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Economic Research Department
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Abstract

This paper evaluates the forecasting performance of several small open economy DSGE models relative to a closed economy benchmark using a long span of data for Australia, Canada and the United Kingdom. We find that opening the model economy usually does not improve, and even deteriorates the quality of point and density forecasts for key domestic variables. We show that this result can be to a large extent attributed to an increase in forecast error due to a more sophisticated structure of the extended setup which is not compensated by better model specification. This claim is based on a Monte Carlo experiment, in which an open economy model fails to consistently beat its closed economy benchmark even if the former is the true data generating process.

JEL: D58, E17, F41, F47

Keywords: Forecasting, DSGE models, New Open Economy Macroeconomics, Bayesian estimation

1 Introduction

Estimated dynamic stochastic general equilibrium (DSGE) models are currently a benchmark tool used around the world for policy analysis and forecasting, especially in central banks and international financial institutions. Arguably, one of the key drivers behind this trend has been the growing evidence that DSGE model-based forecasts can be competitive with predictions obtained from flexible time series models such as vector autoregressions (VAR) or elaborated by experts (see Del Negro and Schorfheide, 2012, for a survey). It should be emphasized, however, that the vast majority of studies evaluating the forecasting performance of DSGE models focus on the US and assume a closed economy set-up. The evaluation of the New Open Macroeconomics (NOEM) framework originating from Obstfeld and Rogoff (1995) is scarce and usually based on a relatively short forecast evaluation sample. The earliest contributions to this literature are Bergin (2003, 2006), who tests the in-sample performance of small open economy DSGE models for Australia, Canada and the United Kingdom, and of a two-country model for the US and G7. To our knowledge, the only studies that look at the quality of out-of-sample forecasts from NOEM models are: Adolfson et al. (2007a) and Christoffel et al. (2010) for the euro area, Lees et al. (2007) for New Zealand, Adolfson et al. (2008) for Sweden, Gupta and Kabundi (2010) and Alpanda et al. (2011) for South Africa, and Marcellino and Rychalovska (2014) for Luxemburg.

In all of these papers the common practice is to compare forecasts generated with a NOEM framework to those obtained with some variants of Bayesian VARs. The overall finding is that open economy DSGE models are quite competitive, even though the conclusions differ by variables and countries. However, these studies are silent about how much we really gain by accounting for an external block in DSGE models, and in particular whether it is essential to include it to have better forecasts for the domestic economy.

We claim that this question is very relevant, at least for the following reasons. First of all, if the only objective is to produce accurate forecasts, the use of a NOEM model might not be cost efficient when its predictions are not competitive in comparison to a closed economy benchmark. Second, a check like this may be an important test of the empirical success of the NOEM framework. Actually, there are reasons to be skeptical. In the influential paper of Justiniano and Preston (2010a) it is demonstrated that an estimated small open economy DSGE model fails to account for the substantial influence of foreign shocks on domestic variables that can be identified in many reduced-form studies. The authors show that capturing the observed co-movement between domestic and foreign macroindicators generates counterfactual implications for international competitiveness variables: the real exchange rate and the terms of trade. This model misspecification may significantly affect the quality of forecasts. It is also well-known that NOEM models have difficulty in explaining swings in nominal exchange rates and current account balances (Engel, 2014; Gourinchas and Rey, 2014), which might distort the indirect impact of foreign variables on the domestic economy. On the other hand, in a recent work Ca' Zorzi et al. (2017) show that real exchange rate forecasts (in contrast to nominal exchange rates) obtained from an open economy DSGE model are competitive in comparison to the random walk.

In this paper we address the above dilemma by evaluating the forecasting performance of a state-of-the-art NOEM model developed by Justiniano and Preston (2010b) relative to its associated New Keynesian (NK) closed economy benchmark. We focus on the forecast accuracy for three key domestic macrovariables showing up in all models: output, consumer prices and the short-term interest rate. As regards the NOEM framework, we consider several variants that differ by the subset of open economy variables used in estimation, which are divided into two groups: (i) international competitiveness variables (the real exchange rate, terms of trade and current account balance) and (ii) foreign economy variables (output, inflation and interest rates abroad). Our conclusions are based on evidence from three economies, i.e. Australia, Canada and the United Kingdom, for which we can collect quarterly data that go back as far as 1975. This allows us to choose the evaluation sample that is much larger when compared to the previous studies.

The main results of our forecasting contest indicate that opening the economy is not crucial for out-of-sample performance of DSGE models. When we consider the richest NOEM model, its point and density forecasts for domestic variables are statistically indistinguishable from, and in many cases even significantly less accurate than, those produced by the closed-economy benchmark. The alternative NOEM model variant, which leaves foreign economy variables unobservable, does not perform better. In contrast, the NOEM model that treats the international competitiveness variables as latent allows for some improvement in the accuracy of forecasts. We interpret this result as an indication that the competitiveness block of the DSGE model is misspecified.

We further explore if the unsatisfactory forecasting performance of the NOEM framework can be attributed just to model misspecification, or maybe also is related to the fact that bigger models are subject to larger estimation error. For that purpose, we perform a similar forecasting competition using Bayesian VARs and find that expanding model dimension to include open economy variables also does not lead to any systematic improvement in the quality of forecasts for domestic output, prices and the interest rates. Finally, we conduct a Monte Carlo experiment in which we show that the largest NOEM model fails to consistently beat the closed-economy DSGE benchmark even if the former is the true data generating process and the prior is correctly specified. This would suggest that, even if the NOEM framework is the correct model, a strategy to ignore the external sector while using DSGE models to forecast domestic variables is warranted. The reason is that an increase in the forecast error attributed to estimation due to opening the standard NK setup is large enough to roughly offset the potential gains arising from a better specification and correct priors. This, combined with the misspecification of the international competitiveness channel, explains why NOEM models are not successful in forecasting domestic variables.

The rest of this paper is structured as follows. Section 2 presents the benchmark NOEM model and its closed economy counterpart. Section 3 discusses the links between the foreign sector and domestic variables implied by the theory underlying the NOEM model structure. Section 4 describes the data and estimation issues. The design of our forecasting test, as well as its main results for Australia, Canada and the United Kingdom, are presented in section 5. In section 6 we use a Monte Carlo experiment to investigate deeper why the NOEM models fail in the forecasting contest. The last section concludes.

2 Models

2.1 Full NOEM model

The full NOEM model is based on the setup proposed by Justiniano and Preston (2010b), which is a generalization of the simple small open economy framework of Gali and Monacelli (2005). In this model households maximize their utility over consumption and labor, which is the only input to production. The consumption good is a composite of varieties produced domestically and imported from abroad. Both domestic producers and importers operate in a monopolistically competitive environment and set their prices in a staggered fashion. The monetary authority sets the nominal interest rate according to a generalized Taylor rule. The foreign economy is modelled as exogenous to the domestic economy.

The model includes a number of nominal and real rigidities that are usually considered in the empirical DSGE literature (Christiano et al., 2005; Smets and Wouters, 2007), also in the open economy context (Adolfson et al., 2007a). There are habits in consumption and prices of non-optimizing firms are partially indexed to past inflation. Imports are priced in the local currency, which allows for short-run deviations from the law of one price. International financial markets are assumed to be incomplete. While the recent financial crisis has highlighted the role of financial factors in driving the business cycle, the existing approaches to incorporate them in DSGE models do not result in an improvement in the accuracy of macroeconomic predictions (Kolasa and Rubaszek, 2015). Therefore, we decided not to include this type of extensions in our benchmark model.

The model's stochastic structure is also fairly rich as it includes shocks to productivity, import markups, household preferences, international risk premium, the current account balance and monetary policy, as well as disturbances driving foreign output, inflation and the interest rate. Note that household preference shocks can be interpreted as exogenous disturbances to a spread between the policy and market interest rates.

A detailed description of the problems faced by agents populating the model economy can be found in the source paper by Justiniano and Preston (2010b). Below we only present the full set of linearized equations characterizing the equilibrium. In what follows, all variables are expressed as log-deviations (or simple deviations in the case of variables that can be negative) from the non-stochastic steady state. We also use the standard notation to indicate foreign variables with an asterisk.

