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# Incorporating judgement with DSGE models*

**Jaromír Beneš, Andrew Binning, Kirdan Lees** †

## Abstract

Central bank policymakers often cast judgement about macroeconomic forecasts in reduced form terms, basing this on off-model information that is not easily mapped to a structural DSGE framework. We show how to compute forecasts conditioned on policymaker judgement that are the most likely conditional forecasts from the perspective of the DSGE model, thereby maximising the influence of the model structure on the forecasts. We suggest using a simple implausibility index to track the magnitude and type of policymaker judgement. This is 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 used in the policy environment at the Reserve Bank of New Zealand.

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# 1 Introduction

Dynamic Stochastic General Equilibrium (DSGE) models deliberately abstract from much economic detail to present a stylised, but theoretically consistent, view of the economy. Recent DSGE models can broadly match the data and produce forecasts competitive with other benchmark models (see Smets and Wouters (2003) and Adolfson, Laseén, Lindé, and Villani (2008)). This has sparked interest from central banks which have designed DSGE models with the goal of using these directly in the forecast and policy environment (see for example, Murchison and Rennison (2006), Brubakk, Husebo, McCaw, Muir, Naug, Olsen, Roisland, Sveen, and Wilhelmsen (2005), the DSGE model in Adolfson *et al* (2007), Harrison *et al* (2005) and Medina and Soto (2006) amongst others).

However, policymakers bring valuable experience and accumulated knowledge to DSGE models that is often not directly interpretable in terms of the structure of a DSGE model. If DSGE models are to operate effectively in the policy environment, modellers need to consider how best to incorporate policymaker judgement that can then be described directly in terms of the structural components of the model.

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 those variables that the policymakers wish to adjust. We expand this approach by searching across the entire set of structural shocks within a DSGE model and select that set of future structural shocks with 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 expected future events (shocks) and adjust Waggoner and Zha (1999) for this expansion.

As a metric for the ‘amount’ of judgement applied, we advocate the construction and monitoring of the Doan, Litterman, and Sims (1983) ‘implausibility index’ to the structural shocks that are 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 New Zealand data. We show how our technique can be applied to an illustrative example where a policymaker believes that a flat interest rate forecast is appropriate. 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, or judgement adjusted forecasts, and unconditional or purely model-generated forecasts. Sustained periods of increased use of judgement may be indicative of specification issues that need to be addressed via recalibration or respecifying the model, if the policymaker cannot point to one-off events motivating the judgement (such as changes in fiscal stance, labour strikes, or freak weather occurrences).

We apply our technique to three specific examples 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 (RBNZ) since 1998 and report the period in which the RBNZ forecasts are most dissimilar from our DSGE model. We also condition forecasts on a constant interest rate forecast and again 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 the properties of the DSGE model needed 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. (Details of the model are 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 forward track for interest rates) a unique combination of exactly identified univariate shocks is added. More generally, when the number of adjusted variables is equal to the number of shocks 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 shocks we can choose from exceeds the number of forecasted variables to be adjusted, 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 set that is most likely to eventuate from the perspective of the DSGE model and thus represents a natural focus point for discussing the judgementally adjusted forecasts.

It is possible to express a DSGE model as:

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

where $y_t$ is a vector of state variables, $\varepsilon_t$ 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 contain identities and lagged economic variables which implies that the vector of model shocks may contain zeros. Also, we restrict the structural shocks to Gaussian processes where the off-diagonal elements of $B$ 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:

$$y_t = F y_{t-1} + D + G\varepsilon_t. \tag{2}$$

where $D = CA_0^{-1}$. Using the reduced form representation at time $t$, we can construct the $h$-step ahead forecast of the deviation of $y_t$ from the vector of constants:

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

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

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

(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 conditions in 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 $F$ and $G$); and (iii) the vector of constants, irrespective of whether these are the structural steady-state parameters $C$ or the reduced form constants $D$.

A core/non-core approach to modelling and adding judgement has been advocated by Alvarez-Lois, Harrison, Piscitelli, and Scott (2005), and Reichlin (2007). This involves a micro-founded theoretical core model combined with a non-core model, that explains the difference between the core model and the data over history. The non-core model includes exogenous variables to help explain the difference. Judgement is added to forecasts from the non-core model by changing the paths of the exogenous variables. Sims (2006) has noted concerns with the core/non-core approach to modelling, including potential inconsistencies between the core and the non-core models, problems over interpreting judgement in terms of the core model or the non-core model, difficulties in generating model-consistent residuals over history, and the method for determining the exogenous variables over history and the future. We believe the techniques outlined in this paper provide greater model consistency. We do not have a non-core model and so all judgement affects the core model. As a consequence, agents respond appropriately based on the information available and the assumptions made, and we get the correct endogenous responses from model variables.

We argue that a metric for the amount of judgement added to a forecast that focuses on the size of the shocks that must be added to the model to return a forecast consistent with the policymaker judgement, is a better metric than simply comparing the judgement adjusted tracks with their no-judgement paths. Waggoner and Zha (1999) show how judgement can be incorporated into a model using a 'least squares' procedure. The algorithm determines the shock combinations with the least variance that is 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 most likely conditional on the structure of the model, historical data and the model's parameterisation.

In Doan, Litterman, and Sims (1983), Leeper and Zha (2003) and Adolfson, Laseén, Lindé, and Villani (2005) the judgement adjusted paths are evaluated relative to the model and history to determine how likely they are. Doan, Litterman, and Sims (1983) outline and use the implausibility index while Leeper and Zha (2003) and Adolfson, Laseén, Lindé, and Villani (2005) outline and use the modesty statistic.

## 2.1 The Modesty Statistic

Leeper and Zha (2003) examine hypothetical monetary policy interventions in the US and construct a modesty statistic to determine the severity of these interventions relative to a baseline. 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 forecasts from the model. This is a particular application of the Lucas critique (Lucas 1976), in the sense that they assess the probability agents assign to these forecasts being generated by the model in question. This assumes that agents do not know the true model in use but have knowledge of the model's properties.

Adopting the notation of Adolfson, Laseén, Lindé, and Villani (2005), the univariate modesty statistic at forecast horizon $h$, is given by

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

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 $\bar{\varepsilon}_{T+1}^{T+h} = (\bar{\varepsilon}_{T+1}, ..., \bar{\varepsilon}_{T+h})$ is added to the model to get back the conditional forecast and $\hat{y}_{i,T+h|T} = \mathrm{E}_T(y_{i,T+h})$ is the realisation of the unconditional forecast (that is, no shocks have been added to the model). Note that $M_i^h(\bar{\varepsilon}_{T+1}^{T+h})$ is normally distributed.

Adolfson, Laseén, Lindé, and Villani (2005) also consider a multivariate version of the statistic.

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

where $\Omega_{T+h} = Cov\left[y_{T+h}\left(\varepsilon_{T+1}^{T+h}\right)\right]$, and $M^h\left(\varepsilon_{T+1}^{T+h}\right)$ follows a chi-squared distribution with $p$ degrees of freedom, where $p$ is the number of observed variables.

