

Incorporating judgement with DSGE models

Draft, Work in progress^{*}

Jaromír Beneš, Andrew Binning, Kirdan Lees

*Economics Department, Reserve Bank of New Zealand,
2 The Terrace, Wellington, 6011, New Zealand.
Tel: +64 4 471 3663, Fax: +64 4 473 1209.
email address: andrew.binning@rbnz.govt.nz*

Abstract

Central bank policymakers often cast judgement in reduced form terms, often based on off-model information, not easily represented in terms of DSGE models. We show how to compute forecasts conditioned on policymaker judgement, that are the most likely conditional forecasts from the perspective of the DSGE model, maximising the influence of the model structure on the forecasts. We suggest using a simple implausibility index that tracks the magnitude and type of policymaker judgement based on the structural shocks required to return policymaker judgement. We show how to use the methods for practical use in the policy environment and also apply the techniques to condition DSGE model forecasts on: (i) the long history of published forecasts from the Reserve Bank of New Zealand; (ii) constant interest rate forecasts; and (iii) inflation forecasts from a Bayesian VAR currently in use in the policy environment at the Reserve Bank of New Zealand.

Keywords: DSGE models; monetary policy; conditional forecasts

JEL classification: C51, C53

1 Introduction

DSGE models deliberately abstract from many things to present a stylized, but theoretically coherent, view of the economy. Recent DSGE models can

^{*} We thank Martin Fukač, Tim Kam, Sharon McCaw, Tao Zha and seminar participants at the Reserve Bank of New Zealand (RBNZ), the Reserve Bank of Australia (RBA), and the 2007 Australasian Macroeconomic Workshop at La Trobe University for comments. Any remaining errors are the responsibility of the authors. The views in the paper are those of the authors and should not be attributed to the Reserve Bank of New Zealand.

broadly match the data and produce forecasts competitive with other benchmark models (see Smets and Wouters (2003) and Adolfson *et al.* (2007)). This has sparked interest from central banks which have designed DSGE models with the goal of working directly in the forecast and policy environment (see for example, Murchison and Rennison (2006), Brubakk *et al.* (2005), the DSGE model in Adolfson *et al.* (2005a), Harrison *et al.* (2005) and Medina and Soto (2006) amongst others).

However, policymakers bring to DSGE models experience and accumulated knowledge that is typically not directly interpretable in terms of the structure of the DSGE model. If DSGE models are to operate effectively in the policy environment, modellers need to consider how to best incorporate policymaker judgement.

A common approach used to incorporate judgement to forecasts generated by structural models is to simply add a sequence of shocks to the future path of variables policymakers wish to judgementally adjust. We expand this approach by searching across the entire set of structural shocks within the DSGE model and use an algorithm to select the set of future structural shocks with the minimal variance that returns the policymaker judgement. This unique set of shocks incorporates policymaker judgement while ensuring the forecast paths that are most consistent with the DSGE model. Thus the conditional forecasts will represent the most likely outcomes (in a probabilistic sense), given the policymaker judgement.

Our algorithm extends Waggoner and Zha (1999) to the case of rational-expectations models where future shocks and more importantly the future paths of variables are anticipated by economic agents. Technically, we expand the standard reduced-form solution of a rational-expectations model forward to take into account the current effect of future expected events (shocks) and adjust Waggoner and Zha (1999) for this expansion.

We advocate applying the Doan *et al.* (1983) “implausibility index”, to the structural shocks required to return the policymaker judgement. This measure can be used to identify judgement that is particularly at odds with the DSGE model.

To illustrate our technique, we use a medium-sized DSGE model calibrated to the case of New Zealand. Firstly, we show how our technique can be applied to an illustrative example where a policymaker’s believes that a flat interest rate forecast is appropriate, as a simple example. This case is useful to show the benefits of a metric based on the structural shocks of the DSGE model rather than the difference between the conditional and unconditional forecasts.

We also apply our technique to three specific applications where the implausibility index is tracked over time. Specifically, we condition on the long history

of endogenous interest rate forecasts published by the Reserve Bank of New Zealand since 1998 and report the period in which the RBNZ forecasts are most dissimilar from our DSGE model. We also condition forecasts on the a constant interest rate forecast and identify the period that is most at odds with this forecast from the perspective of the DSGE model. We also report the nature of the shocks required to return such a forecast. The nature of the structural shocks gives modellers a sense of how the DSGE model would need to act to return the policymaker judgement. Finally, we explore conditioning the inflation forecasts from a simple BVAR model used in the policy process at the RBNZ.

The remainder of the paper is organised in the following sections. Section 2 briefly discusses the central bank forecasting and policy environment before detailing some alternative methods of adding judgement. Section 3 details our three applications of the technology with the description of the DSGE model relegated to the appendix. Concluding comments are made in section 4.

2 A framework for thinking about judgement

Typically, to condition a set of forecasts on specific judgement for the path of a given variable (for example, a flat track for the interest rate) a unique combination of exactly identified univariate shocks is added. More generally when the number of tuned variables is equal to the number of shock types we can choose from, the judgement or the combination of shocks required is unique and the problem is a trivial one. In this particular situation we label the system of shocks as exactly identified. However, when the number of shock types we can choose from exceeds the number of variables to be tuned, there exists an infinite number of potential shock combinations consistent with the judgement, such that the system of shocks is unidentified.¹ The set of structural shocks with the lowest variance represents the most likely set from the perspective of the DSGE model and thus represent a natural focus point.

It is possible to express the DSGE model in the following manner:

$$A_0 y_t = A_1 E_t y_{t+1} + A_2 y_{t-1} + B \varepsilon_t + C \quad (1)$$

where y_t is a vector of state variables, ε_t is a vector that contains a set of model shocks, C contains a vector of constants while the matrices A_0 , A_1 , A_2 and B determine the dynamics of the DSGE. This general representation may

¹ This a generic problem and not a characteristic of DSGE models *per se*.

contain identities and lagged economic variables which implies the vector of model shocks may contain zeros. Also, we restrict the structural shocks to Gaussian processes where the off-diagonal elements of the B matrix are zeros.

When the model is expressed in terms of equation (1), the algorithms of Klein (2000) (based on the generalised Schur decomposition) can be applied to solve for the reduced form of the model:

$$y_t = Fy_{t-1} + D + G\varepsilon_t. \quad (2)$$

where D is the vector of constants in equation (1) post-multiplied by the inverse of A_0 . Using the reduced form representation, at time t , we can construct the h -step ahead forecast of the deviation of the vector of state variables y_t from the vector of constants:

$$\begin{aligned} y_{t+1|t} &= F(Fy_{t-1} + D + G\varepsilon_t) + D + G\varepsilon_{t+1} \\ y_{t+2|t} &= F[F(Fy_{t-1} + D + G\varepsilon_t) + D + G\varepsilon_{t+1}] + D + G\varepsilon_{t+2} \\ &\vdots \\ y_{t+h|t} &= F^{h+1}y_{t-1} + (I + F^{h-1})D + \sum_{i=0}^h F^i G\varepsilon_{t+(h-i)} \end{aligned} \quad (3)$$

Note that equation (3) decomposes forecasts of the state vector into three components: (i) the initial value of the state vector y_{t-1} , (ii) the vector of constants (functions of structural parameters) and (iii) the subsequent shock realisations $\sum_{i=0}^h F^i G\varepsilon_{t+(h-i)}$. Clearly judgement can be added to the DSGE model via any combination of the three arguments that form the forecast variables.

Here, we focus on off-model judgement where the policymaker possesses a belief about the future path of the state vector $y_{t+h|t}$ that is exogenous to the model. Such beliefs might reasonably come from financial markets, business information visits, the acquired wisdom and experience of policymakers but are not directly related to: (i) specific beliefs about the structural parameterisation (captured in the matrices A_0, A_1, A_2, B); or (ii) the reduced form dynamics (captured by the matrices F, G , and D); and (iii) the vector of constants, irrespective of whether this is the structural steady-state parameters C or the reduced form constants D .

We argue that a judgement metric that focuses on the average size of the shocks that must be added to the model to return the policymaker judgement is a better metric for the amount of judgement added to a forecast, compared to simply the judgement adjusted tracks relative to their no judgement paths. Waggoner and Zha (1999) show how judgement can be incorporated into a model using a ‘‘least squares’’ procedure. A mechanical algorithm chooses

shocks with the least variance that are consistent with the conditional forecast. That is, given no other knowledge or beliefs about the future, the endogenous paths for other variables in the model are the most likely conditional on the model, historical data and the model's parameterisation.

