

Evaluating the forecasting accuracy of the closed- and open economy medium-sized DSGE models

Phuong Van Nguyen

The University of Kiel

phuong.nguyen@economics.uni-kiel.de

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Overview

- 1 Introduction
- 2 Theoretical Model
- 3 Data and methodology
- 4 Estimation and result
- 5 Doing forecast and comparison
- 6 Why closed economy DSGE model outperforms open economy framework?
- 7 Conclusion

- In the existing literature, there is a huge number of studies on comparing the forecasting accuracy between the dynamic stochastic general equilibrium (DSGE) model and other conventional time series such as Vector Autoregression (VAR), Bayesian Vector Autoregression (BVAR), factor models etc
- **DSGE model versus VAR model**
- **DSGE model versus Bayesian VAR model**
- **DSGE model versus Factor model**

DSGE model versus VAR model

- The VAR model has been popularly used for both policy analysis and prediction.
- However, the main drawback of the unrestricted VAR is that we have to estimate many parameters and some of them might be **statistically insignificant**. Especially, the parameters of the unrestricted VAR model are imprecisely estimated with small sample.
- It results a fundamental issue such as *over-parameterization* which, in turn, worsens the forecast accuracy of this model.
- Smet and Woters (2004) [*Journal of Common Market Studies*], Adolfson et al.(2007b) [*Econometric Review*], Marcellino and Rychalovska (2014) [*Journal of Forecasting*]

DSGE model versus Bayesian VAR model

- **Case 1:** BVAR model does better the DSGE one.
- **Case 2:** DSGE model does better the BVAR model.

DSGE model versus Bayesian VAR model

- **Case 1: BVAR model does better the DSGE one**
- Theoretically, the DSGE model has **misspecification** but not in BVAR framework. Thus, the BVAR model does forecasting better than the DSGE one.
- Empirically, Gupta and Kabundi (2010) [*Journal of Forecasting*], Langcake and Robinson (2018) [*Applied Economics*].

- **Case 2: DSGE model does better the BVAR model**
- Theoretically, The BVAR model has higher estimation uncertainty than the DSGE model. Thus, DSGE model outperforms the BVAR framework.
- Empirically, Smet and Woters (2004) [*Journal of Common Market Studies*], Adolfson et al.(2007b) [*Econometric Review*], Marcellino and Rychalovska (2014) [*Journal of Forecasting*]

DSGE model versus Factor model

- still in controversial

- The quality of prediction from closed- and open economy DSGE models, however, has not been studied carefully yet.
- **Research Question: Which model, closed- or open economy DSGE model, will perform forecasting better? or these two models do forecasting equally?**
- Adolfson et al. (2008)[Macroeconomic Dynamic]: *"It is not clear what can be expected from this comparison a priori"*.

- **Case 1:** *closed-economy DSGE model may outperform open-economy one.*
- **Case 2:** *open economy DSGE model may outperform closed-economy setting.*
- **Case 3:** *two models may perform forecast equally.*

Case 1: closed-economy DSGE model may outperform open-economy one

- Open-economy DSGE model has two following consequences: *model misspecification* and *estimation uncertainty*.
- Misspecification is related to the fact that the open economy DSGE model may be wrongly specified. For example, a wrong prior is one of problems about model misspecification.
- On the other hand, number of parameter is naturally greater in open economy DSGE model. Therefore, it has higher estimation uncertainty.
- In practise, in order to detect which is a main problem, model misspecification or estimation uncertainty, that impacts the result of forecast, the BVAR model would be applied.

Case 2: open economy DSGE model may outperform closed-economy setting

- In the modern economy, there are hundreds of time series variables available. For example, Federal Reserve Bank of ST. Louis provides a huge store of data .
- In addition, new generation of computer has significantly revolutd.
- Thus, in doing forecast, macroeconomists would incorporate as much information as possible.
- If it is well modeled, larger model can beat smaller one in terms of forecasting performance.
- Banura (2010) [*Journal of Applied Econometrics*], Gupta and Kabundi (2010) [*International Journal of Forecasting*] provide empirical evidence that large-sized Bayesian VAR performs forecast better than smaller one.

Case 3: two models may perform forecast equally

- A well-known paper Justiniano and Preston (2010) [*Journal of International Economics*] reveals that DSGE model fails to capture the effect of foreign disturbances on fluctuations in domestic variables.
- Engel (2014) [*Handbook of International Economics, volume 4*], Gourinchas and Rey (2014) [*Handbook of International Economics, volume 4*] indicates that the open economy DSGE model fails to explain the fluctuations in exchange rate and trade balances. Therefore, it delines the effect of foreign sector on domestic varibales.
- adding foreign sector into closed economy DSGE model may not improve the quality of forecast. As a result, two DSGE setting forecasting-based tools perform equally.