Household optimization leads to the following Euler equation

$$c_t = \frac{1}{1+h}\mathbb{E}_t c_{t+1} + \frac{h}{1+h}c_{t-1} - \frac{1-h}{\sigma(1+h)}(i_t - \mathbb{E}_t\pi_{t+1} - g_t + \mathbb{E}_t g_{t+1}) \tag{1}$$

in which c_t denotes consumption, i_t is the nominal interest rate, g_t stands for a preference shock, h describes the degree of external habits and σ represents the inverse of the intertemporal elasticity of substitution. CPI inflation π_t is defined as a weighted average of domestically produced and imported goods inflation rates $\pi_{H,t}$ and $\pi_{F,t}$

$$\pi_t = (1-\alpha)\pi_{H,t} + \alpha\pi_{F,t} \tag{2}$$

where α is the share of imports in domestic demand.

The market clearing condition can be written as

$$y_t = (1-\alpha)c_t + \alpha y_t^* + \alpha\eta(s_t + q_t) \tag{3}$$

where y_t denotes output, q_t is the (CPI-based) real exchange rate, η denotes the elasticity of substitution between domestic and foreign goods, and s_t is the terms of trade defined as the price ratio of imports and goods produced domestically so that

$$s_t = s_{t-1} + \pi_{F,t} - \pi_{H,t}. \tag{4}$$

The Phillips curves for prices of domestic and imported goods are

$$\pi_{H,t} = \frac{\beta}{1+\beta\delta_H}\mathbb{E}_t\pi_{H,t+1} + \frac{\delta_H}{1+\beta\delta_H}\pi_{H,t-1} + \frac{(1-\theta_H)(1-\beta\theta_H)}{\theta_H(1+\beta\delta_H)}mc_t \tag{5}$$

$$\pi_{F,t} = \frac{\beta}{1+\beta\delta_F}\mathbb{E}_t\pi_{F,t+1} + \frac{\delta_F}{1+\beta\delta_F}\pi_{F,t-1} + \frac{(1-\theta_F)(1-\beta\theta_F)}{\theta_F(1+\beta\delta_F)}(q_t - (1-\alpha)s_t) + cp_t \tag{6}$$

where θ_H and θ_F are the Calvo probabilities, δ_H and δ_F denote the degree of indexation to past inflation, β is households' subjective discount factor and cp_t is a cost-push shock in the import sector. Domestic marginal cost mc_t is given by

$$mc_t = \varphi y_t - (1+\varphi)z_t + \alpha s_t + \frac{\sigma}{1-h}(c_t - hc_{t-1}) \tag{7}$$

where z_t denotes a productivity shock and φ stands for the inverse of the Frisch elasticity of labor supply.

The dynamics of the real exchange rate is governed by the uncovered interest rate parity (UIP) extended for a risk premium

$$(i_t - E_t\pi_{t+1}) - (i_t^* - E_t\pi_{t+1}^*) = \mathbb{E}_t q_{t+1} - q_t - \chi a_t - \phi_t \tag{8}$$

where ϕ_t is a risk premium shock and χ is the risk premium elasticity with respect to a_t, defined as the ratio of net foreign assets to steady state output. The law of motion for a_t is

$$a_t = a_{t-1} + ca_t \tag{9}$$

where the current account balance (also expressed relative to steady state output) is defined as

$$ca_t = y_t - c_t - \alpha(q_t - \alpha s_t) + (\beta^{-1} - 1)a_{t-1} + f_t \tag{10}$$

and f_t is a shock to the current account balance that captures other international financial flows.[1]

The interest rate set by the monetary authority is assumed to follow

$$i_t = \rho_i i_{t-1} + (1-\rho_i)(\psi_\pi \pi_t + \psi_y y_t + \psi_{\Delta y}(y_t - y_{t-1}) + \psi_e(q_t - q_{t-1} - \pi_t^* + \pi_t)) + m_t \tag{11}$$

where m_t is a monetary policy shock, ρ_i is the degree of interest rate smoothing while ψ_π, ψ_y, $\psi_{\Delta y}$ and ψ_e describe how the policy rate reacts to, respectively, inflation, output, output growth and change in the nominal exchange rate.

The shock processes are modelled as simple first-order autoregressions (z_t, g_t, cp_t, ϕ_t and f_t), white noise (m_t), or are jointly determined within a vector autoregression with two lags (π_t^*, y_t^* and i_t^*). The innovations to shocks are assumed to be normally distributed.

[1] The presence of this shock is our only extension to the Justiniano and Preston (2010b) model. It allows us to use the current account balance as an additional observable variable while estimating the largest NOEM model variant.

2.2 Model variants

The full NOEM model described above, which we dub JP+ as it is a (minor) extension of the original Justiniano and Preston (2010b) setup, features nine exogenous shocks. We estimate it using nine observable variables: domestic output $\tilde{y}_t$, inflation $\tilde{\pi}_t$, and the interest rate $\tilde{i}_t$, foreign counterparts of these variables $\tilde{y}_t^*$, $\tilde{\pi}_t^*$ and $\tilde{i}_t^*$, as well as the real exchange rate q_t, the terms of trade $\tilde{s}_t$, and the current account balance $\tilde{ca}_t$.

Additionally, we consider the following four variants, each nested in JP+. The first one leaves out the current account shock f_t so that the model is identical to that developed by Justiniano and Preston (2010b), and hence we call it JP. To keep the number of observables not greater than the number of shocks, we exclude the terms of trade from the set of observed variables.

To understand the reasons for choosing this variable as the one to be dropped, let us combine equations (10) and (3) to obtain

$$s_t = \frac{\frac{1-\alpha}{\alpha} ca_t + y_t - y_t^* + (1-\alpha-\eta) q_t - \frac{1-\alpha}{\alpha} f_t - \frac{(1-\alpha)(\beta^{-1}-1)}{\alpha} a_{t-1}}{\eta + \alpha(1-\alpha)} \tag{12}$$

Note that, when $f_t = 0$ and all variables showing up on the right-hand side of this equation are treated as observable in estimation (as it is the case in the JP variant), the terms of trade can be uniquely determined within the model.[2] Naturally, the thus obtained series of this variable may be very different from the realized data. If, as some of the earlier literature suggests (see e.g. Lubik and Schorfheide, 2007 or Justiniano and Preston, 2010a), the model is misspecified in its ability to match the co-movement of the terms of trade with other variables, including the domestic ones that we focus on, treating it as unobservable in estimation may actually help in forecasting.

In the second alternative to JP+, which we call JP-, all international competitiveness variables are treated as latent. In this case, the transmission from foreign output, prices and interest rates to the domestic economy is not restricted by the realized time series for the real exchange rate, terms of trade or current account balance. The rationale for considering this variant is related to the findings documented

[2]The net foreign assets position is observable in the sense that it depends on the past current account balances, which are treated as observable in the JP variant.

by Justiniano and Preston (2010a), according to whom international co-movement between domestic and foreign macro-indicators in NOEM models requires unrealistic dynamics of international competitiveness variables. As this setup includes three observables less than JP+, we do not include in it shocks to the current account f_t, import markups cp_t and risk premium ϕ_t.

The third alternative to the full NOEM model, which closely resembles the setup used by Lubik and Schorfheide (2007) and hence is denoted as LS, treats all the three foreign economy variables and the terms of trade as unobservables. It is obtained by dropping shocks to the current account f_t, preferences g_t, import markups cp_t and risk premium ϕ_t. Its main feature is that it emphasizes the role of international competitiveness variables for the quality of domestic economy forecasts, and downsizes the importance of observing foreign economy developments. In this sense, it can be treated as a complement to JP-.

