

The Interest Rate Conditioning Assumption: Investigating the Effects of Central Bank Communication in New Zealand

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Abstract

There exists a lively debate on whether central banks should publish an explicit path of future policy rates. Some argue such forward guidance can do more harm than good, particularly if the private sector perceives the interest rate path to be a commitment rather than a conditional statement. In this paper, we investigate this hypothesis for the Reserve Bank of New Zealand, given that we are one of the few central banks with a sufficient history of publishing a policy rate path. To do so, we make use of the conditional forecasting technique in a small Bayesian vectorautoregression to assess how agents' forecasts would differ if they were to condition their model forecast for the 90-day interest rate to follow the RBNZ's published track over history. Implicitly we assume that agents use such a model for forecasting purposes. By examining the change in forecast performance, we are able to assess how much value there is in the RBNZ's published interest rate path. Our results suggest that publication of the rate track can be a double-edged sword: our interest rate projection potentially contains some value provided the public does not interpret the path as a commitment.

1 Introduction

The benefits of an open and transparent central bank are widely recognized and understood. However, what is not so obvious is how central banks should achieve this transparency. In particular, it is not clear to what extent a central bank should reveal information about the policy-intended future instrument rate path.

The Reserve Bank of New Zealand (RBNZ) is one of the most transparent central banks, communicating a significant amount of information to economic agents. In June 1997 the RBNZ was the first central bank to publish interest rate projections in their quarterly Monetary Policy Statement (MPS). Each MPS contains projections for several key economic variables and detailed analysis behind each projection. Yet for the RBNZ's management of expectations about future monetary policy decisions, the publication of the interest rate track for the 90-day interest rate is of particular importance (see Demters and Nautz 2012). In this paper, we investigate the effect, if any, of the information content of the RBNZ's interest rate projections on agents' forecasting ability.

There exists a lively debate on whether central banks should publish an explicit path of future policy rates. Many central bankers fear that the private sector will misinterpret the forecast as more of a commitment or an "unconditional promise" (see Archer 2005). However, others disregard this concern, saying such a worry implies agents cannot understand the concept of a conditional forecast, and further argue that such publication will provide agents with the best aggregate information for making decisions (see Svensson 2011).

In this paper we attempt to add to this debate by making use of the published 90-day interest rate forecast of the Reserve Bank of New Zealand (RBNZ). In particular we investigate two questions. Firstly, does the RBNZ's forecast of the instrument rate help economic agents to better forecast other macroeconomic variables? And, secondly, does the way in which agents interpret these forecasts matter?

To investigate these questions, we consider a simple thought experiment. The experiment goes as follows: consider an economic agent using a simple macro model to forecast the economy. Now consider this agent's forecasts the day before and the day after the publication of the RBNZ's interest rate path. In terms of new data for the agent's model, nothing has changed, and, thus, his forecasts will not change. However, potentially important

information has been revealed to the agent, which he may wish to incorporate into his forecasts. We wish to investigate whether the agent can improve his forecasts by incorporating this information, and whether the way in which he incorporates the information matters.

To conduct this thought experiment we assume that agents use a small Bayesian vectorautoregression (BVAR) to forecast the economy. Although this model may not generate forecasts that replicate market forecasts, we believe it is a reasonable starting point, as the model performs well in terms of forecasting performance and is easy to compute.

Next, we allow agents to differ in terms of how they interpret the information conveyed in the RBNZ forecast. To do so we assume that there exists two types of agents. The first type of agent views the RBNZ track as a conditional forecast. Thus, they believe this track is in line with what the policy rule would suggest, given the agents' expectations of future economic conditions.¹ Therefore, they believe that the RBNZ track differs to their model forecast due to new information on current and expected economic conditions. We refer to this agent as the 'Non-Deviator'.

The second type of agent believes that the published track indicates an unconditional promise or commitment from the RBNZ to deviate from the policy rule. In other words these agents believe that the RBNZ track is not in line with what policy would suggest. Hence, they believe that the RBNZ track differs to their model forecast, not because of new information on expected economic conditions, but rather because the RBNZ plans to deviate from the policy rule. We refer to this type of agent as the 'Deviator'.²

To implement this thought experiment, we use conditional forecasting techniques described in Waggoner and Zha (1999). Over the period 2003Q2 - 2010Q4 we condition the four quarter ahead model forecast to follow the RBNZ published track. The way in which we condition this track depends on which type of agent we choose. We are then able to compare the forecast performance of the agent's model produced (unconditional) forecasts to the conditional forecasts. In doing so we attempt answer the proposed questions. However, our results will be dependent on our key assumption; that agents

¹The policy rule in terms of the agent's model.

²Campbell et al (2012) also distinguish between the way in which the public can interpret central bank forward guidance. They suggest the public can either view forward guidance as an unconditional promise to deviate from the policy rule (what they refer to as Odyssean forward guidance), or view it as guidance conditional on expected economic conditions (what they refer to as Delphic forward guidance). This will be further discussed in the following section.

use this model to forecast the economy.

We find that the agents' conditional forecasting performance relative to the unconditional forecasting performance depends crucially on how the agents interpret the forecast. We find that the RBNZ 90-day rate track performs remarkably better than the model forecast over history. We do not find this to be surprising as we believe the RBNZ has significant informational advantages when forecasting the 90-day rate in the near-term. We find for the Non-Deviator agents, when conditioning on this superior 90-day rate track, that their forecasting performance of the other variables in the model does not get any better (or worse) than the unconditional forecasts. However, for the Deviator agents, we find that the forecasting performance gets significantly worse relative to the model forecasts. To illustrate this idea further, we look at a specific period in history in which the agents' forecasting performance can improve or deteriorate by incorporating the superior 90-day interest rate track into their model.

Thus, from this thought experiment, we conclude that the RBNZ's published rate path potentially contains some value (i.e. there is some potential improvement in the agents' forecast performance) provided the agents do not misinterpret the path as a commitment. We realise that, of course, our results depend on the model we use, and that this simple thought experiment may not accurately reflect reality. However, we believe it is a beneficial exercise to illustrate the importance of effective monetary policy communication.

