RESERVE BANK
OF NEW ZEALAND

DP2008/09

Analysing shock transmission in a data-rich environment: A large BVAR for New Zealand

Chris Bloor and Troy Matheson

May 2008

JEL classification: C11, C13, C33, C53

www.rbnz.govt.nz/research/discusspapers/

Discussion Paper Series

ISSN 1177-7567

DP2008/09

Analysing shock transmission in a data-rich environment: A large BVAR for New Zealand*

Chris Bloor and Troy Matheson†

Abstract

We analyse a large Bayesian Vector Autoregression (BVAR) containing almost one hundred New Zealand macroeconomic time series. Methods for allowing multiple blocks of equations with block-specific Bayesian priors are described, and forecasting results show that our model compares favourably to a range of other time series models. Examining the impulse responses to a monetary policy shock and to two less conventional shocks – net migration and the climate – we highlight the usefulness of the large BVAR in analysing shock transmission.

* The views expressed in this paper are those of the author(s) and do not necessarily reflect the views of the Reserve Bank of New Zealand. We thank Tim Hampton and Rishab Sethi for useful comments on earlier drafts. All errors and omissions are our own.
† Address: Economics Department, Reserve Bank of New Zealand, 2 The Terrace, PO Box 2498, Wellington, New Zealand. *email:* Troy.Matheson@rbnz.govt.nz.

1 Introduction

Central banks are routinely faced with the problem of identifying the macroeconomic impacts of a wide range of shocks. Typically, these impacts are estimated using Vector Autoregressions (VARs) or Dynamic Stochastic General Equilibrium models (DSGEs). These models usually contain up to twenty macroeconomic variables, a very small number relative to the information set monitored by most central banks. The rationale for only utilising a small subset of the available information in DSGEs is that the microeconomic theory that underlies these models is not yet rich enough to incorporate all variables (and shocks) that may be of interest to central banks, such as business confidence, and production and prices across all industries in the economy. On the other hand, the rationale for only utilising a small subset of the available information in VARs is that these models lose degrees of freedom as more variables are added – the so-called 'curse of dimensionality'.

The literature on factor models has gone some way to resolving the curse of dimensionality, allowing the decomposition of very large panels of data into a small number of common factors (Stock and Watson 1999; Forni *et al* 2000; Stock and Watson 2002; Forni *et al* 2005). These methods have been combined with standard VAR techniques to identify the effects of monetary policy on a large number of variables (Bernanke *et al* 2005; Stock and Watson 2005; Boivin and Giannoni 2008).

Recently, another approach to resolving the curse of dimensionality has been explored in the context of Bayesian regression by De Mol *et al* (2008). These authors show that a Bayesian forecast based on point estimates converges to the optimal forecast, as long as the tightness of the prior (the degree of shrinkage) increases as the number of variables increases. Banbura *et al* (2007) apply this result to a large Bayesian VAR (BVAR) with Litterman (1986) and sums of coefficients priors (Doan *et al* 1984). Banbura *et al* (2007) find that the forecasting performance and the impulse responses to a monetary policy shock from their large model, which contains 108 US variables, compare favourably to those of smaller VARs. Moreover, forecasts from the large BVAR are found to outperform forecasts from factor-augmented VARs estimated using the same panel of data.

It appears that both the factor model and Bayesian approaches can deliver good forecasting performance and are capable of providing impulse responses to a wide range of shocks, making them both useful additions to the macroeconomist's toolkit. However, a potential advantage of the Bayesian approach over the factor model approach is that estimation and inference can be conducted in (non-stationary) levels; factor model applications, in contrast, typically work with data that have been transformed to achieve stationarity, destroying the potential influence of long-run, cointegrating relationships. For this reason, this paper focuses on a Bayesian approach for analysing the impact of shocks for New Zealand, leaving the analysis of factor-augmented VARs for future work.

In addition to using New Zealand data, we extend the work of Banbura *et al* (2007) along several dimensions. We augment the Banbura *et al* (2007) prior with the co-persistence prior of Sims (1993), producing what Robertson and Tallman (1999) call the modified Litterman prior. We impose restrictions on the lagged variables entering each equation. This allows us to develop a model with multiple blocks of equations, including those that characterise the small open economy restrictions described by Cushman and Zha (1997). We generalise the Banbura *et al* (2007) algorithm for determining the tightness of the Bayesian prior to the case where restrictions on lags are imposed. Essentially, this allows us to impose different degrees of shrinkage across each of the blocks of equations in the model. Finally, we explore a wider range of shocks than Banbura *et al* (2007).

