Journal of Scientific & Industrial Research
Vol. 79, March 2020, pp. 193-196

Estimating Optimal Military Spending Policy in DSGE Model: Empirical vs Theoretical Approach

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Received 20 October 2019; revised 16 November 2019; accepted 20 January 2020

Public spending on defense has become one of the most recent and complex research topics in macroeconomic policy analysis, which affects both economic growth and the welfare of society. Literature demands works that address the optimal calculation of military spending. This paper tries to respond to the estimation approach used to calculate military spending. Both a DSGE model (theoretical approach), a VAR model (empirical approach) and a DSGE-VAR model (combined approach) are developed. Our results indicate that the DSGE-VAR model offers the most robust estimates with minor deviations, closely followed by the DSGE model.

Keywords: Military spending, DSGE Model, DSGE-VAR, Macroeconomic policy

Introduction

Recently the importance of Dynamic Stochastic General Equilibrium (DSGE) models has increased due to their applications in the analysis of public policies and in the analysis of economic cycles[1,2,3]. These models are being evaluated by the result obtained in the standard deviation, in particular, the Marginal Data Density method, of Bayesian nature, typical of the DSGE models is applied. For its part, the effects and the appropriate level of public spending is a central issue in macroeconomics, as it is a recent line of research yet to be developed, and more specifically, defense spending[1]. Several studies have used both DSGE models and autoregressive vector (VAR) to analyze public spending on defense. Wu, Ho and Lin[1] reviewed military spending by using a DSGE-VAR approach, combining both theoretical and empirical methods. They conclude that future research, such as the exploration of an optimal policy of military spending, could take the empirical, theoretical approach and a combination of both to determine the best model. Muhanj and Ojah[2] related the level of public spending with the external debt of African countries, confirming a positive correlation between military spending and foreign debt for most countries in conflict. Lorusso and Pieroni[3] separated the components of public spending to analyze their effects on the US economy. Their model of Dynamic Stochastic General Balance Model (DSGE) includes civil and military expenses. In order to prove what type of model shows a better fit to analyze military spending policy, this paper develops the DSGE, DSGE-VAR and VAR models. Our results show a more robust estimate by the DSGE-VAR model, but for its part, the DSGE model shows a similar level of precision, a conclusion different from that shown in the previous literature[1,2,3]. These results can be very useful to continue developing this line of research with the right approach, as well as a better estimate of the level of optimal military spending that help policymakers and other related stakeholders.

Specifications

In this document, we have constructed a DSGE model to show the theoretical approach, a VAR model to specify an empirical approach and a DSGE-VAR model to represent a combined approach. A sample of

Table 1 — Log MDD Estimates

Model	MEAN(Log MDD)	STD(Log MDD)
	Prior Distribution	
DSGE	-1653.782	0.78
VAR	-1714.245	0.86
DSGE-VAR	-1622.737	0.72
	Posterior Distribution	
DSGE	-1580.264	0.54
VAR	-1624.375	0.57
DSGE-VAR	-1565.873	0.51

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Table 2 — Prior and Posterior Distribution