The remainder of the paper is set out as follows. Section 2 briefly reviews the literature. Section 3 outlines the BVAR methodology and the conditional forecasting algorithm. Section 4 outlines the data, the model specification, and the identification scheme used. Section 5 presents the results from the forecast comparison exercise, and Section 6 concludes the paper.

2 Thou Shall/Shall Not Publish: Literature

Woodford (2001) argues that “*successful monetary policy is not so much a matter of effective control of overnight interest rates... as of affecting... the evolution of market expectations... [Therefore,] transparency is valuable for the effective conduct of monetary policy... this view has become increasingly widespread among central bankers over the past decade.*” Over the last two decades central banks have become much more transparent in many dimen-

sions.³ One of these dimensions is the publishing of central bank forecasts of key economic variables and communicating these forecasts with the public.

As mentioned above, there has been a considerable debate among macroeconomists and policymakers about central bank publication of the instrument rate track. Svensson (2006) separates this debate into two categories: what instrument rate assumption is appropriate in a central bank's internal decision process, and to what extent should this instrument rate assumption be published.

Svensson, a proponent of estimating and publishing an optimal policy path, explores this debate in great detail (along with others including Goodhart (2009) and Woodford (2005)). In addressing the first part of the debate, Svensson points out that what really matters for a central banks' internal projections, and what really matter for private sector expectations is the entire future path of the instrument rate. He explains that the current instrument rate and announcement of this rate only have an effect on the economy through their ability to influence private sector expectations about future instrument rates and about future inflation and output that these rates gives rise to. Svensson states "*Indeed, it is paradoxical that so much attention and discussion are focused on current instrument rate settings and levels, when what matters are the related plans and expectations about future instrument rates*". He concludes that a central bank should explicitly choose an instrument rate path, specifically the optimal instrument rate path - the projection of the instrument rate that minimises the central bank's loss function.⁴

Svensson, in addressing the communication aspect of debate, argues that announcing the optimal projection and the analysis behind it would have the largest impact on private sector expectations, and be the most effective way to implement monetary policy. He states "*Since the optimal projection is the best projection in the sense of minimising expected squared forecast errors, it also provides the private sector with the best aggregate information for making individual decisions.*"

However, despite the argument laid out by Svensson, many central banks are yet to adopt acknowledging and publicising an optimal projection for the

³See Blinder et al (2008) for a very thorough review of the central bank communication and monetary policy from a theoretical, empirical, and historical perspective.

⁴Svensson notes that the RBNZ uses an ad hoc reaction function in its Forecast and Policy System, which is the old model of the Reserve Bank of New Zealand (discussed in Archer (2005)). However, the resulting instrument-rate path is subject to considerable adjustment that reflects the judgement and policy preferences, making it, practically, very similar to an optimal-rate plan.

policy instrument. Goodhart (2009) argues that it may simply be too difficult for a Monetary Policy Committee (MPC) to agree on a specific quantitative path. However, Goodhart states this problem could be made easier when a Governor has sole responsibility (as in New Zealand) or when the relevant committee is small (as is in Norway and Sweden).

Furthermore, Goodhart (2009) and Mishkin (2004) have warned that the instrument rate projection may be interpreted as a commitment, rather than the best forecast. Svensson suggests such a concern can be mitigated by publishing fan charts around the projection along with additional explanation emphasizing that the instrument rate projection is not a commitment but merely the best forecast conditional on current information. Despite these additional options, Goodhart continues to warn that once there is a published central tendency, this might easily influence the private sector's forecast more than its own inherent uncertainty warranted.

Finally, it is argued that forward guidance which is interpreted as a commitment or “unconditional promise” may actually be beneficial in aiding monetary policy when at the zero lower bound (ZLB). This type of guidance, referred to as Odyssean forward guidance by Campbell et al (2012), changes private expectations of policy actions tomorrow in a way that improves macroeconomic performance today. This is a delicate tool for central banks, as the way in which the central bank communicates the forecast is of extreme importance. For example in December 2008 the Federal Open Market Committee (FOMC) said “the Committee anticipates that weak economic conditions are likely to warrant exceptionally low levels of the federal funds rate for some time.” In January 2012 the FOMC statement lengthened to “late 2014”. Campbell et al (2012) interestingly question whether keeping rates low until “late 2014” is an unconditional promise to keep the funds rate at the ZLB beyond the time policy would normally involve, or whether “late 2014” is simply conditional guidance based upon the sluggish economic activity and low inflation expected through this period?

Thus, how central banks communicate forward guidance with the public is very important, and needs to be well understood before used as a tool by central banks. Dale et al (2011) aptly describe such communication as a double edged sword, which should be used with care.

3 Background and Methodology

3.1 Vector Autoregression

A Vector Autoregression (VAR) is a statistical model based on a system of linear equations, where each variable is modelled as a function of contemporaneous and lagged values of all the variables in the system. They are particularly convenient for estimation and forecasting, with their popularity for analyzing the dynamics of economic systems arising from the influential work of Sims (1980).

Although VARs require somewhat stronger assumptions to be made about the economy than other statistical models (in terms of what variables to be included), they still remain relatively agnostic about the underlying structure of the economy. Some view this as a desirable feature, as forecasts will be based on historical correlations, rather than imposed causal relationships based on strong underlying assumptions. However, others criticize the use of statistical models for forecasting purposes, arguing that it is difficult to form rich economic stories about the particular drivers of the forecasts.

Regardless of this criticism, VAR models are widely used for forecasting purposes due to their simplicity and relatively good forecasting performance. Hence, we believe it is appropriate to assume agents use such a model to construct their forecasts of the economy.

