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Research Article

A New Keynesian DSGE Model on Vietnamese Data

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Abstract. We consider New Keynesian DSGE model with Vietnamese data from January 2000 to April 2015. We study the impact of the preference shock, cost-push shock, technology shock and monetary policy shock to the movement in key macroeconomic variables such as the short-term nominal interest rate, the output gap, inflation, and especially output growth. Moreover, we evaluate how important the information from the DSGE model is by considering the ratio of artificial DSGE observations over actual observations. The comparison of the marginal likelihoods of the DSGE-VAR models with different sample sizes of the artificial data generated from the Ireland model provides the best-fitting value, which shows the information from the DSGE model is useful.

Keywords. Keynesian model; DSGE-VAR; Monetary policy shock; Technology shock; Cost-push shock; Preference shock

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1. Introduction

Throughout many crises from the past, the world has accepted the important role of macroeconomics analysis. Explaining dynamic behaviors of key macroeconomic variables has drawn a lot of interest from researchers. The first to introduce New Keynesian framework were Rotemberg and Woodford (1997). The New Keynesian model builds on the Real Business Cycle model. This model assumes that prices are set by monopolistically competitive firms. Another widespread assumption of this model is nominal rigidities, meaning that prices and wages are adjusted slowly. Working in spirit of Ireland (2004), we consider a New Keynesian model to find out the effects of shocks to some key macroeconomic variables. Our model consists of three equations: the log-linearization of an optimizing household's Euler equation, the optimizing behavior of monopolistically competitive firms, a monetary policy rule proposed by Taylor (1993). With these three equations, the model characterizes the dynamic behavior of three key macroeconomic variables: output growth, inflation, and the nominal interest rate.Then, we use Bayesian method to estimate parameters. To consider the fluctuation of macroeconomics when the shocks occur, we plot the impulse response functions. Moreover, we computes the variance decomposition to determine which key macroeconomics variable affected by shocks most.

As an effective tool for evaluating DSGE models, DSGE-VAR model has been developed by Del Negro and Schorfheide (2004) and Del Negro et al. (2006). We use this model for estimating the parameters in a VAR model in a Bayesian fashion with the prior selected as if artificial data were generated from a DSGE model. How important is the information from the DSGE model can be evaluated by changing the number of data generated from the DSGE model and comparing the fit to the actual data. Thus, we can gain intuition about how useful DSGE restrictions are in explaining the data.

The remaining of the paper is organized as follows. Section 2 proposes the log-linear approximation of the model. Section 3 explains the DSGE-VAR model and how it can be applied to the evaluation of DSGE models. Section 4 then uses the Vietnamese data from January 1995 to April 2015 to estimate the model's parameters. In this section, variance decomposition analysis is conducted to assess the role of the State Bank's monetary policy. We also evaluate the DSGE model for the Vietnam economy using the DSGE-VAR. The last section concludes by summarizing key results and highlighting their implications.

2. Log-Linearized DSGE Model

The model consists of a representative household, a continuum of intermediate-goods firms indexed by $i \in [0,1]$, a final-goods firm, and a central bank. During each period $t = 0,1,2,\ldots$, each intermediate-goods firm produces a differentiated intermediate good. Hence, intermediate goods may also be indexed by $i \in [0,1]$, where firm i produces good i. Intermediate-goods firms are able to set prices but they face a friction in doing so. In order to focus on the analysis in the activities of the representative intermediate-goods firm, the model is assumed to feature enough symmetry.