In Doan, Litterman and Sims (1984), Leeper and Zha (2003) and Adolfson et al (2005) the judgement adjusted paths are evaluated relative to the model and history to determine how likely they are. Doan, Litterman and Sims (1984) outline and use the "Implausibility Index". Leeper and Zha (2003) and Adolfson et al (2005) outline and use the Modesty Statistic.

2.1 The Modesty Statistic

Leeper and Zha (2003) examine hypothetical monetary policy interventions in the US to see whether these would be modest. They set up a simple model for the formulation of monetary policy and then fit interest rate shocks to match a given interest rate track. They use their modesty statistic to determine how consistent the projected interest rate, and the corresponding inflation and output tracks are with model. This is a particular application of the Lucas Critique. In this sense they are assessing the probability agents would assign to these forecasts being generated by the model in question. This assumes agents do not know the true model in use but have knowledge of the model's properties.

Adopting the notation of Adolfson et al (2005), the univariate modesty statistic at forecast horizon h , is given by

$$M_i^h(\bar{\varepsilon}_{T+1}^{T+h}) \equiv \frac{y_{i,T+h}(\bar{\varepsilon}_{T+1}^{T+h}) - \hat{y}_{i,T+h|T}}{Std[y_{i,T+h}(\bar{\varepsilon}_{T+1}^{T+h})]}$$

where $y_{i,T+h}(\bar{\varepsilon}_{T+1}^{T+h})$ is the realisation of y_i at time $t = T + h$ if a sequence of shocks $\bar{\varepsilon}_{T+1}^{T+h} = (\bar{\varepsilon}_{T+1}, \dots, \bar{\varepsilon}_{T+h})$ is added to the model to get back the conditional forecast and $\hat{y}_{i,T+h|T} = E_T(y_{i,T+h})$ is the realisation of the unconditional forecast (no shocks have been added to the model). Where $M_i^h(\bar{\varepsilon}_{T+1}^{T+h})$ is normally distributed.

Adolfson et al (2005) also consider a multivariate version of the statistic.

$$M^h(\bar{\varepsilon}_{T+1}^{T+h}) \equiv [y_{T+h}(\bar{\varepsilon}_{T+1}^{T+h}) - \hat{y}_{T+h|T}]' \Omega_{T+h}^{-1} [y_{T+h}(\bar{\varepsilon}_{T+1}^{T+h}) - \hat{y}_{T+h|T}]$$

where $\Omega_{T+h} = Cov[y_{T+h}(\bar{\varepsilon}_{T+1}^{T+h})]$, and $M^h(\bar{\varepsilon}_{T+1}^{T+h})$ is chi-squared distribution

with p degrees of freedom.

These modesty statistics will map directly into probability space allowing for a probabilistic interpretation of the judgement adjusted forecasts from a model. More specifically given observed projections what is the probability that these are consistent with this model? Could another model be more consistent with these forecasts? From an agents point of view, if they do not observe the model being used, but they do observe the forecasts, and the agents have knowledge of no judgement forecasts from a given model, they can assign probabilities that these judgement adjusted forecasts came from or are consistent with this model.

In Leeper and Zha (2003) the univariate modesty statistic is applied to conditional forecasts of the interest rate, output and inflation, where judgement was only added to the interest rate track via monetary policy shocks. For our particular application we argue that the implausibility index is more sensible than the modesty index used in (Leeper and Zha 2003) and (Adolfson *et al.* 2005b) that evaluates the deviation of the conditional and unconditional forecasts.

In Adolfson et al (2005), they investigate how consistent a constant interest rate forecast is relative to history. They perform this exercise using both monetary policy shocks only, and allowing for other shocks. They use both the univariate index and the multivariate index.

2.2 Implausibility Index

We follow Doan Litterman Sims by using the implausibility index. This measure is constructed using the shocks added to the model, normalised by their standard errors. The Implausibility index is given by

$$Imp = [z^* - \tilde{z}]' \Omega^{-1} [z^* - \tilde{z}],$$

where

$${}_{(h+1) \times 1} z^* = \begin{bmatrix} y_{t-1} \\ \hat{\varepsilon}_t \\ \vdots \\ \hat{\varepsilon}_{t+h} \end{bmatrix},$$

is a vector containing the shocks added over the forecast horizon as well as the initial condition.

$$\underset{(h+1) \times 1}{\tilde{z}} = \begin{bmatrix} y_{t-1} \\ 0_t \\ \vdots \\ 0_{t+h} \end{bmatrix},$$

\tilde{z} is a vector of zeroes and the initial condition

$$\Omega = \begin{bmatrix} MSE(y_{t-1}|t-1) & 0 & \dots \\ & 0 & \Omega_\epsilon \\ & \vdots & \ddots \\ & & & \Omega_\epsilon \end{bmatrix},$$

where Ω contains the mean square error of the initial condition and the variances of each shock on the diagonal for each period.

The implausibility index is the objective function we minimise when fitting the shocks, evaluated at the optimal point. This statistic is both consistent with the model and with the Waggoner Zha algorithm. An implausibility index equal to zero means that no judgement has been added to the model. Lower values of the implausibility are assigned a higher probability while larger values mean more judgement has been added and hence are assigned a lower probability.

2.3 Two Examples

In this section we examine two examples to illustrate how the Implausibility Index and the Modesty Statistic may differ in their conclusions about the amount of judgement added to a model. We use a smaller version of KITT (the RBNZ's DGSE model) to demonstrate. We present graphs for four key observables; interest rates, CPI inflation, the exchange rate and consumption growth.

2.4 *Example 1: Tuning the interest rate track*

In this example we look at a situation where interest rates are held at 7% for eight quarters. We do this by allowing the Waggoner Zha algorithm to choose the shock combination with the lowest variance.

When judgement is added to hold interest rates at 7%, the four observable variables all deviate from their no judgement paths. If we were to use the Modesty Statistic to measure how much judgement has been added under this scenario we would look at the deviations of the judgement adjusted paths relative to the no judgement paths. We could do this for various horizons.

If we were to use the implausibility index we would look at the size of the shocks added to the model for those eight periods relative to history. The implausibility index would say that quite a lot of judgement has been added to the model, while a measure based on the shocks would say very little judgement has been added to the model.

2.5 *Example 2: Tuning all tracks*

In this scenario we repeat what we did in the first scenario, but this time we also tune all other observable variables back to their no judgement paths.

Under this scenario, only the interest rate path deviates from its no judgement path over the forecast horizon. All other observable variables have been forced to their no judgement paths. If we were to use the univariate modesty statistic to measure how much judgement we have added to the model we would only be penalised for the interest rate track. This can be observed in table 1. Since all other observable variables do not deviate from their no judgement paths, they do not enter in the calculation of the modesty statistic. Under the multivariate modesty statistic only the interest rate track would be penalised but this penalty maybe higher because we allow for the expected cross correlation between the interest rate and other variables. The modesty statistic would tell us that very little judgement has been added to the model. If we were to use a measure based on the shock sizes such as the Implausibility index, we see that we have added a lot of shocks or judgement to the model to hold all other variables at their no judgement levels, and hence we would get a measure telling us that a lot of judgement has been added to the model.