VAR models can be written in terms of their structural form or their reduced form. A structural form VAR of lag length p , $\text{VAR}(p)$, has the following representation:

$$\sum_{l=0}^p y_{t-l} A_l = d + \varepsilon_t \quad \text{for } t = 1, \dots, T \quad (1)$$

where $y_t = (y_{1,t}, y_{2,t}, \dots, y_{m,t})$ is a $1 \times m$ vector of observations, T is the number of observations, A_l is a $m \times m$ coefficient matrix of the l th lag where the columns correspond to the equations, d is a $1 \times m$ vector of constant terms, and ε_t is a $1 \times m$ vector of i.i.d. structural shocks that are normally distributed with mean $0_{1 \times m}$ and covariance matrix $E[\varepsilon_t' \varepsilon_t] = I_{m \times m}$ for all t .

We can transform model (1) into its reduced form by multiplying through by A_0^{-1} :

$$y_t = c + \sum_{l=1}^p y_{t-l} B_l + u_t \quad \text{for } l = 1, \dots, p \quad (2)$$

where the relationships between the reduced form parameters and the structural form parameters are:

$$c = dA_0^{-1}, \quad B_l = -A_lA_0^{-1}, \quad u_t = \varepsilon_tA_0^{-1} \quad \text{for } l = 1, \dots, p$$

We denote the variance covariance matrix of reduced form residuals Σ , where:

$$\Sigma = E[u_t'u_t] = A_0^{-1'}A_0^{-1}$$

It can be seen that the reduced form errors u_t are simply a linear combination of the structural form shocks ε_t .

VARs can only be estimated in their reduced form leading to the identification problem (as there are fewer reduced form parameters than there are structural form parameters). As a result, at least $m(m - 1)/2$ identification restrictions need to be placed on the contemporaneous A_0 matrix, in order to recover the structural form parameters from the estimated reduced form parameters.

Finally, it can be shown that model (2) can be written in the following matrix notation:

$$Y = XB + U \tag{3}$$

where $Y = [y_1; \dots; y_T]'$, $X = [X_1; \dots; X_T]$, $X_t = [1, y_{t-1}, \dots, y_{t-p}]$, $B = [d; B_1; \dots; B_p]$, and $U = [u_1; \dots; u_T]$.

3.2 Bayesian Vector Autoregression

VAR models generally require estimation of a large number of parameters relative to the available number of observations. This can lead to coefficients with large standard errors and may ultimately result in poor forecasts. One solution to this overfitting problem is to use Bayesian methods to incorporate prior information into the estimation process. This method generally results in more precise estimates due to the additional non-data information.

In our model we impose the Normal Inverse Wishart prior described in Kadiyala and Karlsson (1997). This prior is a modification of the standard Minnesota prior introduced by Litterman (1986). The Minnesota prior incorporates the beliefs that all variables are centered around a random walk plus drift. Essentially, this is equivalent to shrinking all the diagonal elements of B_1 to one and all remaining elements in B_1, \dots, B_p to zero. In addition to this, the Minnesota prior incorporates the belief that more recent lags play a

more important role than more distant lags, and that own lags provide more useful information than lags of other variables.

These prior beliefs are expressed in the form of a probability distribution. The coefficient matrices B_1, \dots, B_p are independently and normally distribution, while the covariance matrix is assumed to be fixed and diagonal. The prior on the intercept is diffuse i.e. has a mean of zero with a large variance. The Minnesota prior is summarized below:

$$E[(B_l)_{ij}] = \begin{cases} \chi_i & j = i, l = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$Var[(B_l)_{ij}] = \begin{cases} \frac{\lambda_2}{l^s} & i = j \\ \vartheta \frac{\lambda_2 \sigma_i^2}{l^s \sigma_j^2} & \text{otherwise} \end{cases}$$

$$\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_m^2)$$

where the prior parameters are defined as follows

- χ_i is the prior mean for variable i . To impose the random walk prior, set χ_i to 1 for all i . To impose a less persistent prior, set $\chi_i \in [0, 1)$.
- $\frac{\sigma_i}{\sigma_j}$ accounts for differences in variability of the data. It is common to set σ_i equal to the residual standard deviation from an AR(1) model for variable i .
- λ controls the overall tightness of the prior distribution around the random walk and governs the importance of the prior beliefs relative to the information contained in the data. The closer λ is to zero, the tighter the prior.
- s controls the rate at which the prior variance shrinks with increasing lag length. As s increases, the tighter the prior on higher lags (i.e. the tighter the distributions of the higher lag coefficients around zero).
- $\vartheta \in (0, 1]$ governs the extent to which lags of other variables are ‘less important’ than the own lags. The smaller ϑ , the less important other lags are relative to the own lags.
- c controls the tightness of the prior on the constant. As c decreases, the more tightly implemented the prior.

Kadiyala and Karlsson (1997) modify the Minnesota prior by assuming the covariance matrix has an inverse Wishart distribution, thus, allowing for possible correlation amongst the residuals of different variables. Kadiyala and Karlsson are able to match the moments of the Minnesota prior, however, they must set the parameter ϑ to one (i.e. all variables of lag length greater than one are as ‘important’ as each other). This prior is referred to as the Normal Inverse Wishart prior. Using the matrix notation in Equation (3) we can summarize the Normal Inverse Wishart Prior as follows:

$$p(\text{vec}(B) \mid \Sigma) \sim N(\text{vec}(B_0), \Sigma \otimes \Omega_0), \quad p(\Sigma) \sim IW(S_0, \alpha_0)$$

where the expectation of Σ is equal to the fixed diagonal covariance matrix of the Minnesota prior, and where B_0 , Ω_0 , α_0 are chosen to match the moments of the Minnesota prior.

