endogenous variables to feed in. This is known as the stochastic singularity problem in estimating DSGE models. The presence of the stochastic singularity makes traditional econometric methods inapplicable to the model's parameter estimations by creating non-independence between the endogenous variables. To be precise, if $\hat{c}_t$ is observed, $\hat{y}_t$ and $\hat{h}_t$ cannot be observed independently (Ingram et al., 1994; Ruge-Murcia, 2007). Since there are three observable endogenous variables in the current baseline model, we need to add at least two more shocks to the model.

To make the current DSGE model empirically implementable, two approaches are suggested in the empirical literature. One strategy is introducing additional structural disturbances – to preferences, investment, monetary and fiscal policy rules – to the DSGE model. Therefore, the models would be specified at a deep enough level that the differential response to different types of shocks would be properly spelt out. This approach is followed by DeJong et al. (2000), Kim (2000), Schorfheide (2000), Ireland (2003), and Bouakez et al. (2005). In a first-best world, this strategy has its advantages: it gives help to identify sources of aggregate fluctuations beyond the productivity shock and allows for a direct comparison of the relative importance of those additional disturbances in driving aggregate fluctuations. However, the critical shortcoming of this approach is to require too much detailed *ad hoc* assumptions about how the economy evolves.

An alternative strategy to address this problem is attaching *measurement errors* to the observation equations following the tradition of Sargent (1989). This strategy replaces three observation equations in (4.2) with three observation equations with measurement errors, which have VAR(1) structure with three innovations. Namely, the presence of measurement errors implies that the actually observed data contain some noise which cannot be attributed to the theory. This second approach is utilized by McGrattan (1994), Hall (1996), McGrattan et al. (1997) and Ireland (2004).

This paper adopts the latter strategy to avoid *ad hoc* assumptions in the process of estimation. Then, the empirical counterpart to (4.1) and (4.2) consists of (4.1), (4.3), and (4.4)

$$\boldsymbol{s}_{t+1} = A\boldsymbol{s}_t + B\varepsilon_{t+1} \quad \Leftrightarrow \quad \begin{bmatrix} \hat{k}_{t+1} \\ \hat{a}_{t+1} \end{bmatrix} = \begin{bmatrix} A_{kk} & A_{ka} \\ 0 & \rho \end{bmatrix} \begin{bmatrix} \hat{k}_t \\ \hat{a}_t \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \varepsilon_{t+1}, \tag{4.1}$$

$$\boldsymbol{d}_t = C\boldsymbol{s}_t + \boldsymbol{u}_t \quad \Leftrightarrow \quad \begin{bmatrix} \hat{y}_t \\ \hat{c}_t \\ \hat{h}_t \end{bmatrix} = \begin{bmatrix} C_{yk} & C_{ya} \\ C_{ck} & C_{ca} \\ C_{hk} & C_{ha} \end{bmatrix} \begin{bmatrix} \hat{k}_t \\ \hat{a}_t \end{bmatrix} + \begin{bmatrix} u_{yt} \\ u_{ct} \\ u_{ht} \end{bmatrix}, \tag{4.3}$$

and

$$\boldsymbol{u}_{t+1} = D\boldsymbol{u}_t + \boldsymbol{\xi}_{t+1} \quad \Leftrightarrow \quad \begin{bmatrix} u_{yt+1} \\ u_{ct+1} \\ u_{ht+1} \end{bmatrix} = \begin{bmatrix} D_{yy} & D_{yc} & D_{yh} \\ D_{cy} & D_{cc} & D_{ch} \\ D_{hy} & D_{hc} & D_{hh} \end{bmatrix} \begin{bmatrix} u_{yt} \\ u_{ct} \\ u_{ht} \end{bmatrix} + \begin{bmatrix} \xi_{yt+1} \\ \xi_{ct+1} \\ \xi_{ht+1} \end{bmatrix}, \tag{4.4}$$

where three innovations in the vector $\boldsymbol{\xi}_t$ are assumed to be serially uncorrelated in each term and normally distributed with mean zero. We further assume that these three innovations are contemporaneously correlated each other but that they are orthogonal to the technology shock, ε_t as follows.

$$E_t(\boldsymbol{\xi}_t\boldsymbol{\xi}_t') = V = \begin{bmatrix} V_y^2 & V_{yc} & V_{yh} \\ V_{yc} & V_c^2 & V_{ch} \\ V_{yh} & V_{ch} & V_h^2 \end{bmatrix}, \tag{4.5}$$

and

$$E_t\left(\boldsymbol{\xi}_t\varepsilon_t\right) = \mathbf{0}_{3\times 1}, \tag{4.6}$$

for all $t = 0, 1, 2, \cdots$.

The earlier study imposes the diagonal restrictions on matrices D and V. It, thus, assumes that each measurement error follows its own AR(1) process and that ξ_{yt}, ξ_{ct}, and ξ_{ht} are mutually uncorrelated. However, this paper does not impose those restrictions on matrices D and V. The reason is that the residuals from VAR(1) structure of $\boldsymbol{u}_t$ can be interpreted as capturing the movements and co-movements in the data that the real business theory cannot account for (Ireland, 2004). In this way, the augmented DSGE model with VAR structure can incorporate the flexibility of VAR models to the micro-founded DSGE model.