Table 1
Univariate modesty statistics, four- and eight- quarters ahead

	Four quarter		Eight quarter	
	Scenario 1	Scenario 2	Scenario 1	Scenario 2
Interest Rate	0.146	0.146	0.074	0.074
Non-tradable Inflation	0.204	0	0.090	0
Tradable/Non-tradable prices	0.039	0	0.031	0
Rent/Non-tradable relative price	0.036	0	0.025	0
Petrol/Non-tradable price	0.029	0	0.036	0
World Oil/World price	0	0	0	0
Tradable/Import Price	0.032	0	0.017	0
Import/World	0	0	0	0
Consumption	0.009	0	0.004	0
Consumption Housing Services	0.004	0	0.003	0
Exports	0.004	0	0.003	0
Imports	0.022	0	0.020	0
Residential Investment	0.004	0	0.013	0
Business Investment	0.020	0	0.015	0
B/NC	0.018	0	0.005	0
D/NC	0.011	0	0.007	0
World price inflation	0	0	0	0
World Interest Rate	0.001	0	0.001	0
Terms of Trade	0.000	0	0	0
Petrol Price Inflation	0.036	0	0.011	0
Tradable Price Inflation	0.199	0	0.171	0
Foreign Petrol Price Inflation	0	0	0	0
Consumption Growth	0.017	0	0.052	0
CPI inflation	0.246	0	0.026	0
Change in Exchange Rate	0.037	0	0.009	0

2.6 Why we should use a measure based on shock sizes

In the first example we add a smaller amount of judgement (in terms of shock sizes) to hold the interest rate at 7% for eight quarters. The Waggoner Zha

algorithm chooses the combination of shocks with the smallest variance subject to the interest rate track holding. It chooses non-monetary policy shocks as well as monetary policy shocks so that monetary policy rule can respond partially endogenously to the inflation track. Imposing any additional tunes, such that at least one other track differs from the tracks in the first scenario must result in shock combinations that involve adding larger shocks. Hence more judgement has to be added to the model and the model becomes less endogenous. In the second scenario all observable variables have been tuned over the forecast horizon.

The modesty statistic suggests that more judgement has been added in the first scenario than in the second scenario. This is because the interest rate track is the only track to deviate from its no judgement track. This effectively punishes the interest rule and the model for responding partially endogenously to a higher inflation track. It would suggest that a less endogenous model has had less judgement added to it.

3 Applications

Central banks frequently operate a central monetary policy model (for example, the United Kingdom uses the Bank of England Quarterly Model (BEQM), New Zealand uses the Forecast and Policy System (FPS), and for some time Canada used the Quarterly Projection Model (QPM), and is now using the Terms of Trade Economic Model (ToTEM)). However, central banks' rhetoric often refers to the use of a suite of models, primarily as a means of ensuring alternative beliefs and information are incorporated formally in the monetary policy committee process. This schizophrenia develops from the conflict between the desire to bring all viewpoints to bear on the monetary policy decision and a desire for a single organising framework for discussing alternative outcomes.

Policymaker judgement can take many forms. It may be influenced by projections from satellite or indicator models, be driven by information from markets, or the policy makers intuition in general. We use three concrete examples for illustration, conditioning on the market's implied interest rate track, the RBNZ's historical published interest rate tracks, and the projections from a BVAR, to illustrate how interest rate tracks from different sources can be incorporated into a DSGE model using the hard tunes technique of Waggoner and Zha (1999). The model will replicate each alternative interest rate track, but because the shocks required to return each track differ, the forecasts of key macroeconomic variables will differ for each set of conditioning information. By fitting the set of model shocks with the smallest variance we uncover the

conditional DSGE forecasts with the highest probability. In this section we show how we can help resolve this conflict by using a DSGE model as a means of interpreting the forecasts from alternative models and judgement that we think is typical of the policy environment of many central banks. We focus our hard tune exercises on the policy rate track and illustrate how the DSGE model can be used to interpret the type of structural shocks most likely to generate the alternative interest rate paths. But the techniques are general enough to consider conditioning on forecasts for other key macroeconomic variables, such as output and inflation (singly or jointly).

The DSGE model we use to interpret the alternative interest rate paths is a calibrated version of a multi-sector DSGE model currently under development at the Reserve Bank of New Zealand.² The open economy model consists of explicit production functions for export and non-tradable goods. Inflation processes for non-tradable goods, tradable goods and wages are characterized by quadratic adjustment costs that generate costs from monetary policy that seeks to stabilise inflation. Description of the model is relegated to the appendix that details the model including the optimisation problems faced by both households and firms. While the model contains some features specifically designed to address the nature of the New Zealand economy, the model contains many features common to the latest generation of DSGE models in use at several central banks.

Conditioning on RBNZ published forecasts

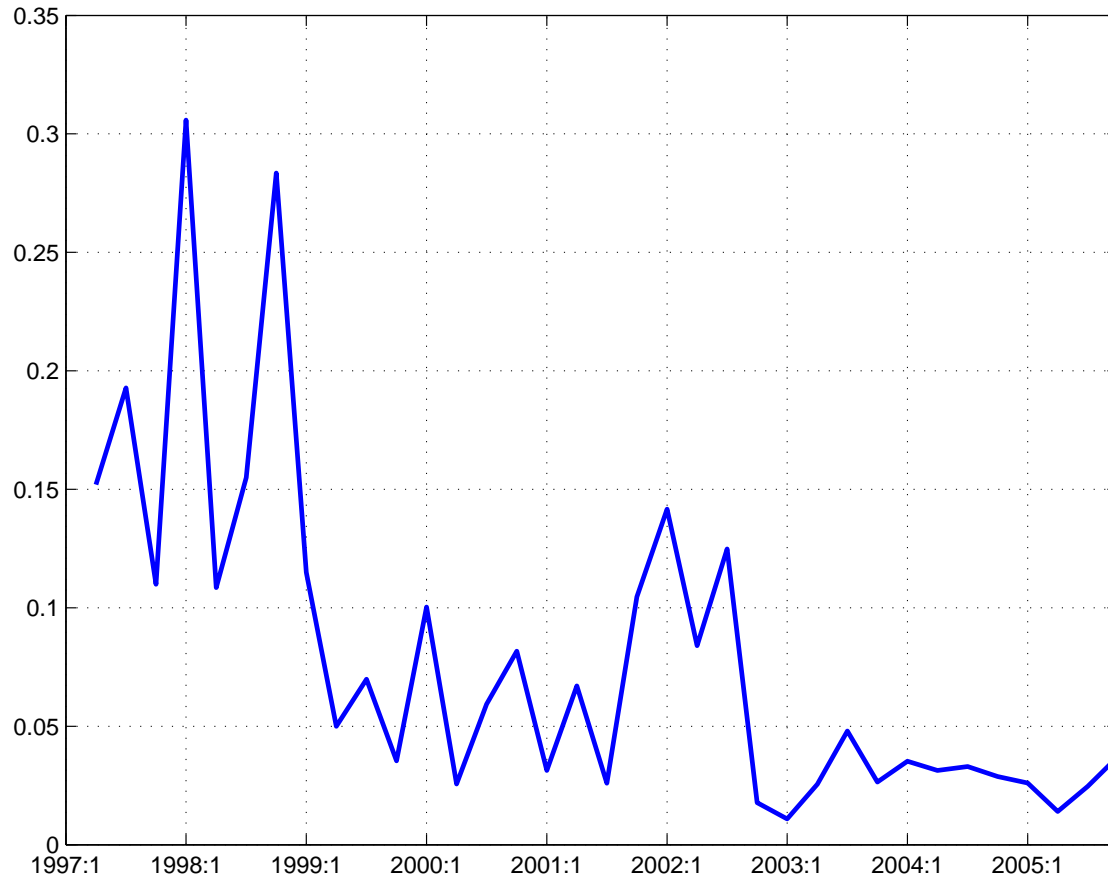
We condition on the long history of the published endogenous forecast track from the Reserve Bank's FPS model. The Reserve Bank of New Zealand is unique in publishing a long history of endogenous interest tracks, mostly determined by a combination of judgement and the Forecast and Policy System (FPS), the RBNZ's core model. FPS has been described as a second generation macroeconomic model and is similar to the Bank of Canada's Quarterly Projection Model (QPM). By tracking the implausibility index we can uncover periods where the published interest rate forecasts have deviated the most from the forecasts suggested by the DSGE model. We can gain a model based understanding of the judgement at these periods by uncovering the structural shocks necessary to recover the published forecasts.

Figure 1 shows the implausibility index computed for the published interest rate track using the DSGE model. The peak in the series occurs in 1998Q1. This point coincides with the Asian crisis, a period where the Reserve Bank's forecasts for output were too optimistic with the benefit of hindsight. Further-

² The standard errors for the calibrated parameters come from the Cramér-Rao covariance matrix. They have been computed via simulation methods given the current calibration of the model.

more, at the time, the Reserve Bank was operating a Monetary Conditions Index that related a mechanistic combination of the interest rate and exchange rate to economic conditions.³ This exacerbated the length of time to which interest rates remained high relative to the economic conditions before interest rates decreased dramatically over the second half of 1998, with the ninety day rate falling from 9.15 in June to 4.38 in December.⁴

Fig. 1. Implausibility index: RBNZ published interest rate forecasts



The magnitude of the discrepancy between the RBNZ’s published interest rate track and the forecast from the DSGE model is perhaps the most stark when confronting the DSGE forecasts conditioned on the published interest rate track. The DSGE model suggests sustained, significant inflation pressure is most consistent with the published track. Indeed, the conditional inflation

³ The Svensson (2001) report criticised the MCI as a period in the Bank’s history that represented a “significant deviation from international best practice”. The Reserve Bank has acknowledged the use of the MCI over this period as “inappropriate”.