The log-linearized version of the model is given by

$$\left.\begin{aligned}
&\widetilde{o}_t = E_t\widetilde{o}_(t+1) - ((\widetilde{r}_t - E_t\widetilde{\pi}_(t+1)) + (1-w)(1-\rho_a)\widetilde{a}_t,\\
&\widetilde{\pi}_t = \beta_t E_t\widetilde{\pi}_(t+1) + \psi\widetilde{o}_t\widetilde{e}_t,\\
&\widetilde{g}_t = \widetilde{y}_t - \widetilde{y}_{t-1} + \widetilde{z}_t,\\
&\widetilde{o}_t = \widetilde{y}_t - w\widetilde{a}_t,\\
&\widetilde{r}_t - \widetilde{r}_{t-1} = \rho_\pi\widetilde{\pi}_t + \rho_g\widetilde{g}_t + \rho_o\widetilde{o}_t + \varepsilon_r t,\\
&\widetilde{a}_t = \rho_a\widetilde{a}_{t-1} + \varepsilon_a t,\\
&\widetilde{e}_t = \rho_e\widetilde{e}_{t-1} + \varepsilon_e t,\\
&\widetilde{z}_t = \varepsilon_z t.
\end{aligned}\right\} \tag{2.1}$$

for all $t = 0,1,2,\ldots$. For more details, see Ireland (2004).

3. DSGE-VAR Estimation

The DSGE-VAR estimation approach used in this paper follows the framework developed in Del Negro and Schorfheide (2004). For a given value of the DSGE model's parameters, and given realizations of the shocks, the DSGE model is simulated to generate artificial data. Adopting a DSGE model prior, in fact, is equivalent to augmenting the data with new, generated, dummy observations. The parameters of the VAR model are subsequently estimated using a sample merging the DSGE simulated data and real data. A key parameter, which will be denoted by λ, can be interpretedas the ratio of artificial DSGE observations over actual observations. If the process is repeated for different values of the DSGE parameters, and if the DSGE is covariance-stationary, a mapping can be defined between the VAR and DSGE parameters. The mapping creates a restriction function for the VAR parameters based on the DSGE model. If $\lambda \to 0$, the DSGE contains no useful information: the best fit is obtained when the artificial DSGE observations and, hence, their implied theoretical restrictions, are entirely ignored. If $\lambda \to \infty$, DSGE prior dummy observation dominate the sample. Therefore, the DSGE model provides a superior description of the data. The parameter λ, therefore, can measure the relative fit of the DSGE model to the VAR model.

In practice, λ will scale the standard deviation of the variance-covariance matrix of the priors for the VAR coefficients. The DSGE-VAR estimation considers all possible cases in the continuum between the VAR and the DSGE model. A small λ indicates that the VAR coefficient prior distributions are centered at the values consistent with DSGE restrictions, but they are extremely diffuse; a large λ indicates a prior that is more tightly centered around the DSGE restrictions (with a lower variance). By finding the best-fitting λ, we can gain intuition about how useful DSGE restrictions are in explaining the data.

To describe the procedure in more technical terms, let's start from a typical VAR model with p lags

$$y = \Phi_0 + \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t,$$

where y_t is an $n \times 1$ vector of endogenous variables and ε_t denotes the error term, distributed as $N(0, \Sigma_\varepsilon)$. The VAR can be rewritten as

$$Y = X\Phi + \Xi,$$

where Y is a $T \times n$ matrix with rows given by y_t', $t = 1, \dots, T, X$ is a $T \times k$ matrix, where $k = 1 + np$, and with rows $x_t' = [1, y_{t-1}', \dots, y_{t-p}']$, $\Phi = [\Phi_0, \Phi_1, \dots, \Phi_p]'$ and Ξ is a $T \times n$ matrix that has a rows ε_t'. The VAR likelihood function is, therefore, given by

$$p(Y|\Phi, \Sigma_\varepsilon) \propto |\Sigma_\varepsilon|^{-T/2} \exp\left\{-\left(\frac{1}{2}\right) tr[\Sigma_\varepsilon^{-1}(Y'Y - \Phi X'Y - Y'X\Phi + \Phi' X' X\Phi)]\right\}.$$

In a DSGE-VAR, the priors for the VAR coefficients Φ and Σ_ε, conditional on the DSGE parameter vector θ, are obtained as if a set of $T^* = \lambda T$ simulated data are generated from the DSGE model and combined with the actual observations T in the estimation. Therefore, the likelihood for the combined sample, including both the T^* artificially-generated observations from the DSGE model $(Y^*(\theta), X^*(\theta))$, and the actual T sample observations, can be computed by multiplying

$$p(Y^*(\theta)|\Phi,\Sigma_\varepsilon) \propto |\Sigma_\varepsilon|^{-\frac{\lambda T}{2}} \exp\left\{-\frac{1}{2} tr[\Sigma_\varepsilon^{-1}(Y^{*\prime})Y^* - \Phi' X^{*\prime})Y^* - Y^{*\prime})X^*\Phi + \Phi' X^{*\prime} X^*\Phi)]\right\}, \quad (3.1)$$

with $p(Y|\Phi,\Sigma_\varepsilon)$ as given by expression.