The final setup is the standard closed economy New Keynesian model (dubbed NK), which is obtained by setting the country openness parameter α to zero so that $y_t = c_t$, $\pi_t = \pi_{H,t}$. As a result, the dynamics of domestic variables (y_t, π_t and i_t), which are also the only ones treated as observable in estimation, can be described by the following system of three equations

$$y_t = \frac{1}{1+h}\mathbb{E}_t y_{t+1} + \frac{h}{1+h} y_{t-1} - \frac{1-h}{\sigma(1+h)}(i_t - \mathbb{E}_t\pi_{t+1} - g_t + \mathbb{E}_t g_{t+1}) \tag{13}$$

$$\pi_t = \frac{\beta}{1+\beta\delta_H}\mathbb{E}_t\pi_{t+1} + \frac{\delta_H}{1+\beta\delta_H}\pi_{t-1} + \frac{(1-\theta_H)(1-\beta\theta_H)}{\theta_H(1+\beta\delta_H)} mc_t \tag{14}$$

$$i_t = \rho_i i_{t-1} + \psi_\pi \pi_t + \psi_y y_t + \psi_{\Delta y}(y_t - y_{t-1}) + m_t \tag{15}$$

where the marginal cost is

$$mc_t = \varphi y_t - (1+\varphi) z_t + \frac{\sigma}{1-h}(y_t - h y_{t-1}) \tag{16}$$

The table below summarizes which observables and shocks are included in the five model variants participating in our forecasting competition.

	variables									shocks								
	$\tilde{y}$	$\tilde{p}$	$\tilde{i}$	$\tilde{s}$	$\tilde{q}$	$\tilde{ca}$	$\tilde{y}^*$	$\tilde{p}^*$	$\tilde{i}^*$	z_t	g_t	m_t	cp_t	ϕ_t	f_t	π_t^*	y_t^*	i_t^*
JP+	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
JP	x	x	x		x	x	x	x	x	x	x	x	x	x		x	x	x
JP-	x	x	x				x	x	x	x	x	x				x	x	x
LS	x	x	x		x	x				x		x				x	x	x
NK	x	x	x							x	x	x						

3 How does the external sector affect domestic variables?

In the NK model, fluctuations in output, inflation and the interest rate depend only on three domestic disturbances, broadly interpretable as affecting supply (z_t), demand (g_t) and monetary policy (m_t). In the NOEM variants LS, JP-, JP and JP+, these three domestic variables are additionally affected by (all or a subset of) the following shocks specific to the open economy: cp_t, ϕ_t, f_t, π_t^*, y_t^* and i_t^*. This impact can be both direct or indirect through the influence on other endogenous variables, and the three competitiveness variables in particular. Naturally, incorporating the external sector in the model also affects the transmission of standard domestic shocks. In this sense, if the model is correctly specified and estimation error is not large, inclusion of variables related to the open economy in estimation should help better describe the evolution of, and generate more accurate forecasts for, domestic variables.

Before we move to our empirical investigation, it is instructive to look at how each of the variables included in the NOEM models, but not in the NK setup, i.e. q_t, s_t, ca_t, y_t^*, π_t^* and i_t^*, may contribute to explaining the evolution of domestic output, inflation and the interest rate. Toward this goal, let us first consider the variant with the richest structure, i.e. JP+. By substituting c_t in equation (1) from the market clearing condition (3) we obtain

$$\begin{aligned} y_t =& \frac{1}{1+h}\mathbb{E}_t y_{t+1} + \frac{h}{1+h} y_{t-1} + \alpha x_t - \frac{\alpha}{1+h}\mathbb{E}_t x_{t+1} - \frac{h\alpha}{1+h} x_{t-1} - \\ & \frac{(1-h)(1-\alpha)}{\sigma(1+h)}(i_t - \mathbb{E}_t \pi_{t+1} + \mathbb{E}_t \Delta g_{t+1}) \end{aligned} \tag{17}$$

where $x_t = \eta(q_t + s_t) + y_t^*$. Hence, if $\alpha > 0$, domestic output depends not only on the domestic real interest rate and preference shocks, but also on current, past and expected future movements in the real exchange rate, terms of trade and foreign output.

Turning to inflation, let us assume for the ease of exposition that the degree of indexation for domestically produced and imported goods is the same, i.e. $\delta_H = \delta_F = \delta$. Then the Phillips curves (5) and (6) together with the definition of CPI (2) imply

$$\pi_t = \frac{\beta}{1+\beta\delta}\mathbb{E}_t\pi_{t+1} + \frac{\delta}{1+\beta\delta}\pi_{t-1} + (1-\alpha)\kappa_H mc_t + \alpha\kappa_F(q_t - (1-\alpha)s_t) + \alpha cp_t \quad (18)$$

where $\kappa_i = \frac{(1-\theta_i)(1-\beta\theta_i)}{\theta_i(1+\beta\delta)}$ for $i = \{H, F\}$. The above equation indicates that the real exchange rate and the terms of trade have an effect on inflation. Moreover, observing these variables and foreign output allows to pin down the level of consumption in equation (3), and hence the marginal cost using equation (7).

Finally, since the interest rate is determined by the feedback rule (11) that depends on output and inflation, its evolution is also affected by the external sector variables listed above. Moreover, as the rule includes changes in the nominal exchange rate, the domestic interest rate is also affected by foreign inflation.

Even though the current account balance and foreign interest rate do not show up in equations (17) and (18), the link between domestic variables and these two external sector indicators occurs indirectly through their impact on the real exchange rate as implied by the UIP condition (8). More specifically, the foreign interest rate enters directly the UIP equation while the current account balance affects the risk premium related to accumulation of net foreign assets.

4 Data and estimation

Our empirical investigation is based on quarterly data for Australia, Canada and the United Kingdom. The database covers the period from 1975:1 to 2013:4, of which 1995:1 marks the beginning of the forecast evaluation sample. For each of the investigated countries, the foreign economy is represented by the US, euro area, Japan and the remaining two analyzed economies.[3] The country weights are based on the BIS narrow effective exchange rate (EER) indices over the period 1993-2010. Their coverage is quite good and ranges from 75% for Australia to 92% for the UK. All data sources and detailed country weights are presented in Appendix A.1. The measurement equations linking the model variables to the observed time series can be found in Appendix A.2.

To evaluate the forecasting performance of the investigated models, we estimate them separately for all three countries using recursive samples, and then generate out-of-sample forecasts. As in Justiniano and Preston (2010b), we calibrate the following three parameters before estimation: the discount factor β, the risk premium elasticity χ, and the openness parameter α. All other structural parameters are estimated using Bayesian methods as described e.g. by An and Schorfheide (2007), with prior assumptions identical to those used by Justiniano and Preston (2010b). For long run trends, which are captured by constants in the measurement equations (Appendix A.2), we assume uniform prior distributions. We use uninformative priors for these parameters to avoid criticism by Faust and Wright (2013), who argue that the good ex-post forecasting performance of DSGE models found in many studies can be largely attributed to tight priors imposed on the long-run values of the observed time series, and on steady-state inflation in particular. The calibrated parameter values and prior assumptions are summarized in Appendix A.3.

For each model variant the posterior distribution of parameters is approximated with 200,000 draws obtained with the Metropolis-Hastings (MH) algorithm, after discarding the initial 50,000 draws. This number of draws was sufficient to achieve convergence according to standard diagnostics. Next, for every twentieth realization

[3] Given the evidence presented by Roos and Russell (1996), we have also checked how the JP+ forecasts for Australia are affected if the foreign economy is represented by the US only. The results of such an exercise, which are available upon request, show that this narrower definition of the external block leads to a slight improvement in the precision of forecasts for output, but is harmful to the quality of forecasts for prices and interest rates.

of the MH chain, we take three sequences of random draws of structural shocks over the forecast horizon. Consequently, at each forecast date we have in total 30,000 draws from the predictive density that can be used to calculate both point (mean across the draws) and density forecasts.

We chose the forecast evaluation sample to consist of 76 quarters spanning the period 1995:1-2013:4. First of all, this choice ensures that the models are estimated with sufficiently long time series: the shortest estimation sample covers 20 years of data, which include three full cycles in the US according to the NBER business cycle dates. At the same time, we can construct a relatively big set of out-of-sample predictions: the H-quarter-ahead forecasts are examined on the basis of $77 - H$ observations.

It is worth noting that, since we have 76 different estimation windows, 5 models and 3 countries, we had to estimate DSGE models, check their convergence and draw from the predictive density as many as 1140 times.