Generally, we find that our large BVAR provides a good description of the data in New Zealand, producing relatively good forecasts of real GDP, tradable and non-tradable prices, 90-day rates and the real exchange rate compared with a range of other time series models. We examine the impulse responses of the large BVAR to a monetary policy shock and find that the responses appear to be reasonable. To further highlight the usefulness of the large BVAR, we also briefly look at its impulse responses to two shocks not typically included in standard small open economy VARs and DSGEs, but which are important determinants of the New Zealand business cycle: a net migration shock and a climate shock. The consequences of a monetary policy shock are of obvious importance to most macroeconomists, but net migration and climate shocks perhaps require more discussion here.

New Zealand is a small open economy with a working age population of around 3.25 million. Historically, changes in net migration account for a large proportion of the cyclical fluctuations in New Zealand's working age population. As a consequence, net migration has been a key determinant of the house price cycle in New Zealand for almost 50 years (see Coleman and Landon-Lane 2007). Likewise, the importance of climate conditions for driving New Zealand's business cycle has been emphasised by Buckle *et al* (2007). This is because exports constitute around 30 per cent of New Zealand's output and a large share of this production is related to the weather-dependent agricultural sector.

As with the monetary policy shock, the impulse responses relating to the net migration and climate shocks appear reasonable in our large BVAR. Overall, like Banbura *et al* (2007), we find that the large BVAR is a useful tool for both forecasting and structural analysis. Moreover, the methods for allowing multiple blocks of equations with block-specific priors outlined here greatly improve the sophistication of structural analyses that can be conducted within this framework.

The paper is organised as follows. Section 2 outlines the BVAR framework and the Banbura *et al* (2007) algorithm for determining the tightness of the Bayesian prior. Section 3 describes how lagged restrictions can be imposed on multiple blocks of equations in the BVAR, and how the tightness of the Bayesian prior can be selected in a block-specific way. Section 4 describes the data and model specifications, and section 5 describes the forecasting results. The impulse responses are discussed in section 6, and we conclude in section 7.

2 Methodology

2.1 The Bayesian VAR

Let $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{n,t})'$ be a set of time series. The VAR(p) representation of these time series is then:

$$Y_t = c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + u_t \tag{1}$$

where $c = (c_1, \ldots, c_n)'$ is an n-dimensional vector of constants, $A_1, \ldots, A_p$ are $n \times n$ autoregressive matrices, and u_t is an n-dimensional white noise process with covariance matrix $\mathrm{E}u_t u_t' = \Psi$.

The Litterman (1986) prior, often referred to as the Minnesota prior, suggests that all equations are centered around a random walk with drift:

$$Y_t = c + Y_{t-1} + u_t. \tag{2}$$

This essentially shrinks the diagonal elements of A_1 towards one and the other coefficients ($A_2, \ldots, A_p$) towards zero. Litterman's prior also embodies the belief that more recent lags provide more useful information than more distant ones, and that own lags explain more of a given variable than the lags of the other variables in the model.

The prior is imposed by setting the following moments for the prior distribution of the coefficients:

$$\mathrm{E}[(A_k)_{ij}] = \begin{cases} \delta_i, & j = i, k = 1 \\ 0, & \text{otherwise} \end{cases} \quad \text{and} \quad \mathrm{V}[(A_k)_{ij}] = \vartheta \frac{\lambda^2}{k^2} \frac{\sigma_i^2}{\sigma_j^2} \tag{3}$$

The coefficients $A_1, \ldots, A_p$ are assumed to be independent and normally distributed. The covariance matrix of the residuals is assumed to be diagonal, fixed and known (i.e. $\Psi = \Sigma$, where $\Sigma = \mathrm{diag}(\sigma_1^2, \ldots, \sigma_n^2)$, and the prior on the intercept is diffuse. Note that the random walk prior, $\delta_i = 1$ for all i, reflects a belief that all the variables are highly persistent. However, the researcher may believe that some of the variables in the VAR are characterised by a substantial degree of mean-reversion. This does not pose a problem for this framework, because a white-noise prior can be set for some or all of the variables in the VAR by imposing $\delta_i = 0$ where appropriate.

The hyperparameter λ controls the overall tightness of the prior distribution around δ_i. This hyperparameter governs the importance of prior beliefs relative to the information contained in the data: $\lambda = 0$ imposes the prior exactly so that the data do not inform the parameter estimates, and $\lambda = \infty$ removes the influence of the prior altogether so that the parameter estimates are equivalent to OLS estimates. The factor $1/k^2$ is the rate at which the prior variance decreases with the lag length of the VAR, and σ_i^2/σ_j^2 accounts for the different scale and variability of the data. The coefficient $\vartheta \in (0, 1)$ governs the extent to which the lags of other variables are less important than own lags.

Under the condition that $\vartheta = 1$, Litterman's assumption that the covariance matrix is fixed and diagonal has been removed by Kadiyala and Karlsson (1997) and Sims and Zha (1998) by imposing a normal prior distribution for the coefficients and an inverse Wishart prior distribution for the covariance matrix of the residuals Ψ, the so-called inverse-Wishart prior.