One way to implement the Normal Inverse Wishart prior is to add T_d dummy observations Y_d and X_d to our data matrices. Adding these T_d dummy observations is equivalent to imposing the Normal Inverse Wishart prior with $B_0 = (X_d' X_d)^{-1} X_d' Y_d$, $\Omega_0 = (X_d' X_d)^{-1}$, $S_0 = (Y_d - X_d B_0)' (Y_d - X_d B_0)$, and $\alpha_0 = T_d - mp - 1$. Banbura et al (2010) suggest these dummy observations take the following form in order to match the Minnesota moments:

$$Y_D = \begin{bmatrix} \text{diag}(\chi_1 \sigma_1, \dots, \chi_m \sigma_m) / \lambda \\ 0_{m(p-1) \times N} \\ \dots \\ \text{diag}(\sigma_1, \dots, \sigma_m) \\ \dots \\ 0_{1 \times m} \end{bmatrix} \quad X_D = \begin{bmatrix} J_p \otimes \text{diag}(\sigma_1, \dots, \sigma_m) / \lambda & 0_{mp \times 1} \\ \dots & \dots \\ 0_{m \times mp} & 0_{m \times 1} \\ \dots & \dots \\ 0_{1 \times mp} & \frac{1}{c} \end{bmatrix}$$

where $J_p = \text{diag}[1^s, 2^s, \dots, p^s]$. Roughly speaking, the first block of dummies in Y_D and X_D impose the priors on the autoregressive coefficients. The second and third block of dummies implement the priors on the error covariance matrix and the constant, respectively.

By adding these dummy observations to the data matrices we can rewrite Equation (3) as follows:

$$Y^* = X^* B^* + U^*$$

where $Y^* = [Y; Y_d]$, $X^* = [X; X_d]$, $B^* = (X^{*'} X^*)^{-1} X^{*'} Y^*$, $U^* = Y^* - X^* B^*$

Hence, the posterior distribution can be written as:

$$P(\text{vec}(B) \mid \Sigma, Y_t) \sim N(\text{vec}(B^*), \Sigma \otimes (X^{*'} X^*)^{-1}) \quad (4)$$

$$P(\Sigma \mid Y_t) \sim IW(S^*, T^*) \quad (5)$$

where $S^* = U^{*'} U^*$ and $T^* = \text{rows}(Y^*)$.

3.3 Conditional Forecasting

In dynamic multivariate models (such as VARs), it is often desirable to impose conditions, prior to forecasting, on the future values of certain endogenous variables. Forecasts associated with such conditions are referred to as conditional forecasts. In doing so, forecasters can answer questions like “how do the forecasts of the other macroeconomic variables in my model change if the short-term interest rate is to remain constant for the next two years?” This technique is described below.

Consider the reduced form VAR in Equation (2). Following Waggoner and Zha (1999), the n -step ahead forecast at time t can be written as:

$$y_{t+n} = \underbrace{cK_{n-1} + \sum_{l=1}^p y_{t+l-1} N_l(n)}_1 + \underbrace{\sum_{j=1}^n \varepsilon_{t+j} M_{n-j}}_2 \quad n = 1, 2, \dots; \quad (6)$$

where

$$K_0 = I \quad K_i = I + \sum_{j=1}^i K_{i-j} B_j \quad i = 1, 2, \dots;$$

$$N_l(1) = B_l \quad l = 1, \dots, p$$

$$N_l(n) = \sum_{j=1}^{n-1} N_l(n-j) B_j + B_{n+l-1} \quad l = 1, \dots, p \quad n = 2, 3, \dots;$$

$$M_0 = A_0^{-1}, \quad M_i = \sum_{j=1}^i M_{i-j} B_j \quad i = 1, 2, \dots;$$

As you can see, Equation (6) is composed of two parts. The first being the dynamic forecast in the absence of shocks, and the second being the dynamic

impact of structural shocks on the forecast. These structural shocks affect the future forecasts through the impulse response matrices M_i . If one were to estimate the unconditional forecast, they would simply set the second term to zero (i.e. all future structural shocks are set to zero). However, if one wishes to condition the future path of an endogenous variable, they do so by appropriately selecting combinations of the structural shocks such that the conditioning path is satisfied.

To consider the condition forecasting procedure, let's make use of the following notation used in Waggoner and Zha (1999):

$$a_0 = \text{vec}(A_0) \quad a_+ = \text{vec} \begin{bmatrix} -A_1 \\ -A_2 \\ \vdots \\ -A_p \\ d \end{bmatrix} \quad a = \begin{bmatrix} a_0 \\ a_+ \end{bmatrix}$$

Denote the j^{th} endogenous variable at time $T + n$, $y_{T+n}(j)$. Consider a condition which constrains the value of $y_{T+n}(j)$ to be a fixed value, $\bar{y}_{T+n}(j)$ (this is known as a hard condition). Using Equation (6) we can write this constraint as:

$$\sum_{i=1}^n \varepsilon_{T+i} M_{n-i}(:, j) = \bar{y}_{T+n} - Z_{n,j}(a) \quad (7)$$

where

$$Z_{n,j}(a) = cK_{n-1}(:, j) + \sum_{l=1}^p y_{T+1-l} N_l(n)(:, j)$$

where $(:, j)$ denotes the j^{th} column of the matrix. Thus, $M_{n-i}(:, j)$ is simply the j^{th} column of the impulse response matrix M_{n-i} .

Constraint (7) can be written in the following form

$$\underbrace{R(a)'}_{h \times k} \underbrace{\varepsilon}_{k \times 1} = \underbrace{r(a)}_{h \times 1} \quad (8)$$

where h is the number of forecast horizons you condition the j^{th} endogenous variable, and $k = mh$ is the total number of future shocks. Thus, $R(a)$ is the stacked matrix of impulse responses of the j^{th} variable; ε is the future shocks of all endogenous variables ; and $r(a)$ is the restricted set of values.

For example, if one was to condition the future path of the j^{th} variable for 3 horizons then Equation (8) will be of the form:

$$\begin{bmatrix} M_0(:, j)' & 0_{(k-m) \times 1} & & \\ M_1(:, j)' & M_0(:, j) & 0_{(k-2m) \times 1} & \\ M_2(:, j)' & M_1(:, j)' & M_0(:, j)' & \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t+1} \\ \vdots \\ \varepsilon_{m,t+1} \\ \vdots \\ \varepsilon_{1,t+3} \\ \vdots \\ \varepsilon_{m,t+3} \end{bmatrix} = \begin{bmatrix} \bar{y}_{t+1}(j) - y_{t+1}(j) \\ \bar{y}_{t+2}(j) - y_{t+2}(j) \\ \bar{y}_{t+3}(j) - y_{t+3}(j) \end{bmatrix}$$

where $y_{t+i}(j)$ is the unconditional forecast of the j^{th} variable at time $t + i$.