5 Results

In order to assess whether inclusion of the foreign sector improves the precision of DSGE model-based forecast for domestic variables, we first compare the root mean squared forecast errors (RMSFE) calculated for the five model variants describing the three considered economies. We complement this univariate analysis by calculating the multivariate forecast error trace statistic (see Adolfson et al., 2007b), which reduces to a simple weighted average of the MSFEs for the individual series. In our application, the weights are taken to be equal to the inverse of the variance for $\Delta\tilde{y}$, $\Delta\tilde{p}$ and $\Delta\tilde{i}$ over the period 1975:1-1994:4. Next, we calculate the square root of the trace statistic so that its magnitude is comparable to the univariate RMSFEs. The results for output, prices, the interest rate as well as the three variables together are shown in Table 1. All figures are presented as ratios of the RMSFE for a given model to the RMSFE for the NK benchmark so that values below unity show that a given NOEM model outperforms the closed economy setup. Moreover, we test whether the values are significantly different from unity with the two-tailed Diebold-Mariano test.

A number of observations are immediately evident. First, the richest NOEM variant JP+ generates forecasts for output, inflation and the interest rate that are at best indistinguishable from, and in most cases significantly less accurate than, those obtained with the NK benchmark. The only exception is the 12-quarters-ahead forecast for output in Canada. Second, the JP variant that treats the terms of trade as unobservable fares on average a little better, but offers significant improvement over the NK benchmark only for the UK interest rates in the short horizon. Third, the most parsimonious NOEM specification (LS) helps better predict output in Canada and Australia at longer horizons, but usually delivers large forecast errors for nominal domestic variables. In general, none of the analyzed NOEM models incorporating international competitiveness variables in the set of observables can consistently beat the NK benchmark for any of the countries included in our sample. Whenever the differences between the RMSFEs are statistically significant, they usually point at the closed economy model as the preferred forecasting tool. The outcome is somewhat more favorable for the JP- model, which is not restricted by the realized time series for the real exchange rate, terms of trade or the current account balance. This framework usually beats the NK model in forecasting output, but tends to lose the contest for prices, whereas the results for the interest rates are mixed. If the three domestic variables are considered together, the JP- model performs comparably to the NK setup for all three analyzed economies.

The picture is slightly different when we compare the quality of density forecasts using the log predictive scores (LPS), which are calculated with the method proposed by Adolfson et al. (2007b). Table 2 presents the average LPS differences of a given model in comparison to the NK benchmark so that positive values indicate that the investigated model outperforms the closed economy setup. We test whether the values are significantly different from zero with the two-tailed Amisano and Giacomini (2007) test. It turns out that none of the three NOEM models that treat international competitiveness variables as observable (JP+, JP and LS) can consistently beat the NK benchmark, and in many cases the LPS differences for individual variables are significantly negative. In the case of the multivariate density forecasts, the LPSs obtained from these three NOEM models are also either comparable or significantly lower than those generated with the close economy benchmark, with only one exception: 12-quarter horizon for Canada in JP+. On the contrary, the JP- model performs relatively well. For the United Kingdom and Australia, the quality of univariate and multivariate density forecasts is significantly better compared to the closed-economy benchmark, whereas for Canada the gains are limited to the interest rate forecasts.

Let us note that our forecast evaluation sample includes years 2009-2013, during which the interest rates in the United Kingdom, as well as in the euro area, Japan and the United States (i.e. countries constituting the external sector of the models), were at the zero lower-bound. This period was also characterized by elevated macroeconomic volatility. Therefore, one might be concerned that the results of the out-of-sample competition reported above may be largely driven by this part of our evaluation sample. To check if this is the case, we have calculated the RMSFE and LPS statistics using predictions that do not go beyond 2008. The results, which are available upon request, lead to the same conclusions as those for the entire forecast evaluation sample.

6 Why do the NOEM models fail?

There are three possible explanations for the disappointing forecasting performance of the NOEM models, and in particular of the most detailed JP+ variant, that we documented in the previous section. The first one is that these models, and especially those of their ingredients that make up the international competitiveness block, are severely misspecified (see e.g. Paccagnini, 2017, for a survey of misspecification issues in DSGE models). The second explanation is related to the model size: since NOEM models are larger than the NK benchmark, they are more prone to estimation error, which can have a detrimental effect on their out-of-sample performance. Third, the prior distributions used while estimating the models with Bayesian methods might be centered at wrong values. To sharpen the intuition on which of the above three factors is most important, we offer two additional analyses. First, we conduct an analogous forecasting competition using Bayesian VARs (BVARs), as these can be considered much less restricted versions of DSGE models. Second, we run a Monte Carlo experiment, in which we check whether the JP+ variant can systematically beat the NK benchmark if the former is the true data generating process.

We first compare the forecasting performance of five BVARs that are estimated on the same set of data as the five variants of DSGE models examined before, and hence we refer to them using the same acronyms (NK, LS, JP-, JP and JP+). We apply the independent Normal-Wishart prior with block exogeneity for the foreign economy variables. The prior is centered around the random walk with precision dependent on the following hyperparameters: overall tightness $\lambda_1 = 0.1$, weight $\lambda_2 = 0.5$, lag decay $\lambda_3 = 1$ and tightness around the constant $\lambda_4 = 10$. The values were chosen on the basis of a grid search that maximizes the marginal likelihood for the period 1975:1-1994:4 using the BEAR toolbox (Dieppe et al., 2016). Since the outcomes of this preliminary exercise (results available upon request) did not provide any clear indication on whether the overall tightness should be lower for larger models, as advocated by De Mol et al. (2008), we decided not to adjust them for BVARs of different size.

There are also two additional reasons why we prefer to keep the hyperparameters constant across models and vintages. First, we have not differentiated the tightness of the priors across the DSGE models. Consequently, drawing comparisons between this section and the previous one requires keeping the prior tightness of BVARs constant. Second, the aim of this exercise is to check if gains related to the use of additional information contained in the external block time series is enough to compensate for the increase in the estimation forecast error related to the model size. By tightening the prior for larger BVARs we would decrease the estimation error by tilting the posterior toward the random walk. Even though this might lead to better out-of-sample performance, as indicated in the Large Bayesian VAR literature (Banbura et al., 2010), such an exercise would clearly not answer the question of our interest.

The results presented in Tables 3 and 4 show that the BVAR with domestic variables only cannot be consistently beaten by any of the four open economy BVARs. This result, though in opposition to the already mentioned Large Bayesian VAR literature, is similar to a recent study by Gürkaynak et al. (2013), who argue that small-scale VARs usually generate better forecasts than their large-scale counterparts. To conclude, the BVAR forecasting competition shows that the advantage of using additional data describing the external block is not enough to compensate for increased estimation forecast error related to a larger number of estimated parameters. This results also holds for the JP- version of BVAR, which turned out to be relatively competitive in the DSGE forecasting competition.

Compared to DSGE models, BVARs can be considered as densely parametrized so the documented evidence of an increase in estimation error is not very surprising. Therefore, we next perform a Monte Carlo experiment, the essence of which is similar to that proposed by Herbst and Schorfheide (2012). Our aim is to check whether a NOEM model can outperform the NK benchmark even if the data are generated by the former. More precisely, we generate an artificial sample of data from the JP+ model with fixed structural parameters, using a random sequence of shocks. We next estimate the JP+ and NK models recursively on this artificial data set, generate out-of-sample forecasts and calculate the RMFSE statistics. The size of the sample (156 quarterly observations) as well as its split between estimation and evaluation subsamples is identical to that applied while we were working with actual data for Australia, Canada and the United Kingdom. We repeat this procedure 100 times, which gives us a distribution of the relative RMFSEs from the two models, conditional on the data generating process coming from the JP+ variant. Note that, given the size of our evaluation sample, we had to estimate each of the two competing DSGE models 7600 times.

