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News and Business Cycles for Korea*

Joonyoung Hur†

Abstract How important is “news” about not-yet-realized economic fundamentals in macroeconomic fluctuations for Korea? To address this question, this paper estimates a small open economy real business cycle model embedded with the anticipated components of exogenous shocks. Three main findings emerge based on an analysis of Korean data ranged from 1960:Q2 to 2014:Q4. First, a substantial fraction of the variability of output, consumption, and investment is accounted for by unanticipated shocks. Anticipated shocks play a critical role in causing fluctuations in government spending and trade balance, but their business cycle implications are weak. Second, the contribution of anticipated shocks to output and consumption fluctuations increases from the late 1980s to the onset of the Asian currency crisis of the late 1990s. Anticipated shocks account for a dominant fraction of investment variability during the recession period associated with the Asian currency crisis, and of trade balance movements in the post-crisis period. Finally, the financial friction mechanism, in which the country's interest rate spread is dependent upon the level of sovereign debt, has substantial implications for the output and investment dynamics in the model.

Keywords News; Bayesian methods; Business cycles

JEL Classification E30; E32; C11

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†Economic Research Institute, The Bank of Korea, joonyhur@gmail.com

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1. INTRODUCTION

How important is "news" about not-yet-realized economic fundamentals in macroeconomic fluctuations? A large and growing body of literature has concerned itself with this question based on the U.S. data [Beaudry and Portier (2006), Barsky and Sims (2011), Fujiwara et al. (2011), and Schmitt-Grohé and Uribe (2012), among many others]. A consensus in this literature is that anticipated shocks account for a substantial fraction of business cycle movements.

The main objective of this study is to assess empirically the contribution of news shocks to aggregate fluctuations in Korea. Despite the critical role of anticipated shocks for U.S. business cycles as documented in the literature, relatively less attention has been given to their importance for non-US macroeconomic fluctuations. A few exceptions may refer to Fujiwara et al. (2011) and Kamber et al. (2014). Fujiwara et al. (2011) document that the role of news shocks on output fluctuations is less critical for the Japanese economy, compared to the United States. Kamber et al. (2014) find that the variance of output explained by news about future shocks on total factor productivity (TFP) is substantially smaller for the advanced small open economies than that of the US. Nevertheless, there has been essentially no exploration about how these shocks affect the Korean economy, which is regarded as an emerging market. As surveyed in Yun (2013), aggregate fluctuations of emerging economies are intrinsically different from those of advanced economies. Therefore, it is hard to formulate an *a priori* prediction for the importance of news shocks as a major driving force for the Korean economy. The article attempts to seek evidence on the issue borne out by the data.

In order to achieve the goal, this paper employs the small open economy dynamic stochastic general equilibrium (DSGE) model of García-Cicco et al. (2010). This is a real business cycle (RBC) model augmented with several model features, which are crucial in accounting for aggregate fluctuations of emerging economies [Aguiar and Gopinath (2007), Uribe and Yue (2006)]. The model features include the permanent component of the aggregate TFP as well as the country risk premium shock. The model also embeds financial frictions, in which the country's interest rate spread is dependent upon the level of sovereign debt.

The RBC model is estimated under two different information structures to assess the importance of these informational assumptions. In the first information structure, agents have no foresight about future realizations of exogenous shocks, while they can only observe contemporaneous changes in the shock processes. This information structure is the conventional one in the existing macroeconomics literature. In the second structure, agents receive news about future structural shocks as in Schmitt-Grohé and Uribe (2012). By observing an innovation which will be realized in the future, for example, agents will know precisely how this innovation impinges upon the shock process and respond as soon as the innovation is observed. These two specifications are estimated with Korean data ranged from 1960:Q2 to 2014:Q4 using Bayesian methods.

Three main findings emerge. First, a major portion of fluctuations in output, consumption, and investment is explained by *unanticipated* shocks. More than 80% of output and consumption variability is attributable to the unanticipated shock components, while surprise movements in investment account for about 70% of investment variability. Notice that the contribution of anticipated shocks is constantly lower than the U.S. evidence based on a DSGE framework. Schmitt-Grohé and Uribe (2012), for instance, show that anticipated shocks explain about one half of the variances of U.S. output, consumption, and investment. Nevertheless, news shocks turn out to be critical in accounting for fluctuations in government spending growth and trade balance, as about a half and two-third of the variance of these two variables are driven by anticipated shocks.

Second, the historical decomposition indicates that there are specific periods over which anticipated shocks have crucial impacts on the economy. The contribution of anticipated shocks to output and consumption fluctuations increases from the late 1980s to the onset of the Asian currency crisis of the late 1990s. Regarding the investment fluctuations, anticipated shocks play a pivotal role during the recession period associated with the Asian currency crisis. The subsequent period, however, is dominated by unanticipated shocks in explaining the variabilities of output, consumption, and investment. In a sharp contrast to these variables, there is a notable difference in the determinant of trade balance between the pre- and post-Asian currency crisis periods. Prior to the crisis period, unanticipated shocks are the main source of trade balance movements. However, the contribution of anticipated shocks surges dramatically from the economic crisis and onward.

Finally, I explore the role of the financial friction in the estimated model. The impulse response functions demonstrate that a higher value for the debt elasticity of the interest rate significantly amplifies and propagates the impact of stationary productivity and preference shocks on output and investment. On the other hand, it dampens the expansionary effect of a nonstationary productivity shock and contractionary effect of a country risk premium shock on output and investment. Regardless of the type of shocks, the key transmission mechanism is associated with the interest rate movements. Higher debt elasticity values enlarge the contractionary effects of a structural shock raising the interest rate, intensifying a surge in the interest rate.

This paper is organized as follows. Section 2 describes the estimated model and information structure. Section 3 presents the econometric method used to estimate the models. Sections 4, 5, and 6 discuss the empirical results and Section 7 concludes.

2. THE ESTIMATED MODEL

2.1. MODEL

The estimated model is taken from the work of García-Cicco et al. (2010). The model is a small open-economy RBC model associated with the permanent component of the aggregate TFP as well as with the interest rate shock, both of which are crucial in accounting for aggregate fluctuations of emerging economies [Aguiar and Gopinath (2007), Uribe and Yue (2006)]. In addition, the model embeds financial frictions, in which the country's interest rate spread is dependent upon the level of sovereign debt. Appendix A details the model employed in the article.

2.2. INFORMATION FLOWS

The model consists of five exogenous shock processes: stationary neutral productivity shock, a_t; shock on the growth rate of nonstationary neutral productivity, g_t; preference shock, ν_t; country spread shock, μ_t; and a government spending shock, s_t where $s_t \equiv S_t/X_{t-1}$. Two information flows are examined in the article. The first information structure is the conventional one in the existing macroeconomics literature. Each exogenous process follows a first-order autoregression with an *i.i.d.* innovation as follows.

$$\hat{\chi}_t = \rho_\chi \hat{\chi}_{t-1} + \varepsilon_{\chi,t} \tag{1}$$

where $\chi = \{a, g, \nu, \mu, s\}$, $\varepsilon_{\chi,t} \sim N(0, \sigma_\chi^2)$, and a hat(ˆ) denotes the log deviation from steady-state. In this specification, agents have no foresight about future realizations of these shocks. I denote this information process by "No News."

The second structure simplifies the news process in Schmitt-Grohé and Uribe (2012) and is given by the following equation:

$$\hat{\chi}_t = \rho_\chi \hat{\chi}_{t-1} + \varepsilon^0_{\chi,t} + \varepsilon^1_{\chi,t-1} + \varepsilon^2_{\chi,t-2} + \dots \tag{2}$$

where $\varepsilon^j_{\chi,t}$ denotes the j-period anticipated changes in the log deviation of the variable χ_t from its steady-state. These shocks are assumed to be independent across time and anticipation horizon, i.e., $E\varepsilon^{j}_{\chi,t}\varepsilon^{k}_{\chi,t-m} = 0$ for $k, j = 0, 1, 2, \ldots$ and $E\varepsilon^{j}_{\chi,t}\varepsilon^{k}_{\chi,t} = 0$ for any $k \neq j$. The information set of the agent consists of current and past realizations of the exogenous shocks $\varepsilon^{j}_{\chi,t}$. By observing $\varepsilon^{2}_{\chi,t}$, for instance, agents know precisely that this shock will be realized after two periods, and respond as soon as the shock is observed. I refer to this information structure as "News."

3. INFERENCE

I use Bayesian inference methods to construct the parameters' posterior distribution, which is a combination of the likelihood function and prior information.[1] The model is estimated using five quarterly Korean time series ranged from 1960:Q2 to 2014:Q4 as follows: the log difference of real per capital GDP (YGR), real per capital consumption (CGR), real per capital investment (IGR), real per capital government spending (SGR), and the trade balance to output ratio (TBY). All the original series are seasonally adjusted.[2] Following García-Cicco et al. (2010), I further assume that the five series are observed with *i.i.d.* measurement errors.[3] Their relationship to the model variables can be expressed as follows.

$$\begin{bmatrix} \mathrm{YGR}_t \\ \mathrm{CGR}_t \\ \mathrm{IGR}_t \\ \mathrm{SGR}_t \\ \mathrm{TBY}_t \end{bmatrix} = \begin{bmatrix} \Delta\log(Y_t) \\ \Delta\log(C_t) \\ \Delta\log(I_t) \\ \Delta\log(S_t) \\ tby_t \end{bmatrix} + \begin{bmatrix} e^{me}_{Y,t} \\ e^{me}_{C,t} \\ e^{me}_{I,t} \\ e^{me}_{S,t} \\ e^{me}_{tby,t} \end{bmatrix} \tag{3}$$

where tby_t denotes the model-implied trade balance to output ratio, and $e^{me}_{X,t}$ denotes the *i.i.d.* measurement error of the variable X with mean zero and standard deviation σ^{me}_{X}.

[1]The Bayesian approach is employed in order to control for the methodological difference between the article and García-Cicco et al. (2010). The parameters, however, can be estimated via classical maximum likelihood (ML) methods. I additionally obtain the ML estimates of the parameters and confirm that the main empirical results are not substantially altered by the choice of the estimation methodology. The ML results are available upon request.

[2]Appendix C provides more details about the data used in the estimation of the model.

[3]In general, it is difficult to formulate economic interpretation for measurement errors. In spite of the caveat, I incorporate measurement errors to be consistent with the empirical framework set by García-Cicco et al. (2010). For a robustness check, I estimate the model without measurement errors and find that the empirical results are quite similar to that with measurement errors. The results without measurement errors are available upon request.

3.1. PRIOR DISTRIBUTIONS

I calibrate several parameters that are difficult to identify from the data, largely drawn from García-Cicco et al. (2010). Table 1 summarizes the calibrated values. The subjective discount factor, β, is set at 0.98, which implies an annual steady-state real interest rate of 8 percent.[4] The intertemporal elasticity of substitution, γ, is set at 2. Notice that the value is typically used for the DSGE models for Korea (e.g., Jung and Yang (2013) among many others). The steady state level of external debt per capita, $\bar{d}$, is set at 0.07. The capital income share of total output, α, is set at 0.32, implying a labor income share of 0.68. The exponent and labor coefficient in the utility function are set at 1.6 and 2.24, respectively. Since it appears to be no consensus in the literature for the calibrated values of α, ω and θ for Korea, the choice of these parameters is to be coherent with the existing literature on emerging-market business cycles, such as García-Cicco et al. (2010) and Chang and Fernández (2013).