- **There are two papers related to this field**
- Adolfson et al. (2008) [Macroeconomic Dynamic]
- Kolasa and Rubaszek (2018) [International Journal of Forecasting]

Differences from these two papers

- In comparison with Adolfson et al. (2008) [*Macroeconomic Dynamic*], they do not reveal whether the differences in RMSEs are statistically significant. To address this issue, thus, in this paper I use the two-tailed Diebold-Mario test.
- Furthermore, Adolfson et al. (2008) [*Macroeconomic Dynamic*] do not give some intuitive explanations for difference in prediction between closed- and open economy DSGE models. In this paper, however, I shows two potential factors which worsen the forecasting accuracy of DSGE model such as *misspecification* and *estimation uncertainty*.

Differences from these two papers

- In comparison with Kolasa and Rubaszek (2018) [*International Journal of Forecasting*], they only evaluate the forecasting accuracy of DSGE model for three domestic variables such as output, interest rate and inflation. In addition, the DSGE model is still simple and relatively small.
- On the other hand, in this paper, I evaluate the forecasting accuracy of a medium-sized DSGE model. Accordingly, the forecasting evaluation are conducted based on seven key domestic variables such as output, real wage, consumption, investment, interest rate, employment and inflation.

- **Open economy DSGE model:** In this paper, I use the open-economy medium-sized DSGE model of Adolfson et al.(2007a) [*Journal of International Economics*] . However, for simplicity, in this paper I exclude government sector. Therefore, the open-economy DSGE model has 4 main blocks. They are firms, households, central bank, and an exogenously foreign economy. In open economy DSGE model, there are 67 log-linearized equations and 50 parameters to be estimated with the Bayesian techniques

- **Closed-economy DSGE model:** 34 linearized equations and 22 parameters related to foreign sector will be shutted down. Consequently, in closed economy DSGE version there are 33 log-linearized equations and 28 model parameters. Also note that, closed-economy DSGE framework uses 7 domestic macroeconomics observed variables rather than 14 ones in open-economy setting to estimate model parameters

Data and methodology

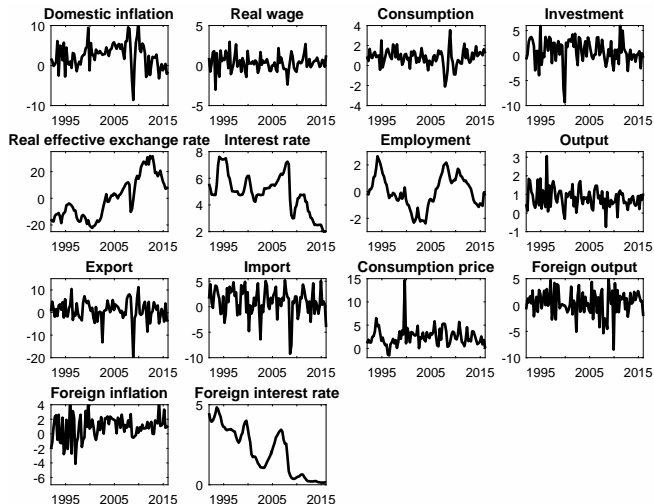


Figure 1: The quarterly Australian data for the period of 1993Q1 to 2016Q1

- Adolfson et al.(2007a) [*Journal of International Economics*] use 15 European macroeconomic observed variables to estimate parameters in open economy DSGE model. In this paper, however, there are 14 Australian macroeconomic observed variables. Thus, in order to make sure that there is no identification problem, an identification test is conducted.

- To compare the quality of forecast, firstly I estimate closed- and open economy DSGE models separately by moving window. The forecasting horizon runs from 1 to 12 quarter horizons for each window.
- Furthermore, there are 92 observations in full sample size and each subsample accounts for 60 observations. As a result, there are 21 windows in total which are re-estimated quarterly. Then the out-of-sample forecast is generated.

- Based on two studies Adolfson et al. (2007a) [*Journal of International Economics*,] and Jaaskela and Nimark (2011) [*Economic Record*] 15 parameters will be calibrated such as discount rate, Labour supply elasticity, real cash holding elasticity etc [See more the text]