Instead of actually generating the artificial data set (Y^*, X^*) and using the sample moments $Y^{*\prime}Y^*, X^{*\prime}Y^*, Y^{*\prime}X^*, X^{*\prime}X^*$, however, if y_t is covariance stationary as implied by the DSGE model, we can replace them with the scaled population moments $\lambda T\Gamma^*_{yy}(\theta) = E_\theta[y_t y_t']$, $\lambda T\gamma^*_{yx}(\theta) = E_\theta[y_t x_t']$, $\lambda T\gamma^*_{xy}(\theta) = E_\theta[x_t y_t']$ and $\lambda T\gamma^*_{xx}(\theta) = E_\theta[x_t x_t']$.

Conditional on the DSGE parameter vector θ, such moments can be obtained analytically, substantially reducing the computational effort.

Thus, with the inclusion of an initial improper prior $p(\Phi,\Sigma_\varepsilon) \propto |\sigma_\varepsilon|^{\frac{(-(n+1)}{2}}$, equation (3.1)

$$p(\Phi,\Sigma_\varepsilon|\theta) = c^{-1}(\theta)|\Sigma_\varepsilon|^{\frac{-(\lambda T+n+1)}{2}} \exp\left\{-\left(\frac{1}{2}\right) tr[\lambda T\Sigma_\varepsilon^{-1}(\gamma^*_{yy}(\theta) - \Phi'\gamma^*_{xy}(\theta) - \gamma^*_{yx}(\theta)\Phi + \Phi'^{\gamma^*_{xx}(\theta)}\Phi)]\right\}, \quad (3.2)$$

where $c^{-1}(\theta)$ is a normalizing constant, obtained so that the density in (3.2) integrates to one. If $\lambda T \geq k+n$ and $\gamma_{xx}(\theta)$ is invertible, equation (3.2) is proper, and $c(\theta)$ is defined as

$$c(\theta) = (2\pi)^{\frac{nk}{2}} |\lambda T\gamma^*_{xx}(\theta)|^{\frac{-n}{2}} |\lambda T\Sigma^*_\varepsilon(\theta)|^{\frac{-(\lambda T-k)}{2}} 2^{\frac{-(\lambda T-k)}{2}} \pi^{\frac{n(n-1)}{4}} \prod_{i=1}^{n} \gamma(\lambda T - k + 1 - i)/2],$$

where $\gamma(.)$ indicates the Gamma function. Conditioning on the DSGE parameter θ, the prior distribution (3.2) for the VAR parameters belongs to the Normal-Inverse Wishart class

$$\Phi|\Sigma_\varepsilon,\theta,\lambda \sim N(\Phi^*(\theta), \Sigma_\varepsilon \otimes (\lambda T\gamma^*_{xx}(\theta))^{-1}), \quad (3.3)$$

$$\Sigma_\varepsilon|\theta,\lambda \sim IW(\lambda T\sigma^*_\varepsilon(\theta), \lambda T - k, n), \quad (3.4)$$

where $\Phi^*(\theta)\gamma^*_{xx}(\theta)^{-1}\gamma^*_{xy}(\theta)$ and $\sigma^*_\varepsilon(\theta) = \gamma^*_{yy}(\theta) - \gamma^*_{yx}(\theta)\gamma^*_{xx}(\theta)^{-1}\gamma^*_{xy}(\theta)$. In our procedure, we also define λ as a parameter to be estimated. Thus, our DSGE-VAR model is modified to include a prior for λ. The new prior, which is independent from θ, takes the form

$$p(\Phi,\Sigma_\varepsilon,\theta,\lambda) = p(\Phi,\Sigma|\theta,\lambda)p(\theta)p(\lambda)$$