Following Doan et al (1984) and Doan (1992), we can solve for ε by minimizing $\varepsilon' \varepsilon$ subject to Equation (8). We obtain the following solution for ε :

$$\varepsilon = R(a)(R(a)'R(a))^{-1}r(a) \quad (9)$$

Note the method described above shows how it is possible to estimate the shock vector ε such that all the structural shocks contribute to forcing the conditioning path. It is possible in the specified framework to only allow certain structural shocks to be responsible for the resulting conditioned path (for example, one may suspect GDP is going to follow a lower path than predicted because of negative demand shocks only). To do so simply replace the columns of the $R(a)$ matrix that correspond to the shocks you want to turn off with zeros.

4 Model Specification and Identification

Our model is estimated using quarterly New Zealand data over 1993Q1 to 2012Q2. We include five domestic variables, all of which are expressed as annual percentages. We include four lags of each variable. These variables include the output gap, non-tradable CPI inflation, tradable CPI inflation, the 90-day interest rate, and the nominal exchange rate. We transform the nominal exchange rate, which is originally expressed as an index, by taking the natural logarithm and multiplying by 100.

4.1 Identification

The conditional forecasting technique uses structural shocks to condition the 90-day rate track to follow the RBNZ forecast. Thus, it is the structural shocks that determine how agents tell a “story” about why the RBNZ forecast for the 90-day rate differs from their model forecast. Therefore, it through these structural shocks that the agents can interpret the information conveyed in the RBNZ forecast. For this reason, we believe it is important that we identify the main structural shocks of this model.

To do so we use the sign restriction method to identify four structural shocks.⁵ Given that our Deviator agent believes the only way the RBNZ forecast differs from their model forecast is through the RBNZ deviating from the policy rule, we must identify a monetary policy shock. We also identify three other shocks, including a demand shock, a cost-push shock, and an exchange rate shock.⁶ We believe these shocks are the main drivers of the economy. We impose the sign restrictions on the contemporaneous period only, although it is possible to impose the restrictions on many horizons. Table (1) summarizes these restrictions.

Table 1: Sign Restrictions

Shock	Output Gap	Non-Tradable CPI	Tradable CPI	90-Day Rate	Exchange Rate
Cost-Push	–	+	×	+	×
Demand	+	+	–	+	+
Monetary Policy	–	–	–	+	+
Exchange Rate	–	–	–	–	+

The temporary cost-push shock is identified as a shock that causes a fall in the output gap and an increase in non-tradable CPI inflation. Responding to this increase in non-tradable inflation, the interest rate rises in the contemporaneous period. We leave the effect on the nominal exchange rate and tradable CPI inflation unrestricted.

The demand shock is thought to increase both the output gap and non-tradable CPI inflation in the contemporaneous period. The interest rate is expected to rise in the contemporaneous period, and the nominal exchange

⁵It should be noted that sign identified VARs are only set identified and, hence, we cannot obtain a unique solution, but rather a set of solutions that are consistent with the identifying restrictions (Kilian and Murphy (2010)).

⁶We remain agnostic about the 5th shock. Thus, the only restriction we place on this shock is that it does not have the same sign pattern as any of the four identified shocks.

rate is expected to appreciate. This appreciation of the nominal exchange rate causes tradable CPI inflation to fall in the contemporaneous period.⁷

The monetary policy shock may be thought of as an idiosyncratic shock to interest rates causing interest rates to rise. As a result the nominal exchange rate is expected to appreciate in the contemporaneous period. The output gap, non-tradable CPI inflation and tradable CPI inflation are expected to fall in the contemporaneous period.

The exchange rate shock is thought to be an idiosyncratic shock causing an appreciation of the exchange rate. As a result, tradable inflation and the output gap are expected to fall. Consistent with the fall in the output gap, non-tradable inflation is expected to fall. Interest rates, in response to the fall in inflation, are also expected to fall.

4.2 Prior Selection

Finally, it is necessary to select appropriate values for the prior parameters. To make our assumption that agents use this model to forecast more believable, we need to ensure we select a model that performs well in terms of forecasting performance. Generally speaking, the tighter the prior, the better the forecasting performance. However, given the purpose of this exercise, and our belief that every variable is endogenous, we do not wish to impose an overly restrictive prior (the tighter the prior, the more strongly we impose the belief that each variable follows an AR(1) process). In addition to this, we want to choose a prior such that our model effectively captures the channels through which the shocks transmit through the economy.

Thus, to select an appropriate prior we examine both the impulse response functions and forecasting performance of the model for a range of values of

⁷We restrict the initial fall of tradable CPI inflation to be less than the initial rise of non-tradable CPI inflation so that the overall effect on CPI inflation is positive. Overall inflation consists approximately of an equal weighting on both tradable and non-tradable CPI inflation

the overall tightness parameter, λ . The prior parameters are set as follows:

$$\begin{aligned} \sigma_i & \text{ is set to the residual standard deviation from the AR(1) model for variable } i \\ \chi_i & \text{ is set to the coefficient value in the AR(1) model for variable } i \\ s & = 1 \\ \frac{1}{c} & = 0.01 \\ \lambda & \in \left\{ \frac{1}{20}, \frac{2}{20}, \dots, 1 \right\} \end{aligned}$$

We find that our impulse responses are reasonably robust to the choice of λ , although we do find that the tighter the prior the smoother the impulse response function, with less oscillation. We also find that the forecasting performance of the model (relative to the published RBNZ forecasts over the period 2003Q1-2010Q4) is reasonably robust to the choice of λ , although the forecasting performance does improve for smaller values of λ . We choose $\lambda = 0.2$.⁸

5 Results

In this section we present the results from our forecast comparison exercise for each of the three agents. We compare the average root-mean-squared-errors over history of the conditional forecasts to the unconditional forecasts. Before we present these results, we must first address the problem of real-time forecasting.