Calibration

Order	Parameters	Description	Calibrated from
1	β 0.999	Discount rate	Jääskelä and Nimark (2011)
2	σ_L 1	Labour supply elasticity	Adolfson et al. (2007a)
3	σ_q 10.62	Real cash holding elasticity	Adolfson et al. (2007a)
4	σ_a 0.049	Capital utilisation cost parameter	Adolfson et al. (2007a)
5	ν 1	Fraction of wage bill paid in advance	Adolfson et al. (2007a)
6	δ 0.013	Depreciation rate	Jääskelä and Nimark (2011)
7	α 0.25	Share of capital in production function	Rees et al. (2016)
8	λ_w 1.05	Wage mark up	Adolfson et al. (2007a)
9	ω_c 0.2	Fraction imported cons. goods in bundle	Jääskelä and Nimark (2011)
10	ω_i 0.5	Fraction imported inv. goods in bundle	Jääskelä and Nimark (2011)
11	μ 1.01	The money growth	Jääskelä and Nimark (2011)
12	A_L 7.5	Labour disutility parameter	Adolfson et al. (2007a)
13	A_q 0.380	Cash in utility function parameter	Adolfson et al. (2007a)
14	η_c 0.885	Elas. of subst. betw. for. and dos. goods	Justiniano and Preston (2010b)
15	ρ_{π^c} 0.975	Persistent param. inflation target	Adolfson et al. (2007a)

- **50 parameters** will be estimated in open economy framework, whereas **22 parameters** will be estimated in closed economy one.
- There are three distributions to be used as prior densities of estimated parameters such as beta, normal and inverse gamma.
- Beta distribution is applied to parameters which are located between 0 and 1. Meanwhile, normal distribution is used for parameters ranging from $-\infty$ to $+\infty$. On the other hand, inverse gamma describes positive parameters.

Prior distribution

Prior distribution					
Order	Parameters			type	mean std.dev
1	Calvo wage	ξ_w	beta	0.675	0.050
2	Calvo domestic price	ξ_d	beta	0.675	0.050
3	Calvo import cons.price	ξ_{me}	beta	0.675	0.050
4	Calvo import invs.price	ξ_{mi}	beta	0.675	0.050
5	Calvo export .price	ξ_x	beta	0.675	0.050
6	Calvo employment	ξ_e	beta	0.675	0.050
7	Indexation wages	κ_w	beta	0.500	0.150
8	Indexation domestic price	κ_d	beta	0.500	0.150
9	Indexation import cons. price	κ_{me}	beta	0.500	0.150
10	Indexation import invs. price	κ_{mi}	beta	0.500	0.150
11	Indexation export price	κ_x	beta	0.500	0.150
12	Markup domestic	λ^d	normal	1.200	0.050
13	Markup import cons.	λ^{me}	normal	1.200	0.050
14	Markup import invs.	λ^{mi}	normal	1.200	0.050
15	Investment adjustment cost	S''	normal	7.694	1.5
16	Habit formation	b	beta	0.650	0.100
17	Subst. elasticity invest	η_i	inv.gamma	1.500	inf
18	Subst. elasticity foreign	η_f	inv.gamma	1.500	inf
19	Technology growth	μ_z	normal	1.0060	0.0005
20	Risk premium	ϕ	inv.gamma	0.010	inf
21	Stationary tech.shock	ρ_{π}	beta	0.850	0.100
22	Unit root tech.shock	ρ_{μ_z}	beta	0.850	0.100
23	Investment specific tech.shock	ρ_{ε}	beta	0.850	0.100
24	Asymmetric tech.shock	ρ_{z*}	beta	0.850	0.100

Prior distribution

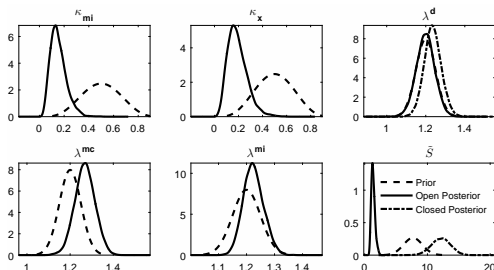
Order	Parameters	Prior distribution			
		type	mean	std.dev	
25	Consumption preference shock	ρ_{ζ_c}	beta	0.850	0.100
26	Labor supply shock	ρ_{ζ_h}	beta	0.850	0.100
27	Risk premium shock	ρ_ϕ	beta	0.850	0.100
28	Domestic markup shock	ρ_{λ^d}	beta	0.850	0.100
29	Imp. cons. markup shock	$\rho_{\lambda^{mc}}$	beta	0.850	0.100
30	Imp. invs. markup shock	$\rho_{\lambda^{mi}}$	beta	0.850	0.100
31	Export markup shock	ρ_{λ^e}	beta	0.850	0.100
32	Unit root tech.shock	σ_μ	inv.gamma	0.200	inf
33	Stationary tech.shock	σ_ϵ	inv.gamma	0.700	inf
34	Invest.spec.tech.shock	σ_Υ	inv.gamma	0.200	inf
35	Asymmetric tech.shock	σ_{z^*}	inv.gamma	0.400	inf
36	Consumption preference shock	σ_{ζ^c}	inv.gamma	0.200	inf
37	Labor supply shock	σ_{ζ^h}	inv.gamma	1.000	inf
38	Risk premium shock	σ_ϕ	inv.gamma	0.050	inf
39	Domestic markup shock	σ_{λ^d}	inv.gamma	1.000	inf
40	Imp. cons.markup shock	$\sigma_{\lambda^{mc}}$	inv.gamma	1.000	inf
41	Invs. cons.markup shock	$\sigma_{\lambda^{mi}}$	inv.gamma	1.000	inf
42	Export markup shock	σ_{λ^e}	inv.gamma	1.000	inf
43	Monetary shock	σ_R	inv.gamma	0.150	inf
44	Inflation target shock	σ_{π^c}	inv.gamma	0.050	inf
45	Interest rate smoothing	ρ_R	beta	0.800	0.050
46	Inflation response	r_π	normal	1.800	0.100
47	Diff.inflation response	$r_{\Delta\pi}$	normal	0.300	0.050
48	Real exch. rate response	r_x	normal	0.010	0.050
49	Output respond	r_y	normal	0.125	0.050
50	Diff. output respond	$r_{\Delta y}$	normal	0.0625	0.050