The posterior distribution can be rewritten

$$p(\Phi,\sigma_\varepsilon,\theta|Y) = p(\Phi,\Sigma|Y,\theta)p(\theta,\lambda|Y). \quad (3.5)$$

We can find an expression for $p(\Phi,\Sigma_\varepsilon|Y,\theta)$. By noting that equations (3.3) and (3.4) define a conjugate prior for $p(\Phi,\Sigma_\varepsilon|Y,\theta)$, we see that the VAR posterior distribution $p(\Phi,\Sigma_\varepsilon|Y,\theta)$ is form the same family of distributions. Thus, the posterior distribution of Φ and Σ_ε are defined as

$$\Phi|Y,\Sigma_\varepsilon,\theta \sim N(\Phi \sim (\theta), \Sigma_\varepsilon \otimes (\lambda T\gamma^*_{xx}(\theta) + X'X)^{-1}),$$

$$\Sigma_\varepsilon|Y,\theta \sim IW((\lambda+1)T\widetilde{\Sigma}_\varepsilon(\theta), (1+\lambda)T - k, n),$$

where

$$\Phi \sim (\theta) = (\lambda T\Gamma^*_{xx}(\theta) + X'X)^{-1}(\lambda T\Gamma^*_{xy} + X'Y),$$

$$\widetilde{\Sigma}_\varepsilon(\theta) = 1/(\lambda+1)T[(\lambda T\Gamma^*_{yy}(\theta) + Y'Y) - (\lambda T\Gamma^*_{yx}(\theta) + Y'X)(\lambda T\Gamma^*_{xx}(\theta) + X'X)^{-1}(\lambda T\Gamma^*_{xy}(\theta) + X'Y)],$$

can be interpreted as Maximum Likelihood estimates of Φ and Σ_ε. The last term in equation (3.5), $(\theta,\lambda|Y)$, does not have a closed form solution, but we use a Random Walk Metropolis-Hastings algorithm, similar to the one described in Del Negro and Schorfheide (2004), to sample values of θ and λ from the posterior distribution.

4. Estimation Strategy and Results

We use Bayesian method to estimate the parameters of system that consists equations of 2.1. The econometric exercise uses monthly Vietnamese data running from January 2000 to April 2015. In these data, annualized monthly percent changes in seasonally-adjusted figures for real GDP serve to measure output growth. The linearized model consisting of equations of 2.1 has 14 parameters estimated: β, ψ, ω, α_o, α_π, ρ_a, ρ_ε, ρ_π, ρ_g, ρ_o, σ_a, σ_ε, σ_z and σ_r. In order to facilitate the estimation in Dynare, it is really necessary to declare priors by indicating the parameters' probability density function. Among parameters estimated, β can be determined via the formula $\beta = (\bar{\pi}\times\bar{z})/\bar{r}$, where $\bar{\pi}$, $\bar{z}$ and $\bar{r}$ are calibrated to the average inflation rate, average growth rate of real GDP, and average nominal interest rate in the data, respectively. Accordingly, the prior mean of β is set equal to 0.367 because the calibrated values of $\bar{\pi}$, $\bar{z}$ and $\bar{r}$ are 7.10 percent, 6.80 percent, and 13.17 percent, respectively. In the model, $1/(\xi-1)$ serves to measure the elasticity of labor supply. Thus, we propose calibrating the elasticity of labor supply to the ratio of labor force growth to real GDP growth. Accordingly, the calibrated elasticity of labor supply over the period is 0.3, resulting in the prior mean of ω of 0.23 since $\omega = 1/\xi$.

Parameter ψ has a gamma distribution with the range $[0,+\infty)$ because $\xi \geq 1$, $\Phi \geq \bar{\theta} \geq 1$. Declaration of the priors is presented in Table 1.