These modesty statistics 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 agent's 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 is added only 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 statistic used in Leeper and Zha (2003) and Adolfson, Laseén, Lindé, and Villani (2005) that evaluates the deviation of the conditional and unconditional forecasts.

In Adolfson, Laseén, Lindé, and Villani (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, and Sims (1983) 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

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

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

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

is a vector of zeros and the initial condition, and

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

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 that we minimise when determining the set of shocks with minimal variance that return judgement-adjusted forecasts, 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 index are assigned a higher probability while larger values mean more judgement has been added and are hence 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 on 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 in figure 1 for four key observables: interest rates, CPI inflation, the exchange rate and consumption growth.

### Example 1: Tuning the interest rate track

In this example we look at a period of two years beginning in the first quarter of 2002 where interest rates are increased by 1.5% to 7% and then held at this level for eight quarters. We produce conditional forecasts for other variables using 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 judgement-free paths. This can be seen in figure 1 where green dashed lines show conditional forecasts based on the new, higher interest rate track.

If we use the implausibility index we examine the magnitude of the *shocks* that return the judgement relative to the observed historical magnitude of these shocks. Instead, if we use the modesty statistic to measure how much judgement has been added, we examine the magnitude of the deviations of the judgement adjusted paths relative to their counterparts under the no-judgement case.

For this example, several of the conditional forecast paths change substantially — implying the modesty statistic would indicate a substantial amount of judgement has been added to the model. However, only comparatively small shocks are required to return the judgement added to the path of a single variable — implying the implausibility index would suggest relatively little judgement has been added to the model.

**Example 2: Tuning all tracks**

In this second example we repeat the first exercise: interest rates are increased substantially and then held at 7% for eight quarters. However, we also tune all other observable variables back to their no-judgement paths, implying we are in fact tuning not just one, but all the observable variables. This can be seen in Figure 1. The blue dotted line is the new conditional forecast where the interest rate track is tuned to the new higher track and all other observables are tuned to the no-judgement path (red dashed line).

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 original, no-judgement paths. If we were to use the univariate Modesty Statistic to measure how much judgement we have added to the model the policy-maker is only penalised for the interest rate track. This can be observed in table 1. Under the multivariate modesty statistic only the interest rate track would be pe-

**Figure 1**
**Adding judgement: A simple illustrative example**

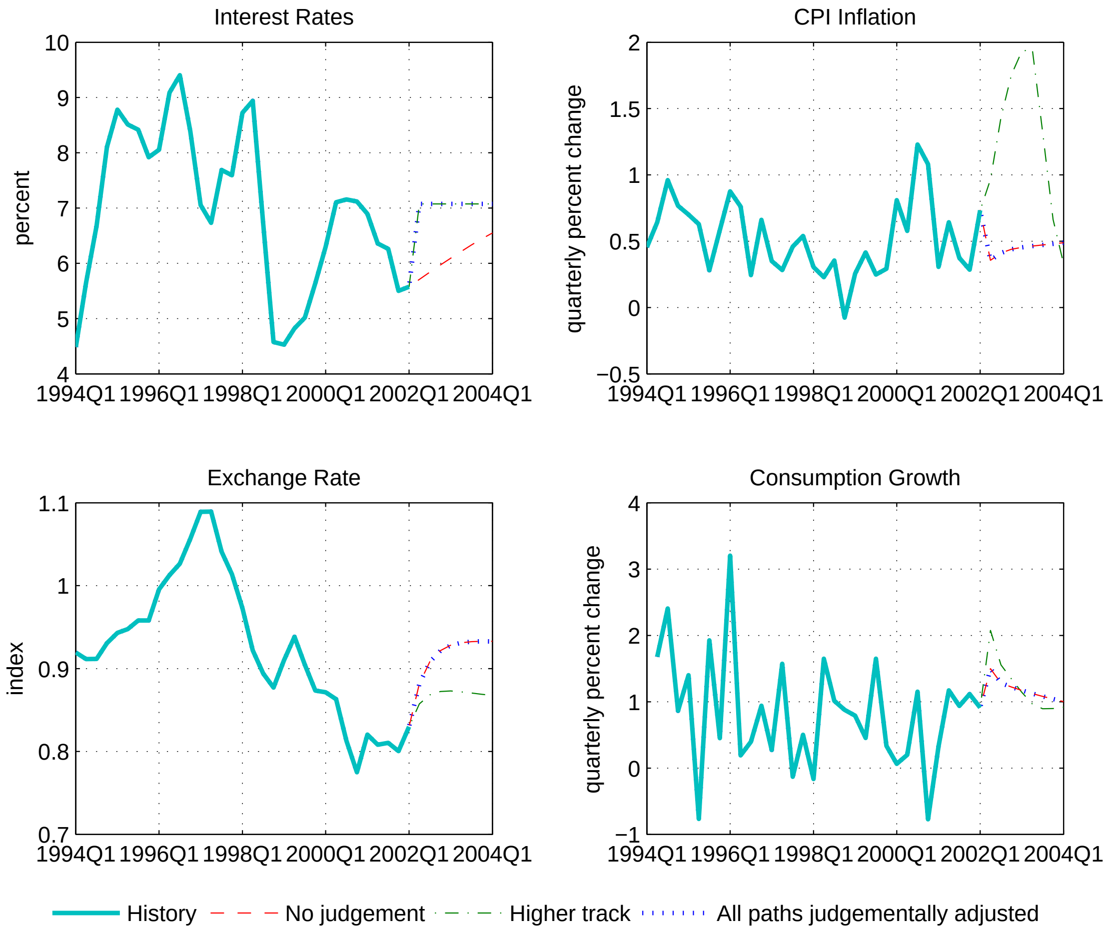


**Table 1**
**Univariate modesty statistics, four- and eight- quarters ahead**

| | 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 |
| Household Debt/Nominal Consumption | 0.018 | 0 | 0.005 | 0 |
| Debt Service/Nominal Consumption | 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 |

nalised directly (although this penalty maybe somewhat higher since we allow for the expected cross correlation between the interest rate and other variables). The modesty statistic would suggest very little judgement has been added to the model since only the interest rate track has changed. Indeed this is the case, the modesty statistic at four quarters is 0.4882 for the first example, and only 0.0538 in the second example. At the eight quarter horizon the modesty statistic is 0.1126 for the first example, and 0.0108 for the second example. If we were to use the implausibility index (or any measure based on shock sizes), we see that we have added a substantial amount of judgement to the model in order to remove the endogeneity embedded in the model and hold each observable variable at its no judgement path. The implausibility index is 0.1713 for the first example, and 0.3989 for the second example.

# 3 Applications

Central banks frequently operate a main 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) before switching recently to using the Terms of Trade Economic Model (ToTEM)). However, central banks also use a suite of models, primarily as a means of ensuring alternative beliefs and information are incorporated formally in the monetary policy decision process.

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 maker's intuition in general. We use three concrete examples for illustration of the techniques to add judgement described in the previous section conditioning on (i) a constant interest rate track; (ii) the RBNZ's historical published interest rate tracks; and (iii) the projections from a BVAR. 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 highest probability.