5.1 Real-Time Forecasting

A frequent problem facing forecasters in real time is that datasets are often unbalanced as observations for variables are released incrementally throughout a quarter. To deal with this problem, we fill in the missing observations with the RBNZ forecasts, which are made in preparation for the quarterly Monetary Policy Statement. Bloor and Matheson (2011) also use this technique to obtain a balanced panel, stating that the RBNZ has significant informational advantages in the very near-term.

⁸The forecasting performance of the model for this prior is presented in the Appendix (relative to the forecasting performance of the published RBNZ forecasts).

5.2 Forecast Comparison

In order to compare forecast performance, we need to calculate the average root-mean-squared-errors (which we denote MRMSEs) for both the conditional forecasts and the unconditional forecasts. This is done by averaging the RMSEs for the conditional and unconditional forecasts calculated for each forecast period (there are 31 forecast periods over 2003Q2 - 2010Q4). The RMSE for each forecast period is calculated by:

$$RMSE_{i,t+h}^f = \sqrt{\frac{1}{N} \sum_{j=1}^N (\hat{y}_{j,i,t+h}^f - y_{i,t+h}^f)^2}$$

where $\hat{y}_{j,i,t+h}^f$ is the h -step ahead forecast of variable i from the j th model for forecast period f ; $y_{i,t+h}^f$ is the actual value of variable i at period $t+h$ for forecast period f . (Note, N is the number of models drawn from the set of admissible models. This is a result of using sign restrictions to identify the model, causing the model to only be set identified. In this case $N = 50,000$ and, thus, $j = 1, \dots, 50,000$).

The average RMSE is calculated by

$$MRMSE_{i,t+h} = \frac{1}{31} \sum_{f=1}^{31} RMSE_{i,t+h}^f$$

We compare the MRMSEs for the conditional and unconditional forecasts to see if there is an improvement in forecasting performance when conditioning the 90-day rate to follow the RBNZ forecast. These results are presented for each type of agent below.

5.2.1 The Non-Deviator

As mentioned earlier, the agents differ in terms of how they interpret the RBNZ forecast relative to their model forecast. In other words the shocks they choose to condition the 90-day track to follow the RBNZ forecast differ. The Non-Deviator believes the RBNZ forecast is a conditional forecast i.e. conditional on current and expected future economic conditions. Hence, they do not believe the RBNZ is deviating from the policy rule (the policy rule in terms of the agent's model), but rather the RBNZ forecast is conveying new information about the economic environment. These agents, therefore,

condition the RBNZ track using all shocks except for the monetary policy shock.

Although the shocks responsible for the RBNZ track may differ from quarter to quarter, we take this rough approach as it is the easiest to implement without having to go through each MPS to deduce the appropriate shock/s for each quarter. The forecast comparison results for the Non-Deviator are presented in Table (2) below.

As you can see, the RBNZ forecast for the 90-day rate does remarkably better than the agent’s model. However, this improvement does not lead to significantly better forecasts of the other four variables in the model. Importantly though, it does not lead to significantly worse forecasts.

Table 2: Non-Deviators: All Shocks Excluding MP

Horizon	Output Gap	Non-Tradable CPI	Tradable CPI	90-Day Rate	Exchange Rate
t+1	0.92**	1.06	1.01	0.53***	1.03
t+2	0.99	1.05	0.98	0.61**	0.99
t+3	1.02	1.06	0.98	0.70	1.01
t+4	1.01	1.09	1.01	0.83	1.01

¹ The numbers displayed are the MRMSEs from the conditional forecasts divided by the MRMSEs from the unconditional forecasts. A ratio less (greater) than one indicates an improvement (deterioration) in the conditional forecast relative to the unconditional forecast.

² *, **, *** denotes a significant difference in the MRMSEs at the 10, 5, 1 percent level respectively, according to the Diebold and Mariano (1995) test.

5.2.2 The Deviator

The Deviator, on the other hand, believes the RBNZ forecast is an unconditional promise from the RBNZ to deviate from the policy rule. In other words, they believe that the RBNZ track is not in line with what the policy rule would suggest given the agents’ views on current and future economic conditions. Thus, these agents condition the 90-day rate track to follow the RBNZ track using only monetary policy shocks. The forecast comparison results for the Deviator are presented in Table (3) below.

Again, the forecast performance of the RBNZ track does remarkably better than the agent’s model forecasts (and, of course, the forecast performance of the 90-day rate is identical to that of the Non-Deviator as they both condition on the same track). However, this time, the forecasting performance of every variable gets significantly worse. Although it may be the case that in some

quarters the Deviator can improve their conditional forecasts relative to the unconditional forecasts, on average, they cannot.

Table 3: Deviators: Monetary Policy Shock Only

Horizon	Output Gap	Non-Tradable CPI	Tradable CPI	90-Day Rate	Exchange Rate
t+1	1.14***	2.00***	1.61***	0.53***	1.27***
t+2	1.57***	2.93***	2.03***	0.61**	1.53***
t+3	3.55***	5.23***	3.90***	0.70	2.01***
t+4	14.53***	12.30***	12.30***	0.83	2.32***

¹ The numbers displayed are the MRMSEs from the conditional forecasts divided by the MRMSEs from the unconditional forecasts. A ratio less (greater) than one indicates an improvement (deterioration) in the conditional forecast relative to the unconditional forecast.

² *, **, *** denotes a significant difference in the MRMSEs at the 10, 5, 1 percent level respectively, according to the Diebold and Mariano (1995) test.

It is important to note that these results are dependent on our model and identification scheme used. We find that when using a model with worse forecasting performance (a looser prior specification), that the forecasting performance of the Non-Deviator agent significantly improves relative to the unconditional forecasts. The forecasting performance of the Deviator remains significantly. We also estimate the model for all variables in log levels (except, of course, the interest rate) and find similar results; the Deviator's conditional forecasts are significantly worse than the model forecasts, and the Non-Deviator's forecasts are no better or worse than the model forecasts.