While generating the artificial data series, we fix the JP+ structural parameters as follows. The openness parameter α is set to 0.18, which is the value we used before for Canada. As regards other parameters, we use the insights from the prior-posterior comparisons documented by Justiniano and Preston (2010a). The foreign VAR parameters are set to their posterior means from the full-sample estimates of the JP+ model for Canada so that the evolution of foreign output, inflation and the interest rate in our artificial samples mimic those observed for this country's main trade partners. As a general rule, other parameters are fixed at the calibrated values or prior means used to estimate the JP+ models in the forecasting evaluation exercise described in Section 5. We deviate from this principle only in the case of standard deviations of structural shocks, motivating our choices by the desire to make the properties of the artificial time series resemble actual data as much as possible. This is a necessary step as the prior assumptions for shock volatility used by Justiniano and Preston (2010b) are not motivated empirically and in particular imply aggregate fluctuations that are much smaller than those observed in the data. More specifically, we set the standard deviation of innovations to 1% for productivity and preference shocks, 0.5% for monetary and risk premium shocks, 3% for import markup shocks and 1.5% for current account shocks. These numbers are chosen so that the artificial time series have roughly the same volatility as actual Canadian data (Table 5) and are consistent with the variance decomposition reported in the DSGE literature.

Note that, by following the rules described above, and in particular by fixing the non-VAR parameters at their prior rather than posterior means, shocks related to the foreign sector are important drivers of the artificial data that we use in our Monte Carlo experiment (Table 6). In this respect, these time series are in line with empirical findings on the importance of international linkages for small open economies, which can be contrasted with the implications of estimated NOEM models (Justiniano and Preston, 2010a). This, together with the fact that while estimating the JP+ model on artificially generated data we use prior distributions that are centered around the exact values that were used to parametrize the data generating process, should give substantial specification advantage to the JP+ variant over the NK competitor. In consequence, the only important reason why the latter could win the forecasting competition is a more parsimonious structure, and hence lower estimation error.

The results of our Monte Carlo experiment are summarized in Table 7. At first glance, the results seem to confirm the superior performance of the JP+ model over its NK rival as in most cases it is the former that generates forecasts with lower RMSFEs for all horizons. However, the gains turn out to be small, with the median gain averaged over forecast horizons equal to 5% for output and only 2% for the price level and the interest rate. More importantly, if we were to apply the Diebold-Mariano test to judge whether the gains in forecast quality are statistically significant, we would give a positive verdict only in 23% cases for output, 10% for prices and 14% for the interest rates.

Overall, these results clearly show that an increase in the forecast estimation error due to opening the standard NK setup is large enough to roughly offset the potential gains arising from a better specification and correct priors. If one takes into account that, as our results for the JP- model suggest, the international competitiveness block in the NOEM framework is misspecified, and additionally the priors can be badly chosen, it is no longer surprising that for the three analyzed economies (Australia, Canada and the United Kingdom) we have found the NOEM model-based forecasts to be less accurate than those obtained from a closed economy variant.

7 Conclusions

In this paper we have shown that adding the foreign sector to estimated DSGE models for Australia, Canada and the United Kingdom does not necessarily result in an improvement of the forecast accuracy for domestic variables, and in many cases makes them even less precise. The comparison of forecasts from five competing DSGE models indicates that a part of this failure might be attributed to misspecification of the international competitiveness block in the NOEM framework. We have also shown using a Monte Carlo experiment that an increase in the forecast estimation error is an additional factor behind this result.

It is important to note that in our forecasting race we used data for three open economies, for which the available time series can be considered rather long. Similarly, our Monte Carlo experiment was based on simulated data of the same length as we used for these three countries. This means that, if one applies the NOEM framework to other countries, and emerging economies in particular, the role of estimation error is very likely to be even larger, with negative consequences for the forecast quality.

Naturally, DSGE models are not used just to generate forecasts and their numerous alternative applications may make the presence of the foreign block highly desired, if not indispensable. For instance, as indicated by Erceg et al. (2007), the effects of opening up the economy are mainly seen on the composition of aggregate expenditures (domestic absorption and net exports), and on the wedge between consumer prices and domestic prices. However, we believe that awareness of possible consequences of including open economy variables for the quality of DSGE model-based forecasts of domestic variables is important.

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Tables and figures

Table 1: Root Mean Squared Forecast Error (RMSFE) for DSGE models

H	United Kingdom				Canada				Australia			
	LS	JP-	JP	JP+	LS	JP-	JP	JP+	LS	JP-	JP	JP+
	Output											
1	1.27°	1.00	$1.11^{\bullet}$	$1.14^{\bullet}$	1.51^{*}	1.08	1.21°	1.08^{*}	1.00	$0.94^{\bullet}$	1.07^{*}	$1.17^{\bullet}$
2	1.22°	1.00	$1.12^{\bullet}$	$1.15^{\bullet}$	1.28^{*}	1.04	1.13	1.02	0.99	$0.92^{\bullet}$	1.07^{*}	$1.24^{\bullet}$
4	1.14^{*}	1.00	1.08^{*}	$1.14^{\bullet}$	1.06	0.97	1.13^{*}	0.97	0.92	$0.90^{\bullet}$	$1.09^{\bullet}$	$1.25^{\bullet}$
6	1.11^{*}	0.99	$1.07^{\bullet}$	$1.13^{\bullet}$	0.95	0.92	$1.13^{\bullet}$	0.95	0.83°	$0.87^{\bullet}$	$1.09^{\bullet}$	$1.19^{\bullet}$
8	1.10°	0.98	$1.07^{\bullet}$	$1.12^{\bullet}$	0.90°	0.89°	$1.12^{\bullet}$	0.94	0.76^{*}	$0.85^{\bullet}$	$1.09^{\bullet}$	1.10^{*}
12	1.08	0.98	$1.07^{\bullet}$	$1.09^{\bullet}$	0.86^{*}	0.84^{*}	$1.10^{\bullet}$	0.92^{*}	$0.66^{\bullet}$	$0.82^{\bullet}$	$1.09^{\bullet}$	0.98
	Prices											
1	1.15^{*}	0.99	1.06	$1.13^{\bullet}$	0.98	1.02	0.91	1.06°	1.04	1.01	1.03	1.08°
2	1.21^{*}	0.97	1.00	$1.20^{\bullet}$	0.97	1.06	0.89	1.13^{*}	1.07	1.03	1.05	1.09°
4	1.24^{*}	0.95	0.93	$1.30^{\bullet}$	0.98	1.14	0.89	1.26^{*}	1.06	1.06	1.07	1.11
6	1.25^{*}	0.97	0.90	$1.36^{\bullet}$	1.01	1.22	0.94	$1.41^{\bullet}$	1.03	1.07	1.08	1.09
8	1.21^{*}	1.00	0.89	$1.37^{\bullet}$	1.04	1.28	0.98	$1.54^{\bullet}$	1.01	1.08	1.09	1.04
12	$1.16^{\bullet}$	1.06°	0.90	$1.40^{\bullet}$	1.11	1.40	1.06	$1.82^{\bullet}$	1.05	1.09	1.11°	0.98
	Interest rates											
1	1.36^{*}	0.98	0.86^{*}	0.91	1.18°	1.00	0.99	0.98	1.04	0.90	1.04	1.15
2	1.33°	0.98	$0.84^{\bullet}$	0.95	1.20°	0.92	0.95	1.05	0.96	0.93	1.10°	1.18
4	1.32^{*}	1.01	$0.89^{\bullet}$	1.06	1.27°	0.87^{*}	0.96	$1.16^{\bullet}$	1.00	0.97	1.14^{*}	1.21^{*}
6	1.32^{*}	1.06	0.95	1.20°	1.28°	0.88°	0.95	$1.22^{\bullet}$	1.08	1.04	$1.18^{\bullet}$	1.23^{*}
8	1.30^{*}	1.09	0.97	1.29^{*}	1.28°	0.89°	0.93	$1.27^{\bullet}$	1.17	1.09^{*}	$1.22^{\bullet}$	1.21^{*}
12	1.29^{*}	1.16°	0.99	$1.45^{\bullet}$	1.28^{*}	0.90^{*}	0.86°	$1.35^{\bullet}$	1.30^{*}	$1.16^{\bullet}$	$1.26^{\bullet}$	$1.18^{\bullet}$
	Three variables											
1	1.28^{*}	1.00	1.05°	$1.09^{\bullet}$	$1.28^{\bullet}$	1.04	1.07	1.05°	1.02	0.96°	1.05^{*}	$1.13^{\bullet}$
2	1.24^{*}	0.99	1.06^{*}	$1.12^{\bullet}$	$1.18^{\bullet}$	1.03	1.03	1.06	1.02	0.97	1.06^{*}	$1.18^{\bullet}$
4	1.18^{*}	0.99	1.04	$1.15^{\bullet}$	1.06	1.01	1.05	1.08	0.99	0.98	$1.09^{\bullet}$	$1.19^{\bullet}$
6	1.16^{*}	1.00	1.04	$1.17^{\bullet}$	1.00	1.00	1.07	1.10^{*}	0.96	0.98	$1.10^{\bullet}$	1.15^{*}
8	1.14^{*}	0.99	1.03	$1.19^{\bullet}$	0.96	0.99	1.08°	$1.13^{\bullet}$	0.92	0.98	$1.10^{\bullet}$	1.08°
12	1.11°	1.01	1.03	$1.20^{\bullet}$	0.94°	0.98	1.08^{*}	$1.17^{\bullet}$	0.90	0.98	$1.11^{\bullet}$	0.99

Notes: The figures in the table represent the ratios of the RMSFE from a given model in comparison to the NK benchmark so that the values below unity indicate that forecasts from a given NOEM variant are more accurate than from the benchmark. Asterisks $^{\bullet}$, * and $^{\circ}$ denote, respectively, the 1%, 5% and 10% significance levels of the two-tailed Diebold-Mariano test, where the long-run variance is calculated with the Newey-West method.