In this section we also show how we can use a DSGE model as a means of interpreting the forecasts from alternative models and the judgement that we think is typical of the policy environment of many central banks. We focus our exercises on the policy interest rate track and illustrate how the DSGE model can be used to determine the 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 RBNZ.[2] The open economy model consists of explicit production functions for exports 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 aims at stabilising inflation. A description of the model is relegated to the appendix together with details on 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, it contains many elements common to the latest generation of DSGE models in use at several central banks.

## 3.1 Conditioning on RBNZ published forecasts

We condition on the long history of the published endogenous forecast tracks from the Reserve Bank's FPS model. The RBNZ is unique in publishing a long history of endogenous interest rate tracks, mostly determined by a combination of judgement and output from the Forecasting and Policy System (FPS), the RBNZ's core model.[3] By tracking the implausibility index we can determine the periods where the published interest rate forecasts have deviated most from the forecasts suggested by the DSGE model. We can gain a model-based understanding of the judgement applied in these periods by uncovering the structural shocks necessary to recover the published forecasts.

Figure 2 shows the implausibility index computed for the published interest rate track using the DSGE model. The peak in the series occurs in fourth quarter of 1997. This point coincides with the Asian crisis, a period where, with the benefit

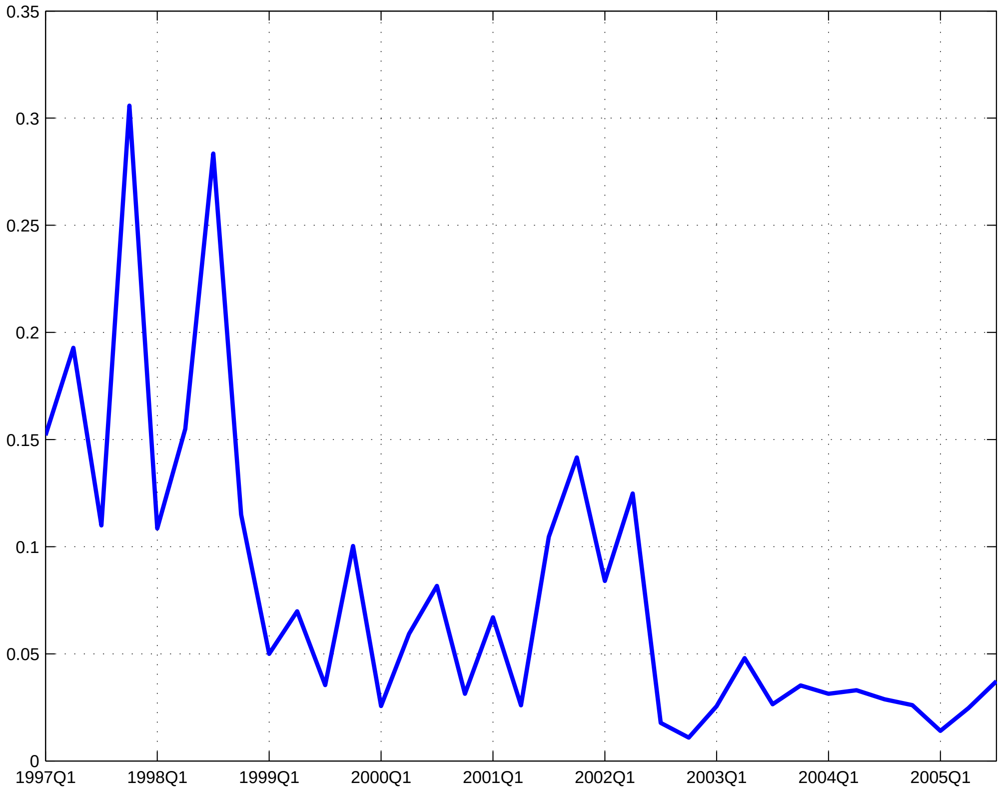
[2] The standard errors for the calibrated parameters come from the Cramér-Rao covariance matrix. They have been computed via simulation methods given the current calibration of the model.

[3] FPS has been described as a second generation macroeconomic model and is similar to the Bank of Canada's Quarterly Projection Model (QPM).

of hindsight, the Reserve Bank's forecasts for output were too optimistic . Furthermore, 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, so that a depreciating exchange rate kept interest rates high.[4] This prolonged the length of time during which interest rates remained excessively high relative to the prevailing economic conditions. Interest rates decreased dramatically over the second half of 1998, with the ninety-day rate falling from 9.15 percent in June to 4.38 percent in December.[5]

**Figure 2**

**Implausibility index: RBNZ published interest rate forecasts**



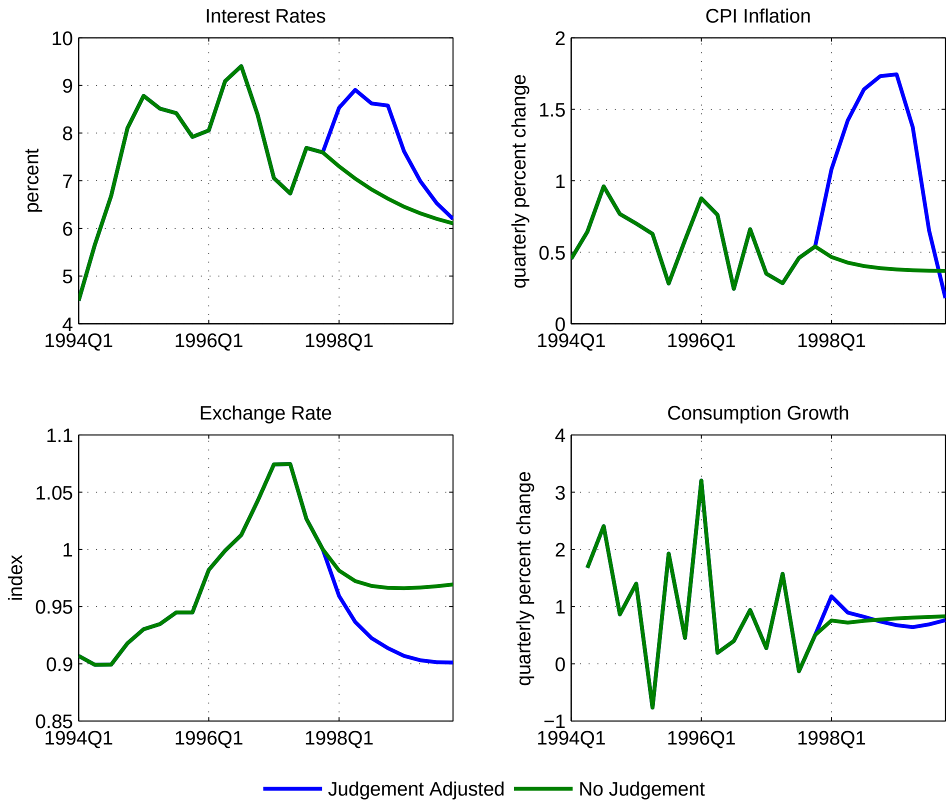

[4] The Svensson (2001) report criticised the MCI as a period in the Bank's history that represented a "significant deviation from international best practice". The Reserve Bank has acknowledged the use of the MCI over this period as "unhelpful" (paragraph 35, RBNZ submission to Independent review of the operation of monetary policy (2000)).