5.3 Example

Finally, we look at a specific forecast period (2004Q3-2005Q2) to illustrate more clearly how the agents' interpretation of the RBNZ track crucially affects their forecasts for the rest of the economy. In this period the model forecasts a lower track for the 90-day rate relative to the RBNZ track. We assume that agents can interpret the information in the RBNZ forecast in two ways. Firstly, we assume that agents interpret the RBNZ forecast as a deviation from the policy rule (i.e. they condition the RBNZ track using only monetary policy shocks). This scenario is shown in Figure (1). Secondly, we assume agents interpret the RBNZ forecast as a response to improvements in global demand (see June 2004 MPS). Thus, we assume agents condition the RBNZ path using demand shocks.⁹ This is shown in Figure (2).

⁹As well as the unidentified 5th shock.

As you can see, in the first scenario, the higher 90-day rate track causes the agent's forecasts for the output gap and non-tradable inflation to fall (relative to the unconditional forecasts). Whereas, in the second scenario, the same higher 90-day rate track causes the agent's forecasts for the output gap and non-tradable inflation to rise. It is also interesting to note, that in the second scenario, the agent's conditional forecasts do better than the model produced forecasts (except for the forecast for non-tradable inflation). This may suggest that agents can potentially improve their forecasts by incorporating (correctly) the information conveyed in the RBNZ track.

Figure 1: MP Shock (Conditional (blue), Unconditional (red), Actual (black))

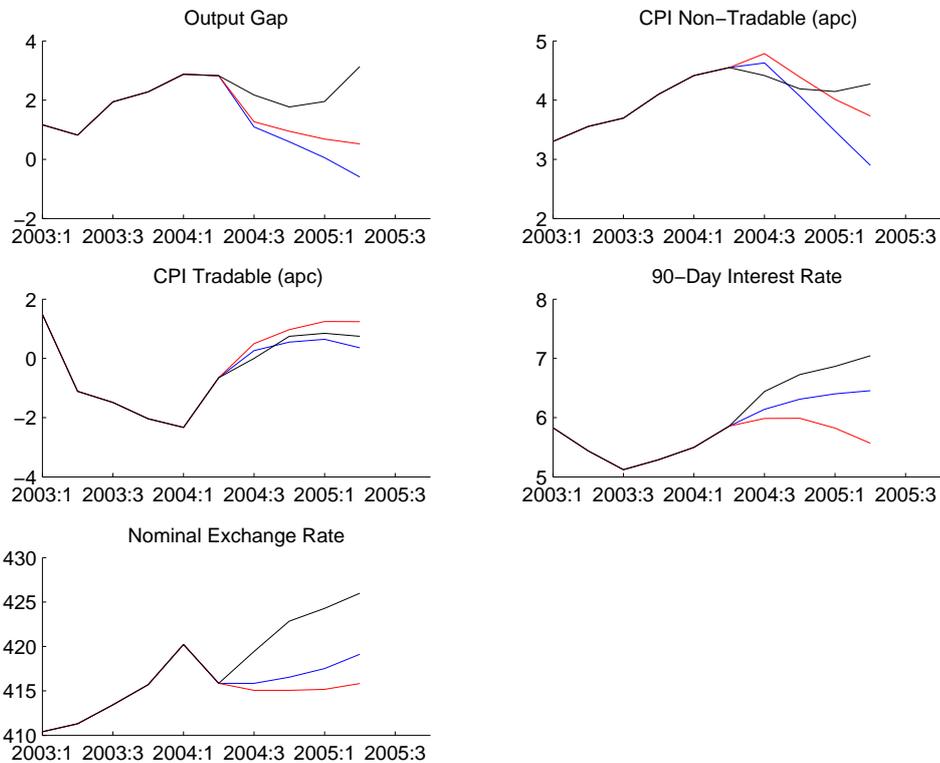
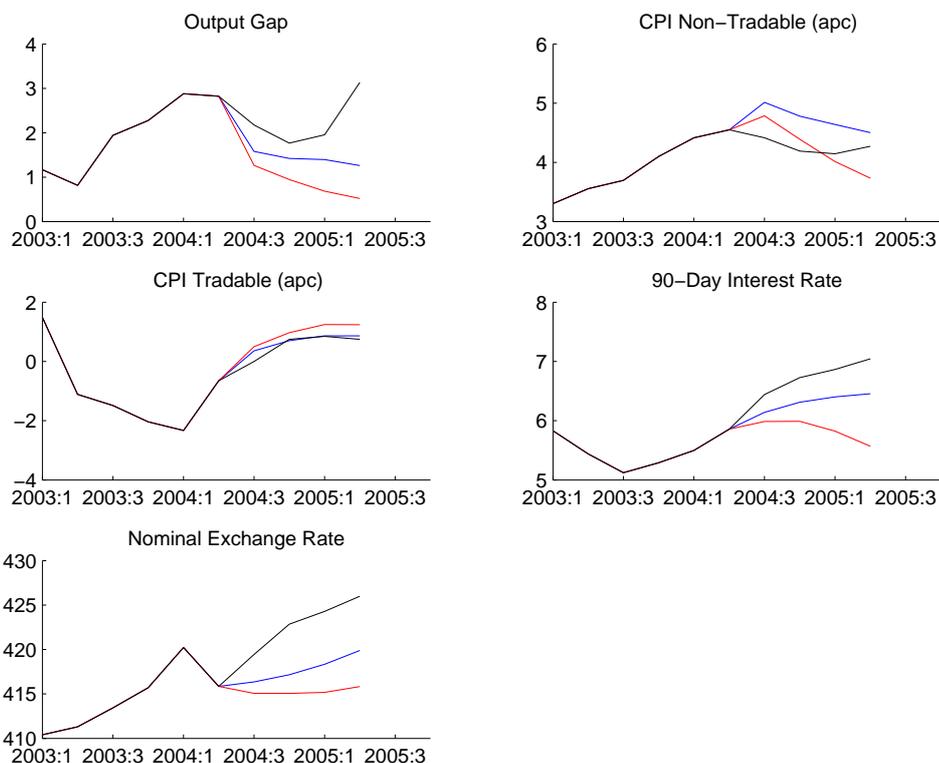


Figure 2: Demand Shock (Conditional (blue), Unconditional (red), Actual (black))



6 Conclusion

In this paper we investigated the effect of the information content in the RBNZ's interest rate projections on agents' forecasting ability. Specifically, we investigated whether agents can improve their forecasts by including this additional information, and whether the way in which agents interpret this information matters.