⁴ In addition, there was a period of drought in early 1998 and early 1999.

forecast increases to over 6.5 percent in annualised quarter-on-quarter inflation, at least partly driven by a relatively large depreciation in the nominal exchange rate (see the bottom left panel of figure 2).⁵

Fig. 2. Conditional and unconditional forecast paths: RBNZ published interest rate forecasts

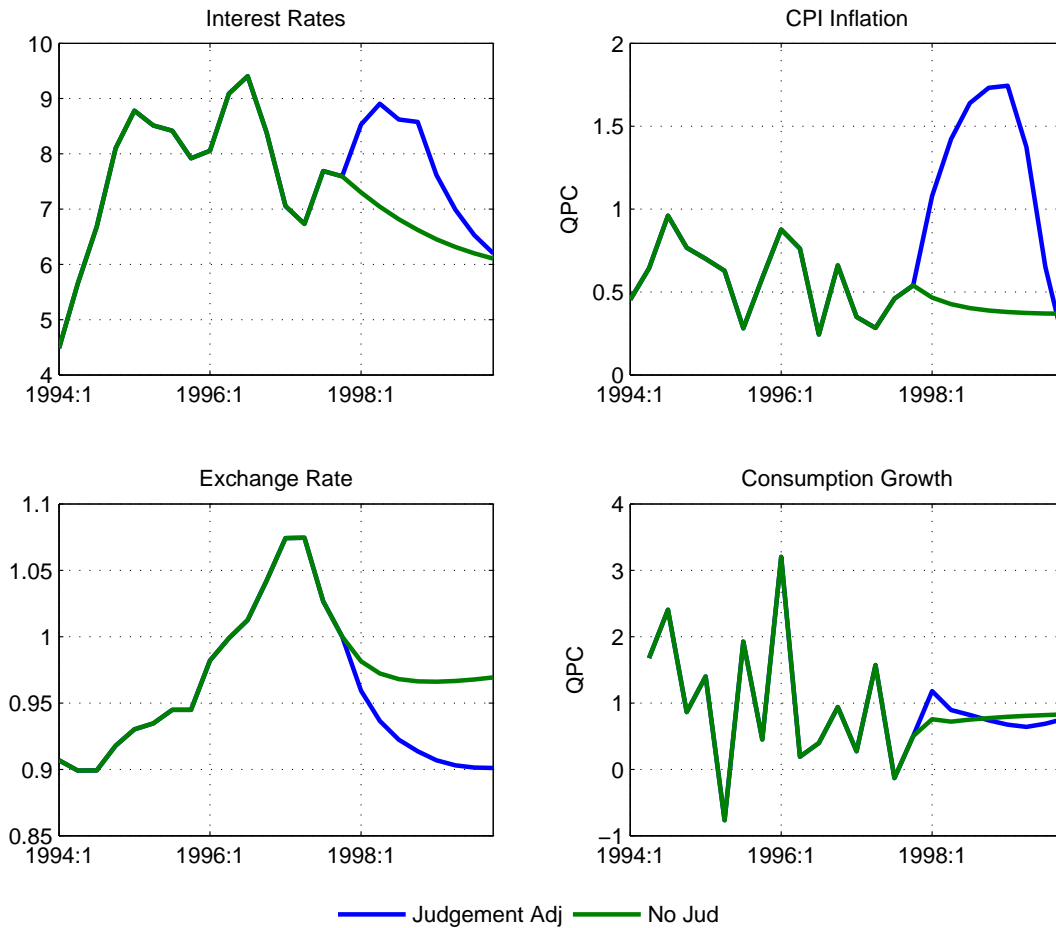
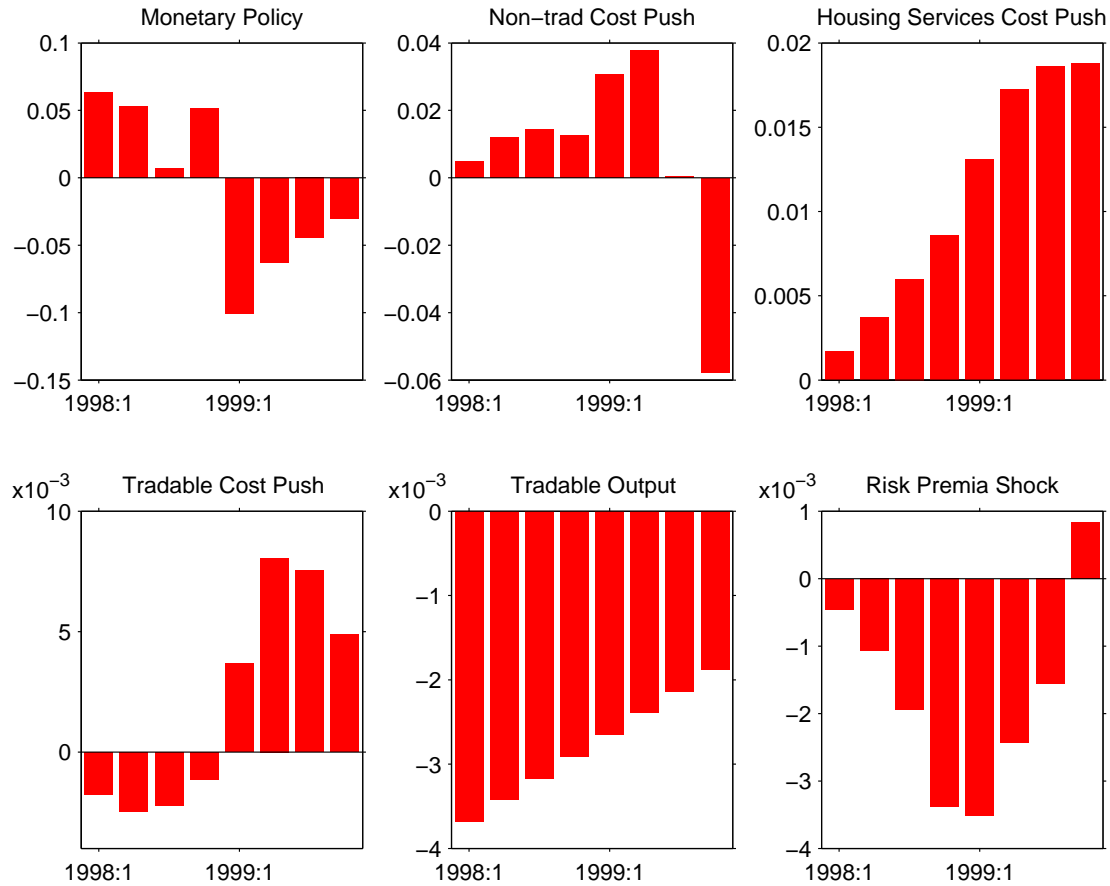


Figure 3 reports the six largest of the structural shocks required to return the DSGE forecasts conditioned on the RBNZ published forecast track. Perhaps unsurprisingly, an initial sequence of positive monetary policy shocks (see the top right panel) is required to return the initially higher policy rates, which drop relatively sharply over 1999 with the assistance of a sequence of negative shocks.

⁵ Clearly, real-time data issues cloud the precise numbers. However, the RBNZ 1998Q1 forecast for the output gap across March year 1997/98 was -0.6, which does not appear supportive of a strong policy response.

Fig. 3. Implied DSGE shocks: RBNZ published interest rate forecasts



Furthermore, the model suggests cost-push shocks to non-tradables inflation help reconcile the two interest rate paths while the contribution from other shocks appears small. However, recent periods return comparatively small implausibility index numbers.

Conditioning on constant interest rate forecasts

We also condition the DSGE model forecasts to a constant interest rate track constructed. Historically this replicates earlier behaviour of the Bank of England monetary policy process where the monetary committee refrain from producing endogenous policy forecasts since the committee feels they cannot agree on the appropriate policy rule. While current Bank of England Inflation Reports contain forecast conditional on market interest rates, recent reports (see Bank of England (2007)) also present forecasts conditional on constant interest rates.