Estimation procedure

- Using the **DYNARE Toolkit 4.4.3** . Estimation setting:
- Number of MCMC is 250,000 draws and number of burn-in accounts for 45 % of number of draws.
- The Metropolist-Hasting jump scales are chosen to target the reiection rate of around 1/3. For example, 0.26 is chosen in estimating open economy DSGE model and 0.38 in estimating closed economy setting.
- Convergence diagnostic test is then applied as the method of Geweke (1992) [*Staff Report 148, Federal Reserve Bank of Minneapolis*] . Accordingly, there is no convergence problem.

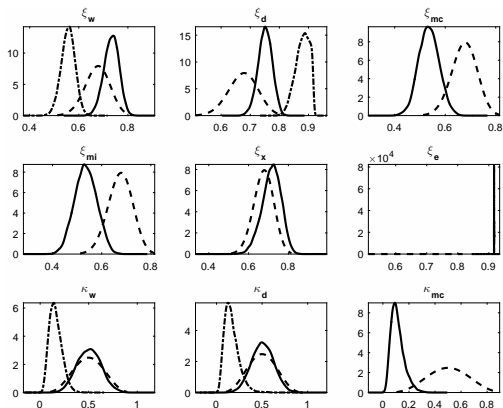
Prior and posterior distribution

Figure 3: Prior and posterior distribution



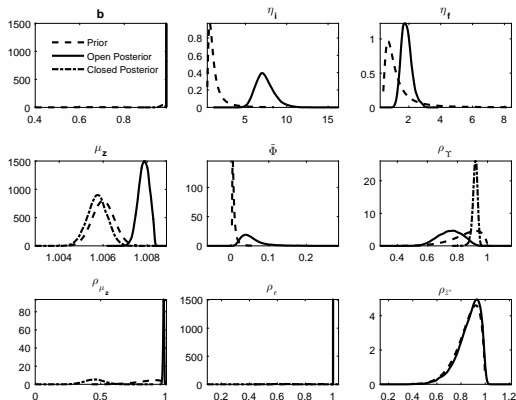
Prior and posterior distribution

Figure 4: Prior and posterior distribution



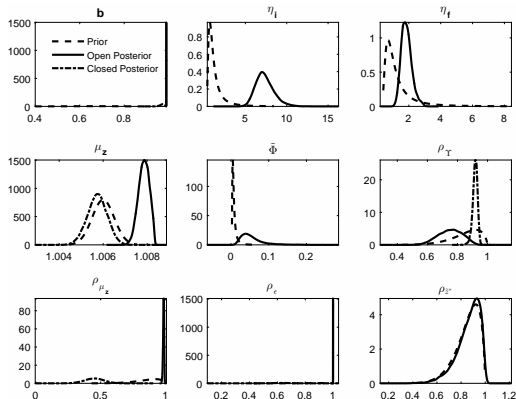
Prior and posterior distribution

Figure 5: Prior and posterior distribution



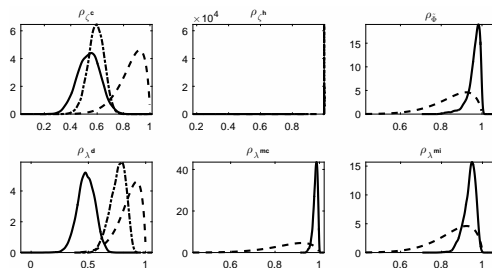
Prior and posterior distribution

Figure 6: Prior and posterior distribution



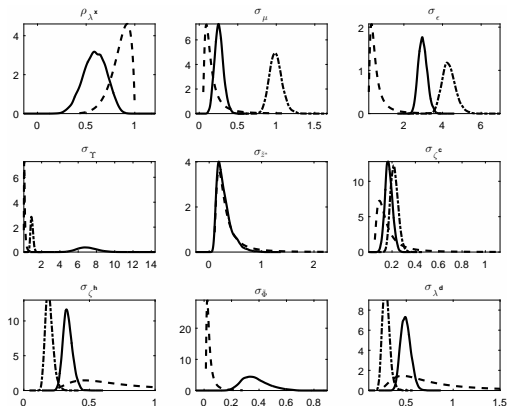
Prior and posterior distribution

Figure 7: Prior and posterior distribution



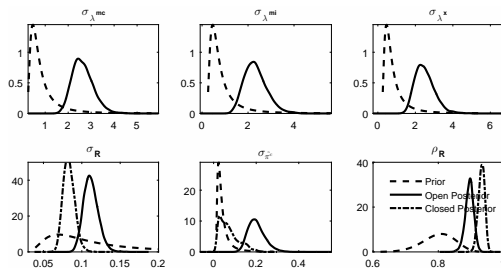
Prior and posterior distribution

Figure 8: Prior and posterior distribution



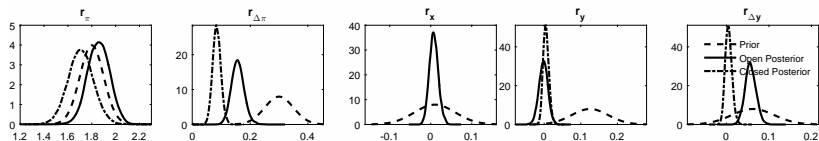
Prior and posterior distribution

Figure 9: Prior and posterior distribution



Prior and posterior distribution

Figure 10: Prior and posterior distribution



- Data is very informative in estimating parameters in both settings. In open economy DSGE model, however, data is uninformative in estimating 5 parameters: wage indexation κ_w , domestic price indexation κ_d , domestic markup λ_d , persistent parameters of asymmetric technology shock ρ_{z*} , standard deviation of asymmetric technology shock σ_{z*} .

Prior and posterior distribution

Table 15: Prior and posterior densities

Order	Parameters	Prior distribution			Full sample posterior distribution				Geweke (1992) convergence test	