Table 2: Log Predictive Scores (LPS) for DSGE models

H	United Kingdom				Canada				Australia			
	LS	JP-	JP	JP+	LS	JP-	JP	JP+	LS	JP-	JP	JP+
	Output											
1	-0.15$^{\bullet}$	0.04*	-0.07$^{\bullet}$	-0.08$^{\bullet}$	-0.39$^{\bullet}$	-0.05	-0.18°	-0.06	0.01	0.03$^{\bullet}$	-0.06$^{\bullet}$	-0.09$^{\bullet}$
2	-0.13°	0.05	-0.06	-0.08$^{\bullet}$	-0.26$^{\bullet}$	-0.03	-0.10	0.00	0.03	0.04$^{\bullet}$	-0.06$^{\bullet}$	-0.12$^{\bullet}$
4	-0.14	0.03	-0.10	-0.12$^{\bullet}$	-0.07	0.01	-0.11°	0.02	0.09°	0.07$^{\bullet}$	-0.06$^{\bullet}$	-0.19$^{\bullet}$
6	-0.17	0.02	-0.17	-0.16$^{\bullet}$	0.06	0.02	-0.16°	0.02	0.15*	0.11$^{\bullet}$	-0.07$^{\bullet}$	-0.24$^{\bullet}$
8	-0.22*	0.02	-0.24	-0.20$^{\bullet}$	0.12*	0.03	-0.21*	0.01	0.22$^{\bullet}$	0.14$^{\bullet}$	-0.08$^{\bullet}$	-0.28*
12	-0.34$^{\bullet}$	0.01	-0.37$^{\bullet}$	-0.29$^{\bullet}$	0.19$^{\bullet}$	0.04	-0.30*	-0.01	0.33$^{\bullet}$	0.20$^{\bullet}$	-0.12$^{\bullet}$	-0.31*
	Prices											
1	-0.12$^{\bullet}$	-0.04$^{\bullet}$	-0.24$^{\bullet}$	-0.03$^{\bullet}$	0.01	-0.03	-0.04	-0.07*	-0.18$^{\bullet}$	0.00	-0.07$^{\bullet}$	-0.07$^{\bullet}$
2	-0.05$^{\bullet}$	0.02$^{\bullet}$	-0.05$^{\bullet}$	-0.01°	0.02	-0.03	0.00	-0.10$^{\bullet}$	-0.16$^{\bullet}$	0.02	-0.05$^{\bullet}$	-0.09$^{\bullet}$
4	0.02	0.09$^{\bullet}$	0.14$^{\bullet}$	-0.01	0.03	0.01	0.08°	-0.13$^{\bullet}$	-0.16$^{\bullet}$	0.04	-0.04*	-0.11$^{\bullet}$
6	0.06°	0.13$^{\bullet}$	0.22$^{\bullet}$	-0.02	0.03	0.03	0.13$^{\bullet}$	-0.14$^{\bullet}$	-0.17$^{\bullet}$	0.04	-0.04*	-0.11$^{\bullet}$
8	0.08*	0.14$^{\bullet}$	0.26$^{\bullet}$	-0.04	0.03	0.05	0.16$^{\bullet}$	-0.15$^{\bullet}$	-0.20$^{\bullet}$	0.03	-0.05*	-0.09$^{\bullet}$
12	0.10$^{\bullet}$	0.13$^{\bullet}$	0.27$^{\bullet}$	-0.09	0.04	0.07	0.19$^{\bullet}$	-0.19$^{\bullet}$	-0.28$^{\bullet}$	0.02	-0.06*	-0.08*
	Interest rates											
1	-0.14$^{\bullet}$	-0.01	-0.06$^{\bullet}$	-0.03$^{\bullet}$	-0.07$^{\bullet}$	0.04°	-0.04*	-0.02	0.03*	0.04$^{\bullet}$	-0.04$^{\bullet}$	-0.03°
2	-0.15*	0.02*	-0.04°	-0.02	-0.05	0.09$^{\bullet}$	-0.02	-0.03	0.02°	0.08$^{\bullet}$	-0.05$^{\bullet}$	-0.03
4	-0.13°	0.05$^{\bullet}$	0.01	-0.02	-0.05	0.14$^{\bullet}$	0.02	-0.05	-0.03°	0.09$^{\bullet}$	-0.06$^{\bullet}$	-0.06$^{\bullet}$
6	-0.11	0.04	0.03	-0.06	-0.05	0.15$^{\bullet}$	0.05$^{\bullet}$	-0.09*	-0.09$^{\bullet}$	0.07$^{\bullet}$	-0.07$^{\bullet}$	-0.07$^{\bullet}$
8	-0.09	0.04	0.04	-0.09°	-0.05	0.14$^{\bullet}$	0.08$^{\bullet}$	-0.11$^{\bullet}$	-0.15$^{\bullet}$	0.06*	-0.08$^{\bullet}$	-0.07$^{\bullet}$
12	-0.05	0.01	0.05*	-0.15$^{\bullet}$	-0.02	0.14$^{\bullet}$	0.13$^{\bullet}$	-0.14$^{\bullet}$	-0.26$^{\bullet}$	0.04	-0.10$^{\bullet}$	-0.06*
	Three variables											
1	-0.44$^{\bullet}$	-0.01	-0.31$^{\bullet}$	-0.11$^{\bullet}$	-0.51$^{\bullet}$	-0.04	-0.31*	-0.17*	-0.13$^{\bullet}$	0.06$^{\bullet}$	-0.15$^{\bullet}$	-0.17$^{\bullet}$
2	-0.41*	0.07$^{\bullet}$	-0.09$^{\bullet}$	-0.06*	-0.50$^{\bullet}$	-0.03	-0.23*	-0.11	-0.12*	0.12$^{\bullet}$	-0.12$^{\bullet}$	-0.24$^{\bullet}$
4	-0.40	0.16$^{\bullet}$	0.02	-0.04	-0.49$^{\bullet}$	0.02	-0.18*	0.01	-0.12	0.19$^{\bullet}$	-0.13$^{\bullet}$	-0.35$^{\bullet}$
6	-0.42	0.23$^{\bullet}$	-0.01	-0.06	-0.40*	0.00	-0.18*	0.10	-0.13	0.23$^{\bullet}$	-0.15$^{\bullet}$	-0.43$^{\bullet}$
8	-0.43	0.29$^{\bullet}$	-0.05	-0.08	-0.28	-0.01	-0.17*	0.16	-0.14	0.27$^{\bullet}$	-0.16$^{\bullet}$	-0.47$^{\bullet}$
12	-0.45	0.36$^{\bullet}$	-0.16	-0.15°	0.04	-0.01	-0.16°	0.23°	-0.19	0.34$^{\bullet}$	-0.21$^{\bullet}$	-0.50$^{\bullet}$

Notes: The figures in the table represent the differences of the LPS from a given model in comparison to the NK benchmark so that positive values indicate that forecasts from a given NOEM variant are more accurate than from the benchmark. Asterisks $^{\bullet}$, * and $^{\circ}$ denote, respectively, the 1%, 5% and 10% significance levels of the two-tailed Amisano and Giacomini (2007) test, where the long-run variance is calculated with the Newey-West method.