4.3 Data and Estimation Methodology

As noted in Section 4.2, the estimation process requires three actual data: Y_t, C_t and H_t because I_t is redundant. C_t is defined as the real private consumption expenditure per capita in 2000 Korean won and I_t is defined as the real gross private domestic investment per capita, also in 2000 Korean won. Then, Y_t is defined as the sum of C_t and I_t. Hours worked per capita H_t is calculated as follows: average quarterly worked hours of the employed is multiplied by the employment rate. Each series is seasonally adjusted and Y_t and C_t are divided by the age 15 and over population. Data for consumption and investment are taken from the Bank of Korea database whereas population data come from National Statistics Office. Lastly, data for hours worked come from the Ministry of Labor. The data are quarterly, and span the first quarter of 1973 through the third quarter of 2008.

Taking the model to the data involves the isolation of cycles from the original data. To this end, among the several empirical techniques, this paper employs the Hodrick-Prescott's (HP) filter developed by Hodrick and Prescott (1997), which is widely used among researchers.[5] Since the current paper uses the quarterly data, we choose $\lambda = 1,600$, relative weight on smoothness, following Hodrick and Prescott's suggestion. In addition, all three variables are logged before filtering.

This paper attempts to estimate parameters of interest using the maximum likelihood estimation method in the Kalman filter framework. Since the current system can be interpreted as the combination of transition equations for hidden states and measurement equations for observable variables, Kalman's (1960) filtering algorithm is exactly fit for the current system.

[5] In extracting cycles, the band pass (B-P) filter developed by Baxter and King (1999) and the linear detrending are also popular in business cycle literature. In the preliminary research, we also estimated the current model with the linearly detrended data and obtained the similar empirical results. However, the examined period includes the Korean financial crisis and this generates blips in the data. As the linear detrending may produce very persistent spurious movements in this case, the current paper uses the HP filter which is at least believed to alleviate the persistence in the cycles.

5 Empirical Results

In what follows, we first present the estimates of the parameters in the current DSGE model. For the purpose of comparison, we also report those in the restricted DSGE model which is restricted in the sense that matrices D and V in the previous section are assumed to be diagonal. This is followed by the responses of endogenous variables to an external shock and variance decomposition analysis. In addition, in order to examine the stability of structural parameters around the financial crisis in 1997, we compare the estimated parameters from the pre-crisis period with those from the post-crisis period. Then, this section compares the forecasting performance of the current DSGE model with those of the pure time series models. Finally, we report the second moments from the HP filtered data and those from the simulated data to see the model's goodness of fit.

5.1 Estimated Parameters

Table 1 reports maximum likelihood estimates of 20 parameters: the five structural parameters $\gamma, \alpha, \bar{A}, \rho, \sigma$ from the real business cycle model, the nine elements of the matrix D governing the persistence of the VAR residuals, and the six elements of the variance-covariance matrix V for the VAR residuals. In the preliminary work, we estimated these parameters and obtained a very low $\beta = 0.9045$ and a very high $\delta = 0.1699$. These numbers seem not to be reasonable because the current parameters are estimated from the quarterly data. It is widely acknowledged that DSGE estimations using maximum likelihood method often yield "the dilemma of absurd parameter estimates" (Christensen and Dib, 2006; An and Schorfheide, 2007).[6] For this reason, Altug (1989) and Ireland (2004) suggest to fix β and δ since this calibration helps to successfully estimate the remaining parameters. Following their suggestion, we therefore set β and δ fixed as 0.99 and 0.025, respectively.

The standard errors are also presented in the last column of Table 1. The standard errors are obtained by using a parametric bootstrapping procedure similar to those employed by Malley et al. (2007) and Ireland (2007) (see, for more details,

[6] Christensen and Dib (2006) and An and Schorfheide (2007) find that the likelihood function has often several local peaks and the optimization stops at one of the local peaks. Furthermore, even if it reaches a global peak, it might provide the parameter estimate which is at odds with extraneous information. As a consequence, An and Schorfheide (2007) strongly argue that additional information that the researcher have should be incorporated.

Efron and Tibshirani, 1993).[7] This procedure is composed of the following three steps. The first step is to simulate the model with the estimated parameters in order to obtain 1000 artificial data sets where each data set contains 143 sample periods. The second step is to run 1000 estimations with those artificial data sets and to save the resulting parameter estimates. The final step is to calculate the standard deviations of individual parameter estimates and to report them as the standard errors of those parameter estimates.