		type	mean	std.dev	open economy mean	open economy std.dev	closed economy mean	closed economy std.dev	open economy (p-value)	closed economy (p-value)
1	Calvo wage	ξ_w beta	0.675	0.050	0.7323	0.0300	0.5550	0.0280	0.8210*	0.6610*
2	Calvo domestic price	ξ_d beta	0.675	0.050	0.7500	0.0240	0.8790	0.0240	0.1820*	0.049***
3	Calvo import cons.price	ξ_{me} beta	0.675	0.050	0.5330	0.0400			0.1300*	
4	Calvo import invs.price	ξ_{mi} beta	0.675	0.050	0.5660	0.0440			0.1290*	
5	Calvo export .price	ξ_x beta	0.675	0.050	0.7140	0.0480			0.7980*	
6	Calvo employment	ξ_e beta	0.675	0.050	0.9000	0.0080	0.9170	0.0000	0.2660*	0.0150***
7	Indexation wages	κ_w beta	0.500	0.150	0.5050	0.1210	0.1570	0.0620	0.284*	0.4990*
8	Indexation domestic price	κ_d beta	0.500	0.150	0.5030	0.1180	0.1630	0.0790	0.7320*	0.2690*
9	Indexation import cons. price	κ_{me} beta	0.500	0.150	0.1120	0.0500			0.8820*	
10	Indexation import invs. price	κ_{mi} beta	0.500	0.150	0.1550	0.0650			0.6870*	
11	Indexation export price	κ_x beta	0.500	0.150	0.1880	0.0790			0.7140*	
12	Markup domestic	λ^d normal	1.200	0.050	1.1970	0.0460	1.2350	0.0440	0.2760*	0.4540*
13	Markup import cons.	λ^{me} normal	1.200	0.050	1.2660	0.0470			0.3380*	
14	Markup import invs.	λ^{mi} normal	1.200	0.050	1.2250	0.0360			0.4210*	
15	Investment adjustment cost	S^n normal	7.694	1.5	1.3330	0.2880	12.135	1.5000	0.8780*	0.2590*
16	Habit formation	b beta	0.650	0.100	0.9890	0.0000	0.9700	0.0100	0.1240*	0.9530*
17	Subst. elasticity invest	η_i inv.gamma	1.500	inf	7.3510	1.1480			0.0920**	
18	Subst. elasticity foreign	η_f inv.gamma	1.500	inf	1.8560	0.3160			0.3500*	
19	Technology growth	μ_z normal	1.0060	0.0005	1.0080	0.0000	1.0060	0.0000	0.3680*	0.4640*
20	Risk premium	ϕ inv.gamma	0.010	inf	0.0540	0.0280			0.6850*	
21	Stationary tech.shock	ρ_T beta	0.850	0.100	0.7540	0.0790	0.9170	0.0160	0.1560*	0.5610*
22	Unit root tech.shock	ρ_{μ_z} beta	0.850	0.100	0.9840	0.0040	0.4480	0.0750	0.0820**	0.4870*
23	Investment specific tech.shock	ρ_ε beta	0.850	0.100	0.9990	0.0000	0.6220	0.0690	0.0130***	0.3420*
24	Asymmetric tech.shock	ρ_{z*} beta	0.850	0.100	0.8550	0.1000			0.8870*	