Parameter		Value
β	(discount factor)	0.98
γ	(intertemporal elasticity of substitution)	2
δ	(depreciation rate)	0.06
$\bar{d}$	(steady state level of external debt per capita)	0.07
s	(steady state share of government spending in GDP)	0.19
α	(capital elasticity of the production function)	0.32
ω	(exponent of labor in utility function)	1.6
θ	(labor coefficient in utility function)	2.24

Table 1: Calibrated parameters.

The rest of the calibrated parameters are set to be consistent with the Korean data. The quarterly depreciation rate for capital, δ, is set at 0.06 to match the average investment to output ratio of Korea over the data span.[5] The share of government consumption in GDP is set at 0.19, which is the mean of the Korean data during the sample period.

[4]The empirical results remain almost unaltered by employing $\beta = 0.99$, another reference value extensively used in the existing literature. Appendix E reports the main empirical results associated with $\beta = 0.99$.

[5]Appendix B provides details of the model's steady-state.

Columns 2 to 3 in Tables 3 and 4 list the prior distribution for all estimated parameters, both for the "No News" and "News" specifications. The priors for the parameters $\bar{g}$, ψ, and ϕ are taken from García-Cicco et al. (2010). The prior for the steady-state gross growth rate of nonstationary TFP, $\bar{g}$, assumes a uniform distribution between 1 and 1.03. Notice that the interval includes the average (gross) growth rate of output for Korea over the sample period, which is 1.013. Lacking reliable empirical benchmarks in specifying the priors for ψ and ϕ, the prior selection is to be fairly diffused and cover a reasonably large range of the parameter space.

The priors for the AR(1) coefficients of the shock processes are assumed to follow Beta distributions, similar to Schmitt-Grohé and Uribe (2012). All the priors for the exogenous processes, except for the growth rate of nonstationary TFP, have a mean of 0.5 and a standard deviation of 0.1. These priors have the same mean, but are less diffused than that of Elekdag et al. (2006) with Korean data, who assume a standard deviation of 0.25. Imposing less diffused priors than the earlier study is guided by the finding in Walker and Leeper (2011), who demonstrate that embedding news shocks on TFP in a DSGE model makes equilibrium dynamics less persistent. They further argue that the model's internal propagation mechanisms, including real rigidities and autocorrelations of the shock processes, should work harder to fit data better by supplementing lower frequency components observed in macroeconomic aggregates. Accordingly, the choice of the priors in the article is designed to attenuate a potential erroneous overestimation of the news shocks' contribution to business cycles. Based on the rationale, the AR(1) coefficient of the growth rate of nonstationary TFP is set to have a mean of 0 and a standard deviation of 0.1, as in Schmitt-Grohé and Uribe (2012).

In choosing the priors for the standard deviation of the shock processes associated with the "News" specification, I follow the empirical strategy of Schmitt-Grohé and Uribe (2012). In particular, the variance of the unanticipated shock components equals to 80% of the total variance of the shock, i.e.,

$$\frac{\sigma_{\chi,0}^2}{\sigma_{\chi,0}^2+\sigma_{\chi,1}^2+\ldots+\sigma_{\chi,j}^2}=0.8 \quad \text{for} \quad j>1, \quad \chi=\{a,g,\nu,\mu,s\}$$

This prior selection posits that any ability of the public to anticipate future shocks has to be small and limited to a few quarters. For instance, agents' observation of contemporaneous chances in productivity is more significant than the news that they learn about its future changes.[6]

[6]In order to be robust, I consider the uniform priors used in (Footnote continued on next page)

For the "No News" specification, the prior distributions of shocks are identical to that of the unanticipated component of the corresponding shock in the "News" specification.

It is worth mentioning that the construction of prior distributions in the article is different from the popular approach adopted by Del Negro and Schorfheide (2008). They group the DSGE parameters into three categories and set prior distributions for each category in a different manner. The three categories are: [1] parameters that can be easily identified from steady-state relationships among observable variables (e.g., labor income share in the production function and discount factor); [2] parameters that characterize the law of motion of the exogenous processes (e.g., AR(1) coefficients and standard deviations of shock processes); and [3] the rest of parameters. The domain of priors for the first category is set based on the pre-sample average, while priors for the third category rely on microeconometric evidence. The construction of priors for the second category proceeds as follows: (1) assume random priors for the parameters in the category and generate parameter values from the priors; (2) simulate the DSGE model using the generated parameter values and calculate moments for the model's key endogenous variables (e.g., output and consumption); and (3) retain the priors if the simulated moments match those of the actual time series, but otherwise repeat (1) and (2) with updated priors. In this article, the parameters in the first category are mostly calibrated, instead of being estimated. This is because the estimation uses the longest available data and thus allows no pre-sample period. The priors for the second and third categories are largely drawn from the existing literature, based on the aforementioned rationale.

3.2. BAYESIAN ESTIMATION: OVERALL PROCEDURE

As the first step of the estimation procedure, equilibrium conditions of the model outlined in Appendix A are derived. Then the log-linearized model around the deterministic steady-state is solved by using Sims's (2002) *gensys* algorithm. The solution is of the following form:

$$\mathbf{x}_t = G(\Theta)\mathbf{x}_{t-1} + M(\Theta)\varepsilon_t, \quad \varepsilon_t \sim N(0,I) \tag{4}$$

where Θ denotes the vector of structural parameters to be estimated or calibrated, $\mathbf{x}_t$ denotes the vector of model variables at time t, and ε_t is the collection of

García-Cicco et al. (2010) for the shock AR(1) coefficients and standard deviations, and find that the alternative priors do not affect any of the empirical conclusions in the article. The results associated with the priors identical to García-Cicco et al. (2010) are reported in Appendix E.

exogenous shocks. If a unique stable solution exists, then a Kalman filter is used to evaluate the likelihood function associated with the linear state-space system in (4) since the true state vector $\mathbf{x}_t$ is assumed to be unobservable. In doing so, the vector $\mathbf{x}_t$ is mapped into the observable variables by the measurement equation in (3). To ease description, I rewrite the measurement equation in (3) as

$$\mathbf{y}_t = H(\Theta)\mathbf{x}_t + D(\Theta)e_t, \quad e_t \sim N(0,I) \tag{5}$$

where $\mathbf{y}_t$ denotes the vector of observable variables at time t, which is consisted of $\{\mathrm{YGR}_t, \mathrm{CGR}_t, \mathrm{IGR}_t, \mathrm{SGR}_t, \mathrm{TBY}_t\}$. e_t is the collection of measurement errors.

Based on the mapping between the observables and model variables in (5), I estimate the model using Bayesian methods. They combine prior beliefs about the vector of structural parameters, Θ, with data, $\mathbf{y}^T = \{\mathbf{y}_t\}_{t=1}^T$. Notice that the relationship of data with structural parameters is embodied in a likelihood function, $p(\mathbf{y}^T|\Theta)$, calculated by a Kalman filter. The prior and likelihood are combined using Bayes' rule to obtain the posterior distribution of Θ as

$$p(\Theta|\mathbf{y}^T) = \frac{p(\mathbf{y}^T|\Theta)p(\Theta)}{p(\mathbf{y}^T)}$$

The posterior of the parameters, $p(\Theta|\mathbf{y}^T)$, is then used to construct the posterior distributions of the estimated parameters. Since there are no closed-form distributions for $p(\Theta|\mathbf{y}^T)$ in the most of applications, the posterior is often simulated using Markov Chain Monte Carlo (MCMC) techniques. The most popular MCMC technique is known as the random walk Metropolis-Hastings (RW-MH) algorithm.

3.3. BAYESIAN ESTIMATION: SAMPLING FROM POSTERIOR DISTRIBUTIONS

In this article, the posterior distribution is sampled by the tailored randomized block MCMC (TaRB-MH) algorithm in Chib and Ramamurthy (2010). The use of the TaRB-MH algorithm, instead of the conventional RW-MH sampler, is due to the presence of news shocks. Having the anticipated components of exogenous shocks in a model can yield a more complicated shape of posterior likelihood, including a multimodality problem. Accordingly, inferences around a specific posterior mode using the RW-MH algorithm may distort the empirical results.

To address this issue in detail, I begin by laying out the estimation procedure associated with the RW-MH sampler.[7] The first step of the algorithm is to maximize the log posterior function, which combines the priors and the likelihood of the data, and find the posterior mode. Then the RW-HM algorithm samples from the posterior distribution around the mode estimate. In doing so, the parameters (Θ) are sampled in a single block by drawing a proposal from a random walk process, in which the negative inverse Hessian evaluated at the posterior mode is used as a proxy for the variance of the proposal density. Each proposal value can be accepted or not according to the MH probability of move; if rejected, the current parameter value is retained.

The TaRB-MH estimation procedure differs primarily from the RW-MH algorithm in two dimensions—how to update the parameter vector drawn from a proposal density and construct the proposal density. First, the TaRB-MH updates the parameters by randomly splitting them into several blocks, so that $\Theta = (\Theta_1, \Theta_2, \ldots, \Theta_\ell)$.[8] Then the TaRB-MH conducts a separated MH to update each block indices, fixing parameters in other blocks at the previous step's value. In this step, the proposal density for each block is tailored to closely approximate the location and curvature of the posterior density in that block. This entails recalculations of the Hessian matrix at every updating stage, which can improve the performance of the algorithm in drawing *i.i.d.* samples even when there is a complication of DSGE posterior likelihoods.[9]

In sum, the TaRB-MH procedure proceeds as follows:

[7] See An and Schorfheide (2007) for more details on the Bayesian estimation of DSGE models using the RW-MH algorithm.

[8] A different grouping strategy is taken by Curdia and Reis (2010), who group the parameters by two types—economic and exogenous ones. The main advantages of their approach over that of Chib and Ramamurthy (2010) are the ease of implementation and less computational time. The bottom line of this algorithm being efficient is that there is no correlation between the parameters in the different groups. As illustrated in Walker and Leeper (2011), however, news shocks categorized as the exogenous group alter the persistence of a DSGE model's equilibrium, which is corrected by internal propagation mechanisms such as real rigidities and autocorrelations of the shock processes. Considering the potential *a priori* interaction between the parameters in the different groups, the use of the random-grouping sampler is a reasonable alternative despite of its computational burden.

[9] Compared to the RW-MH sampler, a caveat of the TaRB-MH algorithm is the computational burden. In general, sampling from the posterior distribution takes a lot more time with the TaRB-MH algorithm, since it entails recalculations of the Hessian matrix at every updating stage which requires a multiple number of likelihood evaluations for each update. For example, the DSGE model with news shocks in the article was coded in Matlab and executed on a Windows 7 32-bit machine with a 3.50 GHz Intel Core i5 CPU. The TaRB-MH algorithm took roughly 7 days to generate 25,000 draws.