Another modification of the Minnesota prior, motivated by the frequent practice of specifying a VAR in first differences, is the sums of coefficients prior of Doan *et al* (1984). Consider the VAR in its error correction form:

$$\Delta Y_t = c - (I_n - A_1 - \ldots - A_p) Y_{t-1} + B_1 \Delta Y_{t-1} + \ldots + B_{p-1} \Delta Y_{t-p+1} + u_t. \tag{4}$$

The sums of coefficients prior shrinks $(I_n - A_1 - \ldots - A_p)$ towards zero. The hyperparameter τ controls the degree of shrinkage of this prior. As $\tau \to 0$ the VAR will increasingly satisfy the prior. Higher values of τ, on the other hand, will loosen the prior until, when $\tau = \infty$, the prior has no influence on VAR estimates. Notice that the sums of coefficients restriction implies that there are as many stochastic trends in the VAR as there are $I(1)$ variables. It might, however, be reasonable to assume that there are stable, long-run cointegrating relationships in the system. Sims (1993) introduced a prior that makes some allowance for this possibility. This 'co-persistence' prior is governed by the hyperparameter θ. As $\theta \to 0$ the VAR will increasingly satisfy the prior, so that there is one stochastic trend in the system when $\theta = 0$. On the other hand, the prior has no influence on the VAR estimates when $\theta = \infty$. Together, the Minnesota, inverse-Wishart, sums of coefficients, and co-persistence priors are what Robertson and Tallman (1999) call the modified Litterman prior.[1]

Writing the VAR in matrix notation yields:

$$Y = XB + U \tag{5}$$

where $Y = (y_1, \ldots, y_T)'$, $X = (X_1, \ldots, X_T)'$, $X_t = (Y'_{t-1}, \ldots, Y'_{t-p}, 1)$, $U = (u_1, \ldots, u_T)'$, and $B = (A_1, \ldots, A_p, c)'$ is the $k \times n$ matrix containing all coefficients with $k = np + 1$. The form of the inverse-Wishart prior is then:

$$\Psi \sim iW(S_0, \alpha_0) \quad \text{and} \quad B|\Psi \sim N(B_0, \Psi \otimes \Omega_0) \tag{6}$$

where the parameters B_0, Ω_0, S_0, and α_0 are chosen to satisfy our prior expectations for B and Ψ. In this paper, we implement the modified Litterman prior by adding dummy observations to the system (5). It can be shown that adding T_d dummy observations Y_d and X_d is equivalent to imposing the inverse-Wishart prior with $B_0 = (X_d'X_d)^{-1}X_d'Y_d$, $\Omega = (X_d'X_d)^{-1}$, $S_0 = (Y_d - X_dB_0)'(Y_d - X_dB_0)$, and $\alpha_0 = T_d - k - n - 1$. We add the following dummy observations to match our prior moments:

[1] Robertson and Tallman (1999) find that the modified Litterman prior produces relatively good forecasts of unemployment, inflation, and GDP growth in the US compared to the Litterman (1986) prior and the Sims and Zha (1998) prior.

$$Y_d = \begin{pmatrix} \text{diag}(\delta_1\sigma_1,\ldots,\delta_n\sigma_n)/\lambda \\ 0_{n(p-1)\times n} \\ \ldots\ldots\ldots\ldots \\ \text{diag}(\delta_1\mu_1,\ldots,\delta_n\mu_n)/\tau \\ \ldots\ldots\ldots\ldots \\ J \\ \ldots\ldots\ldots\ldots \\ \text{diag}(\sigma_1,\ldots,\sigma_n) \\ \ldots\ldots\ldots\ldots \\ 0_{1\times n} \end{pmatrix} X_d = \begin{pmatrix} K_d \otimes \text{diag}(\sigma_1,\ldots,\sigma_n)/\lambda & 0_{np\times 1} \\ \ldots\ldots\ldots\ldots & \ldots \\ K \otimes \text{diag}(\delta_1\mu_1,\ldots,\delta_n\mu_n)/\tau & 0_{n\times 1} \\ \ldots\ldots\ldots\ldots & \ldots \\ (J_1,\ldots,J_p)_{1\times np} & 1/\theta \\ \ldots\ldots\ldots\ldots & \ldots \\ 0_{n\times np} & 0_{n\times 1} \\ \ldots\ldots\ldots\ldots & \ldots \\ 0_{1\times n} & \varepsilon \end{pmatrix} \quad (7)$$

where $J = (\delta_1\mu_1,\ldots,\delta_n\mu_n)/\theta$, $K = 1,\ldots,p$, $K_d = \text{diag}(K)$, and ε is a very small number.[2] Generally speaking, the first block of dummies impose prior beliefs on the autoregressive coefficients, the second block of dummies impose the sums of coefficients prior, the third block of dummies impose the co-persistence prior, and the fourth and fifth blocks impose the priors for the covariance matrix and the intercepts, respectively. Following common practice, we set the prior for the scale parameter σ_i equal to the residual standard deviation from a univariate autoregressive regression with p lags for variable y_{it}. Likewise, the parameter μ_i (the prior for the average level of variable y_{it}) is set equal to the sample average of variable y_{it}.