[5] In addition, there was a period of drought in early 1998 and early 1999.

The magnitude of the discrepancy between the RBNZ's published macroeconomic forecasts and the forecasts from the DSGE model conditioned on the published interest rate track are quite stark. The DSGE model suggests a sustained increase in inflation is most consistent with the published track. Indeed, the conditional inflation forecast increases to over 6.5 percent in annualised quarter-on-quarter terms, at least partly driven by a relatively large depreciation in the nominal exchange rate (see the bottom left panel of figure 3).[6] The lower nominal exchange rate is due to the algorithm adding risk premium shocks to the modified UIP equation.

**Figure 3**

**Conditional and unconditional forecast paths: RBNZ published interest rate forecasts: 1997Q4**

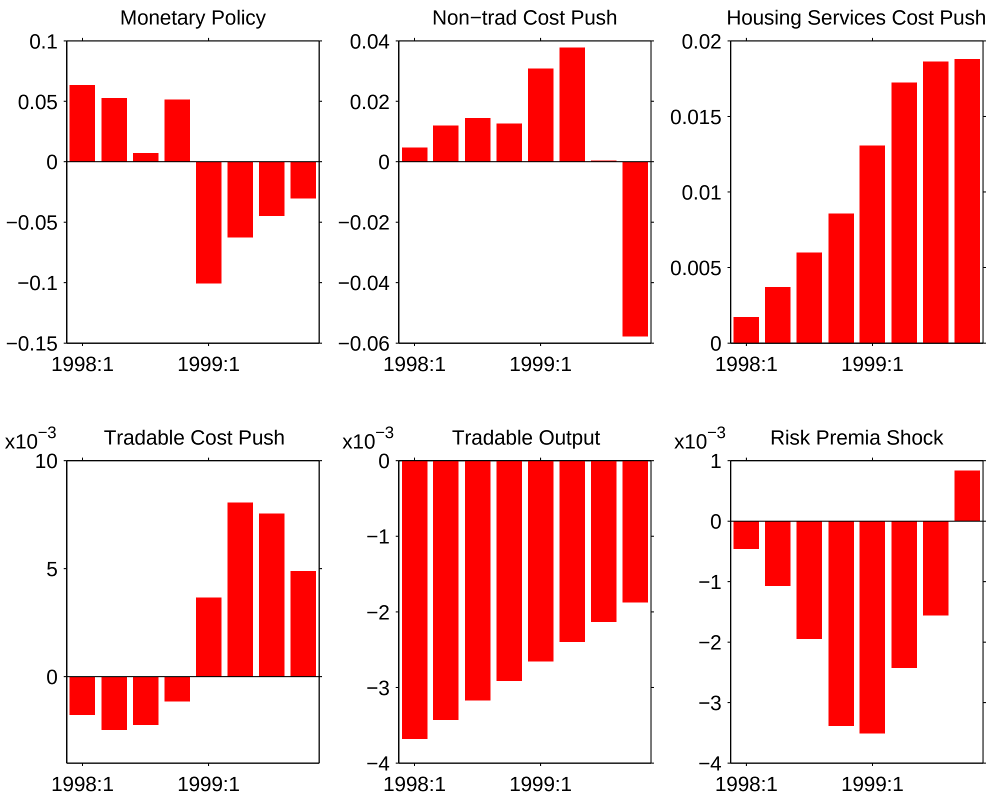



[6] Real-time data issues cloud the precise numbers, although the 1997Q4 forecast for the March year 1997/98 output gap was -0.6 — not particularly supportive of a strong policy response.

Figure 4 reports the six largest structural shocks (normalised by their historical standard errors) required to return the DSGE forecasts to the RBNZ's published forecast track in the four quarter of 1997. 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 a sequence of negative shocks.

**Figure 4**

**Implied DSGE shocks: RBNZ published interest rate forecasts: 1997Q4**




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 values.

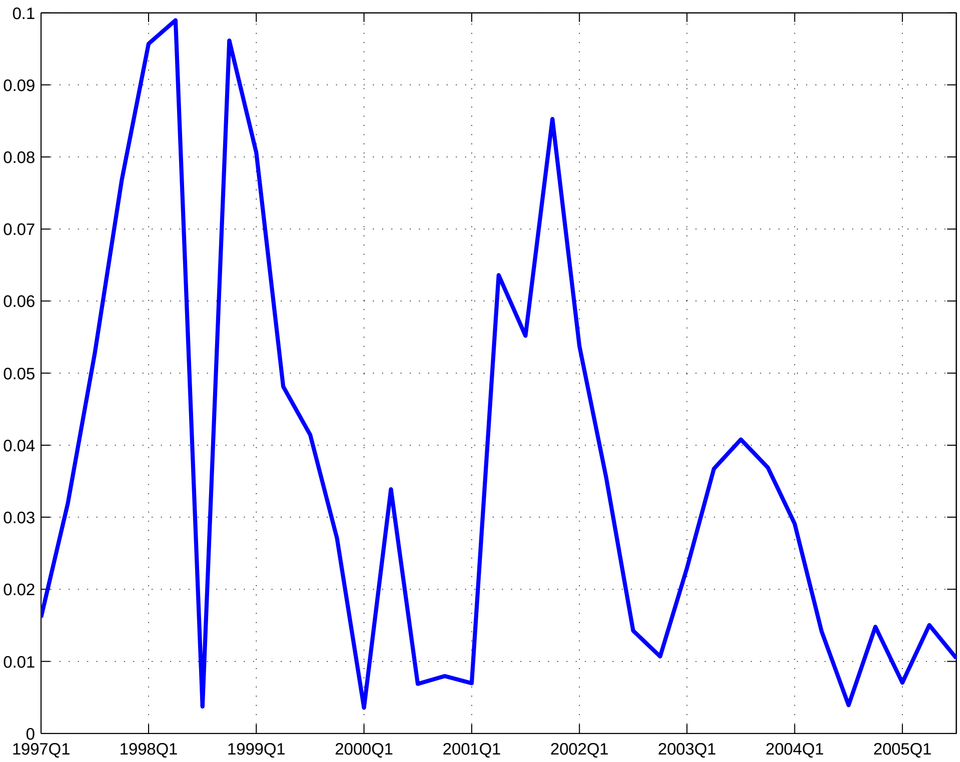
## 3.2 Conditioning on constant interest rate forecasts

We also condition the DSGE model forecasts to a constant interest rate track. Historically this replicates earlier behaviour of the Bank of England monetary policy process where the monetary policy committee refrained from producing endogenous policy forecasts. While current Bank of England Inflation Reports contain forecasts conditional on market interest rates, recent reports (see Bank of England (2007)) also present forecasts conditional on constant interest rates.

Figure 5 shows the implausibility index from conditioning on a constant interest rate assumption.