- Step 1: Initialize $\Theta^{(0)} \subset \Lambda_D \cap \Lambda_P$ where Λ_D and Λ_P are the domain of the parameters yielding determinacy of the model and of the one yielding finite prior likelihoods, respectively. Set n_0 (the number of initial burn-ins) and n (the number of MCMC draws). Let $N = n_0 + n$
  - Substep 1-1: the sampler is initialized at the prior mean of each parameter
  - Substep 1-2: with the given set of parameters, the log-linearized model is solved to obtain the solution as in (4), and the posterior likelihood is evaluated using a Kalman filter based on the measurement equation in (5)
- Step 2: Generate randomly blocks $(\Theta_{k,1}, \Theta_{k,2}, \ldots, \Theta_{k,p_k})$ in each iteration k, where $k = 1, \ldots, K$
- Step 3: Sample each block $\Theta_{k,l}$, $l = 1, \ldots, p_k$, within each iteration by an MH step with a tailored proposal density
  - Substep 3-1: conduct Substep 1-2 whenever the subset of the parameters is block-updated
  - Substep 3-2: keep the updated block if it satisfies the MH probability of move, but otherwise retain the current block as the new value of the block
  - Substep 3-3: iterate Substeps 3-1 and 3-2 until all of the parameter indices are considered
- Step 4: Repeat Steps 2 and 3 N times, discard the draws from the first n_0 iterations and save the next n draws

Appendix D details Step 3 as well as the estimation configuration for the TaRB-MH algorithm in practice. I set the number of initial burn-ins at 5,000, and draw 20,000 posterior samples.

4. ESTIMATION RESULTS

4.1. OPTIMAL HORIZON FOR THE ANTICIPATED SHOCKS

The “News” specification entails a selection of the anticipation horizons for the exogenous shock processes. In this paper, I choose the optimal horizon based on the goodness-of-fit statistic, a strategy employed by Fujiwara et al. (2011). The measure for model fit uses the average log marginal density calculated with the Geweke's (1999) modified harmonic mean estimator, which is a conventional measure of model fit for the class of linearized DSGE models.[10]

The maximum anticipation horizon is restricted to be 4 quarters, lower than the values employed in the literature on news shocks with U.S. data. The anticipation horizon employed in the previous studies on the U.S. economy is all over the map. Schmitt-Grohé and Uribe (2008) use the horizon in news shocks from 1 to 3 quarters, whereas the published version of their work (Schmitt-Grohé and Uribe (2012)) focuses on 4- and 8-quarter anticipated shocks. Fujiwara et al. (2011) obtain the optimal anticipation horizon of 1 to 5 quarters, which maximizes the model's fit to the data. The selection in this article is based on the rationale that signals about shocks realized in the future may be weaker in emerging market economies than in advanced economies.

Table 2 reports the average log marginal densities for models with various anticipation horizons. The best-fitting combination, guided by the log marginal density criterion, emerges from the model with the horizon $j = 0, 1, 2, 3$. Accordingly, I set the anticipation horizons at 0, 1, 2, and 3 for the empirical analyses.

Anticipation Horizons	Log Marginal Data Densities
$j = 0, 1, 2$	2487.1
$j = 0, 1, 2, 3$	2493.5
$j = 0, 1, 2, 3, 4$	2489.0

Table 2: 1: Log marginal data densities of the models with various anticipation horizons. The average log marginal density is calculated by using the Geweke's (1999) modified harmonic mean estimator.

4.2. POSTERIOR ESTIMATES

The last two columns of Tables 3 and 4 provide the mean and 90th percentile intervals from the posterior distributions for the both specifications. The estimates of the $\bar{g}$ parameter are not sensitive to the information structures as they

[10]The average log marginal density is the mean of the Geweke's (1999) modified harmonic mean estimator associated with truncation parameters from 0.1 to 0.9, with an increment of 0.1.

are close to 1.03 for the both specifications. On the contrary, the ψ and ϕ parameters vary across the two specifications. Embedding the news structure results in larger estimates of the debt elasticity of the interest rate, while it lowers the capital adjustment cost estimates. The AR(1) coefficients of the shock processes are not severely affected by the choice of the information structure as the 90th percentile intervals for ρ's largely overlap across the specifications.

Figure 1 plots the probability density functions for the structural parameters that correspond to the priors and posteriors under the "News" specification. Overall, the data seem to be informative in identifying these parameters as the posterior distributions are a lot less diffused than the priors. Focusing on the ψ estimates, they are larger than the values estimated or calibrated in previous studies on more developed countries. Justiniano and Preston (2010) use the calibrated value of 0.01 for the elasticity parameter in fitting the data of Australia, Canada and New Zealand.[11] Based on the U.K. data, Liu and Mumtaz (2011) estimate the parameter and find that it is close to zero. On the other hand, the estimated value in this article is much smaller than the estimates in García-Cicco et al. (2010) using the time series of Argentina. As García-Cicco et al. (2010) make explicit, the parameter can be regarded as the reduced form of a financial friction, capturing how sensitive the domestic interest rate is to the country's indebtedness. The estimates in this article indicate that the country premium plays a more crucial role in driving the domestic interest rate of Korea than that of the more developed economies.

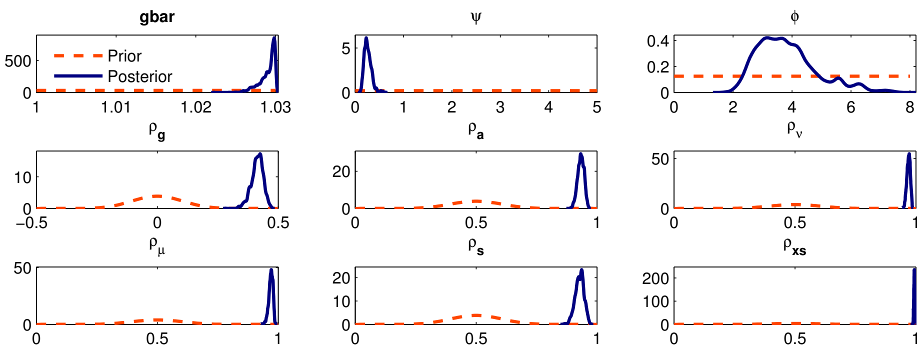

Figure 1: Prior and posterior distributions of the structural parameter estimates.

[11]Choi and Hur (2015) employ the calibrated value in Justiniano and Preston (2010) to fit the Korean data from 1976 to 2013.

Parameter	Dist.	Prior Mean (Std)	Posterior No News	Posterior News
$\bar{g}$	U	[1.00, 1.03]	1.029	1.029
(s.s. gross growth rate of nonstationary TFP)			[1.027, 1.030]	[1.027, 1.030]
ψ	U	[0, 5]	0.18	0.26
(interest rate elasticity w.r.t. debt)			[0.12, 0.25]	[0.16, 0.39]
ϕ	U	[0, 8]	5.23	3.83
(capital adjustment cost)			[3.77, 6.93]	[2.50, 5.92]
ρ_g	B	0 (0.1)	0.41	0.41
(nonstationary TFP AR(1))		[−0.16, 0.16]	[0.36, 0.45]	[0.37, 0.45]
ρ_a	B	0.5 (0.1)	0.92	0.93
(stationary TFP AR(1))		[0.34, 0.66]	[0.90, 0.94]	[0.91, 0.95]
ρ_v	B	0.5 (0.1)	0.97	0.97
(preference AR(1))		[0.34, 0.66]	[0.96, 0.98]	[0.96, 0.98]
ρ_μ	B	0.5 (0.1)	0.97	0.97
(country risk premium AR(1))		[0.34, 0.66]	[0.96, 0.99]	[0.95, 0.98]
ρ_s	B	0.5 (0.1)	0.93	0.93
(government spending AR(1))		[0.34, 0.66]	[0.90, 0.96]	[0.90, 0.96]
ρ_{xs}	B	0.5 (0.1)	0.99	0.99
(smoothness of the trend in govt spending)		[0.34, 0.66]	[0.99, 1.00]	[0.99, 1.00]
σ_g^0	IG	0.01 (0.2)	0.017	0.017
(current nonstationary TFP std.)		[0.002, 0.028]	[0.015, 0.019]	[0.015, 0.019]
σ_g^1	IG	0.003 (0.2)		0.002
(1-qrt anticipated nonstationary TFP std.)		[0.001, 0.008]		[0.000, 0.004]
σ_g^2	IG	0.003 (0.2)		0.002
(2-qrt anticipated nonstationary TFP std.)		[0.001, 0.008]		[0.001, 0.004]
σ_g^3	IG	0.003 (0.2)		0.002
(3-qrt anticipated nonstationary TFP std.)		[0.001, 0.008]		[0.000, 0.005]
σ_a^0	IG	0.01 (0.2)	0.014	0.012
(current stationary TFP std.)		[0.002, 0.028]	[0.012, 0.016]	[0.009, 0.014]
σ_a^1	IG	0.003 (0.2)		0.002
(1-qrt anticipated stationary TFP std.)		[0.001, 0.008]		[0.001, 0.004]
σ_a^2	IG	0.003 (0.2)		0.003
(2-qrt anticipated stationary TFP std.)		[0.001, 0.008]		[0.001, 0.006]
σ_a^3	IG	0.003 (0.2)		0.003
(3-qrt anticipated stationary TFP std.)		[0.001, 0.008]		[0.001, 0.007]

Table 3: Prior and posterior distributions of each estimated parameter. For the prior distributions following a uniform distribution, the numbers in parenthesis denote the minimum and maximum values, respectively. Otherwise, this table reports the mean and associated [5%, 95%] percentile intervals (in brackets).

Parameter	Dist.	Prior Mean (Std)	Posterior No News	Posterior News
σ_{ν}^{0} (current preference std.)	IG	0.5 (0.5) [0.16, 1.23]	0.433 [0.332, 0.587]	0.391 [0.302, 0.513]
σ_{ν}^{1} (1-qrt anticipated preference std.)	IG	0.14 (0.5) [0.03, 0.38]		0.028 [0.017, 0.043]
σ_{ν}^{2} (2-qrt anticipated preference std.)	IG	0.14 (0.5) [0.03, 0.38]		0.029 [0.016, 0.044]
σ_{ν}^{3} (3-qrt anticipated preference std.)	IG	0.14 (0.5) [0.03, 0.38]		0.027 [0.015, 0.040]
σ_{μ}^{0} (current country risk premium std.)	IG	0.01 (0.2) [0.002, 0.028]	0.007 [0.005, 0.009]	0.004 [0.002, 0.007]
σ_{μ}^{1} (1-qrt anticipated country risk premium std.)	IG	0.003 (0.2) [0.001, 0.008]		0.002 [0.000, 0.004]
σ_{μ}^{2} (2-qrt anticipated country risk premium std.)	IG	0.003 (0.2) [0.001, 0.008]		0.004 [0.001, 0.010]
σ_{μ}^{3} (3-qrt anticipated country risk premium std.)	IG	0.003 (0.2) [0.001, 0.008]		0.007 [0.001, 0.012]
σ_{s}^{0} (current government spending std.)	IG	0.01 (0.2) [0.002, 0.028]	0.018 [0.017, 0.020]	0.012 [0.003, 0.019]
σ_{s}^{1} (1-qrt anticipated government spending std.)	IG	0.003 (0.2) [0.001, 0.008]		0.004 [0.001, 0.017]
σ_{s}^{2} (2-qrt anticipated government spending std.)	IG	0.003 (0.2) [0.001, 0.008]		0.004 [0.001, 0.013]
σ_{s}^{3} (3-qrt anticipated government spending std.)	IG	0.003 (0.2) [0.001, 0.008]		0.007 [0.001, 0.018]

Table 4: Prior and posterior distributions of each estimated parameter (continued). For the prior distributions following a uniform distribution, the numbers in parenthesis denote the minimum and maximum values, respectively. Otherwise, this table reports the mean and associated [5%, 95%] percentile intervals (in brackets).