Augmenting the system (5) with the dummy observations (7) yields:

$$Y^* = X^*B + U^* \quad (8)$$

where $Y^* = (Y', Y_d')'$, $X^* = (X', X_d')'$ and $U^* = (U', U_d')'$. After adding the diffuse prior $\Psi \propto |\Psi|^{-(n+3)/2}$ (to ensure the existence of the prior expectation of Ψ), the posterior has the form:

$$\Psi|Y \sim iW(\hat{\Sigma}, T_d + 2 + T - k) \;\text{ and }\; B|\Psi,Y \sim N(\hat{B}, \Psi \otimes (X^{*\prime}X^*)^{-1}) \quad (9)$$

where $\hat{B} = (X^{*\prime}X^*)^{-1}X^{*\prime}Y^*$ and $\hat{\Sigma} = (Y^* - X^*\hat{B})'(Y^* - X^*\hat{B})$ (Banbura *et al* 2007). The dummy observations (7) make it clear that as λ, τ, and θ tend to infinity the Minnesota, sums of coefficients, and co-persistence dummies will tend to zero, and the posterior parameter estimates will tend to the OLS estimates from the original, un-augmented system (5). More generally, the posterior expectation of the parameters coincide with the OLS estimates of the dummy-augmented system (8).

[2] Note: if v is a vector of dimension $1 \times v_n$, the operation $\text{diag}(v)$ is defined here to yield a $v_n \times v_n$ matrix with v on the diagonal and zeros elsewhere.

2.2 Penalising over-fitting by imposing tighter priors

Adding more variables to a classical regression leads to a deterioration in the parameter estimates – over-fitting. However, in the context of Bayesian regression, De Mol *et al* (2008) show that a forecast based on point estimates converges to the optimal forecast for n and T going to infinity along any path, as long as the tightness of the prior (the degree of shrinkage) increases as n becomes larger. Banbura *et al* (2007) apply this result to a large BVAR with a modified Litterman prior without co-persistence dummy observations. The tightness of the prior is increased as n increases by using the following algorithm:

1. Select n^* (where $n^* < n$) benchmark variables for which in-sample fit will be evaluated;

2. Evaluate the in-sample fit of a VAR estimated with OLS on the n^* benchmark variables;

3. Set the sums of coefficients hyperparameter τ to be proportionate to the overall tightness hyperparameter λ ($\tau = \phi_1\lambda$, where $\phi_1 \geq 0$);

4. Choose the overall tightness hyperparameter λ (and τ) to have the same in-sample fit as the benchmark VAR.

We use a similar algorithm to penalise over-fitting in this paper. Our modified Litterman prior, however, has one more hyperparameter that needs to set – the tightness of the co-persistence prior θ. Following the Banbura *et al* (2007) rule for choosing the sums of coefficients hyperparameter, we set the co-persistence hyperparameter θ to be proportionate to the overall tightness hyperparameter λ ($\theta = \phi_2\lambda$, where $\phi_2 \geq 0$). In this paper, we set $\phi_1 = \phi_2 = 1$.[3]

We define in-sample fit as a measure of relative 1-step-ahead mean squared error (MSE) evaluated using the training sample $t = 1, \ldots, T-1$, as in Banbura *et al* (2007). The MSE for variable i for a given λ is:

$$MSE_i^\lambda = \frac{1}{T-p-1} \sum_{t=p}^{T-2} (y_{i,t+1|t}^\lambda - y_{i,t+1})^2 \tag{10}$$

where the parameters are estimated using the training sample. The variables are then ordered so that the n^* baseline variables are ordered first. The overall tight-

[3] Banbura *et al* (2007) find that the forecasting performance of their model is robust to different values of $\phi_1 \in (0, 1, 10, 100)$. Likewise, we find that the forecasting performance our model is robust to different configurations of ϕ_1 and ϕ_2. These results are available from the authors on request.

ness hyperparameter (λ) for a given measure of baseline fit (FIT) is then found by a grid search over λ:

$$\lambda(\text{FIT}) = \arg\min_{\lambda} \left| \text{FIT} - \frac{1}{n^*} \sum_{i=1}^{n^*} \frac{MSE_i^{\lambda}}{MSE_i^{0}} \right| \quad (11)$$

where MSE_i^0 is the MSE of variable i with the prior restriction imposed exactly ($\lambda = 0$), and baseline fit is defined as the average relative MSE from an OLS-estimated VAR containing the n^* baseline variables:

$$\text{FIT} = \frac{1}{n^*} \sum_{i=1}^{n^*} \frac{MSE_i^{\infty}}{MSE_i^{0}} \quad (12)$$