To conduct this exercise, we assumed agents used a small BVAR model to forecast the economy. We allowed agents to condition their model forecasts to follow the RBNZ track for the 90-day rate. The way in which the agents conditioned the track depended on how the agents interpreted this forward guidance. Specifically, we had two types of agents. The first type of agent, the Non-Deviator, viewed the RBNZ forecast as a conditional forecast. Hence,

this agent believed the RBNZ forecast differed to his model forecast due to new information on current and future economic conditions. The second type of agent, the Deviator, did not believe the RBNZ forecast conveyed any new information, and, hence, believed such a forecast indicated a commitment from the RBNZ to deviate from the policy rule.

We found that the forecasting performance of the agents' conditional forecasts relative to their model (unconditional) forecasts depended crucially on how the agents interpreted the forward guidance. We found that the RBNZ's published rate path potentially contained some value provided the agents did not interpret the path as a commitment. We believe our findings emphasize the importance of effective central bank communication, and support the statement of Dale et al (2011): Central bank communication is a double edged sword and should be used with care.

References

- Archer, D (2005), ‘Central bank communication and the publication of interest rate projections’, Paper prepared for Inflation Targeting: Implementation, Communication and Effectiveness, a workshop at Sveriges Riksbank, Stockholm, June 10-12.
- Banbura, M, D Gianonne, and L Reichline (2010), ‘Large Bayesian VARs’, *Journal of Applied Econometrics*, vol. 25(1), pages 71-92.
- Blinder, A, J de Haan, M Ehrmann, M Fratzscher, and D-J Jansen (2008), ‘Central bank communication and monetary policy: a survey of theory and evidence’, *Journal of Economic Literature*, vol. 46(4), pages 910-945.
- Bloor, C and T Matheson (2011), ‘Real-time conditional forecasts with Bayesian VARs: An application to New Zealand’, *The North American Journal of Economics and Finance*, vol. 22(1), pages 26-42.
- Campbell, J, C Evans, J Fisher, and A Justiniano (2012), ‘Macroeconomic effects of FOMC forward guidance’, *Working Paper Series, Federal Reserve Bank of Chicago*, WP-2012-03.
- Dale, S, A Orphanides, and P Österholm (2011), ‘Imperfect central bank communication: information versus distraction’, *International Journal of Central Banking*, vol. 7(2), pages 3-39.
- Detmers, G-A, and D Nautz (2012), ‘The information content of central bank interest rate projections: Evidence from New Zealand’, *Discussion Paper, Reserve Bank of New Zealand*, Discussion Paper Series, February 2012.
- Doan, T, R Litterman, and C Sims (1984), ‘Forecasting and conditional projection using realistic prior distributions’, *Econometric Review*, vol. 3(1), pages 1-100.
- Fry, R and A Pagan (2011), ‘Sign restrictions in structural vector autoregressions: A critical review’, *Journal of Economic Literature*, American Economic Association, vol. 49(4), pages 938-960.
- Goodhart, C (2009), ‘The interest rate conditioning assumption’, *International Journal of Central Banking*, vol. 5(2), pages 85-105.
- Kadiyala, K and S Karlsson (1997), ‘Numerical methods for estimation and inference in Bayesian VAR-models’, *Working Paper Series in Economics and Finance 12*, Stockholm School of Economics, pages 99-132

- Mishkin, F S (2004), 'Can central bank transparency go too far?', *The Future of Inflation Targeting*, Reserve Bank of Australia, 48-66, www.rba.gov.au.
- Morris, S and H Shin (2002), 'Social value of public information', *American Economic Review*, vol. 92(5), pages 1521-1534.
- Litterman, R (1986), 'Forecasting with Bayesian vector autoregressions - Five Years of Experience', *Journal of Business and Economic Statistics*, vol. 4, pages 25-38.
- Robertson, J and E Tallman (1999), 'Vector autoregressions: forecasting and reality', *Federal Reserve Bank of Atlanta, Economic Review*, pages 4-18.
- Sims, C (1980), 'Macroeconomics and reality', *Econometrica*, vol. 48(1), pages 1-48.
- Svensson, L (2006), 'The instrument-rate projection under inflation targeting: the Norwegian example', *Working Papers 75*, Princeton University.
- Waggoner, Z and T Zha (1999), 'Conditional forecasting in dynamic multivariate models', *The Review of Economics and Statistics*, vol. 81(4), pages 639-651.
- Woodford, M (2001), 'Monetary policy in the information economy', in *Economic Policy for the Information Economy*, Kansas City: Federal Reserve Bank of Kansas City, 2001.
- Woodford, M (2005), 'Central bank communication and policy effectiveness', *NBER Working Paper Series*, WP 11898.
- Zha, T (1999), 'Block recursion and structural vector autoregressions', *Journal of Econometric*, vol. (90), pages 291-316.

Appendix

Forecast performance of unconditional forecasts relative to published RBNZ forecasts

We present the average RMSEs of the four-step ahead model forecasts relative to the average RMSEs of the four-step ahead published RBNZ forecasts over 2003Q2-2010Q4. As you can see the agents' model is better on average at forecasting the output gap, and is no better or worse at forecasting non-tradable inflation, tradable inflation, and the exchange rate. However, the agents model is worse at forecasting the 90-day rate.

Horizon	Output Gap	Non-Tradable CPI	Tradable CPI	90-Day Rate	Exchange Rate
t+1	0.93	1.00	1.02	1.86	0.99
t+2	0.86	1.00	1.02	1.65	1.04
t+3	0.85	0.99	1.01	1.42	0.99
t+4	0.84	0.99	0.99	1.21	0.98

¹ The numbers displayed are the MRMSEs from the BVAR forecasts divided by the MRMSEs from the RBNZ published forecasts. A ratio less (greater) than one indicates an improvement (deterioration) in the BVAR forecast relative to the RBNZ forecast.