Figure 2 depicts how the volatilities of key macroeconomic variables are affected by different ψ values, while the other parameters are remained at the posterior mean estimates. By construction, the figure demonstrates a counterfactual exercise by asking how the second moments would have altered if there had been different degrees of financial friction. For all the variables considered, the standard deviations diminish dramatically with ψ when it is close to zero.

For the debt elasticity values exceeding a certain level, however, the volatilities become largely insensitive to the ψ value. Accordingly, the higher ψ estimate reported in García-Cicco et al. (2010) has a similar implication to the estimates in this article on macroeconomic stability.

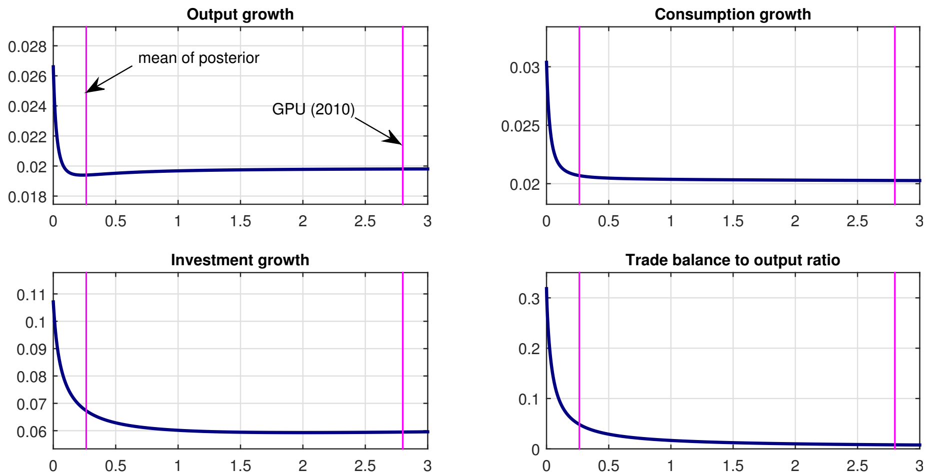

Figure 2: Standard deviations of key macroeconomic variables with respect to the ψ values, evaluated at the mean of the posterior parameter estimates. The left and right vertical lines indicate the mean of the posterior estimate in this work ($\psi = 0.26$) and that of García-Cicco et al. (2010, $\psi = 2.8$), respectively.

Turning to the shock standard deviation estimates associated with the "News" specification, as summarized in Figure 3, the anticipated shock components stand out for the country risk premium process, while their evidence is limited for the other structural shocks. More specifically, the anticipated components of nonstationary and stationary TFP processes tend to be of smaller importance compared to the unanticipated ones. As the mean estimates in Table 3 show, the standard deviations of unanticipated a_t and g_t shocks are even higher than the sum of the anticipated components' standard deviations of the corresponding shock. This tendency is also observed from the preference shock variances as in Table 4.

The country risk premium shock process entails a different pattern, in which relatively more weights are given to the anticipated components than to the unanticipated ones. In particular, the three-quarter-ahead anticipated shock component is most important in driving the risk premium shock. Based on the mean

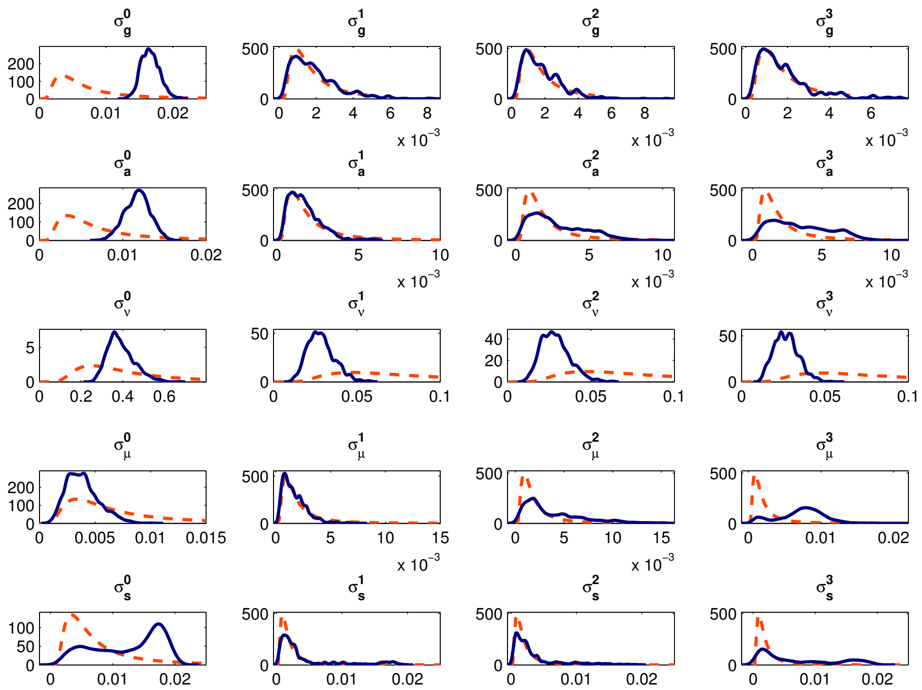

Figure 3: Prior and posterior distributions of the shock standard deviation estimates. In each figure, the prior (dashed lines) and posterior (solid lines) probability density functions are reported.

estimates, the standard deviation of the unanticipated component is half of the estimates for the three-quarter-ahead anticipated shock. A similar but less pronounced pattern is obtained with the government spending shock process.

4.3. POSTERIOR LIKELIHOOD

A potential issue regarding the estimation of DSGE models with news shocks is the weak identification problem. In particular, the likelihood function may lack information about some of the anticipated shock standard deviations, which can raise skepticism about the importance of anticipated shocks.

In order to address this issue, Figure 4 plots the slices of the posterior likelihood around the posterior mode. The figure makes clear that the identification problem is unlikely to occur through the dimension of the structural parameters, including the shock AR(1) coefficients. The marginal likelihood functions with respect to the parameters are steep around the posterior mode. A similar observation is made with the unanticipated components of the structural shocks.

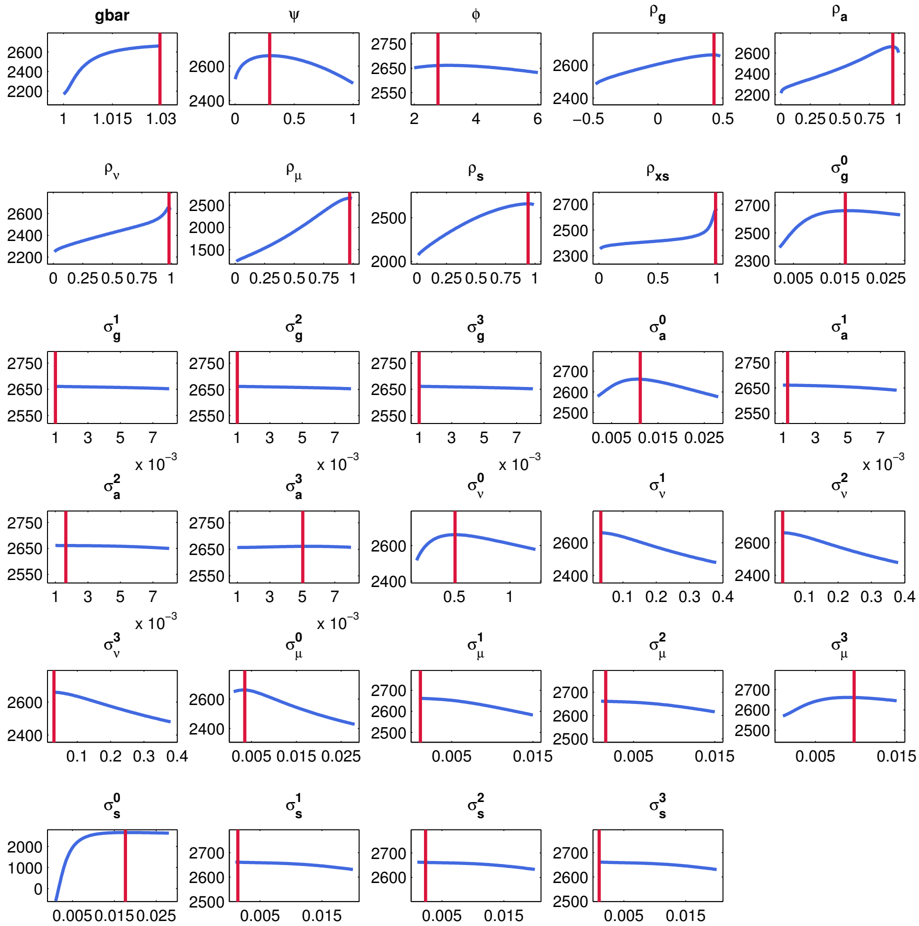

Figure 4: Plots of slices of the likelihood around the posterior mode. The vertical lines indicate the posterior mode.

The likelihood functions, however, display a quite different feature in the dimensions of news shocks on nonstationary and stationary TFP processes as well as on government spending. The posterior likelihoods are quite flat along the dimensions of these parameters, indicating that the evidence of agents' anticipation of these shocks is hardly borne out by the data.

In contrast, the 3-period anticipated risk premium shock standard deviation is well identified as the likelihood function increases with the parameter. This confirms that news shocks on the country risk premium play a crucial role in improving the model's fit to the data. Finally, the posterior likelihoods decrease sharply with the standard deviations of the news shocks on preference, which is strong evidence against the presence of the shocks.

All these findings have implications for the prior selection associated with news shocks. Due to the weak evidence of anticipated shocks, data revision for many of them is likely to be only marginal. As depicted in Figure 3, this explains why the prior and posterior distributions for some of the news shocks are largely identical. In this regard, constructing priors as in Schmitt-Grohé and Uribe (2012) seems to have more of an empirical justification than assuming the same priors across the unanticipated and anticipated shock components, which tends to overestimate the role of news shocks on the economy.