3 Restrictions on lags (B)

Restrictions on the lagged variables entering into each equation can be important for correct inference in VARs in the small open economy context (Cushman and Zha 1997 and Zha 1999). So far, we have outlined a BVAR methodology that is symmetric; each variable is a linear function of lags of all variables in the system. Undoubtedly, in a small open economy like New Zealand, foreign variables are key determinants of the business cycle. Domestic variables, on the other hand, are not likely to have much influence on foreign variables. It thus makes economic sense to make the foreign variables exogenous to the domestic variables. Likewise, oil prices might be exogenous to *both* the domestic variables and the foreign variables (Zha 1999). Bayesian inference with these types of exogeneity restrictions on lagged variables can be readily made using the block by block estimation method laid out in Zha (1999).[4]

A potential problem with a block by block approach here is that the tightness of the Bayesian prior (λ, τ and θ) will be the same across each block of equations; all blocks of equations will be linked to the in-sample fit for the n^* baseline variables (section 2.2). To break this link, we define λ^m, τ^m and θ^m to be block-specific hyperparameters for each block of equations, where $m = 0, 1, \ldots, M$ and $m = 0$ identifies a large endogenous block of domestic variables.

For each of the M blocks of equations, we can then re-define the hyperparameters in (7), select the appropriate columns from the dummy-augmented matrices

[4] Our shock identification strategy leads to what Zha (1999) calls strongly recursive blocks (see section 6). More generally, models with weakly recursive blocks can be estimated using a methods outlined in Zha (1999) or Waggoner and Zha (2003).

(8), and estimate the posterior parameters from the block-specific version of (9). Notice that this method affords much flexibility in specifying the lagged relationships in each block, allowing the variables contained in any particular block to be exogenous to any other block (or subset of blocks), where the hyperparameters λ^m, τ^m and θ^m can be chosen in a block-specific way. Indeed, if there is more than one large block of equations in the system, the algorithm outlined in section 2.2 can be used to set the hyperparameters for each of the large blocks.[5] In this paper, we only have one large block $m = 0$, the endogenous block of domestic variables. For the remaining M blocks of equations, we use the hyperparameters employed by Robertson and Tallman (1999) for their modified Litterman prior, $\lambda^m = \tau^m = \theta^m = 0.2$ for all $m = (1, \ldots, M)$.

4 Data and model specifications

4.1 Data

The large BVAR is estimated using quarterly data ranging from the first quarter of 1990 to the second quarter of 2007. The panel consists of 94 time series covering a broad range of categories, including business and consumer confidence, the housing market, consumption and investment, production, and financial markets. All series in the panel are seasonally adjusted using Census X12 prior to estimation. The series that are expressed in percentages (e.g. interest rates and unemployment rates) and those that can take negative values (e.g. balances of opinion and net migration) are retained in levels. We transform the remainder of the series by applying natural logarithms and multiplying by 100. For most of the variables in the panel we use the random walk prior $\delta_i = 1$. However, some of the variables in the panel can be characterised as being mean-reverting. For these variables, we impose the white noise prior $\delta_i = 0$. The variables, transforms, and priors we use are displayed in appendix A.

The main purpose of this paper is to analyse the dynamic responses of a large number of time series to a handful of shocks. However, as an initial robustness check of the quality of our model, we first compare its forecasting performance to some smaller models. We adopt a small open economy monetary VAR containing

[5] Simply choose $n^{m,*}$ baseline variables from large block m (where $n^{m,*} < n^m$ and n^m is the number of endogenous variables in block m) and select the hyperparameters λ^m, τ^m and θ^m using the algorithm in section 2.2.

real GDP, tradable and non-tradable consumer prices, 90 day interest rates, and the real exchange rate as our baseline specification.[6] All other VARs we consider nest this baseline specification. Note that the lag length p in all VARs is set to 4 unless otherwise stated.

4.2 Model specifications

BL is our baseline VAR for determining the overall tightness of our Bayesian prior λ and is estimated with OLS. To guard against possible over-parameterisation – which will lead to poor forecasting performance – we also estimate the baseline VAR using the Schwartz-Bayesian Information Criteria (SBC) to determine the lag length, allowing lags to range from 1 to p. (This estimated version of the model is called BL^{SBC}.) In addition, we estimate this model using data-determined Bayesian priors, BL^{BVAR}, as in Del Negro and Schorfheide (2004).[7] We also estimate two univariate models for the forecasting exercise: an autoregressive model *AR* and a random walk model *RW*.[8] The remaining BVARs are estimated using the methods described in sections 2.2 and 3 and are displayed in table 1.

In table 1, the first column identifies the left hand side (endogenous) variables contained in each block of equations m, and the second column identifies the blocks in which these blocks appear as right hand side (explanatory) variables. For example, the *BL* model only contains one block of equations ($m = 0$), and all of these variables appear as explanatory variables within this block.