Prior and posterior distribution

Table 17: Prior and posterior densities

Order	Parameters	Prior distribution			Full sample posterior distribution				Geweke (1992) convergence test		
		type	mean	std.dev	open economy		closed economy		open economy	closed economy	
					mean	std.dev	mean	std.dev			(p-value)
25	Consumption preference shock	ρ_c	beta	0.850	0.100	0.5360	0.0850	0.5890	0.0610	0.5890*	0.4280*
26	Labor supply shock	ρ_h	beta	0.850	0.100	0.5600	0.0600	0.9990	0.0000	0.5970*	0.0110***
27	Risk premium shock	ρ_ϕ	beta	0.850	0.100	0.9610	0.0310			0.4050*	
28	Domestic markup shock	$\rho_{\lambda d}$	beta	0.850	0.100	0.4790	0.0750	0.7590	0.0660	0.4320*	0.0240***
29	Imp. cons. markup shock	$\rho_{\lambda mc}$	beta	0.850	0.100	0.9820	0.0110			0.8540*	
30	Imp. invs. markup shock	$\rho_{\lambda mi}$	beta	0.850	0.100	0.9350	0.0300			0.6900*	
31	Export markup shock	$\rho_{\lambda x}$	beta	0.850	0.100	0.5890	0.1210			0.5860*	
32	Unit root tech.shock	σ_μ	inv.gamma	0.200	inf	0.2550	0.0560	0.9930	0.0820	0.5730*	0.0480***
33	Stationary tech.shock	σ_ϵ	inv.gamma	0.700	inf	2.9790	0.2280	4.3230	0.3450	0.3770*	0.2830*
34	Invest.spec.tech.shock	σ_T	inv.gamma	0.200	inf	6.9460	1.0580	0.9250	0.1440	0.1590*	0.6970*
35	Asymmetric tech.shock	σ_{z*}	inv.gamma	0.400	inf	0.2820	0.1390			0.6540*	
36	Consumption preference shock	$\sigma_{\zeta c}$	inv.gamma	0.200	inf	0.1720	0.0310	0.2200	0.0340	0.7990*	0.9790*
37	Labor supply shock	$\sigma_{\zeta h}$	inv.gamma	1.000	inf	0.3340	0.0350	0.1940	0.0300	0.8080*	0.7790*
38	Risk premium shock	σ_ϕ	inv.gamma	0.050	inf	0.3710	0.0880			0.2180*	
39	Domestic markup shock	$\sigma_{\lambda d}$	inv.gamma	1.000	inf	0.4970	0.0540	0.2830	0.0370	0.9540*	0.5100*
40	Imp. cons.markup shock	$\sigma_{\lambda mc}$	inv.gamma	1.000	inf	2.6610	0.4640			0.0690**	
41	Invs. cons.markup shock	$\sigma_{\lambda mi}$	inv.gamma	1.000	inf	2.3140	0.4820			0.1250*	
42	Export markup shock	$\sigma_{\lambda x}$	inv.gamma	1.000	inf	2.4850	0.5170			0.6510*	
43	Monetary shock	σ_R	inv.gamma	0.150	inf	0.1110	0.0100	0.0830	0.0080	0.1270*	0.3260*
44	Inflation target shock	σ_{π^e}	inv.gamma	0.050	inf	0.2010	0.0390	0.0730	0.0470	0.0530**	
45	Interest rate smoothing	ρ_R	beta	0.800	0.050	0.8950	0.0130	0.9320	0.0100	0.0480*	0.0640**
46	Inflation response	r_π	normal	1.800	0.100	1.8550	0.0920	1.7050	0.1040	0.3290*	0.3860*
47	Diff.inflation response	$r_{\Delta\pi}$	normal	0.300	0.050	0.1560	0.0220	0.0830	0.0140	0.0910**	0.4710*
48	Real exch. rate response	r_x	normal	0.010	0.050	0.0070	0.0110			0.8110*	
49	Output respond	r_y	normal	0.125	0.050	-0.0020	0.0120	0.0050	0.0080	0.1360*	0.2840*
50	Diff. output respond	$r_{\Delta y}$	normal	0.0625	0.050	0.0570	0.0130	-0.0330	0.0090	0.1320*	0.6020*
Log data density						-2473.1311		-1163.0036			

Difference in estimation result

- There are some fundamental differences between the estimated parameters in two settings.
- Nominal friction in terms of Calvo wage ξ_w is smaller in closed economy setting. On the other hand, Calvo domestic price ξ_d and Calvo employment ξ_e are bigger in closed economy model.
- Regarding to nominal frictions such as wage and domestic price indexations are significantly smaller in closed economy setting.