[Table 1 about here]

All the estimated structural parameters in the model are quite reasonable and statistically significant. First of all, the estimates $\bar{A} = 29.0280$ and $\gamma = 0.0023$ help match the steady-state values of output, consumption, and hours worked in the model with the average levels of the same variables in the data. Note that the leisure preference parameter γ is about a half of U.S. economy (0.0045) reported by Ireland (2004). This seems to be related with the longer working hours in Korea.[8] The estimated value of α, capital's share in output, is 0.4851, which is larger than the usual estimate from other countries. However, this is highly consistent with actual average capital income ratio, 46.6%, of Korea during the examined period. The estimate $\rho = 0.7061$ implies that the productivity shock is very persistent but still lower than that of the U.S. economy. The estimate $\sigma = 0.0051$, volatility of technical shock, is of the same order of magnitude used in the literature.[9]

The other non-structural estimates in Table 1 suggest, however, that the pro-

[7]Alternatively, one can obtain the standard errors as the square roots of the diagonal elements of the covariance matrix of the maximum likelihood estimators. The covariance matrix can be obtained using the inverse of the negative of the second derivative of the log likelihood function (Hessian) evaluated at estimated parameters $\hat{\boldsymbol{\theta}}_{ML}$ (Kim and Nelson, 1999, Ch.2).

$$Cov(\hat{\boldsymbol{\theta}}_{ML}) = \left[-\frac{\partial^2 \ln \mathscr{L}(\boldsymbol{\theta}|\boldsymbol{d}_T, \cdots, \boldsymbol{d}_1)}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}'}|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}_{ML}} \right]^{-1},$$

where $\boldsymbol{\theta}$ is the parameter vector, $\boldsymbol{d}$ is the collection of data, and $\ln \mathscr{L}$ is the log likelihood.

However, it is often argued that this approach is problematic when the likelihood in a nonlinear dynamic model has a highly nonlinear surface.

[8]According to OECD (2008), over the period from 1980 to 2006, the average hours worked per year per employed person in Korea was 2,669, which was much longer than 1,821 in the U.S. and 1,833 of average in OECD countries.

[9]In the preliminary research using the linearly detrended data, we found that higher persistence and volatility of the technology shock ($\rho = 0.9497$ and $\sigma = 0.0104$). As noted in Canova (2008), this difference seems to be partly related with the filtering technique.

ductivity shock does not successfully account for some important parts of the data. For instance, if the real business cycle theory explains the business cycles of Korea well, the volatility of productivity shock should be sufficiently higher than those of measurement errors. However, as shown in Table 1, the volatilities of three measurement errors (0.0267, 0.0188 and 0.0129) are much higher than that of productivity shock (0.0063). Thus, this result implies that, to an extent, the real business cycle theory has a difficulty to account for the Korean business cycles.

On the other hand, following Hamilton (1994), we can construct estimates for shocks to productivity and measurement errors ($E_T(\varepsilon_t)$ and $E_T(\boldsymbol{\xi}_t)$) by employing the Kalman smoothing procedure. Given $E_T(\varepsilon_t)$ and $E_T(\boldsymbol{\xi}_t)$, we can verify the orthogonality assumption between ε_t and the vector $\boldsymbol{\xi}_t$, which is made in (4.6). This examination is crucial in the sense that if they are not orthogonal each other, the variance decomposition analysis is not much meaningful. Table 2 reports the correlation between shocks to productivity and measurement errors. The correlation between $E_T(\varepsilon_t)$ and $E_T(\xi_{yt})$ is -0.0205, the correlation between $E_T(\varepsilon_t)$ and $E_T(\xi_{ct})$ is -0.0256, and the correlation between $E_T(\varepsilon_t)$ and $E_T(\xi_{ht})$ is -0.0312. All these correlations are quite small as well as not statistically significant even at the 10% significance level, as shown in high p-values. Therefore, the orthogonality assumption between two sources of shocks in (4.6) is not violated.

[Table 2 about here]

Lastly, for the purpose of comparison, Table 3 reports the estimated parameters and their standard errors in the restricted DSGE model. This model is restricted in the sense that contrary to Table 1, matrices D and V are constrained to be diagonal. This constraints reflect the implicit assumption that all of the co-movements between the observed variables can be captured by the real business cycle theory and the residuals are not correlated.

In Table 3, note that the the persistence and the volatility of the technology shock is much higher than those in Table 1. It seems that the role of technology shock increases in the restricted DSGE model since it is not augmented with VAR structure.

The maximum values of the log-likelihood function are 1,143.68 in the restricted DSGE model and 1,218.65 in the unrestricted DSGE model. Then, the goodness-of-fit between two models can be compared with likelihood ratio test and Akaike information criteria (AIC).

With respect to likelihood ratio test, the likelihood ratio statistic 149.94 is significantly larger than the 1% critical value 21.67 of $\chi^2_{0.01}(9)$. That is, the null hypothesis of no difference between models can be sufficiently rejected and thus the restrictions are not binding. According to the AIC, the value (-16.90 in the unrestricted model is significantly less than the value (-15.93) in the restricted model. Hence, these two test statistics jointly imply that the unrestricted DSGE model is superior to the restricted DSGE model in the goodness-of-fit for the data. Therefore, the following analysis will be implemented with the unrestricted model.