Table 3: Root Mean Squared Forecast Error for BVAR models

H	United Kingdom				Canada				Australia			
	LS	JP-	JP	JP+	LS	JP-	JP	JP+	LS	JP-	JP	JP+
	Output											
1	1.04°	1.07*	1.08*	1.06*	1.01	0.98	1.05	1.05	1.05*	1.00	1.06°	1.06*
2	1.05*	1.06*	1.06*	1.05°	1.02	1.00	1.08°	1.11°	1.11*	1.01	1.11°	1.13*
4	1.07*	1.04	1.05	1.04	1.00	1.01	1.10	1.15°	1.17*	1.01	1.15	1.17°
6	1.08*	1.03	1.04	1.05	0.96	1.01	1.08	1.11	1.22*	1.03	1.20°	1.23°
8	1.09°	1.02	1.03	1.06	0.96	0.98	1.06	1.09	1.25*	1.06	1.22*	1.27*
12	1.13*	1.05	1.07	1.11	0.97	0.94°	1.01	1.03	1.25*	1.10	1.26*	1.27*
	Prices											
1	0.93*	1.20*	1.01	1.01	1.04°	1.04°	1.05°	1.07	0.99	1.02	0.98	1.00
2	0.92*	1.23*	1.01	1.01	1.08°	1.09*	1.09*	1.11*	0.99	1.04	0.98	1.00
4	0.90*	1.24*	1.00	1.00	1.17°	1.20$^{\bullet}$	1.16$^{\bullet}$	1.17$^{\bullet}$	0.96	1.08	0.96	0.98
6	0.91*	1.23*	0.98	0.98	1.24	1.29$^{\bullet}$	1.20$^{\bullet}$	1.23$^{\bullet}$	0.93	1.12	0.94	0.97
8	0.92*	1.23*	0.99	0.98	1.29	1.33$^{\bullet}$	1.21$^{\bullet}$	1.22$^{\bullet}$	0.91	1.15	0.93	0.98
12	0.95°	1.24*	1.03	1.01	1.42°	1.39$^{\bullet}$	1.25$^{\bullet}$	1.25$^{\bullet}$	0.92	1.18	0.96	1.02
	Interest rates											
1	0.98	1.01	0.96	1.04	1.07	0.98	1.00	1.05	0.84	1.06	0.88	0.99
2	0.97	1.04	0.97	1.07	1.12	0.96	0.95	1.00	0.86°	1.12	0.92	1.06
4	0.97	1.13	1.03	1.10	1.18	0.95	0.91*	0.96	0.94	1.20°	1.03	1.15
6	1.02	1.21°	1.13	1.18	1.21	0.96	0.93°	0.96	1.00	1.28*	1.11	1.21°
8	1.05	1.26°	1.19	1.22*	1.24	0.96	0.93	0.95	1.02	1.36*	1.17°	1.29*
12	1.09	1.34*	1.27°	1.25*	1.22	0.94	0.89	0.90	1.06	1.46$^{\bullet}$	1.31$^{\bullet}$	1.47$^{\bullet}$
	Three variables											
1	1.02	1.08$^{\bullet}$	1.05*	1.05*	1.03	1.00	1.04*	1.05*	1.00	1.02	1.00	1.03
2	1.03	1.08$^{\bullet}$	1.04°	1.05	1.05	1.02°	1.07*	1.09$^{\bullet}$	1.01	1.05°	1.02	1.06
4	1.03	1.08*	1.04	1.04	1.07	1.05*	1.09*	1.13*	1.04	1.08*	1.05	1.09
6	1.04	1.08°	1.03	1.05	1.06	1.07*	1.09	1.12°	1.05	1.12$^{\bullet}$	1.06	1.11°
8	1.05	1.09	1.04	1.05	1.07	1.07*	1.09	1.10	1.05	1.15$^{\bullet}$	1.07	1.13°
12	1.08°	1.12	1.07	1.10	1.09	1.05	1.06	1.07	1.06°	1.18$^{\bullet}$	1.11	1.16°

Notes: The figures in the table represent the ratios of the RMSFE from a given model in comparison to the NK (3-variable) benchmark so that the values below unity indicate that forecasts from a given open economy BVAR variant are more accurate than from the benchmark. Asterisks $^{\bullet}$, * and $^{\circ}$ denote, respectively, the 1%, 5% and 10% significance levels of the two-tailed Diebold-Mariano test, where the long-run variance is calculated with the Newey-West method.

Table 4: Log Predictive Scores for BVAR models

H	United Kingdom				Canada				Australia			
	LS	JP-	JP	JP+	LS	JP-	JP	JP+	LS	JP-	JP	JP+
	Output											
1	-0.02	-0.05	-0.05	-0.04	0.00	0.04°	-0.04	-0.06	-0.01	0.03*	0.03	0.03
2	-0.08	-0.10	-0.13	-0.11	-0.03	-0.03	-0.20*	-0.30$^{\bullet}$	-0.04°	0.03	-0.01	-0.01
4	-0.17°	-0.18*	-0.20*	-0.21*	-0.02	-0.12	-0.43$^{\bullet}$	-0.64$^{\bullet}$	-0.08*	0.02	-0.06	-0.06
6	-0.19°	-0.17°	-0.20*	-0.26*	0.01	-0.17	-0.61*	-0.83$^{\bullet}$	-0.12$^{\bullet}$	0.00	-0.11	-0.11
8	-0.19*	-0.17	-0.22	-0.30*	-0.02	-0.14	-0.81*	-1.15*	-0.15$^{\bullet}$	-0.02	-0.16°	-0.17°
12	-0.21*	-0.22	-0.35°	-0.50*	-0.04	0.02	-0.92°	-1.49°	-0.18*	-0.07	-0.24*	-0.26*
	Prices											
1	0.06$^{\bullet}$	-0.07	0.08°	0.11*	-0.08*	-0.12*	-0.18°	-0.21°	0.00	-0.02	0.01	-0.02
2	0.08$^{\bullet}$	-0.17°	0.04	0.04	-0.15*	-0.22*	-0.28*	-0.32*	0.00	-0.06	0.00	-0.04
4	0.11$^{\bullet}$	-0.34*	0.00	-0.04	-0.20°	-0.36$^{\bullet}$	-0.34$^{\bullet}$	-0.38*	0.02	-0.14	0.00	-0.05
6	0.14*	-0.44*	0.02	-0.03	-0.23	-0.44$^{\bullet}$	-0.31$^{\bullet}$	-0.35*	0.04	-0.22	0.00	-0.07
8	0.15*	-0.51*	0.02	-0.04	-0.26	-0.46$^{\bullet}$	-0.27$^{\bullet}$	-0.28*	0.04	-0.26	-0.01	-0.09
12	0.11°	-0.54*	-0.01	-0.06	-0.35°	-0.43$^{\bullet}$	-0.21*	-0.21*	0.01	-0.26	-0.06	-0.14
	Interest rates											
1	0.06$^{\bullet}$	0.12$^{\bullet}$	0.15$^{\bullet}$	0.23$^{\bullet}$	0.03	0.25$^{\bullet}$	0.29$^{\bullet}$	0.27$^{\bullet}$	0.07$^{\bullet}$	0.08$^{\bullet}$	0.14$^{\bullet}$	0.15$^{\bullet}$
2	0.06$^{\bullet}$	0.10$^{\bullet}$	0.15$^{\bullet}$	0.21$^{\bullet}$	-0.02	0.22$^{\bullet}$	0.25*	0.21°	0.07$^{\bullet}$	0.05°	0.14$^{\bullet}$	0.12$^{\bullet}$
4	0.07*	0.07	0.15$^{\bullet}$	0.18$^{\bullet}$	-0.09	0.10	0.12	0.07	0.04*	0.00	0.09$^{\bullet}$	0.06
6	0.06*	0.04	0.11°	0.13°	-0.14°	-0.01	0.01	-0.03	0.02	-0.03	0.05	0.02
8	0.05*	0.01	0.08	0.11	-0.17*	-0.03	0.00	-0.03	0.01	-0.04	0.04	-0.01
12	0.04°	-0.01	0.05	0.08	-0.19$^{\bullet}$	0.05	0.13	0.11	0.01	-0.03	0.03	-0.02
	Three variables											
1	0.11$^{\bullet}$	0.02	0.17°	0.28*	-0.04	0.21$^{\bullet}$	0.11	0.04	0.06	0.08*	0.17$^{\bullet}$	0.14*
2	0.06	-0.13	0.04	0.09	-0.17	0.07	-0.20	-0.40*	0.04	0.00	0.11	0.04
4	0.03	-0.34°	-0.05	-0.06	-0.29	-0.21	-0.67*	-1.06$^{\bullet}$	-0.02	-0.14	-0.02	-0.11
6	0.07	-0.36	0.07	0.02	-0.30	-0.39	-0.94*	-1.40$^{\bullet}$	-0.08	-0.26	-0.14	-0.26
8	0.13	-0.33	0.23	0.14	-0.35	-0.40	-1.08*	-1.58*	-0.12	-0.34°	-0.26	-0.43
12	0.10	-0.19	0.38	0.27	-0.44°	-0.19	-0.95°	-1.57°	-0.20*	-0.41°	-0.45	-0.69°