Parameter	Concept	Distribution	Prior Distribution Mean	Prior Distribution STD(Mean)	Posterior Distribution Mean	Posterior Distribution [0.05,0.95]	Posterior Distribution STD(Mean)
θ_H	Calvo price: domestic	Beta	0.5	0.15	0.53	[0.32, 0.68]	0.14
θ_F	Calvo importing price: domestic	Beta	0.5	0.15	0.55	[0.33, 0.67]	0.13
θ^*_H	Calvo price: foreign	Beta	0.75	0.15	0.73	[0.45, 0.98]	0.15
θ^*_F	Calvo importingprice: foreign	Beta	0.75	0.15	0.72	[0.41, 0.97]	0.16
τ	Relative risk aversion	Gamma	2	0.5	2.07	[1.62, 2.48]	0.51
h	Habit persistence	Beta	0.3	0.1	0.32	[0.14, 0.49]	0.11
α	Share of imported consumption	Beta	0.12	0.05	0.15	[0.04, 0.32]	0.06
η	Elasticity of Substitution, consumption	Gamma	1	0.5	0.98	[0.65, 1.22]	0.48
ψ_1	Domestic Taylor rule: inflation	Gamma	1.5	0.25	1.56	[1.31, 1.80]	0.24
ψ_2	Domestic Taylor rule: output	Gamma	0.5	0.25	0.53	[0.33, 0.78]	0.23
ψ^*_1	Foreign Taylor rule: inflation	Gamma	1.5	0.25	1.55	[1.24, 1.84]	0.26
ψ^*_2	Foreign Taylor rule: output	Gamma	0.5	0.25	0.56	[0.34, 0.79]	0.28
ψ^*_3	Foreign Taylor rule: exchange rate	Gamma	0.1	0.05	0.11	[0.04, 0.27]	0.07
α_g	Response to military spending	Normal	0	0.5	0.03	[0.00, 0.11]	0.47
α_m	Response to non-military spending	Normal	0	0.5	0.02	[0.00, 0.10]	0.48
ρ_A	Technology shock: domestic	Beta	0.8	0.1	0.7	[0.51, 0.95]	0.12
ρ_R	Interest rate smoothing: domestic	Beta	0.5	0.2	0.5	[0.31, 0.68]	0.18
ρ_G	Non-military spending	Beta	0.8	0.1	0.7	[0.56, 0.91]	0.07
ρ_M	Military spending	Beta	0.8	0.1	0.6	[0.43, 0.86]	0.1
ρ^*_A	Technology shock: foreign	Beta	0.6	0.2	0.8	[0.67, 1.03]	0.22
ρ^*_R	Interestratesmoothing: foreign	Beta	0.5	0.2	0.47	[0.28, 0.71]	0.17
ρ^*_G	ForeignGov. Expenditure	Beta	0.8	0.1	0.7	[0.52, 0.93]	0.13
ρ_z	Stationary world Technology	Beta	0.66	0.15	0.59	[0.33, 0.78]	0.12
$\rho\varsigma$	Preference shock: domestic	Beta	0.75	0.15	0.71	[0.52, 0.96]	0.15
$\rho\varsigma$	Preference shock: foreign	Beta	0.75	0.15	0.72	[0.53, 0.95]	0.14
$\rho_{\lambda H}$	Price markup shock: domestic	Beta	0.75	0.15	0.72	[0.51, 0.96]	0.16
$\rho^*_{\lambda H}$	Price markup shock: foreign	Beta	0.75	0.15	0.74	[0.54, 0.97]	0.13
r	Steady State of interest rate	Gamma	0.5	0.5	0.57	[0.34, 0.82]	0.47
γ	Steady State growth rate of $A_{W;t}$	Normal	0.4	0.2	0.44	[0.26, 0.67]	0.23
π	Steady State of inflation	Gamma	0.72	2	0.71	[0.49, 1.02]	1.92
σ_A	Technology shock: domestic	InvGamma	1	4	0.95	[0.66, 1.28]	4.07
σ_R	Monetary shock: domestic	InvGamma	0.4	4	0.46	[0.21, 0.88]	4.12
σ_G	Non-military spending shock	InvGamma	1	4	0.96	[0.67, 1.25]	4.01
σ_M	Military spending shock	InvGamma	1	4	0.94	[0.68, 1.24]	3.89
σ^*_A	Technology shock: foreign	InvGamma	0.4	4	0.47	[0.22, 0.73]	3.97
σ^*_R	Interestratesmoothing: foreign	InvGamma	0.2	4	0.22	[0.06, 0.71]	3.91
σ^*_G	ForeignGov. Expenditure	InvGamma	1	4	1.06	[0.72, 1.68]	4.05
σ_z	Stationary world Technology shock	InvGamma	0.5	4	0.54	[0.18, 0.92]	4.01
σ_C	Preference shock: domestic	InvGamma	0.4	4	0.42	[0.09, 0.86]	3.88
σ^*_C	Preference shock: foreign	InvGamma	0.4	4	0.43	[0.07, 0.89]	4.09
$\sigma_{\lambda H}$	Price markup shock: domestic	InvGamma	0.4	4	0.45	[0.08, 0.91]	4.14
$\sigma^*_{\lambda H}$	Price markup shock: foreign	InvGamma	0.4	4	0.41	[0.10, 0.85]	4.12
σ_e	Exchange rate shock	InvGamma	3.5	4	3.42	[2.83, 3.89]	3.92

data for the US economy has been prepared for the period 1985Q1-2017Q4. The DSGE model used is the one developed by Wu, Ho and Lin[1], where the difference between military and non-military spending is public expenditure. Finally, we apply the Bayesian Marginal Data Density (MDD) selection function with which the standard deviations (STD) of the different models applied are obtained.