[Table 3 about here]

5.2 Impulse Response Analysis

An exogenous shock to the productivity, which leads the technology to deviate from its steady state level, not only directly affects the productivity but is also transmitted to model's four variables – output, consumption, investment and hours worked – through the dynamic structure of the model. That is, after the impulse of exogenous shock initiates a business cycle, the propagation mechanism in the current model will perpetuate that cycle (Lucas, 1975).

Figure 1 shows the impulse responses to a temporary technology shock over 40 quarters using the estimated parameters. Note that the responses to the highly persistent technology shocks die out to zero after all as the estimated system is stationary.

[Figure 1 about here]

The impulse response functions based on the estimated parameters seem to be quite reasonable. First, a positive technology shock in period t represents a higher-than-average growth rate of productivity. Thus, the economy is able to produce more output. Higher productivity raises wages, so labor supply in period t increases as workers find work more profitable than leisure. Thus higher labor input as well as higher productivity raises period t output. On the other hand, although the return to capital increases as well, capital stock cannot be increased at time t when the shock is not expected. This comes as no surprise in this standard model since the current capital level is the result of decision in the previous period.

Next, the increased output in period t is consumed or invested. The allocation decision hinges on consumer's preference and the expected persistence of the productivity shock. A desire to smooth consumption over time decides the portion of the saving out of temporary increased output. In addition, if the productivity shock is expected to be persistent, it will be more profitable to save and invest. Then, this will raise capital stock in period $t+1$, too.

Due to the propagation mechanism, all macroeconomic variables display autocorrelation and co-movement. Furthermore, the response of investment is higher than that of output and much higher than that of consumption since there is no investment smoothing incentive in this economy. The effects of a temporary shock eventually die out since the productivity process is mean-reverting. In addition, decreasing returns to capital bring investment back to the steady state. Hence this mechanism is stable.

5.3 Variance Decomposition Analysis

Another way to look at the implications of the current model is to compute the fractions of the forecast-error variance of the observed output, consumption, investment and hours worked attributable to each type of shock.

Note first that since the productivity shock ε_t and the innovations to measurement errors $\boldsymbol{\xi}_t$ are orthogonal as empirically shown in Section 5.1, the relative importance of ε_t to the evolution of endogenous variables can be properly evaluated by variance decomposition analysis. This can be done by dividing the forecast error variance of each variable due to ε_t by the total variance of forecast error of each variable.[10] Table 4 presents the proportion of k-step-ahead forecast error variance explained by the technology shock and its standard error.[11]

[Table 4 about here]

Several features in the table are worth addressing. First, the productivity shock

[10]On the other hand, by construction, the variations due to three exogenous shocks ξ_{yt}, ξ_{ct} and ξ_{ht} cannot be separated because they are contemporaneously correlated.

[11]The detailed procedure is available upon request to the author.

explains below one fifth of one-quarter-ahead forecast error variance in output. Furthermore, the explanatory power of productivity shock on output decreases as the forecasting horizon increases. Real business cycle theory seems to have more difficulty accounting for output fluctuations over the longer horizons. On the other hand, most of the variance in aggregate output arises from three exogenous shocks to measurement errors, which are assumed to reflect the combined effects of shocks, including monetary and fiscal policy shocks, not present in the baseline RBC theory. Notice also that the last line of panel (A), with $k = \infty$, implies that the technology shock accounts for only 9.7% of the unconditional variance in detrended output.

Second, panel (B) displays how much the variance of detrended consumption is explained by the productivity shock. As shown in this panel, the productivity shock has significant difficulty in explaining the fluctuations of consumption. Although the percentage of variance due to the productivity shock increases along the time periods, all numbers are very low.

On the other hand, the productivity shock seems to explain relatively well the variation of aggregate investment and hours worked. In particular, it accounts for over half of the one-quarter-ahead forecast error variance in the investment.

In sum, although the significant amount of fluctuations in investment and hours worked is caused by the productivity shock, the productivity shock has a limited power to explain the movements of consumption and output in Korea. In one sense, these empirical results should not be surprising since the simple model used here omits possibly important shocks for Korean business cycles such as monetary and fiscal policy shocks. In the other sense, the results signal monetary and fiscal policy shocks may also be the important sources in understanding the behavior of business cycles in Korea.

5.4 Parameter Stability

Until mid 1980's, the main works of macroeconomists were to set up a very large econometric system and to analyze the effects of monetary and fiscal policy changes in this system based on the implicit assumption of parameter stability in a reduced econometric model.

This approach in macroeconomics was, however, severely criticized by Lucas (1976) because this econometric model fails to capture the rational expectation of individuals to policy changes. From this perspective, Lucas (1976, p. 41) wrote,

> *Given that the structure of an econometric model consists of optimal decision rules vary systematically with changes in the structure of series relevant to the decision maker, it follows that any change in policy will systematically alter the structure of econometric models.*

Accordingly, the parameters in a reduced-form macroeconometric model cannot be stable over different policy regimes. Lucas critique implies that a policy based on historical relationship between macroeconomic variables is not effective and one cannot evaluate that policy effects properly. As a result, Lucas (1976) argues that a model attempting to analyze the effects of a policy change should be based on the deep structural parameters, which are policy invariant. This irrefutable critique encouraged many economist to establish various DSGE models describing the economy with the structural parameters such as tastes and technology since DSGE models are presumed to free from Lucas critique. Thus, the stability of structural parameters is the fundamental assumption for validity of DSGE models.