Figure 4 shows the implausibility index from conditioning on a constant inter-

est rate assumption. Again the period around the time of the Asian crisis, and the Reserve Bank's subsequent policy response, is selected by the implausibility index as indicating the period where the most judgement must be added to the DSGE model to return in this case, a constant interest rate track. In particular, the index is highest at 1998Q3 but falls dramatically in 1998Q4 at the time when the ninety day rate was slashed.

Fig. 4. Implausibility index: constant interest rate

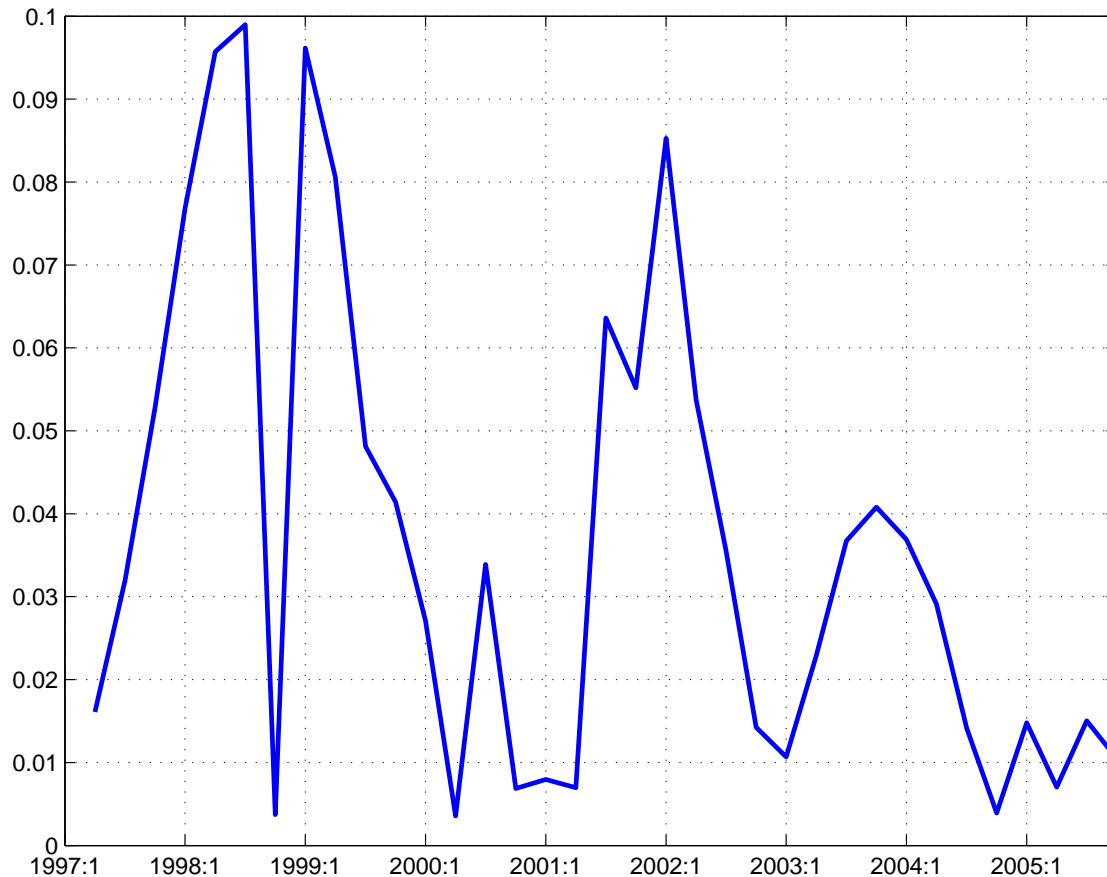


Figure 5 displays the forecasts conditioned on the constant interest rate assumption for 1998Q2 which demands that the ninety-day interest rate stay at almost 9 percent for eight quarters. This stands in marked contrast to the actual path for interest rates that were cut dramatically in light of the Asian crisis and low domestic growth. In order to return the radically different policy track, the model suggests a particularly large non-tradables shock at the last period in the forecast horizon, which acts to push quarter-on-quarter CPI inflation to almost four percent in annualised terms. This can be shown in figure 6.

Fig. 5. Conditional and unconditional forecast paths: constant interest rate: 1998Q2

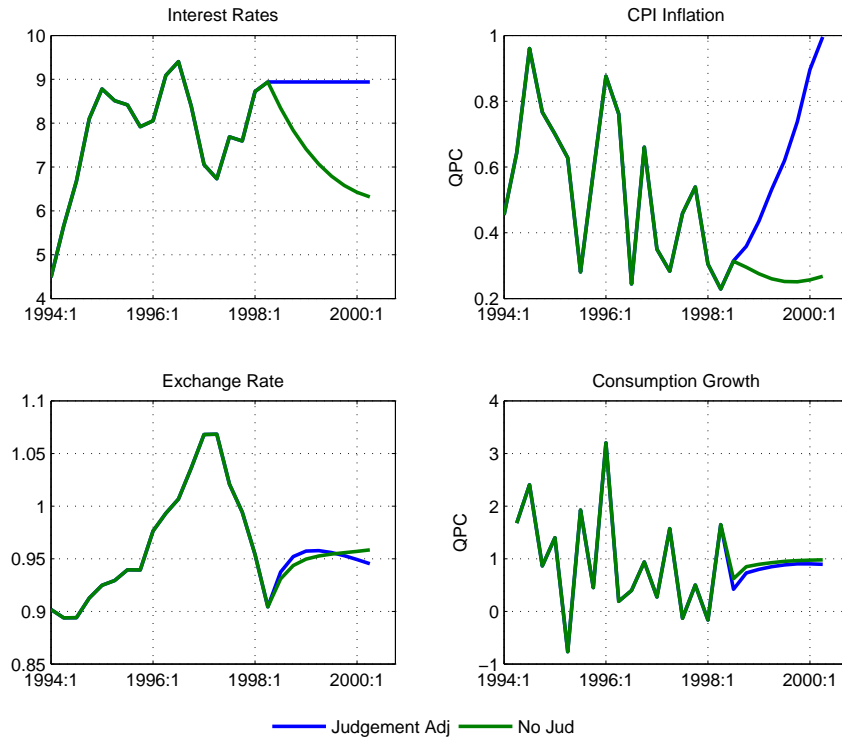
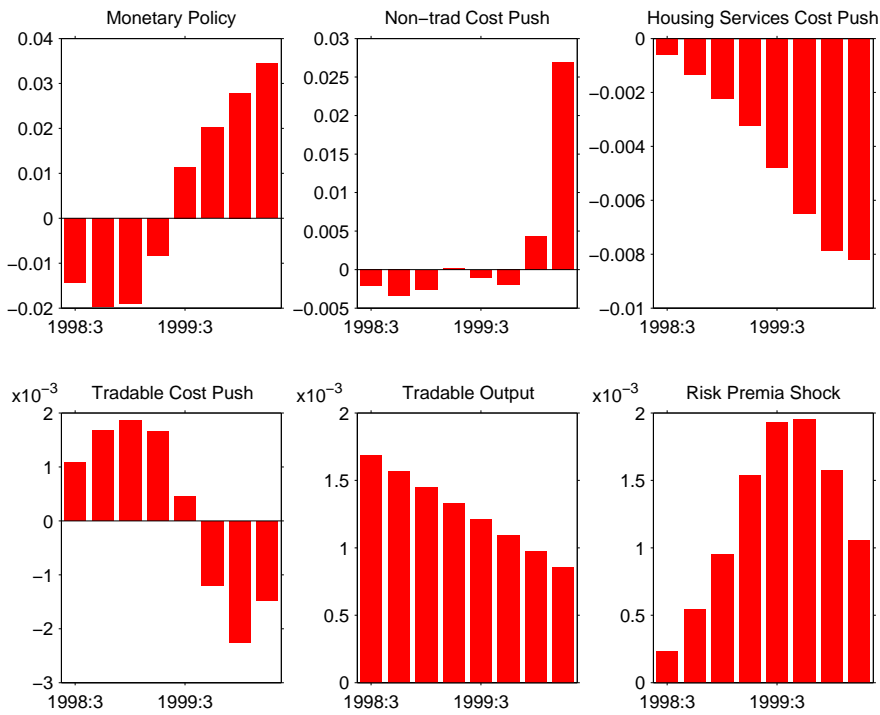
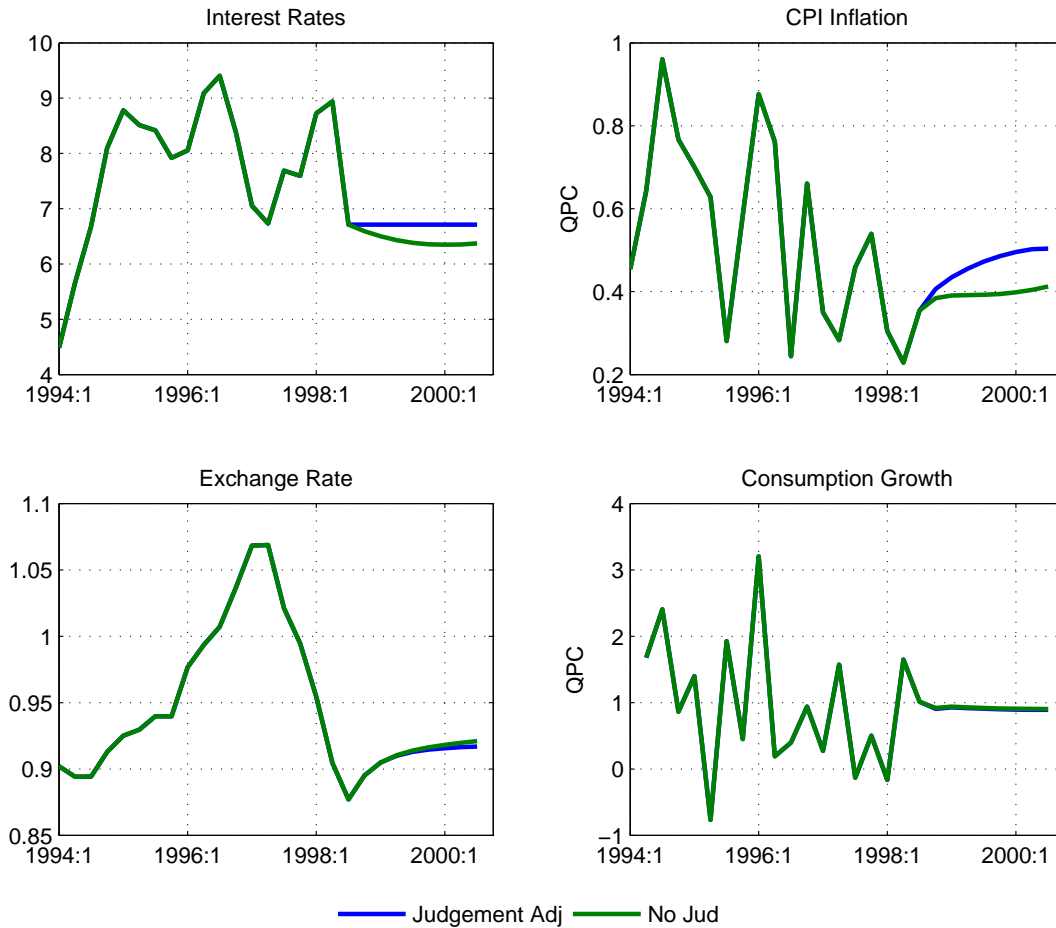