Difference in estimation result

- Real frictions in terms of investment adjustment cost is considerably bigger in closed economy model. They are 1.3330 and 12.135 for open and closed economy versions, respectively. Meanwhile, the estimated habit formation is 0.97 in closed economy which is slightly smaller than that of 0.989 in open economy.
- The estimated persistent parameters in structural shocks are bigger in closed economy exception for non-stationary and investment specific technology shocks.

Difference in estimation result

- In terms of log data densities, they are -2473.1311 for open economy model and -1163.0036 for closed economy model. It implies that closed economy DSGE model provides a better description of the seven domestic variables.
- Thus, it is fair to say that adding six observed variables does not help better description of data. Moreover, it results some fundamental differences in estimating parameters in between closed- and open economy DSGE models.
- These fundamental differences may influence the forecasting ability of two models.

Doing forecast and comparison

- To compare the forecasting accuracy of closed and open economy DSGE models, simply I use the rolling window technique.
- Accordingly, each window has a sample size of 60 observations and does forecast up to the 12-quarter horizons.
- Thus, 21 windows in total are needed to re-estimate quarterly.

Root Mean Square Errors (RMSEs)

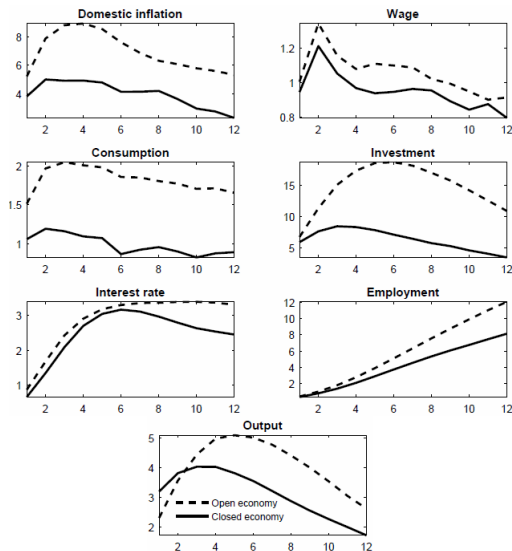


Figure 2: Root Mean Square Error generated from DSGE model

Doing forecast and comparison

- The blank line shows RMSE generated from closed economy DSGE mode and the dash line represents RMSE generated from open economy DSGE setting.
- Accordingly, it is clear that dash line lies above black line for seven key domestic variables at almost forecasting horizons.
- It implies that the quality of forecast generated from open economy DSGE model is poorer than that with closed-economy DSGE setting.
- The two-tailed Diebold-Mario test is then conducted.

The two-tailed Diebold-Mario test

Table 1: The relative RMSE of open-economy to closed-economy DSGE model

Horizon quarters	Relative root mean squared errors						
	Domestic inflation	Real wage	Consumption	Investment	Interest rate	Employment	Output
1	1.3744*	1.0631	1.4330*	1.1392**	1.3097*	1.1854**	0.7207**
2	1.5808*	1.1079	1.6545*	1.4811*	1.2431*	1.2681*	0.9345
3	1.8014*	1.0988	1.7698*	1.7821*	1.1614**	1.3164*	1.1031
4	1.8219*	1.1142***	1.8419*	2.0811*	1.0757	1.3344*	1.2380*
5	1.7929*	1.1820**	1.8550*	2.3619*	1.0440	1.3502*	1.3351*
6	1.8482*	1.1610**	2.1541*	2.6195*	1.0416	1.3709*	1.4148*
7	1.6669*	1.1291***	2.0160*	2.8021*	1.0781	1.3950*	1.4879*
8	1.5102*	1.0701	1.8953*	2.9431*	1.1335**	1.4185*	1.5382*
9	1.6844*	1.1138***	1.9780*	2.9711*	1.2107*	1.4440*	1.5699*
10	1.9722*	1.1247**	2.0818*	3.0738*	1.2859*	1.4688*	1.5644*
11	2.0511*	1.0293	1.9630*	3.0744*	1.3257*	1.4805*	1.5305*
12	2.3388*	1.1487**	1.8653*	3.1218*	1.3458*	1.4839*	1.5287*

Notes: The values in the table reveal the relative RMSE of open economy DSGE model to closed-economy DSGE one. These values below unity suggests that forecast from open economy DSGE framework are more accurate than from closed-economy DSGE one. On the other hand, these values above unity implies that forecast from open economy DSGE framework are worse than from closed-economy DSGE one. Meanwhile, these values are slightly different from unity, it concludes that forecast from both closed- and open-economy BVAR models are equally accurate. Asterisks ***, **, and * represent the 1%, 5 %, and 10 % significant levels of the two-tailed Diebold-Mario test, respectively.