In the empirical literature, the non-structural parameter instability in macroeconometric models is well documented, but there is little research on the structural parameter stability. One possible reason for this asymmetry is that calibrated DSGE models just assume the stability of structural parameters rather than estimate structural parameters. Contrary to calibration approach, estimation approach used in this chapter seems to be useful in examining the parameter stability.

From this perspective, Korean economy provides a useful laboratory to examine this fundamental assumption in DSGE models because Korea, often-cited success story like other East Asian tigers, experienced several important institutional and regime changes since the financial crisis in 1997. Among others, the central bank of Korea adopted an inflation targeting regime as its monetary operational framework and implemented market-friendly monetary policy, taking the call rate as the operating target. Moreover, the free-floating exchange rate system replaced the currency basket system (i.e., partially pegging the values of Korean won with a moving band to currencies of large trading partners such as the U.S.and Japan) at the end of 1997.

In order to address an interesting question whether the structural parameters in DSGE models are actually stable across the different regimes, the DSGE model is estimated over two subsample periods: the pre-crisis period from 1973:1Q to 1997:4Q and the post-crisis period from 1998:1Q to 2008:3Q. The choice of breakpoint is motivated by the fact that major changes in Korean monetary and fiscal policies are widely thought to have occurred just after the outbreak of the Korean financial crisis.

Table 5 reports estimates for the DSGE model's parameters, along with their standard errors, for the two sample data sets. Two features are worth noting from the table. First, the persistence of productivity shock ρ is a little higher in the pre-crisis period, and this can be interpreted that the explanatory power of the real business cycle theory decreased since the Korean financial crisis.

[Table 5 about here]

Note also that the indicator of volatility of macroeconomy σ is a little lower in the post-crisis period, which implies that volatility of the economy decreased after the financial crisis. Importantly, this finding seems to imply that the recent stability of Korea economy is at least partly caused by good luck.[12]

Overall, however, the 5 structural parameter estimates seem not to be significantly different across the two periods. To check formally this argument, we test the parameter stability using the Wald statistics developed by Andrews and Fair (1988). They propose a Wald statistic for testing the structural stability of some or all of the parameters. The paper follows the explanation in Greene (2003, pp. 133–134). Suppose that $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ are two consistent and asymptotically normally distributed estimator vectors from two samples, with asymptotic covariance matrices H_1 and H_2. Then, under the null hypothesis that the true parameters are the same in two samples, the difference between $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ has a mean zero vector and an asymptotic covariance matrix $(H_1 + H_2)$. Under the null hypothesis, the Wald statistic,

$$W = (\boldsymbol{\theta}_1 - \boldsymbol{\theta}_2)'(H_1 + H_2)(\boldsymbol{\theta}_1 - \boldsymbol{\theta}_2) \sim \chi^2(q), \tag{5.1}$$

has an asymptotical χ^2 distribution with q degrees of freedom, which is the number of parameters being tested for stability. A large value of this statistic leads us to

[12]Since the 1990s, most developed countries experience such unusual stability of output growth. This improved macroeconomic performance is referred to as 'Great Moderation' in the United States and 'Great Stability' in the United Kingdom (Stock and Watson, 2002; Bean, 2005). One explanation for this phenomena is 'good luck' story which states that this stability mostly resulted from the fact that the shocks hitting the economy became smaller and more infrequent (Ahmed et al., 2004; Cogley and Sargent, 2005; Stock and Watson, 2003). For other explanations, see Ahmed et al. (2004); Bernanke (2004); Clarida et al. (2000); Lubik and Schorfheide (2004)

reject the null hypothesis.

Table 6 reports the Wald statistics and their p-values for all 20 estimated parameters, 5 structural parameters $\gamma, \alpha, \bar{A}, \rho, \sigma$, and 15 non-structural parameters. In the first panel, for all parameters and non-structural parameters, the null hypothesis of parameter stability is highly rejected. On the other hand, for structural parameters, the null hypothesis of parameter stability cannot be rejected even at the 10% significance level. To check the robustness of this test result, two different breakpoints (at the end of 1980's and 1995) are chosen in the second and third panels. In those, one cannot still reject the structural parameter stability.

[Table 6 about here]

Therefore, although important policy changes have taken place during the financial crisis, the structural parameters do not change. This empirical finding is encouraging in the sense that it reinforces the validity of DSGE modeling strategy by confirming its fundamental assumption. In addition, the finding of the non-structural parameter instability seems to be consistent with the aforementioned argument that the measurement errors may capture the policy shocks in the economy.