Fig. 6. Implied DSGE shocks: constant interest rate



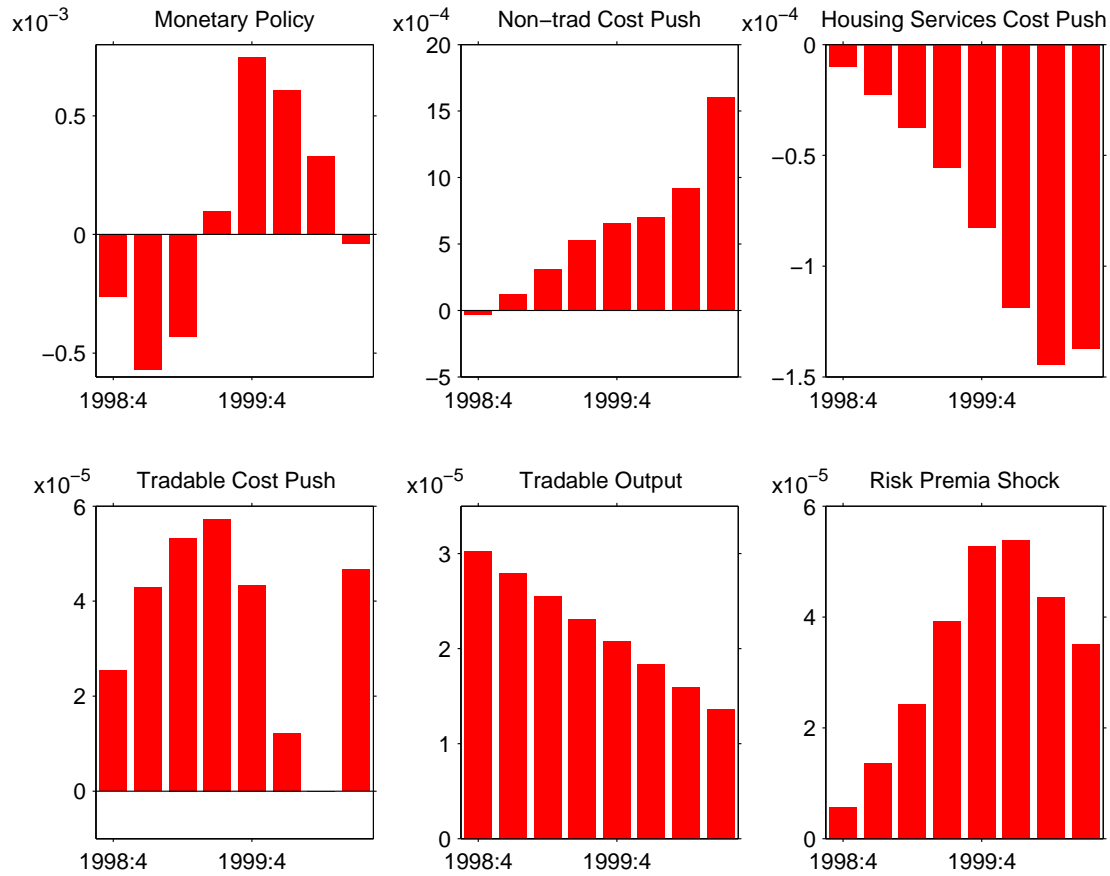
That the model chooses to place such a large weight on a single shock, appears confusing initially. However, we assume that agents anticipate these shocks and this leads to higher inflation in periods prior to the large shock. Of course, the policymaker or modeller may the particular time dimension of shocks if the rational for a particular judgement can be attributed to particular shocks or time periods.

Fig. 7. Conditional and unconditional forecast paths: constant interest rate: 1998Q3



Interestingly, rates were cut so drastically that the very next quarter the implausibility index records a very low number — the flat interest track for 1998Q3 is much more palatable to the DSGE model, largely because the ninety day rate has dropped to below 7 percent. The top left panel of figure 7 shows that the constant interest rate forecast is indeed much closer to the DSGE forecast and consequently, the structural shocks required to return the conditional forecast (see figure 8 are very small).

Fig. 8. Implied DSGE shocks: constant interest rate



Conditioning on forecasts from a Bayesian VAR

Our final exercise shows the generality of our techniques by conditioning on the inflation forecasts from a Bayesian VAR model currently in use in the policy environment at the Reserve Bank of New Zealand. We show how the BVAR forecasts can be viewed in relation to the DSGE model to generate a structural interpretation, often absent from discussion of statistical model forecasts which tend to be predicated on time series properties of data series.

We choose a Bayesian VAR in particular because BVARs have been shown to produce good forecasting performance (see Litterman (1986) and Lees *et al.* (2007) for the case of New Zealand). Conditioning directly on aspects of the BVAR forecasts may be considered an alternative to applying the full blown DSGE-VAR methodology of Del Negro and Schorfheide (2004) in the policy process.