Notes: The figures in the table represent the differences of the LPS from a given model in comparison to the NK (3 variable) benchmark so that positive values indicate that forecasts from a given open economy BVAR variant are more accurate than from the benchmark. Asterisks $^{\bullet}$, * and $^{\circ}$ denote, respectively, the 1%, 5% and 10% significance levels of the two-tailed Amisano and Giacomini (2007) test, where the long-run variance is calculated with the Newey-West method.

Table 5: Volatility of artificial data

Variables	Artificial data	Canadian data
Output	0.71	0.74
Inflation	0.90	0.84
Interest rate	3.75	3.98
Terms of trade	2.27	1.98
Real exch. rate	2.07	2.48
Current account	2.30	2.27
Foreign output	0.69	0.70
Foreign inflation	0.70	0.75
Foreign int. rate	2.70	3.52

Notes: This table compares the unconditional standard deviations of artificial data generated from the JP+ model, and used in the Monte Carlo experiment described in section 6, to actual Canadian data. All variables are defined in the same way as when they are used in estimation, see the left-hand sides of the measurement equations reported in Appendix A.2.

Table 6: Share of shocks to the foreign block in unconditional variance decomposition

Variables	Artificial data	Australia	Canada	United Kingdom
Output	0.25	0.02	0.06	0.03
Inflation	0.29	0.07	0.22	0.12
Interest rate	0.54	0.19	0.34	0.26

Notes: This table shows the share of foreign block shocks (i.e. affecting import markups, risk premium, current account, and three foreign variables) in the unconditional variance decomposition for domestic variables in our artificial data used in the Monte Carlo experiment described in section 6, and implied by the full-sample estimates of the JP+ model for Australia, Canada and the UK, with the numbers evaluated at the posterior mean of the estimated parameters. All variables are defined in the same way as when they are used in estimation, see the left-hand sides of the measurement equations reported in Appendix A.2.

Table 7: Relative RMSFE of JP+ versus NK - Monte Carlo experiment

	H=1	H=2	H=4	H=6	H=8	H=12
	Output					
Median value	0.95	0.95	0.95	0.95	0.94	0.95
Fraction of <1	0.98	0.89	0.81	0.83	0.8	0.74
Fraction of signif. <1	0.29	0.3	0.26	0.25	0.27	0.26
	Price level					
Median value	0.99	0.98	0.97	0.97	0.97	0.97
Fraction of <1	0.78	0.79	0.78	0.75	0.7	0.69
Fraction of signif. <1	0.11	0.13	0.12	0.16	0.16	0.18
	Interest rate					
Median value	0.99	0.97	0.97	0.97	0.98	0.98
Fraction of <1	0.78	0.77	0.75	0.68	0.65	0.63
Fraction of signif. <1	0.1	0.13	0.15	0.15	0.13	0.11

Notes: This table presents the RMSFE statistics of the JP+ model relative to the NK model obtained in a Monte Carlo experiment, in which the data are generated from the JP+ model with fixed parameters. The differences in the RMSFEs are evaluated with the Diebold-Mariano test at the 5% significance level.

Appendix

A.1 Data sources

In our empirical analysis we use the following quarterly macroeconomic time series for the period 1975-2013:

- $\tilde{y}_t$ - GDP at constant prices divided by population (log); source: IFS, AWM (GDP) and AMECO (population)
- $\tilde{p}_t$ - CPI index (log); source: MEI and AWM
- $\tilde{i}_t$ - Short-term nominal money market rate; soure: IFS
- $\tilde{e}_t$ - Nominal exchange rate against the USD (log), quarterly average; source: MEI, AWM
- $\tilde{s}_t$ - Terms of trade (log); source: IFS
- $\tilde{ca}_t$ - Current account balance to GDP ratio; source: MEI
- $\tilde{q}_t$ - CPI-based real effective exchange rate (log), calculated using $\tilde{p}_t$, $\tilde{p}_t^*$ and $\tilde{e}_t$.

Where applicable, data are seasonally adjusted using the Tramo/Seats procedure. The source acronyms indicate: MEI - Main Economic Indicators (OECD), IFS - International Financial Statistics (IMF), AWM - Area-Wide Model database (ECB), AMECO - AMECO database (European Commission).

Foreign variables $\tilde{y}_t^*$, $\tilde{p}_t^*$ and $\tilde{i}_t^*$ are constructed as weighted averages of respective indicators, with trading partner weights that are based on the effective exchange rate (EER) published by the Bank for International Settlements (Klau and Fung, 2006). More specifically, we compute the average values of the EER weights over the period 1993-2010 and subsequently adjust them so that they sum to unity. The final weights and achieved coverage are

	Australia	Canada	UK	US	euro area	Japan	Coverage
Australia	.	2.4	8.8	32.5	30.2	26.1	74.3
Canada	0.3	.	2.5	81.5	9.6	6.1	90.8
UK	1.0	2.0	.	18.5	70.9	7.5	91.9

A.2 Measurement equations

The following measurement equations link the model variables to the data described in the previous appendix

$$\tilde{y}_t - \tilde{y}_{t-1} = \mu_y + y_t - y_{t-1} \tag{A.1}$$

$$\tilde{p}_t - \tilde{p}_{t-1} = \mu_\pi + \pi_t \tag{A.2}$$

$$\tilde{i}_t = \mu_i + i_t \tag{A.3}$$

$$\tilde{q}_t - \tilde{q}_{t-1} = q_t - q_{t-1} \tag{A.4}$$

$$\tilde{ca}_t = \mu_{ca} + ca_t \tag{A.5}$$

$$\tilde{y}^*_t - \tilde{y}^*_{t-1} = \mu^*_y + y^*_t - y^*_{t-1} \tag{A.6}$$

$$\tilde{p}^*_t - \tilde{p}^*_{t-1} = \mu^*_\pi + \pi^*_t \tag{A.7}$$

$$\tilde{i}^*_t = \mu^*_i + i^*_t \tag{A.8}$$

$$\tilde{s}_t - \tilde{s}_{t-1} = s_t - s_{t-1} \tag{A.9}$$

Note that we do not detrend or demean the data prior to estimation. Instead, we do it within the estimation procedure by including intercepts in the measurement equations wherever applicable.

All of these measurement equations are used in the JP+ variant, the JP model drops equation (A.9), LS does not include equations (A.6)-(A.9) and the NK variant uses only equations (A.1)-(A.3).

A.3 Calibration and prior assumptions

As Justiniano and Preston (2010b), we calibrate β to 0.99 and χ to 0.01. We also fix α to 0.14 for Australia, 0.18 for Canada and 0.19 for the UK. These numbers correspond to these countries' average GDP shares of exports and imports, corrected for the import content of exports estimated by the OECD.

The remaining parameters are estimated using Bayesian methods implemented in Dynare. The prior assumptions for structural parameters are the same as in Justiniano and Preston (2010b). The prior distributions for the constants in measurement equations are assumed to be uniform over intervals wide enough to ensure their uninformativeness.

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