4.4. MODEL FIT

Figure 5 plots the autocorrelations and cross-correlations for the actual data (solid lines) and the 90 percent posterior intervals for the theoretical moments from the model (dashed lines). The theoretical moments are based on model-implied samples generated by a Monte Carlo simulation with the posterior draws. Most of the cross-correlations fall within the posterior intervals, suggesting that the model is able to mimic several cross-correlations in the data up to two year horizon. Many autocorrelations fall within the posterior intervals, with the exception of trade balance to output ratio which is consistently underestimated by the model.

5. THE ROLE OF ANTICIPATED SHOCKS

This section draws empirical implications of the "News" structure. In particular, I demonstrate the contribution of anticipated shocks in driving business cycles for the Korean economy, based on two quantitative results—the variance decomposition and historical decomposition.

5.1. VARIANCE DECOMPOSITION

Table 5 summarizes the shares of variance of the observable variables accounted for by unanticipated and anticipated shocks. For each variable, the decomposition can be interpreted by two criteria: (1) the type of exogenous shocks

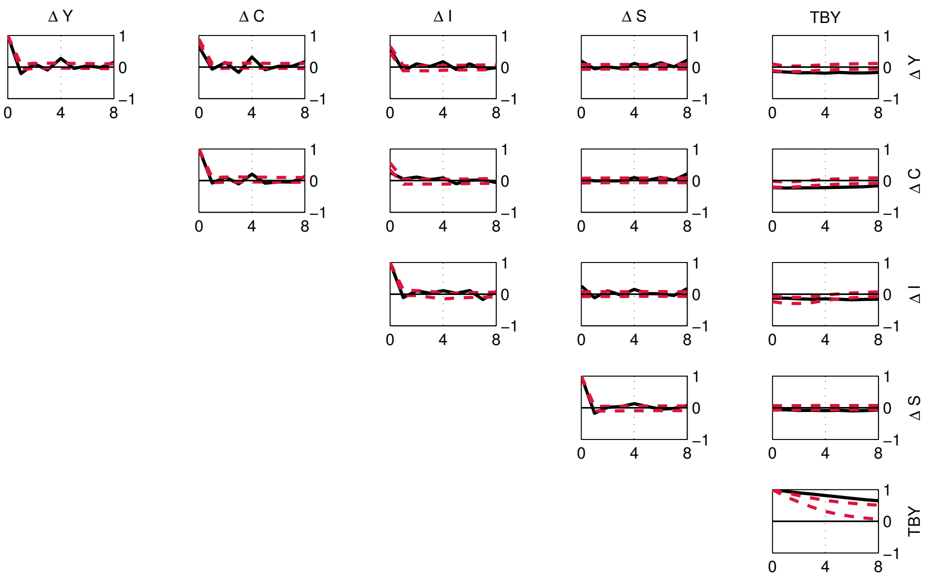

Figure 5: Autocorrelations and cross-correlations for the actual data (solid lines) and the model (dashed lines—90 percent posterior intervals). ΔY, ΔC, ΔI, ΔS are the growth rates of output, consumption, investment and government spending respectively, and TBY denotes the trade balance to output ratio. The x-axis is in quarters.

driving the variables; and (2) the relative importance of unanticipated and anticipated shocks. Regarding the first criterion, the variables are categorized by three groups. Output and consumption growths are mainly driven by the nonstationary and stationary TFP shocks, which jointly account for more than two-third of fluctuations in the variables. On the contrary, the country risk premium shock is the most important driver of investment growth and trade balance to output ratio. Notice that these results are consistent with García-Cicco et al. (2010), who document mutually uninterchangeable two separate blocks: output-consumption and investment-trade balance.[12] In the model, government spending is an isolated block as its variability is mostly accounted for by the government spending

[12]More specifically, they report that output and consumption variabilities are largely explained by the TFP shocks, and the contribution of the country risk premium shock to these variables' movements is quite limited. In contrast, a substantial fraction of fluctuations in investment and trade balance ascribe to the country risk premium shock, while the contribution of the TFP shocks is negligible.

Shock	Output growth	Consumption growth	Investment growth	Govt spending growth	Trade balance to GDP ratio
Nonstationary TFP : unanticipated	0.39 [0.32, 0.47]	0.22 [0.17, 0.27]	0.17 [0.11, 0.23]	0.01 [0.00, 0.01]	0.03 [0.02, 0.04]
Nonstationary TFP : anticipated	0.03 [0.01, 0.07]	0.01 [0.00, 0.03]	0.01 [0.00, 0.02]	0.00 [0.00, 0.01]	0.01 [0.00, 0.02]
Stationary TFP : unanticipated	0.42 [0.28, 0.54]	0.41 [0.31, 0.50]	0.23 [0.15, 0.30]	0.00 [0.00, 0.00]	0.02 [0.01, 0.03]
Stationary TFP : anticipated	0.11 [0.02, 0.22]	0.05 [0.01, 0.11]	0.02 [0.01, 0.03]	0.00 [0.00, 0.01]	0.05 [0.01, 0.09]
Preference : unanticipated	0.03 [0.02, 0.04]	0.23 [0.18, 0.29]	0.12 [0.08, 0.17]	0.00 [0.00, 0.00]	0.18 [0.08, 0.31]
Preference : anticipated	0.00 [0.00, 0.00]	0.03 [0.03, 0.10]	0.00 [0.00, 0.01]	0.00 [0.00, 0.01]	0.02 [0.01, 0.04]
Country risk premium : unanticipated	0.00 [0.00, 0.01]	0.00 [0.00, 0.01]	0.18 [0.05, 0.35]	0.00 [0.00, 0.00]	0.13 [0.03, 0.29]
Country risk premium : anticipated	0.02 [0.01, 0.03]	0.01 [0.01, 0.02]	0.27 [0.14, 0.41]	0.00 [0.00, 0.01]	0.56 [0.34, 0.72]
Government spending : unanticipated	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	0.52 [0.03, 0.96]	0.00 [0.00, 0.01]
Government spending : anticipated	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.01]	0.45 [0.02, 0.95]	0.01 [0.00, 0.02]
Overall: anticipated	0.15 [0.06, 0.27]	0.13 [0.08, 0.21]	0.31 [0.17, 0.44]	0.46 [0.03, 0.96]	0.65 [0.41, 0.81]

Table 5: Variance decomposition predicted by the model with news shocks. This table reports the mean and associated [5%, 95%] percentile intervals (in brackets). Each column may not total one due to rounding.

shock itself.

Tuning to the relative importance of unanticipated and anticipated shocks, a substantial portion of variances of government spending growth and trade balance to output ratio is attributable to the anticipated component.[13] In terms of the

[13]However, the contribution of the anticipated government spending shocks is somewhat diffused as their posterior intervals are fairly wide.

mean estimates, about a half and two-third of the variance of these two variables are driven by anticipated shocks, respectively. The notable degree of foresight about government spending is comparable to the U.S. evidence documented in Schmitt-Grohé and Uribe (2012) showing that about 60% of the variance of government spending is due to anticipated shocks. The results, however, differ from their finding regarding the role of government spending shocks in impinging on output fluctuations. Schmitt-Grohé and Uribe (2012) ascribe about 10% of output movements to government spending shocks, whereas the empirical results in this article indicate that the contribution of government spending shocks to output is minuscule.

A major portion of fluctuations in output, consumption, and investment is explained by unanticipated shocks. More than 80% of output and consumption variability is attributable to the unanticipated shock components, while surprise movements in investment account for about 70% of investment variability. Schmitt-Grohé and Uribe (2012) document that anticipated shocks explain about one half of the variances of output, consumption, and investment. Compared to Schmitt-Grohé and Uribe (2012), the importance of anticipated shocks to output and consumption is relatively smaller, whereas anticipated shocks play a more crucial role for investment movements. The discrepancy in results between the present study and Schmitt-Grohé and Uribe (2012) may be attributable to the modeling assumption. In particular, Schmitt-Grohé and Uribe (2012) find that the anticipated components of a wage markup shock are one of the most significant drivers of hours and output, as they explain about 67% and 17% of fluctuations in the variables, respectively. As in Smets and Wouters (2007), the shock is likely to be important in accounting for the variability of hours, and thus improve a DSGE model's fit to the postwar U.S. data. This feature, however, is abstracted from the benchmark model in this article, which may downplay the role of anticipated shocks in driving business cycles of Korea.

The existing literature offers a harmonious view that news shocks are given relatively less weights in accounting for business cycles of non-US economies than for that of the U.S. economy. Fujiwara et al. (2011) document that the role of news shocks on output fluctuations is less critical for the Japanese economy, than for the United States. Kamber et al. (2014) find that the variance of output explained by news about future TFP shocks is substantially smaller in the advanced small open economies than in the US.

Figure 6 displays the prior and posterior distributions for the fraction of output growth, consumption growth, investment growth, and trade balance to output ratio explained by anticipated shocks. Overall, the data seems to be informative

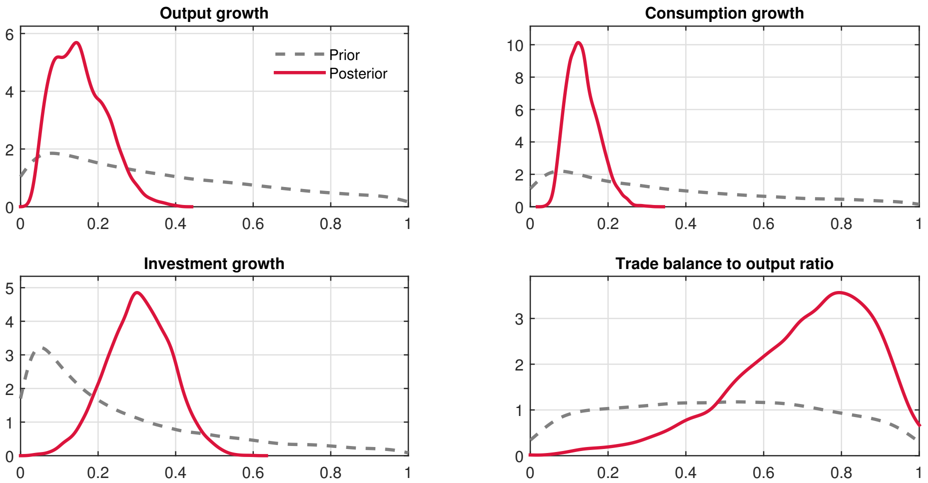

Figure 6: Prior and posterior probability densities of the share of the unconditional variance of key macroeconomic variables attributable to anticipated shocks. In each figure, the prior (dashed lines) and posterior (solid lines) probability density functions are reported.

in identifying the contribution of the anticipated shock components as the comparison of the prior to posterior distributions reveals. The prior distribution for trade balance to output ratio is fairly diffused, while a quite restricted contribution of anticipated shocks is assumed *a priori* for output growth, consumption growth and investment growth. The posterior distributions characterize that the data assign a considerable role of anticipated shocks in accounting for fluctuations in trade balance to output ratio, as opposed to the other variables considered.