The two-tailed Diebold-Mario test

- almost the relative RMSE values are greater than unity. It suggests that closed economy DSGE model does forecasting better than open economy framework.
- This finding is identical to analysis by using plot above. Moreover, the two-tailed Diebold-Mario test confirms that almost these RMSE values are statistically significant at least 5 %.

DSGE model vs BVAR model

- There exists a fundamental difference in prior setting between these two models.
- For instance, priors on parameters in DSGE model strongly depends on theory. On the other hand, priors on parameters in BVAR model only depends on statistic.
- Thus, misspecification is not big problem in the BVAR model but in DSGE framework. As a result, BVAR model can be used to detect misspecification or uncertainty which worsens the forecasting ability of DSGE model.

Root Means Square Errors (RMSEs)

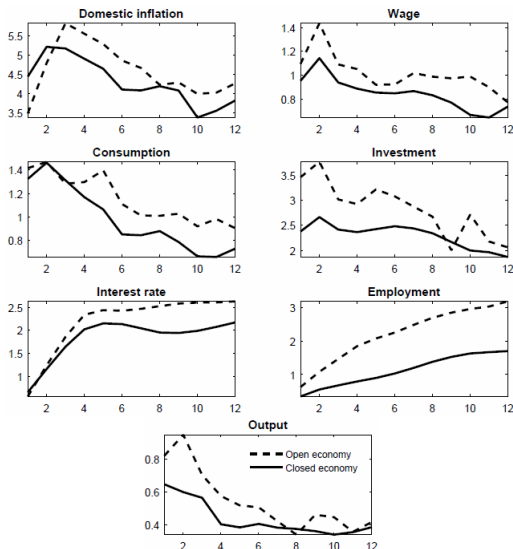


Figure 3: Root Mean Square Error generated from BVAR model

the two-tailed Diebold-Mario test

Table 3: The relative RMSE of open-economy to closed-economy BVAR model

Horizon quarters	Relative root mean squared errors						
	Domestic inflation	Real wage	Consumption	Investment	Interest rate	Employment	Output
1	0.7840**	1.1488***	1.0687	1.4552*	0.8617	1.8263*	1.2719**
2	0.9192	1.2563**	1.0047	1.4130*	1.0686	1.9673*	1.5871*
3	1.1271***	1.1612***	0.9778	1.2488**	1.1295***	2.1757*	1.2481***
4	1.1326**	1.1848**	1.1094	1.2360**	1.1566***	2.3376*	1.4320*
5	1.1384**	1.0762	1.3114**	1.3261**	1.1343***	2.3207*	1.3518**
6	1.1839**	1.0881	1.3021**	1.2400**	1.1357***	2.1904*	1.2525* *
7	1.1437**	1.1734***	1.1991***	1.1783***	1.2071**	2.0769*	1.1027
8	1.0078	1.1871***	1.1479**	1.1409***	1.2936**	1.9557**	0.9048
9	1.0516	1.2642**	1.3050**	0.9243	1.3290**	1.8691*	1.2796**
10	1.1823**	1.4807*	1.3816**	1.3580**	1.3096**	1.8171*	1.3161**
11	1.1327***	1.3926**	1.4888*	1.1086	1.2569**	1.8196*	1.0053
12	1.1165***	1.0472	1.2376**	1.1024	1.2113**	1.8768*	1.0814

Notes: The values in the table reveal the relative RMSE of open economy BVAR model to closed-economy BVAR one. These values below unity suggests that forecast from open economy BVAR framework are more accurate than from closed-economy BVAR one. On the other hand, these values above unity implies that forecast from open economy BVAR framework are worse than from closed-economy BVAR one. Meanwhile, these values are slightly different from unity, it concludes that forecast from both closed- and open-economy BVAR models are equally accurate. Asterisks ***, **, and * represent the 1%, 5 %, and 10 % significant levels of the two-tailed Diebold-Mario test, respectively.

- **Estimation uncertainty** is main reason which worsens the forecasting ability of open economy DSGE model.
- Eventhough this paper use the open-economy medium-sized DSGE model of Adolfson et al. (2007a) [*Journal of International Economics*] which is different from Kolasa and Rubaszek (2018) [*International Journal of Forecasting*], my finding is in line with them

Thank you for listening