Table 1. Priors

Parameter	Probability density function	Range
β	Beta	$[0,1]$
ψ	Gamma	$[0,+\infty)$
ω	Beta	$[0,1]$
α_o	Beta	$[0,1]$
α_π	Beta	$[0,1]$
ρ_π	Normal	$\mathbb{R}$
ρ_g	Uniform	$[0,1]$
ρ_o	Uniform	$[0,1]$
ρ_a	Beta	$(0,1)$
σ_ε	Beta	$(0,1)$
σ_a	Inverse Gamma	$\mathbb{R}^+$
σ_ε	Inverse Gamma	$\mathbb{R}^+$
σ_z	Inverse Gamma	$\mathbb{R}^+$
σ_r	Inverse Gamma	$\mathbb{R}^+$

Table 2 shows the Bayesian estimates of the model's parameters together with their confidence intervals. The estimate of $\beta = 0.3628$ is smaller than the prior mean value of 0.367, meaning that the discounted factor is smaller than expected. Since ψ inversely depends on the costs of nominal price adjustment, the significant estimate of $\psi = 0.1017$ implies that the costs of nominal price adjustment are relatively large. It is interesting that this estimate of ψ is almost similar to the value set in Ireland (2004), which equals 0.1. As $\omega = 1/\xi$ by definition, this estimate of $\omega = 0.2334$ results in the estimate of $\xi = 4.2845$, which is relatively smaller than the estimate by Ireland (2004) for the US economy, meaning that Vietnamese labor supply is more elastic than the US labor supply. The estimates of $\alpha_o = 0.0409$ and $\alpha_\pi = 0.1613$ are statistically significant, meaning that backward-looking terms in the IS and Phillips curves are relevant. Furthermore, comparing α_o and α_π, indicates that the information on past inflation is much more important than the information on past output gap in influencing behaviors of firms and households. In contrast to the significance of α_o and α_π for Vietnam, Ireland (2004) found that the IS and Phillips curves for the US are purely forward looking. The estimates of parameters of the Taylor rule are all statistically significant, meaning that the State Bank of Vietnam has responded to movements in inflation, output growth, and the output gap. Furthermore, the fairly small estimate of $\rho_o = 0.0115$ indicates that the output gap as defined by the New Keynesian model has played less of a role in the policymaking process.

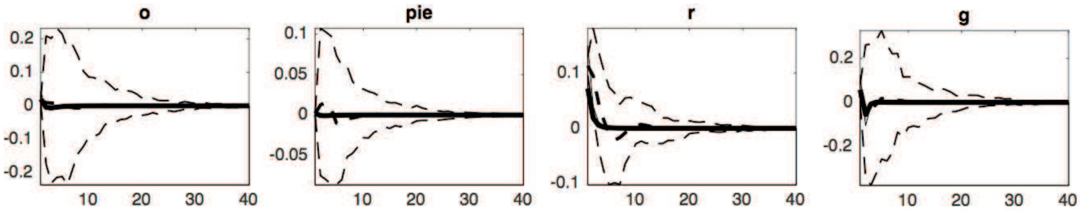
Table 2. Bayesian estimates and confidence intervals

Parameter	Estimate	Confidence interval
β	0.3628	[0.3479, 0.3770]
ψ	0.1017	[0.0855, 0.1149]
ω	0.2334	[0.3207, 0.3466]
α_o	0.0409	[0.0243, 0.0535]
α_π	0.1613	[0.1483, 0.1773]
ρ_π	1.3485	[1.1942, 1.5189]
ρ_g	0.2053	[0.1883, 0.2233]
ρ_o	0.0115	[0.0083, 0.0169]
ρ_a	0.8951	[0.7766, 0.9996]
ρ_ε	0.9119	[0.8068, 1.0000]
σ_a	0.1606	[0.1169, 0.2204]
σ_ε	6.0363	[5.0887, 6.0809]
σ_z	23.2983	[21.0954, 25.5082]
σ_r	1.0686	[1.0400, 1.0890]