5.5 Forecast Accuracy and Goodness of Fit

Comparisons of forecast accuracy of the current DSGE model against those of the pure time series models are crucial to assess the DSGE model adequacy. To this end, this section compares the accuracy of the unconstrained DSGE model's out-of-sample forecasts with those of restricted DSGE model, VAR(1) and VAR(2). As noted above, the restricted model is the specific case of the DSGE model where the matrices D and V are restricted to be diagonal.

A k-quarter-ahead forecast at time t, $\boldsymbol{d}_{t+k|t}$, is computed as follows. Firstly, one-to-four quarter ahead forecasts are calculated using the data from 1973:1Q to 1997:3Q. Secondly, one-to-four quarter ahead forecasts are calculated using the data from 1973:1Q to 1997:4Q. Thus, one quarter ahead forecasts range from 1997:4Q to 2008:3Q, two quarter ahead forecasts do from 1998:1Q to 2008:3Q, and so forth.

[Table 7 about here]

Table 7 reports the root mean square errors (RMSEs) for the k-step-ahead prediction and lower values in RMSEs imply better performance in forecasting. In the table, forecasting performance of unrestricted DSGE model is better than those of the VAR models in most cases. Nonetheless, note that as shown in panels (A), (B) and (C), relative forecasting power of the current DSGE model declines, compared to the VAR models, as its forecasting horizon increases.

Finally, to check the adequacy of the current DSGE model, we report the second moments for the HP filtered data and the simulated data in Table 8. In this case, the estimated unrestricted DSGE model has been simulated 1000 times, with each simulation being 143 periods long, to match the number of observations. Then, we present the average second moments of 1000 simulated data. It seems that the model successfully reproduces the relative volatility of consumption and hours worked as well as the pattern of contemporaneous correlations of output with consumption, investment and hours worked.

[Table 8 about here]

As found in the HP filtered data, the simulated data show that consumption fluctuates significantly less than output and is highly correlated with output. In addition, investment from the simulation fluctuates much more than output and is highly correlated with output. Lastly, worked hours from simulation fluctuate significantly less than output and are moderately correlated with output as shown in the actual data.

6 Conclusion

Rather than calibrating a baseline DSGE model, this paper estimates it for Korean economy with HP-filtered data by augmenting VAR-structured measurement errors. Hence, one contribution of this paper is that these estimated parameters can be utilized for future research in calibrated DSGE models for Korea economy.

By comparing the estimated parameters in the pre-crisis and post-crisis periods, this paper finds that the structural parameter stability cannot be statistically rejected in spite of 1997 Korean financial crisis. This empirical result is encouraging because it reinforces the validity of DSGE modeling strategy by confirming its fundamental assumption.

We find that the forecasting performance of the current DSGE model is better than those of VAR models in most cases. In addition, by comparing the HP filtered data with the simulated data, this paper finds that the estimated model successfully reproduces the relative volatility of consumption and hours worked as well as the pattern of contemporaneous correlations of output with consumption, investment and hours worked.

On the other hand, using the variance decomposition analysis, we find that the productivity shock is the important source of business cycles in Korea, in particular for hours worked and investment, but it has a difficulty to explain fluctuations of some key variables. From this perspective, the current DSGE model seems to serve as a starting point for further complicated but realistic DSGE models.

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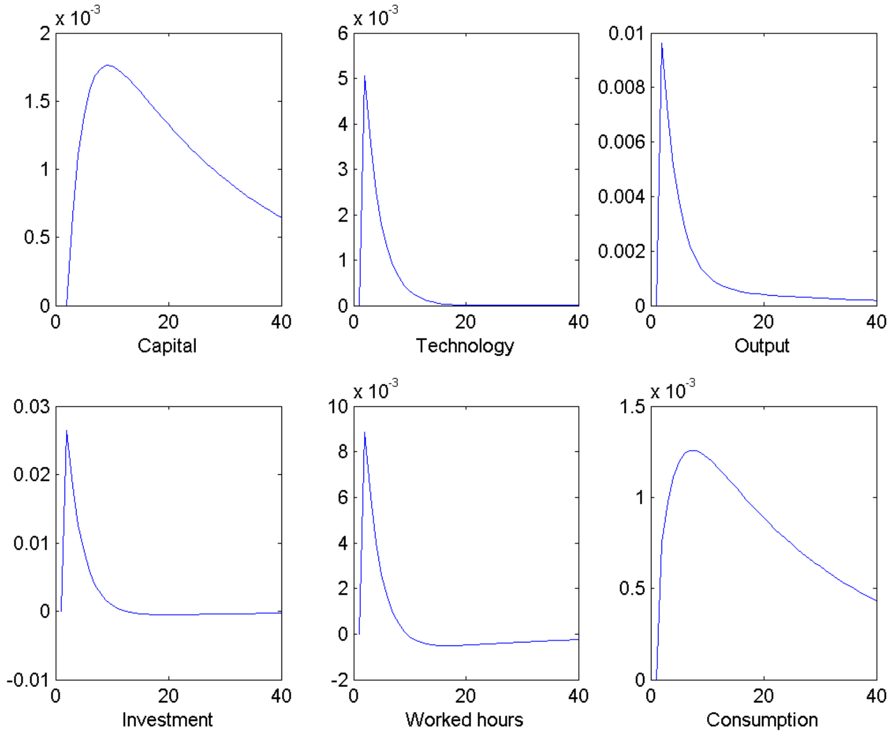