**Figure 5**

**Implausibility index: constant interest rate**

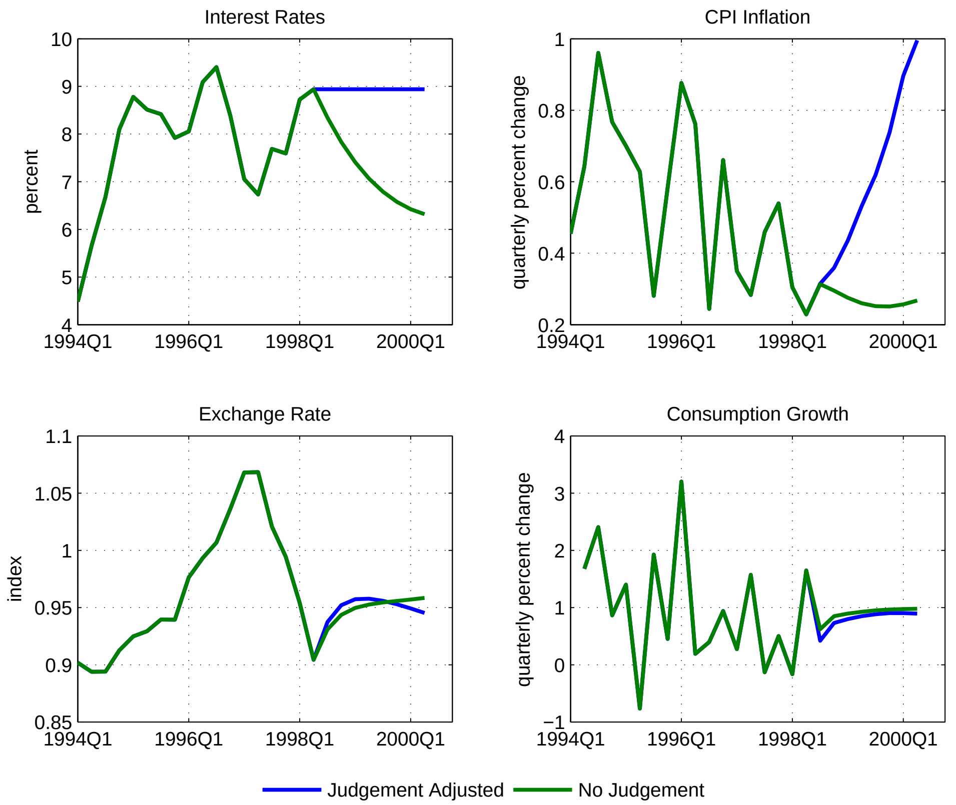



Again, the period around the time of the Asian crisis, and the Reserve Bank's subsequent policy response, is selected by the implausibility index as indicating the period where the most judgement must be added to the DSGE model to return a constant interest rate track. In particular, the index is highest in the second quarter of 1998 but falls dramatically in the third quarter of 1998 at the time when the ninety day rate was slashed. It rises again in the following quarter implying that rates were cut too much.

Figure 6 displays the forecasts conditioned on the constant interest rate assumption for the second quarter 1998 which restricts the ninety-day interest rate to almost 9 percent for eight subsequent 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 in 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 seen in figure 7.

**Figure 6**

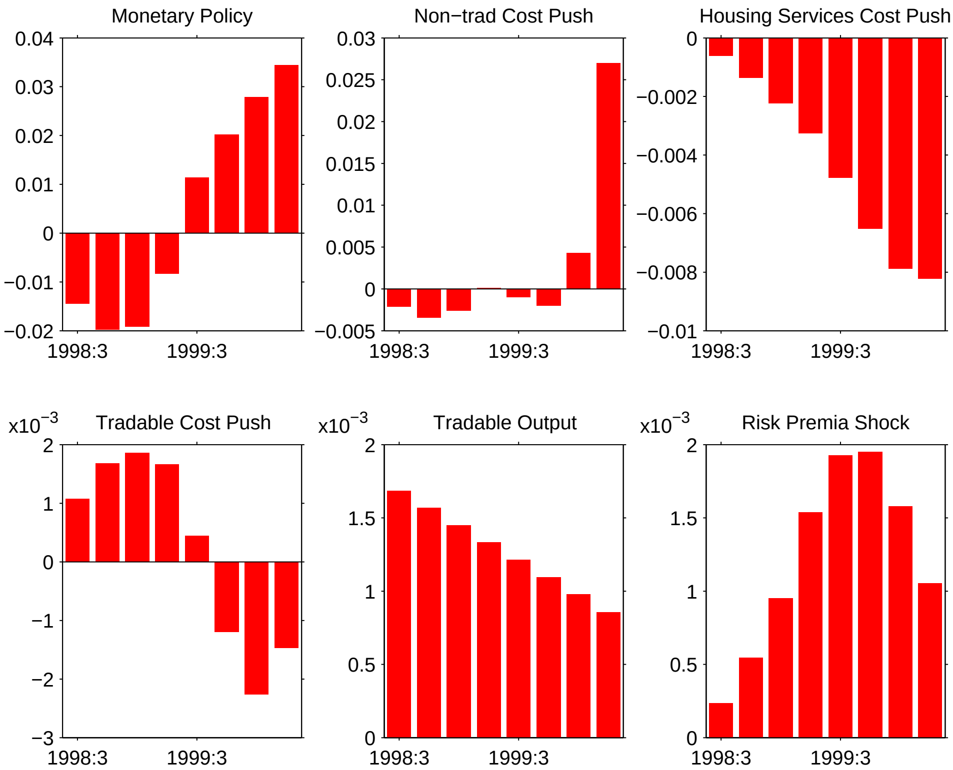
**Conditional and unconditional forecast paths: constant interest rate: 1998Q2**




The fact 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 choose a particular time dimension of shocks if the rationale for a particular judgement can be attributed to particular shocks or time periods.

**Figure 7**

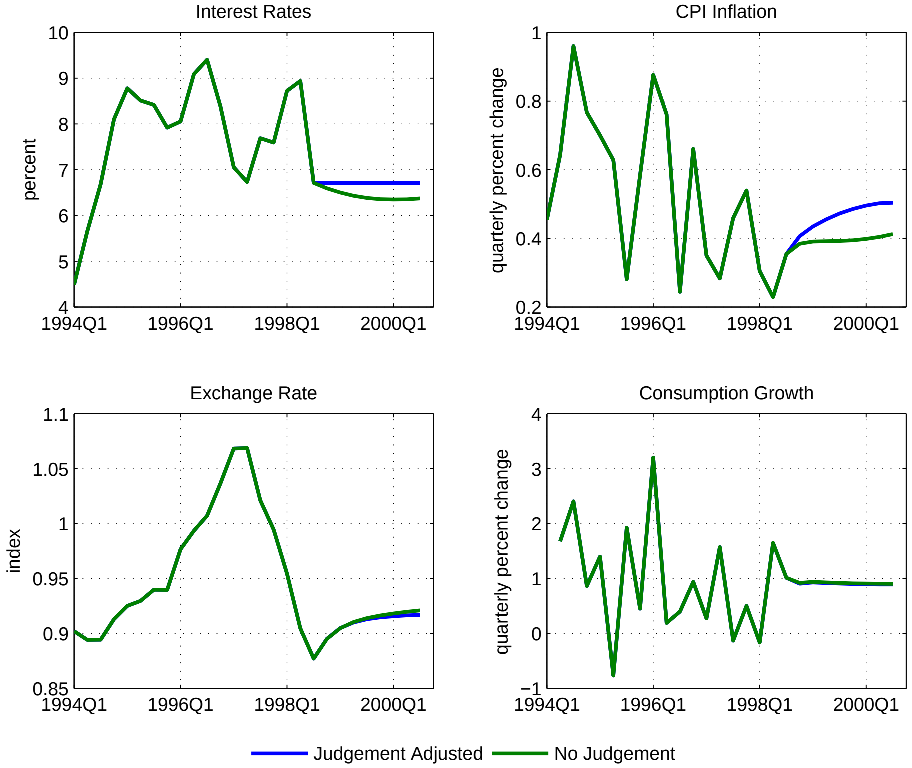
**Implied DSGE shocks: constant interest rate: 1998Q2**