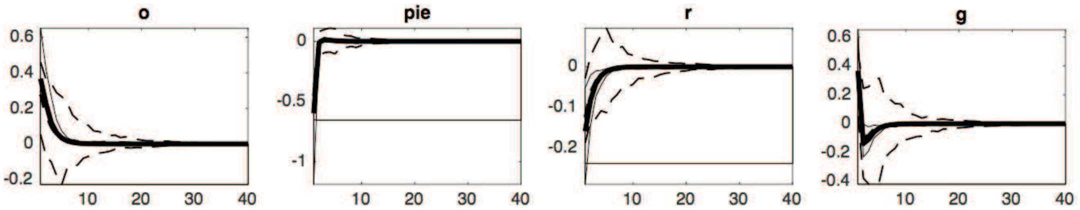
However, one notable thing is that the estimates of the Taylor rule's parameters are fairly small, implying that the State Bank of Vietnam has adopted the Taylor rule quite loosely throughout the period. The estimate of $\rho_\varepsilon = 0.9119$ implies that, like the technology shock, the cost-push shock is highly persistent. The estimate of $\rho_\alpha = 0.8951$ shows that the preference shock is less persistent than the cost-push and technology shocks. Finally, the estimates of

$\sigma_\alpha = 0.1606$, $\sigma_\varepsilon = 6.0363$, $\sigma_z = 23.2983$, and $\sigma_r = 1.0686$ are statistically significant, suggesting that the technology, cost-push and monetary policy shocks contribute in some way towards explaining movements in the data. However, the estimate of $\sigma_\alpha = 1.0606$ is relatively smaller than the other shocks, suggesting that the preference shock might have trivial importance in explaining movements in the data. This estimate also implies that, historically, the preference of Vietnamese households has been fairly stable.

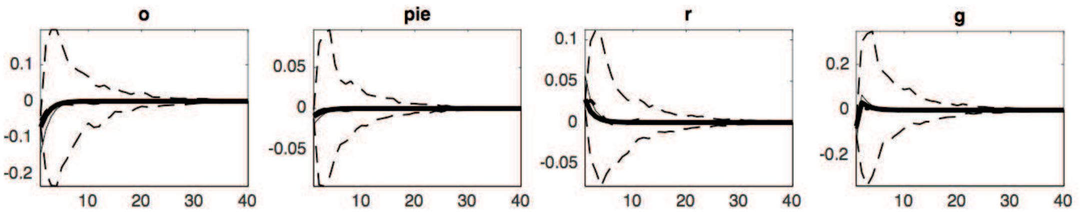
Thus, like in the real business cycle model, the technology shock continues to play an important role in the New Keynesian model. In addition, the cost-push, preference and monetary policy shocks also take on some importance. In order to have insight into the role of the shocks, impulse response and forecast error variance decomposition analysis will be conducted in the following part.



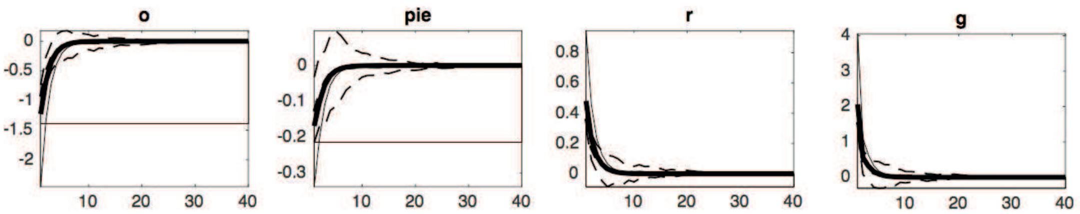
a) Preference shock



b) Cost-push shock



c) Technology shock



d) Monetary shock

Figure 1. Impulse responses.

There are several notable things about identifying the various shocks in the estimated New Keynesian model according to the impulse responses above. First, both the preference shock and the monetary shock work to increase the nominal interest rate. However, in the case of the preference shock, the increase in the interest rate occurs with the rise in output growth and inflation. In contrast, the monetary shock causes output growth and inflation to decline. Second, the (negative) cost-push shock and the technology shock both work to increase the rate of output growth and lower the inflation rate, but the (negative) cost-push shock leads to a fall in the nominal interest rate and leaves a positive output gap while the technology shock causes the nominal interest rate to increase and creates a negative output gap. Furthermore, the nature of the technology shock indicates that only it can have permanent impact on the level of output. Hence, the impulse response of output growth shows that the increase in output growth in response to a favorable technology shock is never reversed while the positive response of output growth that follows immediately from a negative cost-push shock must be offset later by a sustained period of slightly negative output growth.