5.2. HISTORICAL DECOMPOSITION

Figure 7 summarizes the historical contribution of the unanticipated and anticipated shocks to output growth, consumption growth, investment growth, and trade balance to output ratio. The decomposition is designed to identify the timing over which anticipated shocks have sizable impacts on movements in the observed data, and therefore can shed some light on the plausibility of the "News" structure. Together with the decomposition results, the vertical lines in each figure indicates the onset of the Asian currency crisis of 1997-98, regarded as one of the most significant economic events for the Korean economy [Cho (2007),

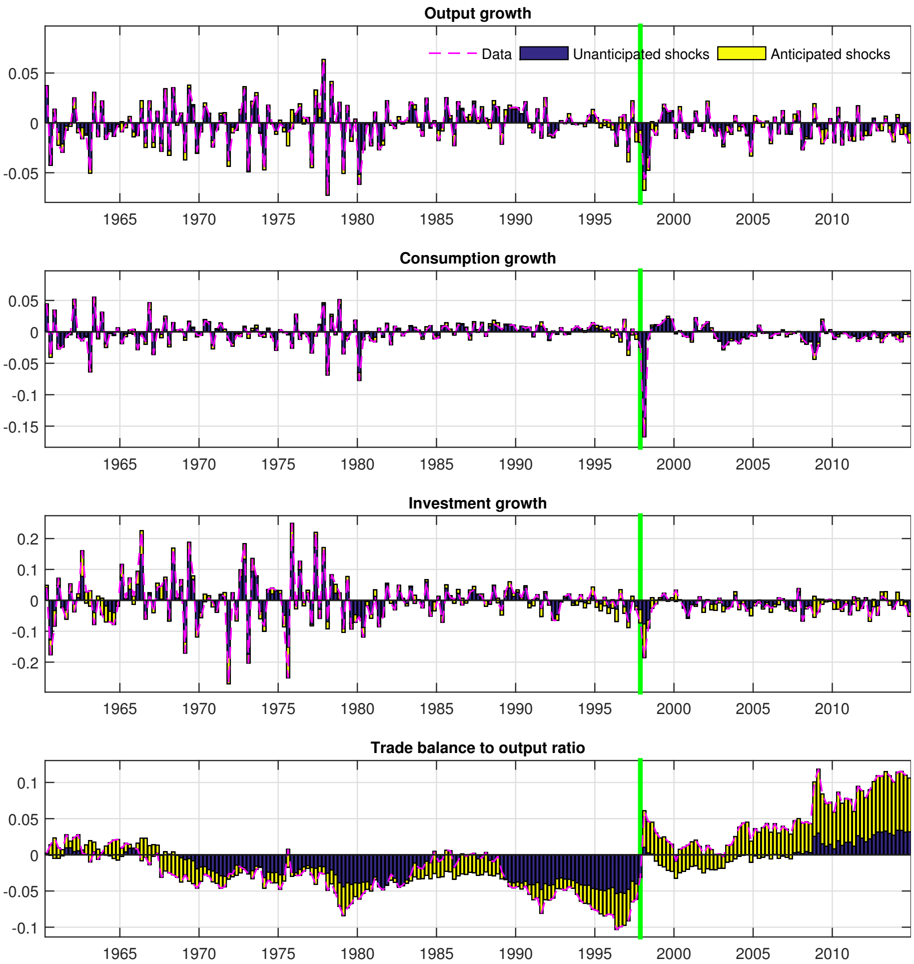

Figure 7: Historical decompositions of key macroeconomic variables driven by unanticipated and anticipated shocks. In each figure, the posterior mean estimates for the actual data (dashed lines), unanticipated shocks (dark-shaded areas) and anticipated shocks (light-shaded areas) are reported. The vertical lines indicate the onset of the Asian currency crisis.

Huh and Nam (2010)].

Regarding the decompositions of output growth and consumption growth, it is evident that the variability of these variables is consistently accounted for by unanticipated shocks. This is in line with the results from the variance decomposition. A similar tendency is observed from the decomposition of investment growth. Anticipated shocks, however, are given relatively more weight in the late 1990s, which coincides approximately with the period right after the Asian currency crisis.

The relative role of the anticipated shock components is much more pronounced for the decomposition of trade balance to output ratio. Anticipated shocks are the predominant factor behind the fluctuations in the variable at the beginning of the sample period and from the late 1990s onward. Interestingly, a dominant fraction of trade balance variability after the onset of the Asian currency crisis is driven by anticipated shocks.

In order to detail the decompositions of the variables, I additionally calculate the ratio of the Root Mean Squared Deviation (RMSD) defined as

$$\text{RMSD ratio}_t^X = \frac{\left(X_t^{acutal} - X_t^{anticipated}\right)^2}{\left(X_t^{acutal} - X_t^{unanticipated}\right)^2 + \left(X_t^{acutal} - X_t^{anticipated}\right)^2} \quad (6)$$

where $X = \{Y, C, I, tby\}$, and $X_t^{unanticipated}$ and $X_t^{anticipated}$ denote the model-implied series for the corresponding variable X generated by unanticipated and anticipated shocks, respectively.[14] By construction, the ratio takes values from zero to one, and the contribution of anticipated shocks declines with the ratio as $X_t^{anticipated}$ deviates further from X_t^{acutal}.

Figure 8 displays the estimates for the mean (solid lines) and 90-percent interval (dashed lines) of the RMSD ratio. As the first two plots show, the mean estimates for output and consumption surge from the late 1980s and remain high until the crisis period. The 90-percent intervals, however, are also wide, indicating that the role of news shocks on fluctuations in output and consumption over the period is hardly significant. The subsequent period is dominated by unanticipated shocks in explaining the variabilities of these variables. Regarding the investment fluctuations, anticipated shocks play a pivotal role during the recession period associated with the Asian currency crisis. During the period, the RMSD ratio is lower than 0.5 in terms of the mean estimates even though the 90-percent interval is dispersed to some extent. This tendency, however, is short-lived as the contribution of anticipated shocks to investment movements is quite limited afterward, with the tight 90-percent interval close to one.

In a sharp contrast to the other variables, there is a notable difference in the determinant of trade balance between the pre- and post-Asian currency crisis

[14]The leveled variables for output, consumption, and investment—instead of their growth—are considered to highlight the empirical finding.

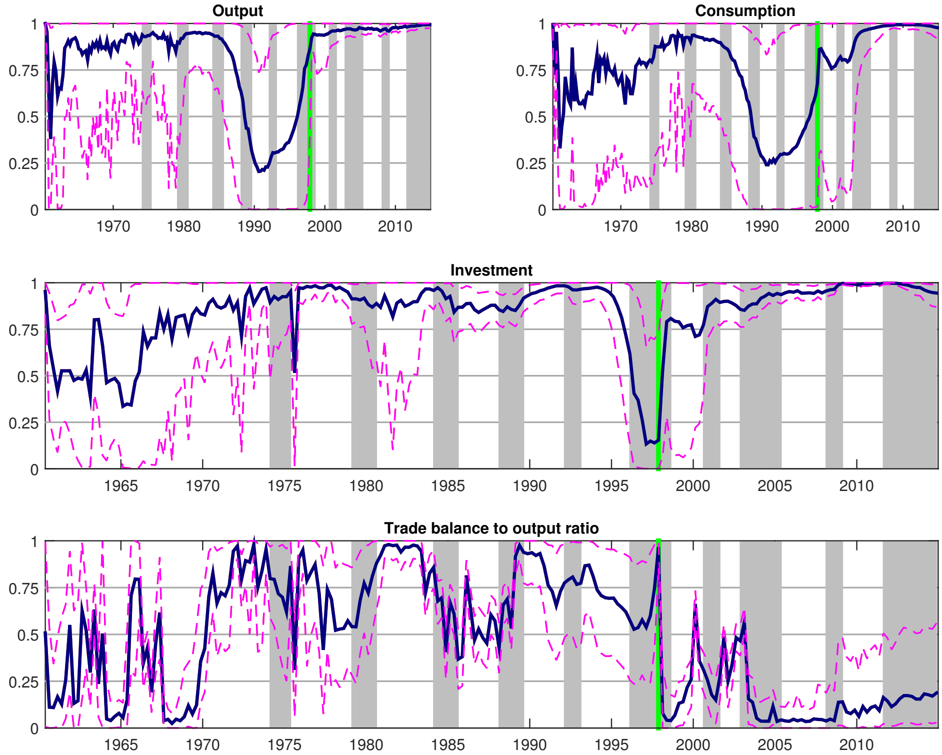

Figure 8: Historical shares of RMSD for output, consumption, investment and trade balance to output ratio, caused by anticipated shocks. In each figure, the posterior mean (solid lines) and 90% interval (dashed lines) estimates are reported. The vertical lines indicate the onset of the Asian currency crisis. Shaded areas indicate the recession dates by the Korean Statistical Information Service (KOSIS).

periods. As the last plot reveals, the contribution of anticipated shocks surges dramatically from the economic crisis and onward. From the mid 2000s, the 90-percent interval of the RMSD ratio is consistently below 0.5, indicating that a dominant fraction of fluctuations in trade balance over the period is accounted for by anticipated shocks.

It is worth mentioning that the historical contribution of anticipated shocks to trade balance to output ratio displays a countercyclical pattern, as the RMSD ratio tends to fall during a recession. This tendency may be related to the evidence of the state-dependent information updating framework, as in Coibion and Gorodnichenko (2012) and Andrade and Le Bihan (2013). Using the survey of professional forecasters' dataset in the U.S. and Europe respectively, the both studies report that the degree of agents' attention toward economic shocks entails a countercyclical pattern—more (less) attention during recessions (booms).[15] Agents in the model of this work update their information set every period and are able to observe all the structural shocks, excluding the possibility of agents' incomplete information. Under the perfect information setup, the time-varying pattern of the RMSD statistic for trade balance to output ratio can be characterized by agents more actively seeking for shocks—particularly risk premium shocks—that will be realized in the future over a recession.

6. THE ROLE OF FINANCIAL FRICTIONS

This section illustrates empirical implications of the presence of a financial friction for the model dynamics. To this end, I plot the impulse responses of key macroeconomic variables to the structural shocks associated with three values for ψ: (1) $\psi = 0.26$, the mean of posterior estimates in the article; (2) $\psi = 0.001$, the calibrated value in García-Cicco et al. (2010); and (3) $\psi = 2.8$, the estimated value in García-Cicco et al. (2010) using the data of Argentina. In doing so, all of the other parameter values are fixed at their mean posterior estimates.

Figure 9 plots the responses to a one-standard-deviation positive stationary TFP shock. Following this shock, output, consumption, investment, and labor increase on impact and decline over time. Capital rises and falls gradually. A higher value for the debt elasticity parameter induces positive responses of the interest rate in the short-run, which flip sign in the medium-run. This in turn implies a significant amplification and propagation of the stationary productivity shock on output, consumption, investment, capital and labor, as the responses of these variables become much more persistent than that associated with a smaller ψ value. The impulse responses of external debt and trade balance to output ratio tend to be more volatile under a smaller ψ value, but their impacts on output and its component are spurned by the low debt elasticity parameter.

Figure 10 shows that following a one-standard-deviation positive nonstationary TFP shock, the impulse responses of the interest rate take opposite signs of that followed by a stationary TFP shock. When associated with a higher ψ value, the interest rate responses are negative in the short-run but become positive af-

[15]Unlike this study, the main focus of their work is to find evidence of agents' information rigidities, such as sticky information as in Mankiw and Reis (2002) or noisy information as in Lucas (1972) and Kydland and Prescott (1982).