Interestingly, rates were cut so drastically that the very next quarter the implausibility index records a very low number — the flat interest track for third quarter 1998 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 8 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 9 are very small).

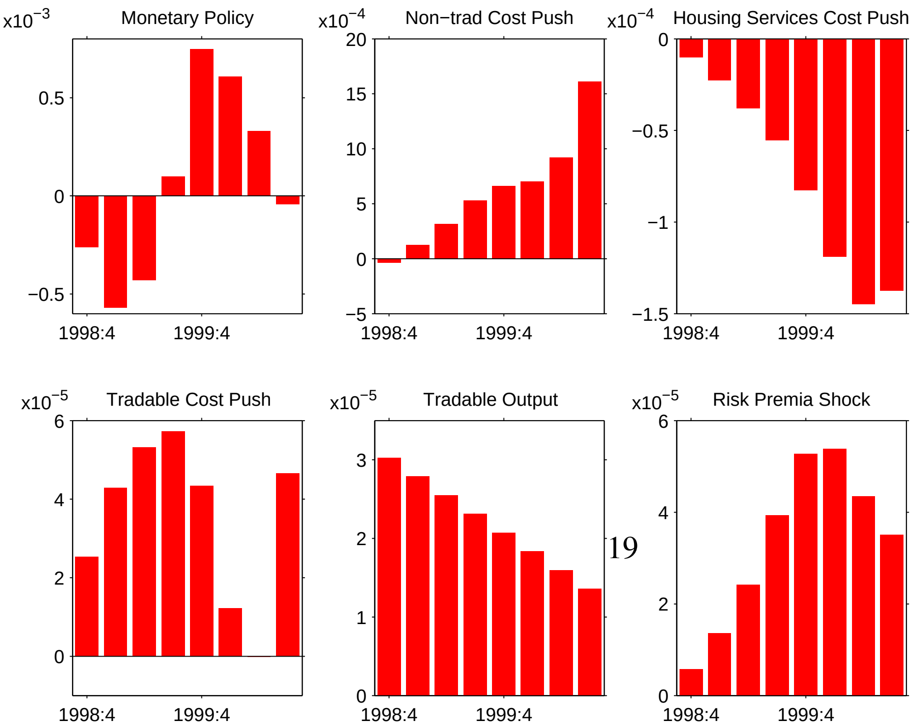
## Figure 8

## Conditional and unconditional forecast paths: constant interest rate: 1998Q3




## Figure 9

## Implied DSGE shocks: constant interest rate: 1998Q3



## 3.3 Conditioning on forecasts from a Bayesian VAR

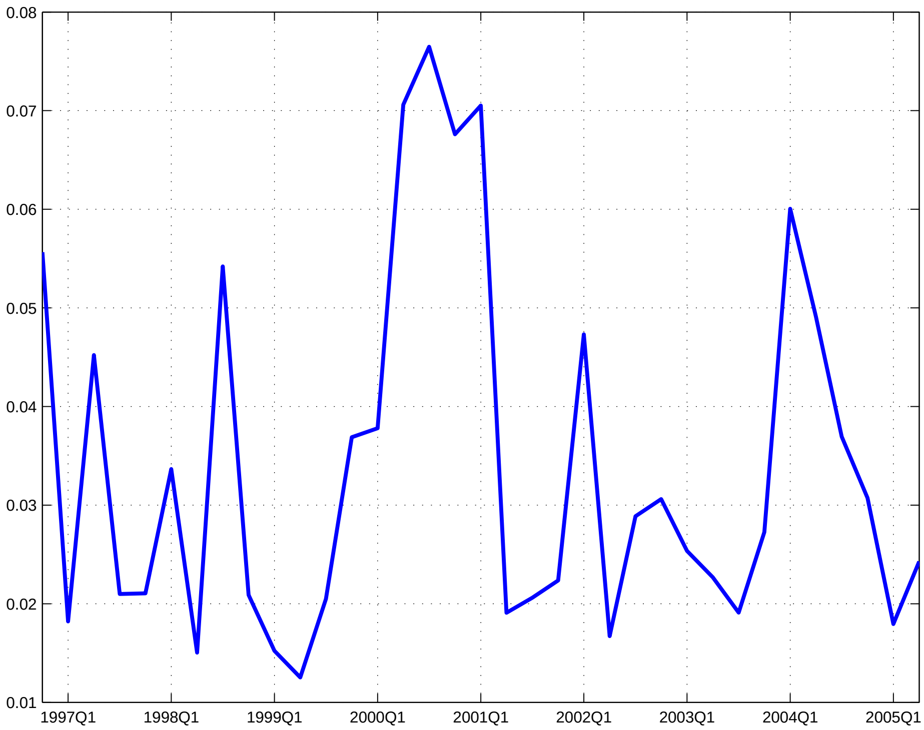
Our final exercise shows the generality of our techniques by conditioning on the inflation forecasts from a Bayesian VAR (BVAR) model currently in use in the policy environment at the RBNZ. We show how the BVAR forecasts can be viewed in relation to the DSGE model to generate a structural interpretation, 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, Matheson, and Smith (2007) for the case of New Zealand). Conditioning directly on aspects of the BVAR forecasts may be considered an alternative to applying the full DSGE-VAR methodology of Del Negro and Schorfheide (2004).

Figure 10 show the implausibility index applied to the BVAR inflation forecasts.