In this estimated New Keynesian model, the impulse responses analysis above suggests that the technology shock continues to play the most important role in driving the fluctuations in output growth. In addition, Figure 1 shows that the cost-push shock generates the largest movements in inflation, the nominal interest rate and the output gap. The monetary policy shock also generates considerable changes in output growth and inflation. These findings are confirmed by decomposing the forecast error variances in output growth, inflation, the short-term nominal interest rate, and the output gap into components attributable to each of the four shocks.

The results of the variance decompositions are presented in Table 3, which shows that the technology shock plays the most important role in explaining the movements in output growth, accounting for about 69.08 percent of fluctuations in that variable across all forecast horizons. It is notable that the cost-push shock accounts for 92.97 percent, 85.55 percent and 84.49 percent of variations in the short-term nominal interest rate, the output gap and inflation, respectively. Approximately 12.30 percent of fluctuations in output growth and 5.90 percent of movements in inflation are attributed to the monetary policy shock. In this estimated New Keynesian model, the role of the preference shock in explaining the data is almost insignificant. We then estimate the ratio of artificial DSGE observations over actual observations, DSGE-VAR (λ) is 0.84. We calculate the logarithm of the marginal likelihood of DSGE-VAR (λ) for different values of λ. Moreover, it increases as λ moves from 0.31 to 0.84 and decreases as λ moves from 0.84 to ∞. On one hand, the substantial drop in marginal likelihood between $\lambda = 0.84$ and ∞ provides strong evidence of misspecification for the DSGE model. The rise in marginal likelihood between $\lambda = 0.31$ and 0.84 provides evidence that the information from the DSGE model is still useful.

Table 3. Forecast error variance decompositions.

Output growth				
Months ahead	Preference shock	Cost-push shock	Technology shock	Monetary shock
1	0.00	6.84	77.65	12.81
6	0.00	18.23	68.85	12.50
12	0.00	18.58	67.75	12.23
24	0.00	18.84	67.25	12.13
48	0.00	19.25	66.80	12.06
∞	0.01	19.51	66.23	12.04
Inflation				
Months ahead	Preference shock	Cost-push shock	Technology shock	Monetary shock
1	0.00	91.64	2.32	6.45
6	0.00	92.08	2.21	6.31
12	0.00	92.75	2.01	6.12
24	0.00	93.22	1.84	5.94
48	0.00	93.84	1.65	5.53
∞	0.01	94.30	1.49	5.02
Interest rate				
Months ahead	Preference shock	Cost-push shock	Technology shock	Monetary shock
1	0.00	50.52	15.64	55.21
6	0.00	85.42	3.21	12.85
12	0.00	90.21	1.01	6.24
24	0.00	95.68	0.86	2.23
48	0.00	98.41	0.54	0.84
∞	0.01	99.04	0.21	0.62
Output gap				
Months ahead	Preference shock	Cost-push shock	Technology shock	Monetary shock
1	0.00	40.74	18.54	60.04
6	0.00	84.62	4.03	13.35
12	0.00	89.21	1.34	7.48
24	0.00	95.22	1.01	3.95
48	0.00	98.10	0.66	1.44
∞	0.01	99.03	0.22	0.63

5. Concluding remarks

In this paper, we reproduce a New Keynesian model developed by preference, cost-push, and monetary policy shocks compete with the real business cycle's technology shock in generating aggregate fluctuations. The data is collected in Vietnam from 2000-2015. The empirical results described in detail above show that the cost-push shock is the major source of the fluctuations in the short-term nominal interest rate, inflation, and the output gap. Throughout, the technology shock is identified as the most important contributor to movements in output growth. Finally, we measure the relative fit of the DSGE model to the VAR model. The results show that this model is useful for determining the effects of shocks to many macroeconomics variables.

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