Figure 9 show the implausibility index applied to the Bayesian VAR inflation forecasts. The index implies that the most judgement must be applied to the

DSGE forecast in 2000Q4 in order to return the BVAR inflation forecast. However, the index number is quite low relative to the two previous interest rate exercises. It appears that the BVAR forecasts are more easily accepted from the perspective of the DSGE model.

Fig. 9. Implausibility index: BVAR inflation forecasts

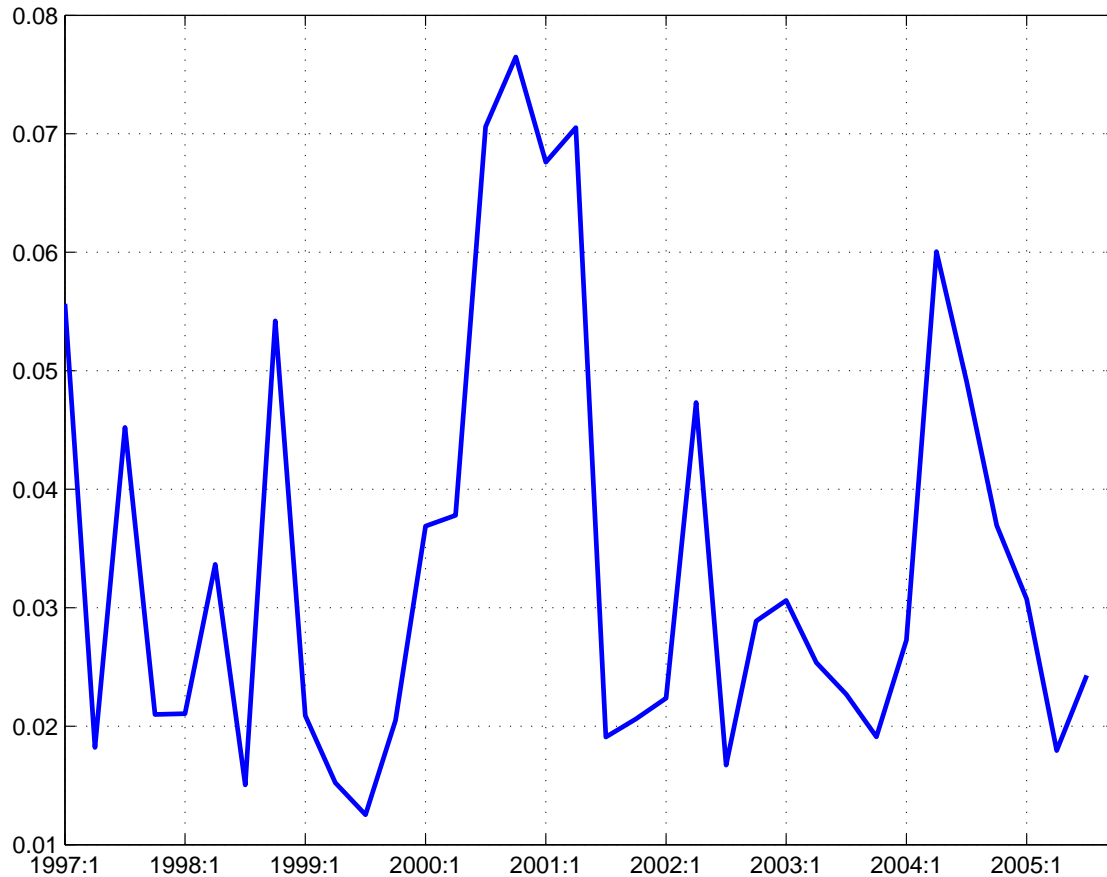


Figure 10 displays the unconditional DSGE forecasts and the DSGE forecasts conditional on the BVAR inflation path. Conditioning on the BVAR inflation path calls for a stronger policy response than the DSGE model otherwise would suggest.

Since the BVAR forecasts are higher initially, the DSGE model requires a large non-tradable cost push shock in the first forecast period in order to recover the higher inflation path in the BVAR forecast. The remainder of the structural shocks are particular small (see figure 11).

Fig. 10. Conditional and unconditional forecast paths: BVAR inflation forecasts

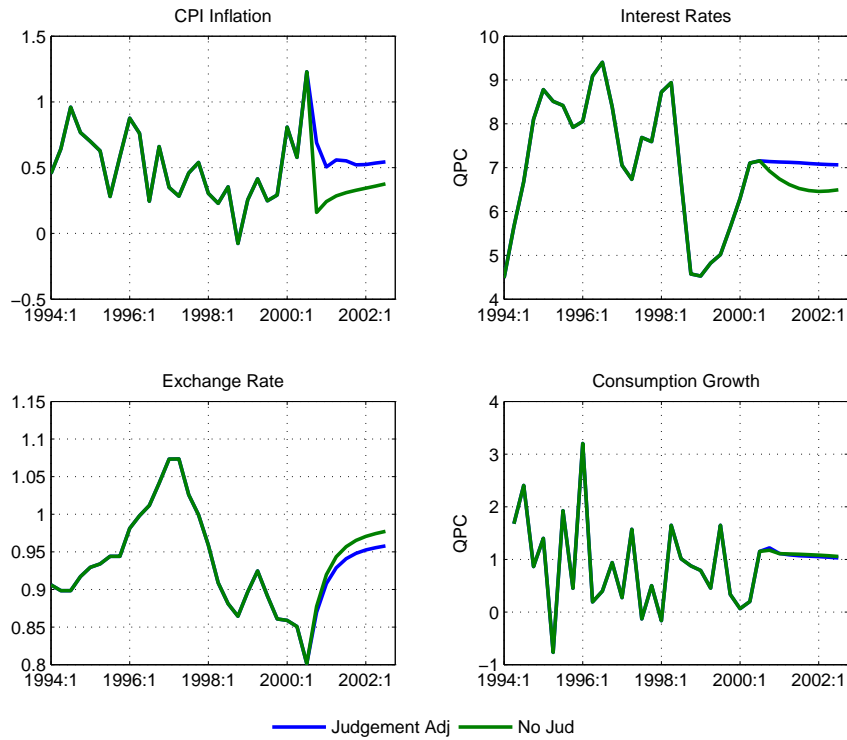
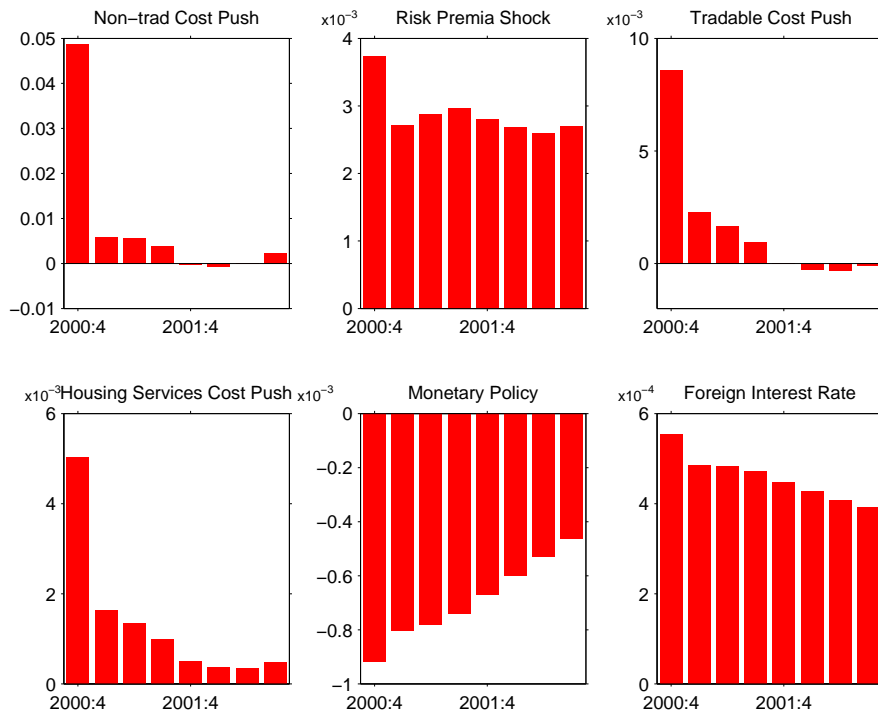


Fig. 11. Implied DSGE shocks: BVAR inflation forecasts



4 Conclusion

Policymaker judgement is most often expressed in terms of observable paths for key macroeconomic variables rather than the deep parameters and shocks that make up DSGE models. However several easily implemented techniques allow the addition of judgement to both point and density forecasts produced by macroeconomic models. Using a multiple shock approach allows judgement to enter forecasts with the least amount of disruption to the model-consistency of the forecasts.