DSGE Model

In the first place, it will be treated in the specifications to the United States as the domestic country, and the rest of the world, as the foreign country.In what follows, we define the specifications for households, domestic importing firms, the international dynamics, production firms, monetary policy, the resource constraint, and the foreign country. The specifications of DSGE model can be checked in the work of Wu, Ho and Lin[1]

DSGE-VAR Model

Let y_t^vdenote an $n_H \times 1$ vector consisting of endogenous variables for t = 1,…, T. The VAR is represented by:

$$y_t^v = c + B_1 y_{t-1}^v + \cdots + B_p y_{t-p}^v + u_t \quad \ldots (1)$$

where c is a set of deterministic terms; p denotes the VAR lag length [B_1; . . .; B_p] are parameter matrices; and u_t is a vector of forecast errors following the multivariate normal distribution N (0; $\sum_u$). Denote the vector consisting of VAR variables as:

$$y_t^{v'} 100\ [\Delta\log(M_t), \Delta\log(G_t), \Delta\log(C_t), \Delta\log(GDP_t), 4\Delta\log(P_t), R_t, \Delta\log(EX_t) \quad \ldots (2)$$

where M_t denotes per capital real military spending, *Gt* denotes per capita real non-military spending, C_t stands for per capita real consumption, GDP_t is the per capita real GDP, P_t implies the GDP deflator, Rt represents the federal funds rate adjusted at the annual rate, and *EXt* refers to the trade weighted nominal exchange rate in the United States. An increase in *Ext* implies that the U.S. dollar depreciates. Wu, Ho and Lin[1] expose in greater depth the mathematical development of this DSGE-VAR model.

Results and conclusion

For the construction of the model, US economy data have been used for the period 1985Q1-2017Q4, obtained from the Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis. On the other hand, for our estimations, we use a two four-core Intel Core I7-6500U and the code is made from MATLAB package (R2016b version). In addition to estimating the subsequent distribution, it is usual to estimate for the DSGE models the so-called Marginal Data Density (MDD)$(Y) = \int p(Y|\theta)P(\theta)d\theta$, since it provides a summary on the evidence contained in the results obtained by the model, becoming an essential indicator for the comparison of models and predictive analysis[1,4]. Table 1 shows the MDD estimates after the estimation of the models developed. These results demonstrate the greater stability offered by the DSGE-VAR model compared to the rest, especially in the light of the deviations obtained.

We estimate posterior moments con los tres modelos propuestos. We use the Metropolis algorithm to simulate the posterior distribution to assess the precision of the models, running these algorithms 10000 times and compute means and standard deviations of posterior moment estimates across runs. Table 2 shows the results of the estimates made by the different models with the prior distribution previously introduced and the subsequent distribution obtained in the estimate. Also included are a 5% confidence interval where the value of each estimated parameter fluctuates. For example, the standard deviation of the estimate of the mean for σe (the coefficient for the exchange rate shock) is 3.92. The average estimate of this coefficient is 3.42, while, for any estimate, the coefficient of this variable would yield an average value between 2.83 and3.89 within a 95% confidence level.

This study presents a comparative methodological approach to estimate optimal military spending. We demonstrate that the combined approach DSGE-VAR model is the strongest option than the other two versions of modeling most used in macroeconomics. Our results show a greater robustness of the DSGE-VAR model after a high number of simulations, this being a concern shown by the previous literature in the estimation of DSGE models. Finally, the precision shown by this approach implies an improvement in the optimization of the calculation of economic projections without using a large amount of available resources, nor having to make a broad specification of macroeconomic models, being of vital importance for public institutions and other stakeholders in macroeconomic policy.

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