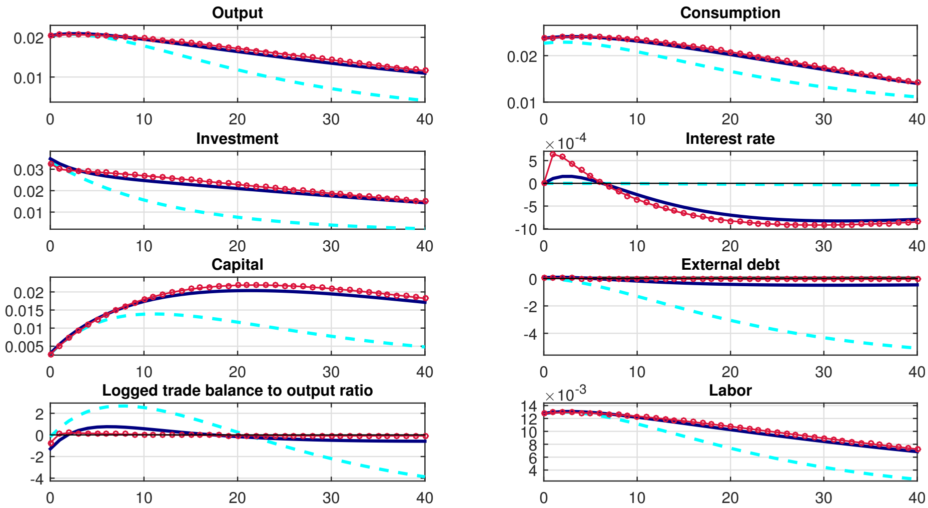

Figure 9: Impulse responses to a stationary TFP shock associated with different values for interest rate elasticity w.r.t. debt: $\psi = 0.001$ (dashed lines); $\psi = 0.26$ (solid lines); and $\psi = 2.8$ (solid lines with circles). Except for ψ, the mean values of posterior parameters are used to calculate the impulse responses. The x-axis is in quarters.

terward. This tendency suggests reversed implications of the financial friction on the model dynamics. It dampens the rise of output, consumption, investment and capital, and exacerbates the fall in labor followed by permanent productivity shocks. The responses of external debt and trade balance to output ratio are amplified under a lower value of the debt elasticity parameter.

Figure 11 demonstrates the impulse responses to a one-standard-deviation positive preference shock, which worsens the trade balance. Under the substantial degree of a financial friction, the interest rate rises gradually, while investment and capital fall significantly. This effect dominates the initial increase in consumption so that the preference shock has contractionary effects on output. Despite the more volatile responses of external debt and trade balance to output ratio associated with $\psi = 0.001$, there is a negligible impact of a preference shock on output, consumption, and investment.

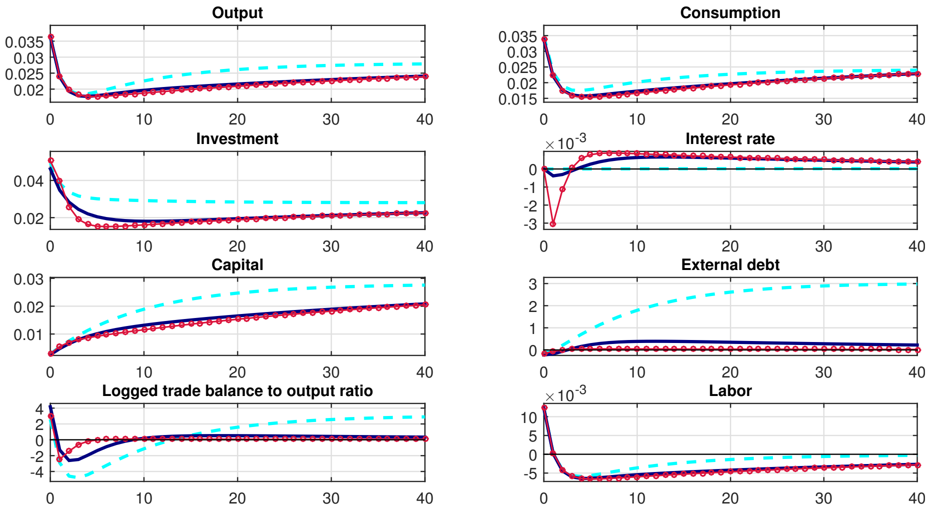

Figure 10: Impulse responses to a nonstationary TFP shock associated with different values for interest rate elasticity w.r.t. debt: $\psi = 0.001$ (dashed lines); $\psi = 0.26$ (solid lines); and $\psi = 2.8$ (solid lines with circles). Except for ψ, the mean values of posterior parameters are used to calculate the impulse responses. The x-axis is in quarters.

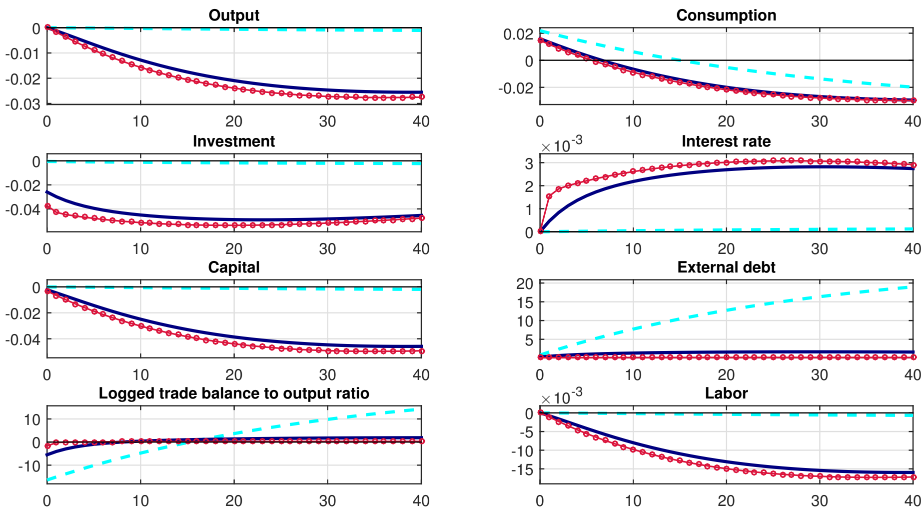

Figure 11: Impulse responses to a preference shock associated with different values for interest rate elasticity w.r.t. debt: $\psi = 0.001$ (dashed lines); $\psi = 0.26$ (solid lines); and $\psi = 2.8$ (solid lines with circles). Except for ψ, the mean values of posterior parameters are used to calculate the impulse responses. The x-axis is in quarters.

The responses to a one-standard-deviation positive country risk premium shock are depicted in Figure 12. A country premium shock raises the interest rate, having positive impacts on trade balance. The effects of the shock on the other variables hinge critically upon the magnitude of the debt elasticity parameter. The smaller the ψ value is, the larger the contractionary effect of the shock is. This is because the surge in the interest rate is more prolonged as the elasticity becomes smaller. Consequently, the country premium shock has almost no effect on output and consumption when associated with $\psi = 2.8$.

Overall, a higher value for the debt elasticity significantly amplifies and propagates the impacts of stationary productivity and preference shocks on output and investment. On the other hand, it dampens the expansionary effect of a nonstationary productivity shock and contractionary effect of a country risk premium shock on output and investment. Regardless of the type of shocks, the key transmission mechanism is associated with the interest rate movements. Higher ψ values enlarge the contractionary effects of a structural shock raising the interest rate, by which they intensify the surge in the interest rate. A sym-

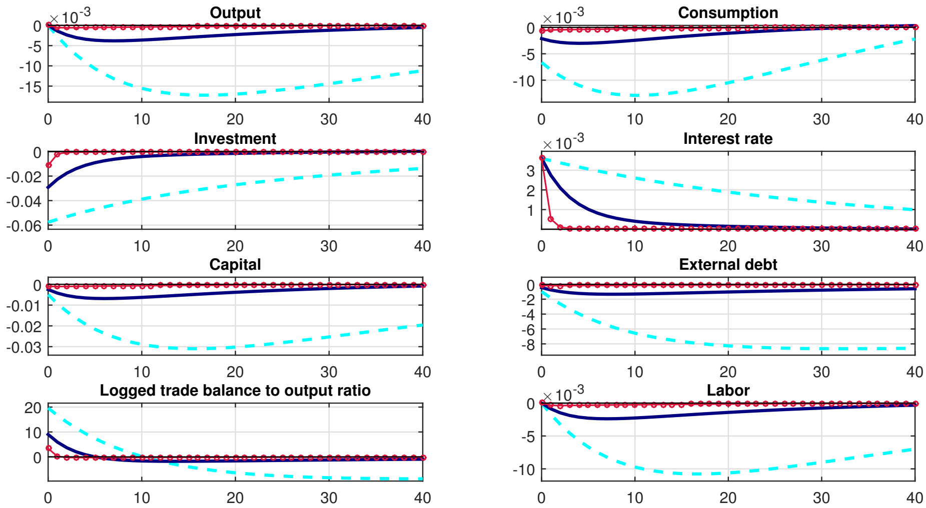

Figure 12: Impulse responses to a country risk premium shock associated with different values for interest rate elasticity w.r.t. debt: $\psi = 0.001$ (dashed lines); $\psi = 0.26$ (solid lines); and $\psi = 2.8$ (solid lines with circles). Except for ψ, the mean values of posterior parameters are used to calculate the impulse responses. The x-axis is in quarters.

metric argument is applicable to a shock lowering the interest rate, and thus has expansionary effects on output and investment.

7. CONCLUSION

This paper draws the business cycle implications of anticipated shocks in a small open economy RBC model estimated using data for Korea. The empirical results indicate that the contribution of news shocks to fluctuations in output, consumption, and investment is somewhat more limited than the U.S. evidence. Rather, the anticipated components of exogenous shocks play a critical role in the trade balance variability, which is more pronounced during and after the Asian currency crisis of the late 1990s.

The article has largely focused on news shocks in Schmitt-Grohé and Uribe (2012) as an alternative information structure. Other prominent information structures, which may have potential implications for business cycles for Korea, are not explored in this study. They are noisy information models in Lucas (1972) and Kydland and Prescott (1982), and sticky information models in Mankiw and Reis (2002). A comprehensive analysis nesting these alternative information flows is left for future research.

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APPENDIX A. MODEL DETAILS

A representative household derives utility from consumption C_t and disutility from labor h_t, and maximizes its utility function given by

$$E_0 \sum_{t=0}^{\infty} \nu_t \beta^t \frac{\left[C_t - \theta\omega^{-1} X_{t-1} h_t^{\omega}\right]^{1-\gamma} - 1}{1-\gamma} \tag{7}$$

where ν_t is a preference shock, β is the discount factor, θ is the labor coefficient, ω is the exponent of labor, and γ determines the intertemporal elasticity of substitution. X_t is a nonstationary productivity process defined by its growth rate, $g_t \equiv X_t / X_{t-1}$.