Figure 1: Impulse responses to an unexpected temporary technology shock

Tables

Table 1: Parameter estimates and standard errors: unrestricted DSGE model

Parameters	Estimates	Standard Errors
γ	0.0023	0.00001
α	0.4851	0.0018
$\bar{A}$	29.0280	0.5835
ρ	0.7061	0.0683
σ	0.0051	0.0006
d_{yy}	-0.4402	0.5078
d_{yc}	1.7125	0.5870
d_{yh}	-0.4750	0.1721
d_{cy}	-1.0152	0.5831
d_{cc}	2.1490	0.7056
d_{ch}	-0.4168	0.1882
d_{hy}	-0.5931	0.2578
d_{hc}	0.9294	0.3197
d_{hh}	0.1897	0.1683
v_y	0.0193	0.0021
v_c	0.0186	0.0019
v_h	0.0141	0.0012
v_{yc}	0.00035148	0.00006259
v_{yh}	0.00005181	0.00003012
v_{ch}	0.00009998	0.00002808

Table 2: Correlation between shocks to productivity and measurement errors

	Correlation	P-values
$E_T(\varepsilon_t), E_T(\xi_{yt})$	-0.0205	0.8085
$E_T(\varepsilon_t), E_T(\xi_{ct})$	-0.0256	0.7621
$E_T(\varepsilon_t), E_T(\xi_{ht})$	-0.0312	0.7121

Note: The p-values are computed with *corrcoef* function in MATLAB.

Table 3: Parameter estimates and standard errors: restricted DSGE model

Parameters	Estimates	Standard Errors
γ	0.0023	0.00001
α	0.4842	0.0064
$\bar{A}$	26.4160	0.6986
ρ	0.9999	0.0002
σ	0.0173	0.0010
d_{yy}	0.1881	0.0122
d_{cc}	0.7629	0.0317
d_{hh}	0.5443	0.0048
v_y	0.00001	0.0015
v_c	0.0114	0.0007
v_h	0.0166	0.0009

Table 4: Contribution of technology shocks to the variance of the forecast error

Quarter ahead	Percentage of Variance due to Technology	Standard Errors
(A) Output		
1	18.8830	6.4454
4	10.8160	4.3898
8	10.7210	5.2693
12	10.7670	4.8636
20	10.8440	4.8267
40	10.9110	4.8477
∞	10.9200	4.8512
(B) Consumption		
1	0.3186	0.1141
4	0.7523	0.3337
8	1.6458	0.8383
12	2.3244	1.1003
20	3.1121	1.4965
40	3.6238	1.7621
∞	3.6893	1.7963
(C) Investment		
1	50.8680	16.5350
4	28.1090	10.7060
8	25.4910	11.9690
12	25.2530	11.2880
20	25.1370	11.0420
40	25.1490	11.0290
∞	25.1510	11.0290
(D) Hours Worked		
1	25.4150	5.1882
4	25.7310	6.9734
8	25.3540	7.5349
12	25.1010	6.9703
20	25.4140	6.9926
40	25.6920	7.0355
∞	25.7280	7.0418

Table 5: Comparison between pre-crisis and post-crisis periods

Parameters	1973:1Q-1997:4Q estimates	Standard errors	1998:1Q-2008:3Q estimates	Standard errors
γ	0.0022	0.00001	0.0023	0.00003
α	0.4856	0.0026	0.4818	0.0039
$\bar{A}$	28.9540	0.8844	30.0920	1.4038
ρ	0.7892	0.0545	0.7702	0.0936
σ	0.0050	0.0004	0.0044	0.0006
d_{yy}	-0.2953	0.5771	-0.8519	0.4623
d_{yc}	1.1936	0.6075	2.1035	0.5102
d_{yh}	-0.3452	0.2460	-0.2240	0.1375
d_{cy}	0.1449	0.5344	-1.4916	0.4257
d_{cc}	0.6743	0.5647	2.6186	0.4722
d_{ch}	0.0925	0.2304	-0.1048	0.1626
d_{hy}	-1.1078	0.4579	-0.9489	0.5030
d_{hc}	1.1743	0.4847	1.3720	0.5717
d_{hh}	0.1115	0.2014	0.0769	0.2084
v_y	0.0124	0.0004	0.0064	0.0011
v_c	0.0118	0.0004	0.0082	0.0016
v_h	0.0118	0.0007	0.0151	0.0023
v_{yc}	0.00013355	0.00008339	0.00004542	0.00001689
v_{yh}	-0.00005456	0.00004459	0.00000151	0.00002724
v_{ch}	0.00000532	0.00004117	0.00002954	0.00002983