The *MED* model is a variant of the medium-sized model used in Haug and Smith (2007).[9] The model has a domestic endogenous block ($m = 0$), and a foreign block ($m = 2$) containing world GDP, the world CPI, and world 90-day rates. The domestic variables do not appear as right-hand-side variables in the foreign sector, but the foreign variables appear both in the foreign block and the domestic block.

[6] We exclude the volatile petrol price category from the tradable price index, and we exclude the large fall in rents in 2001Q1 from the non-tradable price index. This fall resulted from a shift to income-related rents for state-owned houses.

[7] BL^{BVAR} is estimated using the Bayesian priors discussed in section 2. Following Del Negro and Schorfheide (2004), the hyperparameter λ is chosen to maximise the marginal data density using a grid search over a range of values of λ. As in the case of the large BVAR, the other hyperparameters τ and θ chosen such that $\tau = \theta = \lambda$.

[8] The *AR* model uses the *SBC* to determine the lag length, allowing lags to range from 1 to p.

[9] This model differs from the Haug and Smith (2007) model in that the CPI is split into the tradable CPI and the non-tradable CPI.

The *MEDL* model is a variant of the large model used in Buckle *et al* (2007). This model differs from the Buckle *et al* (2007) model in three main respects. First, we express our model in levels, while Buckle *et al* (2007) specify their model in terms of deviations from trend. Second, we use slightly different data in our model. Specifically, our model splits the CPI into the tradable CPI and the non-tradable CPI; includes the real exchange rate instead of the nominal exchange rate; includes the Southern Oscillation Index as the climate variable instead of the Soil Moisture Deficit; and includes exports of goods prices expressed in world prices instead of total export prices expressed in world prices.[10] Third, our model imposes fewer restrictions on the variables entering each equation.[11]

In this model, the baseline domestic block ($m = 0$) is augmented with GNE, real exports, and real equity prices, and the foreign block ($m = 2$) is augmented with goods export prices and import prices (both expressed in world prices), and world equity prices. There is also a climate block ($m = 1$) containing the Southern Oscillation Index. The variables in the foreign block ($m = 2$) enter the foreign and domestic blocks ($m = 0, 2$), and the climate variable ($m = 1$) enters the climate block and the domestic block ($m = 0, 1$).

Our large model *LAR* contains all of the variables in the *MEDL* model plus another 80 variables. The domestic block ($m = 0$) is augmented with real GDP and GDP deflator data, housing market data, labour market data, survey (business and consumer confidence) data, and money market data. The foreign block ($m = 2$) is augmented with world 10-year interest rates, and the climate block ($m = 1$) is the same as in the *MEDL* model. Together, the domestic, foreign, and climate blocks interact in the same way as in the *MEDL* model. The *LAR* model, however, contains oil prices ($m = 3$), which appear in the oil price block, the foreign block, and the domestic block ($m = 0, 2, 3$).

[10] The Southern Oscillation Index measures the difference in standardised monthly mean air pressure between Tahiti and Darwin, and is indicative of the Southern Oscillation phenomenon, which can bring major changes to climate conditions in New Zealand. A reading below -10 on the Southern Oscillation Index is associated with the El Nino climate pattern, while a reading above 10 is associated with the La Nina weather pattern. Both El Nino and La Nina tend to be associated with drought conditions in different parts of New Zealand.

[11] For example, Buckle *et al* (2007) have four blocks of equations, and export and import prices are determined in a foreign block containing lags of export and import prices and world GDP. Our model, in contrast, determines all foreign variables endogenously within one block.

Table 1
The lag structure of the VARs

BLOCK (LHS)	APPEARS IN BLOCK (RHS)	*BL*	*MED*	*MEDL*	*LAR*
$m = 0$	$m = 0$	GDP Tradable CPI Non-tradable CPI 90-day rates Real exchange rate	*BL*	*MED plus* GDE Exports Real equity prices	*MEDL plus* Real production GDP components Real expenditure GDP components Housing market data Labour market data Survey data Money market data
$m = 1$	$m = 0, 1$			Southern Oscillation index	*MEDL*
$m = 2$	$m = 0, 2$		World GDP World CPI World 90-day rates	*MED plus* Goods export prices Import prices World equity prices (excludes world CPI)	*MEDL plus* World 10-year rates
$m = 3$	$m = 0, 2, 3$				Dubai oil prices ($US)
Number of variables		5	8	14	94

5 Forecasting results

We compare the forecasting performance of the models up to four quarters ahead over an out-of-sample period ranging from 2000Q1 and 2007Q1. At each point t in the out-of-sample evaluation period all parameters – including the tightness of the BVAR hyperparameters – are re-estimated conditional on data up to $t-1$. Forecasting performance is evaluated using the n^* benchmark variables: real GDP, tradable CPI, non-tradable CPI, 90-day rates, and the real exchange rate.