The representative household's choices are constrained by:

$$\frac{D_{t+1}}{1+r_t} = D_t - Y_t + C_t + S_t + I_t + \frac{\phi}{2}\left(\frac{K_{t+1}}{K_t} - g\right)^2 K_t \tag{8}$$

where D_{t+l} is the stock of debt acquired in period t and r_t is the domestic interest rate on bonds between t and t+1. Y_t, S_t, I_t, and K_t denote output, government spending, gross investment, and capital in period t, respectively. ϕ is the capital adjustment cost parameter and g denotes the steady-state growth rate of the nonstationary productivity process.

Households are assumed to own physical capital and control the size of the capital stock. The law of motion for capital is given by

$$K_{t+1} = (1-\delta)K_t + I_t \tag{9}$$

where δ denotes the depreciation rate.

The production technology takes the form

$$Y_t = a_t K_t^{\alpha} (X_t h_t)^{1-\alpha} \tag{10}$$

where a_t is a stationary productivity shock process.

The country premium is given by

$$r_t = r^* + \psi\left[\exp(\tilde{D}_{t+1}/X_t - \bar{d}) - 1\right] + \exp(\mu_t - 1) - 1 \tag{11}$$

where r^* is the world interest rate, $\tilde{D}_t$ is the aggregate level of external debt per capita, and $\bar{d}$ is the steady-state level of $\tilde{D}_t$. ψ is the parameter governing the debt elasticity of the interest rate and μ_t is a country premium shock.

The government consumes an exogenous and stochastic quantity of goods S_t. As in Schmitt-Grohé and Uribe (2012), I assume that government spending displays a stochastic trend given by X_t^S, which is cointegrated with the trend in output X_t. In order to allow for the possibility of a smoother trend of government spending than output, I further assume that

$$X_t^S = (X_{t-1}^S)^{\rho_{xs}}(X_{t-1})^{1-\rho_{xs}}$$

where the parameter ρ_{xs} governs the smoothness of the trend in government spending. The aggregate resource constraint is given by

$$C_t + I_t + S_t + tb_t = Y_t \tag{12}$$

where tb_t denotes the level of trade balance.

APPENDIX B. STEADY-STATE

The steady-state real interest rate is given by

$$r_{ss} = \frac{\bar{g}^{\gamma}}{\beta}$$

where the subscript 'ss' denotes the steady-state level of the variable.

Hours, capital, investment, output, government spending, consumption, logged trade balance to output ratio, and the marginal utility of wealth can be solved for jointly from the following system of equations:

$$\begin{aligned}
h_{ss} &= \left\{(1-\alpha)\bar{g}\left[\frac{\bar{g}^{\gamma}/\beta - 1 + \delta}{\alpha}\right]^{\alpha/(\alpha-1)}/\theta\right\}^{1/(\omega-1)} \\
k_{ss} &= \left[\frac{\bar{g}^{\gamma}/\beta - 1 + \delta}{\alpha}\right]^{1/(\alpha-1)}\bar{g}h_{ss} \\
i_{ss} &= (\bar{g} - 1 + \delta)k_{ss} \\
y_{ss} &= k_{ss}^{\alpha}(\bar{g}h_{ss})^{1-\alpha} \\
s_{ss} &= sy_{ss} \\
c_{ss} &= (\bar{g}/r_{ss} - 1)\bar{d} + y_{ss} - s_{ss} - i_{ss} \\
tby_{ss} &= \frac{y_{ss} - c_{ss} - s_{ss} - i_{ss}}{y_{ss}} \\
muc_{ss} &= \left(c_{ss} - \frac{\theta h_{ss}^{\omega}}{\omega}\right)^{-\gamma}
\end{aligned}$$

APPENDIX C. DATA

The model is estimated using Korean quarterly data from 1960:Q2 to 2014:Q4. Detailed data descriptions are as follows.

$$\begin{aligned}
\text{Output Growth} &= \log\left[\text{Real GDP Per Cap.}/\text{Real GDP Per Cap.}(-1)\right], \\
\text{Consumption Growth} &= \log\left[\text{Real Consumption Per Cap.}/\text{Real Consumption Per Cap.}(-1)\right], \\
\text{Investment Growth} &= \log\left[\text{Real Investment Per Cap.}/\text{Real Investment Per Cap.}(-1)\right], \\
\text{Govt. Spending Growth} &= \log\left[\text{Real Govt. Spending Per Cap.}/\text{Real Govt. Spending Per Cap.}(-1)\right], \\
\text{Trade Balance to Output Ratio} &= \text{Real Trade Balance}/\text{Real GDP Per Cap.}
\end{aligned}$$

where each per capita real variable is obtained by dividing the seasonally adjusted real variables by population. The real variables are drawn from the Bank of Korea's Economic Statistics System database (BOK-ECOS), and the population data is taken from the Korean Statistical Information Service (KOSIS). I use the annual population series with no transformation since a quarterly population measure is not available.

APPENDIX D. ESTIMATION PROCEDURE IN DETAIL

D.1. DETAILS OF STEP 3

The details of Step 3 is as follows. Suppose there are p_k randomly constructed blocks $(\Theta_{k,1},\ldots,\Theta_{k,p_k})$ that at the end of the $(k-1)$st MCMC iteration. Let $\Theta_{k,-l}$ denote the most current value of all the blocks except the lth. Then to construct the tailored proposal density for the block update $\Theta_{k,l}$ can be found by

$$\hat{\Theta}_{k,l} = \text{argmax}_{\Theta_{k,l}} \log\{f(y|\Theta_{k,l}\Theta_{k,-l}) \times \pi(\Theta)\}, \tag{13}$$

where f and π denote the data likelihood and the prior likelihood, respectively. In particular, the maximization procedure is conducted by the simulated annealing (SA) optimization method as in Chib and Ergashev (2009). I conduct a version of the SA algorithm proposed in Chib and Ramamurthy (2010). The first step for the SA is to set the number of stages, denoted by $q = 1,2,\ldots,Q$, with the length of each stage l_q given by $b + l_q$, where $b \in \mathbb{N}$ is the stage expansion factor. Then set the initial temperature t_0 which is held constant in each stage but reduced across states following the linear cooling schedule $t_q = at_{q-1}$, where $0 < a < 1$ is the cooling constant. Finally, set the critical value ε. In each stage, the SA searches and updates the maximum in (13) as follows:

SA procedure in detail

1. Search for the maximum by proposing values from a random walk process as

$$\Theta_m^{'} = \Theta_m + sN(0,I)$$

where Θ_m is a randomly chosen element of $\Theta_{k,l}$ and $s > 0$ is a suitable scale factor. Note that the proposed parameter values should be in $\Lambda_D \cap \Lambda_P$

2. Calculate the change in posterior log-likelihood due to the parameter updates in the previous step as

$$p = \exp\{\Delta\left[\log(f(y|\Theta_{k,l}\Theta_{k,-l}) \times \pi(\Theta)\right]/t\} < 1$$

3. Always accept the proposed parameters if $\Delta\left[\log(f(y|\Theta_{k,l}\Theta_{k,-l} \times \pi(\Theta))\right] > \varepsilon$. Otherwise, accept them based upon the rule that $p > U[0,1]$

Once $\hat{\Theta}_{k,l}$ is found as above, the next step is to calculate the curvature of the target posterior distribution of that block by the negative inverse of the Hessian:

$$V_{k,l} = \left(-\frac{\partial^2 \log\{f(y|\Theta_{k,l}\Theta_{k,-l}) \times \pi(\Theta)\}}{\partial\Theta_{k,l}\partial\Theta_{k,l}'}\right)^{-1}\Bigg|_{\Theta_{k,l}=\hat{\Theta}_{k,l}}$$

The proposal density $q_l(\Theta_{k,l}|\Theta_{k,-l},y)$ of $\Theta_{k,l}$ is then given by a multivariate t-distribution with $\nu > 2$ degrees of freedom as

$$q_l(\Theta_{k,l}|\Theta_{k,-l},y) = t(\Theta_{k,l}|\hat{\Theta}_{k,l},V_{k,l},\nu)$$

Then the last step for the TaRB-MH algorithm is to draw a proposal value $\Theta_{k,l}^{\dagger}$ from the proposal distribution given as a multivariate t-distribution. If the proposal value is not in $\Lambda_D \cap \Lambda_P$ the procedure rejects the value immediately. Otherwise, the proposed value is accepted as the new block value with the MH probability of move given by

$$\alpha_l(\Theta_{k,l},\Theta_{k,l}^{\dagger}|\Theta_{k,-l},y) = \min\left[\frac{f(y|\Theta_{k,l}^{\dagger},\Theta_{k,-l})\pi(\Theta_{k,l}^{\dagger})}{f(y|\Theta_{k,l},\Theta_{k,-l})\pi(\Theta_{k,l})}\frac{t(\Theta_{k,l}|\hat{\Theta}_{k,l},V_{k,l},\nu)}{t(\Theta_{k,l}^{\dagger}|\hat{\Theta}_{k,l},V_{k,l},\nu)},1\right]$$

If the proposed value is rejected, the current value of the block is retained as the new value of that block. Step 3 of the algorithm is completed by repeating these procedures for each block.

D.2. ESTIMATION SETUP FOR THE TARB-MH ALGORITHM

For the implementation of the algorithm, I employ the setting in Chib and Ramamurthy (2010) as follows; (1) the block updating probability is 0.15; (2) the linear cooling schedule AR(1) coefficient a is 0.4; (3) the initial temperature t_0 is 5; (4) the stage expansion factor b is 6; (5) the initial number of stages Q_0 is 10; (6) the inverse of the scale factor of the random walk update $1/s$ is 50; (7) the number of states Q is 4; and (8) the critical value ε is 1^{-5}.

APPENDIX E. ROBUSTNESS

This section reports the variance share of anticipated shocks for the two alternative model specifications. The first specification employs prior distributions identical to that of García-Cicco et al. (2010). Accordingly, the priors for the anticipate shock components are assumed to be the same as that of the unanticipated component. The second specification uses the discount factor $\beta = 0.99$, instead of $\beta = 0.98$, while the other model features are identical to the benchmark specification. Table 6 tabulates the results.

Specification	Output growth	Consumption growth	Investment growth	Govt spending growth	Trade balance to GDP ratio
Benchmark specification	0.15 [0.06, 0.27]	0.13 [0.08, 0.21]	0.31 [0.17, 0.44]	0.46 [0.03, 0.96]	0.65 [0.41, 0.81]
Priors identical to García-Cicco et al. (2010)	0.27 [0.16, 0.38]	0.15 [0.09, 0.23]	0.36 [0.25, 0.46]	0.74 [0.31, 0.95]	0.77 [0.59, 0.89]
Benchmark specification with $\beta = 0.99$	0.11 [0.04, 0.21]	0.11 [0.06, 0.17]	0.29 [0.15, 0.43]	0.20 [0.02, 0.83]	0.64 [0.38, 0.84]

Table 6: Variance share of anticipated shocks across different model specification. This table reports the mean and associated [5%, 95%] percentile intervals (in brackets).