Table 6: Tests for parameters stability

breakpoint : end of 1997:4Q	Wald statistics	p-values
Stability of all 20 estimated parameters:	294.8	0.0000
Stability of all 5 structural estimated parameters:	2.8	0.7248
Stability of all 15 remaining estimated parameters:	281.4	0.0000

breakpoint : end of 1989:4Q	Wald statistics	p-values
Stability of all 20 estimated parameters:	1,301.2	0.0000
Stability of all 5 structural estimated parameters:	3.710	0.7993
Stability of all 15 remaining estimated parameters:	1,070.3	0.0000

breakpoint : end of 1995:4Q	Wald statistics	p-values
Stability of all 20 estimated parameters:	1,943.0	0.0000
Stability of all 5 structural estimated parameters:	0.7	0.9836
Stability of all 15 remaining estimated parameters:	1,440.4	0.0000

Table 7: Tests for forecast accuracy using root mean square errors: 1997:4Q – 2008:3Q

Quarters Ahead (%)	1	2	3	4
(A) Output				
Unrestricted DSGE	3.4393	4.2751	4.5694	4.6931
Restricted DSGE	3.8357	4.6743	4.7088	4.3969
VAR(1)	3.6389	4.5586	4.9118	4.9732
VAR(2)	3.4843	4.4097	4.6458	4.4815
(B) Consumption				
Unrestricted DSGE	3.1461	3.5867	3.8312	3.9980
Restricted DSGE	3.2090	3.6887	3.9092	4.0030
VAR(1)	3.2962	3.8163	4.0631	4.1351
VAR(2)	3.2239	3.7716	4.0009	3.9225
(C) Investment				
Unrestricted DSGE	4.4859	6.2853	6.8272	6.9065
Restricted DSGE	6.0778	7.8075	7.7189	6.7880
VAR(1)	4.7888	6.7119	7.4285	7.5395
VAR(2)	4.5191	6.3573	6.7972	6.5847
(D) Hours Worked				
Unrestricted DSGE	2.2438	2.4664	2.4938	2.6897
Restricted DSGE	2.2710	2.4703	2.4631	2.6030
VAR(1)	2.3122	2.6180	2.7253	2.8862
VAR(2)	2.3106	2.6131	2.6655	2.7424

Note: The lowest RMSEs are highlighted in bold faced.

Table 8: Volatility and contemporaneous correlations with output for actual data and simulated data : 1973:1Q – 2008:3Q

	Volatility				Corr. with Output	
	Actual		Simulated		Actual	Simulated
	SD%	Relative to Output	SD%	Relative to Output		
Output	4.49	1.00	4.19	1.00	1.00	1.00
Consumption	3.48	0.77	3.43	0.82	0.94	0.95
Investment	7.14	1.59	8.29	1.98	0.95	0.90
Hours Worked	2.26	0.50	2.10	0.50	0.62	0.56

<Abstract in Korean>

이지호*

DSGE모형은 정책이나 경제환경 변화 등에도 불구하고 안정적인 구조적 모수(structural parameter)에 기반하고 있어 Lucas 비판에서 자유로운 것으로 알려져 있다. 이에 따라 본 논문은 우리나라의 1973.1/4~2008.3/4분기중 통계자료를 이용하여 1997년 외환위기를 전후하여 모형내 기술적 충격의 지속성 및 변동성, 여가에 대한 선호 등 구조적 모수들이 과연 안정적이었는지를 검증하고자 하였다. 이를 위해 본 연구는 Peter Ireland (2004)가 개발한 칼만필터링(Kalman filtering)을 이용한 DSGE-VAR 최우추정법을 적용하여 우리나라의 실물경기변동모형을 추정하였다.

추정결과 비구조적 모수(non-structural parameters)의 안정성은 통계적으로 기각된 반면, 구조적 모수의 안정성은 기각할 수 없었다. 이는 임의성을 최소화하기 위해 구조적 충격으로서 기술적 충격만을 모형에 포함하였기 때문에 각종 경제정책에서의 변화가 기술적 충격과 관련된 구조적 모수에는 영향을 주지 못한 데에 기인하는 것으로 보인다. 동 결과의 강건성을 검증하기 위해 다른 시점에 대해서도 이를 테스트한 결과 동일한 결과를 얻었다.

아울러 주요 변수를 예측함에 있어 현 DSGE모형이 VAR모형에 비해 우월하였을 뿐만 아니라 모의실험 결과 추정된 DSGE모형이 소비, 투자 및 노동시간의 소득에 대한 상대적 변동성 및 소득과의 동행성을 비교적 잘 설명하는 것으로 나타났다.

향후 연구에서는 통화정책이나 재정정책 등에서의 충격을 모형에 추가함으로써 모형의 현실성을 제고하는 한편 이러한 변화가 구조적 모수의 안정성에는 어떠한 영향을 미치는 지 등에 대해서도 검토할 필요가 있는 것으로 보인다.

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연구내용은 집필자의 개인의견이며 한국은행의 공식견해와는 무관합니다. 따라서 본 논문의 내용을 보도하거나 인용할 경우에는 집필자명을 반드시 명시하여 주시기 바랍니다.