Table 2
Large BVAR (*LAR*) MSFEs relative to the other models

		Univariate		Multivariate				
Horizon	Variable	*AR*	*RW*	*BL*	BL^{SBC}	BL^{BVAR}	*MED*	*MEDL*
1	GDP	0.83	0.83	0.29*	0.83	0.73*	0.45*	0.64
	Tradable CPI	0.81	0.53*	1.21	1.16	1.25*	0.97	1.03
	Non-tradable CPI	1.16	1.13	0.41*	0.65	0.67	0.32*	0.47*
	90-day rates	0.75	0.68	0.29*	0.53*	0.74	0.32*	0.48*
	Real exchange	1.04	0.85	0.58*	1.09	1.07	0.73*	0.73*
2	GDP	0.76	0.79	0.23*	0.74	0.73*	0.36*	0.52*
	Tradable CPI	0.70	0.53*	1.35	1.35*	1.29	0.98	1.00
	Non-tradable CPI	1.21	1.12	0.41*	0.60	0.57*	0.33*	0.42*
	90-day rates	0.57*	0.54*	0.27*	0.52*	0.78	0.16*	0.36*
	Real exchange	1.17	0.50*	0.29*	0.76	1.02	0.47*	0.51*
3	GDP	0.65*	0.77	0.15*	0.57	0.68*	0.24*	0.41*
	Tradable CPI	0.67	0.61*	1.08	1.64*	1.26	0.97	0.92*
	Non-tradable CPI	1.41	1.44	0.67	0.75	0.66*	0.42*	0.49*
	90-day rates	0.43*	0.37*	0.24*	0.45	0.54	0.13*	0.19*
	Real exchange	1.20	0.45*	0.23*	0.71	1.02	0.45*	0.44*
4	GDP	0.72	1.04	0.16*	0.49*	0.83	0.23*	0.37*
	Tradable CPI	0.70	0.78	1.11	2.29*	1.38*	1.03	1.03
	Non-tradable CPI	1.92	2.14	1.13	1.26	0.88	0.58*	0.65*
	90-day rates	0.46*	0.35*	0.30*	0.51*	0.60	0.17*	0.15*
	Real exchange	1.27	0.49*	0.23*	0.71	1.04	0.38*	0.45*

The numbers displayed are MSFEs from *LAR* relative to the MSFEs from the models displayed in columns. A ratio greater (less) than one indicates a deterioration (improvement) relative to *LAR*. $*$ denotes a significant difference in MSFEs at the 10 per cent level, according to the Diebold and Mariano (1995) test.

For the purposes of the forecast comparison, our benchmark model is the large BVAR. Following Diebold and Mariano (1995), we test the null hypothesis that model f and the large BVAR (denoted $f=0$) have equal forecast accuracy on the basis of mean squared forecast error (MSFE) comparisons. Specifically, squared forecast errors are constructed over the evaluation period for each model, each variable, and each horizon:

$$\varepsilon^{f}_{i,t+h} = (\hat{y}^{f}_{i,t+h} - y_{i,t+h})^2 \tag{13}$$

where $y_{i,t+h}$ is the ex-post variable at horizon h, $\hat{y}^{f}_{i,t+h}$ is the h-step-ahead forecast from model f, and $h = 1,\ldots,4$. The difference between the squared forecast errors of the competing models and the large BVAR, $d_t = \varepsilon^{f}_{i,t+h} - \varepsilon^{0}_{i,t+h}$, is used to produce a sequence of squared forecast error differentials $\{d_t\}^{T}_{t=1}$, where $T = ((T_2 - 4) - T_1)$ and T_1 and T_2 are the first and last dates over which the the out-of-sample forecasts are made. The mean difference in MSFEs is then tested by regressing the sequence of squared error differentials on a constant. A statistical difference in forecast accuracy between the competing models and the large BVAR is indicated by a constant that is statistically different from zero.[12]

For most forecast variables and horizons, the large BVAR performs at least as well as the competing model specifications (table 2). The model has particularly good performance for 90-day interest rates, outperforming most model specifications (with the exception of the AR and some of the restricted VARs, BL^{SBC} and BL^{BVAR}).

The large BVAR also generally outperforms the other specifications when forecasting GDP and the real exchange rate. However, the results for tradable prices are less clear-cut, with the restricted small VARs, BL^{SBC} and BL^{BVAR} significantly outperforming the large BVAR over a number of horizons. For non-tradable prices, the large BVAR forecasts generally as well as the best of the competing specifications.

Overall, the forecasting performance of the large BVAR is good relative to the other model specifications we consider, suggesting that the model is a reasonable description of the data in New Zealand.

6 Impulse responses

We consider impulse responses to a monetary policy shock, a net migration shock, and a climate shock. Following Christiano *et al* (2005) and Bernanke *et al* (2005), these shocks are identified using a recursive, shock-specific identification scheme.