**Figure 10**

**Implausibility index: BVAR inflation forecasts**

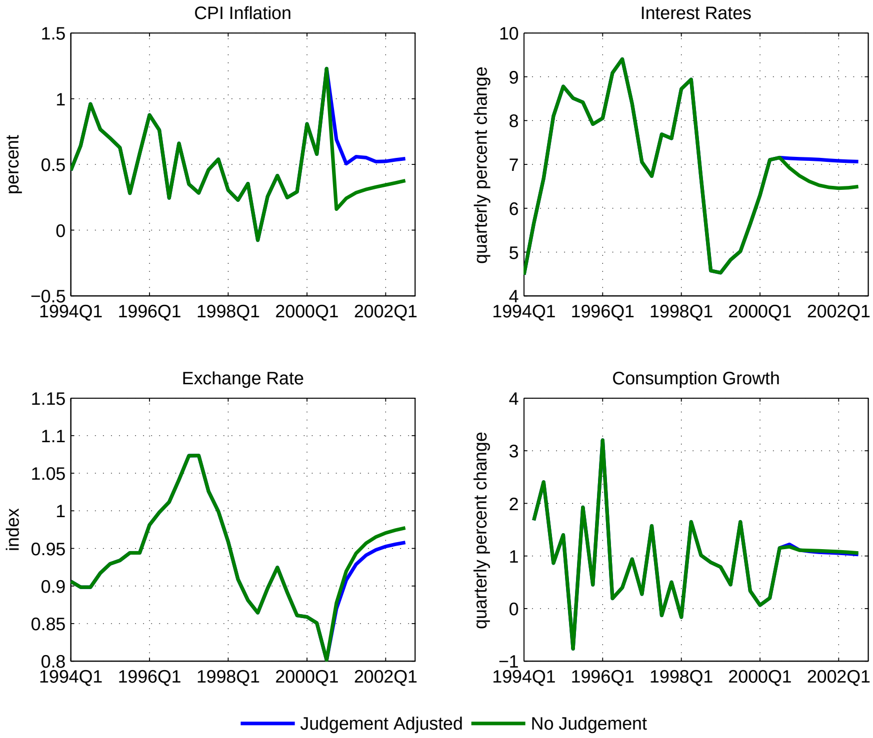


The index implies that the most judgement must be applied to the DSGE forecast in the third quarter 2000 in order to return the BVAR inflation forecast. However, the index number is quite low relative to the two previous interest rate exercises. It appears that the BVAR forecasts are more easily accepted from the perspective of the DSGE model.

Figure 11 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 suggests.

**Figure 11**

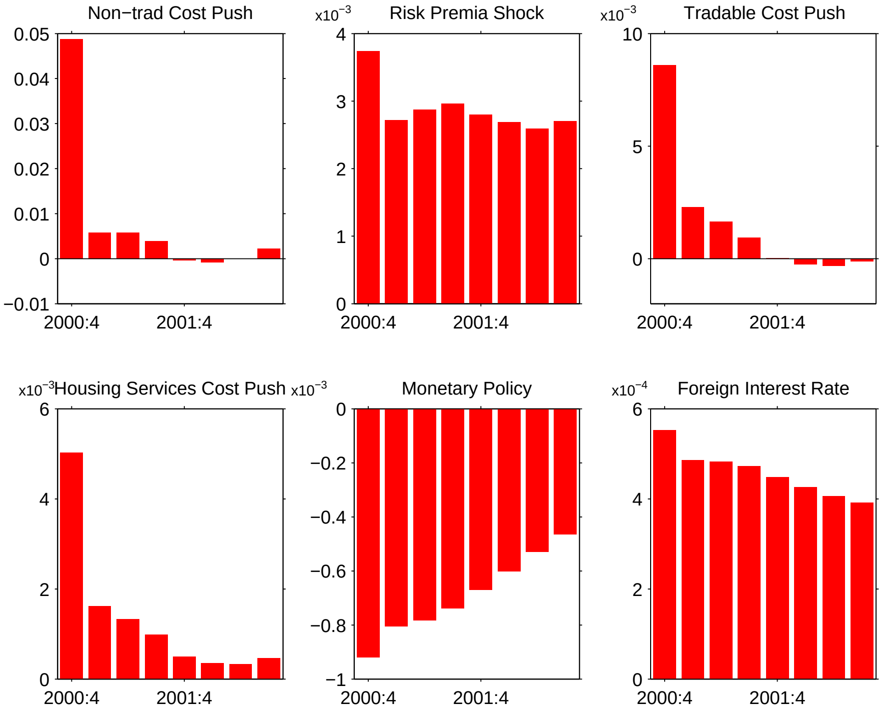
**Conditional and unconditional forecast paths: BVAR inflation forecasts: 2000Q3**




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 small (see figure 12).

**Figure 12**

**Implied DSGE shocks: BVAR inflation forecasts: 2000Q3**




# 4 Conclusion

Policymaker judgement is most often expressed in terms of observable paths for key macroeconomic variables rather than in terms of the deep parameters and shocks that make up DSGE models. However several easily implemented techniques allow the addition of judgement to 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 1997Q4, 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 1998Q2, when the model suggests much lower interest rates than implied by the assumption of 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 on 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 the incorporating policymakers' off-model judgement difficult. 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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# Appendices

## A Appendix: Summary of the KITT Setup

**Non-tradable production**

$$y_t^n = (z_t^n)^{\gamma_n} (A_t^n l_t^n)^{1-\gamma_n} \tag{4}$$

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 $A_t^n$. $\gamma_n$ is the non-tradable intermediate's share of income. The non-tradable sector is monopolistically competitive and subject to Calvo adjustment costs.

**Tradable production**

$$y_t^\tau = A_t^\tau \left( \frac{m_t \cdot \exp(u_t^y)}{1-\omega^\tau} \right)^{\gamma_\tau} \tag{5}$$

Tradable output $y_t^\tau$ is produced using imported goods $m_t$, and tradable technology $A_t^\tau$. $\gamma_\tau$ is import's share of production and $\omega^\tau$ 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**

$$X_t = \left(U_t^x K_{t-1}^x\right)^{\gamma_x} (A_t^x L_t^x)^{1-\gamma_x} \tag{6}$$

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. $\gamma_x$ is capital's share of income. The export sector is perfectly competitive.

Export specific capital $K_t^x$ accumulates in a perpetual inventory process:

$$K_t^x = (1-\Delta_x) K_{t-1}^x + I_t^x \tag{7}$$

where $I_t^x$ is business sector investment.

**Households**

$$E_t \sum_{k=0}^{\infty} \beta^k \log \Gamma_{t+k} \tag{8}$$

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

$$\Gamma_t = \frac{\left(C_t^{\tau} - \chi_c C_{t-1}^{\tau}\right)^{\omega_\tau} \left(C_t^{s} - \chi_c C_{t-1}^{s}\right)^{\omega_s} \left(C_t^{n} - \chi_c C_{t-1}^{n}\right)^{(1-\omega_\tau-\omega_s)}}{1-\chi_c} \tag{9}$$

Where $C_t^{\tau}$,$C_t^{s}$ and $C_t^{n}$, are tradable, housing services and non-tradable consumption respectively. $\omega_\tau$ and $\omega_s$ are tradable's and housing service's share of consumption respectively.

$$c_t^s = A_t^s u_t^h k_{t-1}^h \tag{10}$$

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 $A_t^s$. Landlords are monopolistically competitive and Calvo adjustment costs make rents sticky.

Housing capital accumulates according to the perpetual inventory process

$$k_t^h = (1-\delta_h)\, k_{t-1}^h + i_t^h \tag{11}$$

where $i_t^h$ is residential investment and $\delta_h$ depreciates housing capital.