While we advocate using our techniques within the policy environment, we show that the techniques can be used to monitor the amount of judgement used over time and to compare the plausibility of conditioning on alternative types of information. Comparing unconditional forecasts to forecasts conditioned on the long history of the Reserve Bank's published forecasts, we find that the most judgement must be added to the model in 1998Q1, immediately after the Asian crisis. Relatively large monetary policy and non-tradable cost-push shocks must be added to the model to reconcile the DSGE forecasts with the published forecasts.

This result is echoed in the constant interest rate forecasts that show most judgement must be added to the model in 1998Q3, when the model suggests much lower interest rates than suggested by constant interest rates. In addition, we show that conditioning on inflation forecasts from a BVAR has historically required adding less judgement than conditioning on the RBNZ's published interest rate path or constant interest rate forecasts.

These techniques offer an appealing method of tracking the magnitude and type of judgement that is often added to forecasts by policymakers. Certainly there appears little to suggest formal modelling of the economy makes it difficult to incorporate policymakers' off-model judgement. The structure that DSGE models impose on forecasts implies that they can assist in the interpretation of other forecasts in the policy environment.

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A Appendix: Summary of the KITT Setup

Non-tradable production

$$y_t^n = (z_t^n)^{\gamma_n} (A_t^n l_t^n)^{1-\gamma_n} \quad (\text{A.1})$$

Non-tradable output y_t^n is produced using a non-tradable intermediate good z_t^n , labour l_t^n and non-tradable labour augmenting technology A_t^n . γ_n is the non-tradable intermediate's share of income. The non-tradable sector is monopolistically competitive and subject to Calvo adjustment costs.

Tradable production

$$y_t^\tau = A_t^\tau \left(\frac{m_t \cdot \exp(u_t^y)}{1 - \omega^\tau} \right)^{\gamma_\tau} \quad (\text{A.2})$$

Tradable output y_t^τ is produced using imported goods m_t , and tradable technology A_t^τ . γ_τ is import's share of production and ω^τ is oil's share of production in imports, where u_t^y is a disturbance term. The tradable sector is monopolistically competitive and subject to Calvo adjustment costs.

Export production

$$X_t = (U_t^x K_{t-1}^x)^{\gamma_x} (A_t^x L_t^x)^{1-\gamma_x} \quad (\text{A.3})$$

Export goods X_t are produced using capital K_t^x with variable utilisation U_t^x , labour L_t^x and labour augmenting export technology. γ_x is capital's share of income. The export sector is perfectly competitive.

Export specific capital K_t^x accumulates in the following perpetual inventory process

$$K_t^x = (1 - \Delta_x) K_{t-1}^x + I_t^x \quad (\text{A.4})$$

Where I_t^x is business sector investment.

Households

$$E_t \sum_{k=0}^{\infty} \beta^k \log \Gamma_{t+k} \quad (\text{A.5})$$

Households maximise their discounted stream of future utility, where Γ_t is the habit adjusted stock of consumption.

$$\Gamma_t = \frac{\left(C_t^\tau - \chi_c C_{t-1}^\tau\right)^{\omega_\tau} \left(C_t^s - \chi_c C_{t-1}^s\right)^{\omega_s} \left(C_t^n - \chi_c C_{t-1}^n\right)^{(1-\omega_\tau-\omega_s)}}{1 - \chi_c} \quad (\text{A.6})$$

Where C_t^τ, C_t^s and C_t^n , are tradable, housing services and non-tradable consumption respectively. ω_τ and ω_s are tradable's and housing service's share of consumption respectively.

$$c_t^s = A_t^s u_t^h k_{t-1}^h \quad (\text{A.7})$$

Housing services c_t^s are produced using $t-1$ housing capital services k_{t-1}^h with variable utilisation u_t^h , and housing services technology A_t^s . Landlord's are monopolistically competitive and subject to Calvo adjustment costs so that rents are sticky.

Housing capital accumulates according to the perpetual inventory process

$$k_t^h = (1 - \delta_h) k_{t-1}^h + i_t^h \quad (\text{A.8})$$

where i_t^h is residential investment and δ_h is the depreciation rate on the housing capital stock.

Consumers deposit savings with a financial intermediary. The financial intermediary pays a deposit rate on deposits.

$$i_t^d = i_t + \zeta \left(\frac{B_t}{Q_{t+1}^h K_t^h} - \lambda \right) \quad (\text{A.9})$$

The deposit rate i_t^d is a function of the 90 day rate i_t and deviation of the loan to value ratio from its steady state level λ , where B_t is foreign debt, Q_{t+1}^h is the shadow value of housing and K_t^h is the housing capital stock.

Modified UIP

$$\Delta S_{t+1} + i_t + i_t^f = ex_t + fx_t \quad (\text{A.10})$$

Where ΔS_{t+1} is the change in the nominal exchange rate, i_t is the nominal

interest rate, i_t^f is the world interest rate, $ex_t = \theta (\Delta S_t + i_{t-1} - i_{t-1}^f)$ is the endogenously determined disparity term and fx_t is the exogenously determined autoregressive disparity term.

Monetary Policy

$$i_t = \rho_i i_{t-1} + (1 - \rho_i)(\bar{\pi}_{t+1} + \kappa \Theta_t) + \varepsilon_t^{mp} \quad (\text{A.11})$$

Interest rates i_t are set according to a rule that is concerned about deviations of inflation from the inflation target $\bar{\pi}_{t+1}$ in the future and with a monetary authority that is concerned with interest rate smoothing. Where the sequence of future deviations Θ_t is given by

$$\Theta_t = \beta_{mp} \Theta_{t+1} + (1 - \beta_{mp})(\pi_t - \bar{\pi}_t) \quad (\text{A.12})$$

where π_t is quarterly CPI inflation, which is given by

$$\pi_t = v_\tau \pi_t^\tau + v_p \pi_t^p + (1 - v_\tau - v_p) \pi_t^n \quad (\text{A.13})$$

where π_t^τ is tradable price inflation, π_t^p is petrol price inflation and π_t^n is non-tradable price inflation.

Market Clearing Conditions

$$Y_t^n = (C_t^n + I_t^h) \exp(\sigma^n) + Z_t^n \quad (\text{A.14})$$

Non-tradables output can either be consumed, invested in housing or used in the production of future non-tradables goods. σ^n represents government's share of non-tradable output.

$$Y_t^\tau = (C_t^\tau + I_t^x) \exp(\sigma^\tau) \quad (\text{A.15})$$

Tradables output can be consumed or invested in the export sector. σ^τ represents government's share of tradable output.

Exogenous processes

Technology: there are four exogenous technology processes in the model, one for each sector, non-tradables (n), tradables (τ), housing services (s) and the export sector (x). The general technology process is given by

$$\log(A_t^\dagger) = \rho_{A^\dagger} \log(A_{t-1}^\dagger) + (1 - \rho_{A^\dagger}) \log(\bar{A}^\dagger) + \varepsilon_t^{A^\dagger} \quad (\text{A.16})$$

where $\dagger = n, \tau, s, x$, \bar{A}^\dagger is trend technology, $\varepsilon_t^{A^\dagger}$ is a sector specific technology shock and ρ_{A^\dagger} is the sector autoregressive parameter on the technology A_t^\dagger .

Terms of trade trend:

$$\bar{T}_t = \rho_{\bar{T}} \log(\bar{T}_{t-1}) + \varepsilon_t^{\bar{T}} \quad (\text{A.17})$$

Trend terms of trade \bar{T}_t follow an autoregressive process, where $\varepsilon_t^{\bar{T}}$ is a Terms of Trade shock and $\rho_{\bar{T}}$ is the autoregressive parameter.

Terms of trade gap:

$$\log(T_t) - \log(\bar{T}_t) = \rho_T \left(\log(T_{t-1}) - \log(\bar{T}_{t-1}) \right) + \varepsilon_t^{TOT} \quad (\text{A.18})$$

The Terms of Trade gap $\log(T_t) - \log(\bar{T}_t)$ follow an autoregressive process, where ε_t^{TOT} is a shock to the Terms of Trade gap and ρ_T is the autoregressive parameter.