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

$$i_t^d = i_t + \zeta \left( \frac{B_t}{Q_{t+1}^h K_t^h} - \lambda \right) \tag{12}$$

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 it's steady state level $\lambda$, 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**

$$\Delta S_{t+1} + i_t + i_t^f = ex_t + fx_t \tag{13}$$

Where $\Delta S_{t+1}$ is the change in the nominal exchange rate, $i_t$ is the nominal interest rate, $i_t^f$ is the world interest rate, $ex_t = \theta\left(\Delta S_t + i_{t-1} - i_{t-1}^f\right)$ is the endogenously determined disparity term and $fx_t$ is the exogenously determined autoregressive disparity term. $\theta$ is the proportion of "chartists" or backward looking currency traders.

**Monetary Policy**

$$i_t = \rho_i i_{t-1} + (1-\rho_i)(\bar{\pi}_{t+1} + \kappa\Theta_t) + \varepsilon_t^{mp} \tag{14}$$

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 $\Theta_t$ is given by

$$\Theta_t = \beta_{mp}\Theta_{t+1} + (1-\beta_{mp})(\pi_t - \bar{\pi}_t) \tag{15}$$

where $\pi_t$ is quarterly CPI inflation, which is given by

$$\pi_t = v_\tau \pi_t^\tau + v_p \pi_t^p + (1 - v_\tau - v_p)\pi_t^n \tag{16}$$

where $\pi_t^\tau$ is tradable inflation, $\pi_t^p$ petrol inflation and $\pi_t^n$ non-tradable inflation.

**Market Clearing Conditions**

$$Y_t^n = \left(C_t^n + I_t^h\right)\exp\left(\sigma^n\right) + Z_t^n \tag{17}$$

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

$$Y_t^\tau = (C_t^\tau + I_t^x)\exp(\sigma^\tau) \tag{18}$$

Tradables output can be consumed or invested in the export sector. $\sigma^\tau$ 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 ($\tau$), housing services ($s$) and the export sector ($x$). The general technology process is given by

$$\log(A_t^{\dagger}) = \rho_{A^{\dagger}} \log(A_{t-1}^{\dagger}) + (1-\rho_{A^{\dagger}}) \log(\bar{A}^{\dagger}) + \varepsilon_t^{A^{\dagger}} \tag{19}$$

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

### Terms of trade

$$\bar{T}_t = \rho_{\bar{T}} \log(\bar{T}_{t-1}) + \varepsilon_t^{\bar{T}} \tag{20}$$

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

$$\log(T_t) - \log(\bar{T}_t) = \rho_T \left(\log(T_{t-1}) - \log(\bar{T}_{t-1})\right) + \varepsilon_t^{TOT} \tag{21}$$

### Match to data

The model is calibrated to the New Zealand data focussing on matching key impulse responses. The calibration also incorporates beliefs about the transmission mechanism across the economics department at the Reserve Bank of New Zealand. Table 3, on page 28 displays the calibration of the key parameters in the model, while table 2 shows the match of the model to selected moments in the data. These data moments were computed using a VAR(4) estimated over consumption, inflation, interest rate and the nominal exchange rate over the period 1992Q1 to 2006Q4. Consumption and the exchange rate are estimated in differences.

The first column of the table shows the model predicts positive autocorrelation in the change in consumption which falls within a 90% confidence interval for the population data equivalent. The autocorrelation counterparts for inflation and the interest rate also fall well within the 90% confidence interval but the model predicts negative autocorrelation in the nominal exchange rate which is rejected

**Table 2**
**Model match to selected data moments**

| | autocorrelations | | | | cross-correlations | | | |
|---|---|---|---|---|---|---|---|---|
| | $\rho_{\Delta c}$ | $\rho_{\pi}$ | $\rho_{i}$ | $\rho_{\Delta e}$ | $\rho_{\pi-i}$ | $\rho_{\pi-\Delta c}$ | $\rho_{\pi-\Delta e}$ | $\rho_{i-\Delta c}$ |
| Model | **0.216** | **0.105** | **0.838** | **-0.148** | **0.099** | **0.043** | **-0.290** | **-0.445** |
| VAR - 5% | -0.363 | 0.065 | 0.747 | 0.042 | -0.423 | -0.086 | -0.470 | -0.465 |
| VAR - 95% | 0.304 | 0.577 | 0.928 | 0.572 | 0.103 | 0.486 | 0.174 | 0.006 |

by the data. Increasing the proportion of chartists in the model ($\theta = 0.5$) increases the positive autocorrelation in the nominal exchange rate but weakens the extent to which uncovered interest rate parity holds in the short run. Columns four to eight of the table show that key cross-correlations in the model are not rejected by the data.

**Table 3**
**Key model parameters**

| Parameter | Description | Value |
|---|---|---|
| $\beta$ | Discount factor | 0.990 |
| $\chi_c$ | Habit in consumption | 0.850 |
| $\omega_\tau$ | Tradables share of consumption | 0.391 |
| $\omega_s$ | Housing services share of consumption | 0.192 |
| $\bar{L}_n$ | Labour in the non-tradable sector | 1 |
| $\bar{L}_x$ | Labour in the export sector | 1 |
| $\delta_h$ | Depreciation rate of housing capital | 0.026 |
| $\gamma_\tau$ | Import's share of tradable production | 0.8 |
| $\gamma_n$ | Non-tradable intermediate's share of income | 0.5 |
| $\rho_j$ | Interest rate smoothing parameter | 0.879 |
| $\kappa$ | Policy response to future inflation deviations in the reaction function | 3.5 |
| $\beta_{mp}$ | The discount factor in the reaction function | 0.8 |
| $v_\tau$ | The weight on tradable inflation in CPI inflation | 0.391 |
| $v_p$ | The weight on petrol price inflation in CPI inflation | 0.045 |
| $v_s$ | The weight on housing services inflation in CPI inflation | 0.104 |
| $\sigma_\tau$ | Government's multiplier on tradable goods | 0.2 |
| $\sigma_n$ | Government's multiplier on non-tradable goods | 0.2 |
| $\lambda$ | Steady state loan to value ratio | 0.8 |
| $\gamma_x$ | Capital's share of income in the export sector | 0.541 |
| $\delta_x$ | The depreciation of capital used in the export sector | 0.026 |
| $\bar{A}^\tau$ | Steady state tradable technology | 1 |
| $\bar{A}^s$ | Steady state housing services technology | 0.100 |
| $\bar{A}^n$ | Steady state non-tradable technology | 10 |
| $\bar{A}^x$ | Steady state export sector technology | 0.020 |
| $\rho_{A\tau}$ | Autoregressive parameter on tradables technology | 0 |
| $\rho_{As}$ | Autoregressive parameter on housing services technology | 0 |
| $\rho_{Ax}$ | Autoregressive parameter on export sector technology | 0 |
| $\rho_{An}$ | Autoregressive parameter on non-tradable technology | 0 |
| $\rho_T$ | Autoregressive parameter on the Terms of Trade gap | 0.899 |
| $\rho_{\bar{T}}$ | Autoregressive parameter on the Terms of Trade trend | 0 |