[12] The variance of the coefficient estimate is adjusted for heteroskedasticity and autocorrelation using the Newey and West (1987) estimator with a truncation lag of $h-1$. The test statistic is compared to a Student's t distribution with $T-1$ degrees of freedom.

For each shock, the variables are grouped into two categories: slow-moving variables S_t and fast-moving variables F_t. With r_t identifying the variable being shocked, the variables are ordered as $Y = (S_t, r_t, F_t)$. The ordering of the variables in Y_t embodies two key identifying assumptions: the variables in F_t respond contemporaneously to the shock r_t and the variables in S_t do not. Our VAR can be written as:

$$Y_t = c + A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + Ce_t \tag{14}$$

where $A_1, \ldots, A_p$ impose the zero restrictions outlined in section 4.2, and C is an $n \times n$ lower triangular Cholesky matrix of the reduced form residuals, i.e., $Ce_t = u_t$. The resulting impulse responses to a particular shock r_t are invariant to the ordering of the variables in S_t and F_t (Christiano *et al* 2005). For the monetary policy and net migration shocks, the ordering of the variables changes only for S_t and r_t; the domestic financial variables are always included in F_t.[13] For the climate shock, on the other hand, we assume all variables are slow-moving.[14] The classifications of each variable for each shock are displayed in appendix A. For each shock, we compute confidence intervals for our impulse responses by drawing from the estimated posterior distribution of the VAR parameters using the block by block Monte Carlo method laid out in Zha (1999).

The impulse responses for all three shocks appear very reasonable. Almost all variables move in the expected direction, and a clear link between migration and the housing market, and between climate and agricultural production is evident. Figure 1 shows the responses of GDP, tradable CPI, non-tradable CPI, 90-day interest rates, and the real exchange rate for each of the three shocks we consider. In addition, figures 2 and 3 show further responses to a monetary policy shock, figure 4 shows some responses to a net migration shock, and figure 5 shows some responses to a climate shock. For each graph, the grey shaded region represents the 68 percent confidence interval around the impulse responses. Point estimates for the impulse responses to all three shocks are displayed in appendix B.

6.1 Monetary policy shock

We consider a 100 basis point increase in 90-day interest rates. The responses to this shock look very reasonable, and move in the expected direction in almost

[13] Of course, if we considered shocks emanating from the foreign sector, it would make sense to include the foreign financial variables in F_t, along with the domestic financial variables.

[14] The climate shock that we consider represents a drought. Because these types of weather events are themselves slow-moving, we assume that all other variables respond with a lag.

every case. The real exchange rate appreciates by 0.5 percent almost immediately, before returning to its starting point after three years. The level of GDP drops by around 0.2 percent over the year following the shock, with this effect persisting for some time. Prices for tradable goods fall by around 0.1 percent after about two years, reflecting the lagged effects of exchange rate appreciation. Prices of non-tradable goods show a similarly sized reaction, but the response is much more delayed.

An advantage of our large BVAR is that we are able to look at impulse responses of a wide range of variables that would not be included in a typical VAR. Figures 2 and 3 show a selection of these impulse responses to the monetary policy shock in this model. Across expenditure GDP components, investment shows the largest response, while the consumption response is more muted. The effects of policy tightening are evident in the labour market, with employment falling by 0.2 percent, and unemployment rising by 0.1 percentage points.

Across production GDP components, construction shows the largest response, falling by 0.5 percent. Retail trade, wholesale trade, transportation and manufacturing also show reasonably large responses. Responses are much smaller across primary and service sectors.

6.2 Net migration shock

We consider a 10,000 person shock to net migration of working age population.[15] The effects of this shock are most apparent in the housing market. House prices rise by around 2 percent initially, although this increase is eventually reversed. House sales also rise by around 2 percent, and construction costs increase by 0.5 percent. Residential investment increases by 2 percent, and household consumption rises by just under 0.5 percent. As well as a demand channel through the housing market, a supply channel is evident, with unemployment rising by 0.2 percentage points and skilled labour shortages easing.

[15] This shock is equivalent to a 0.3 percent increase in New Zealand's working age population. By way of context, in New Zealand's most recent net migration cycle, net migration's peak contribution to New Zealand's annual working age population growth was 1 percent.

6.3 Climate shock

In order to assess the effects of a climate shock, we consider a 20 point shock to the absolute value of the Southern Oscillation Index. A reading of 20 in either direction on this index would usually be associated with a severe drought.

Our model suggests that a climate event of this nature reduces both agricultural and manufacturing production by around 1 percent.[16] Value added in the electricity sector falls by almost 0.5 percent, as production switches from hydroelectric generation to the more resource-intensive thermal generation. The aggregate level of GDP falls by 0.3 percent and exports fall by 1 percent.

[16] The processing of meat and dairy products constitutes almost 20 percent of the manufacturing sector in New Zealand.

Figure 1
Responses of the baseline variables

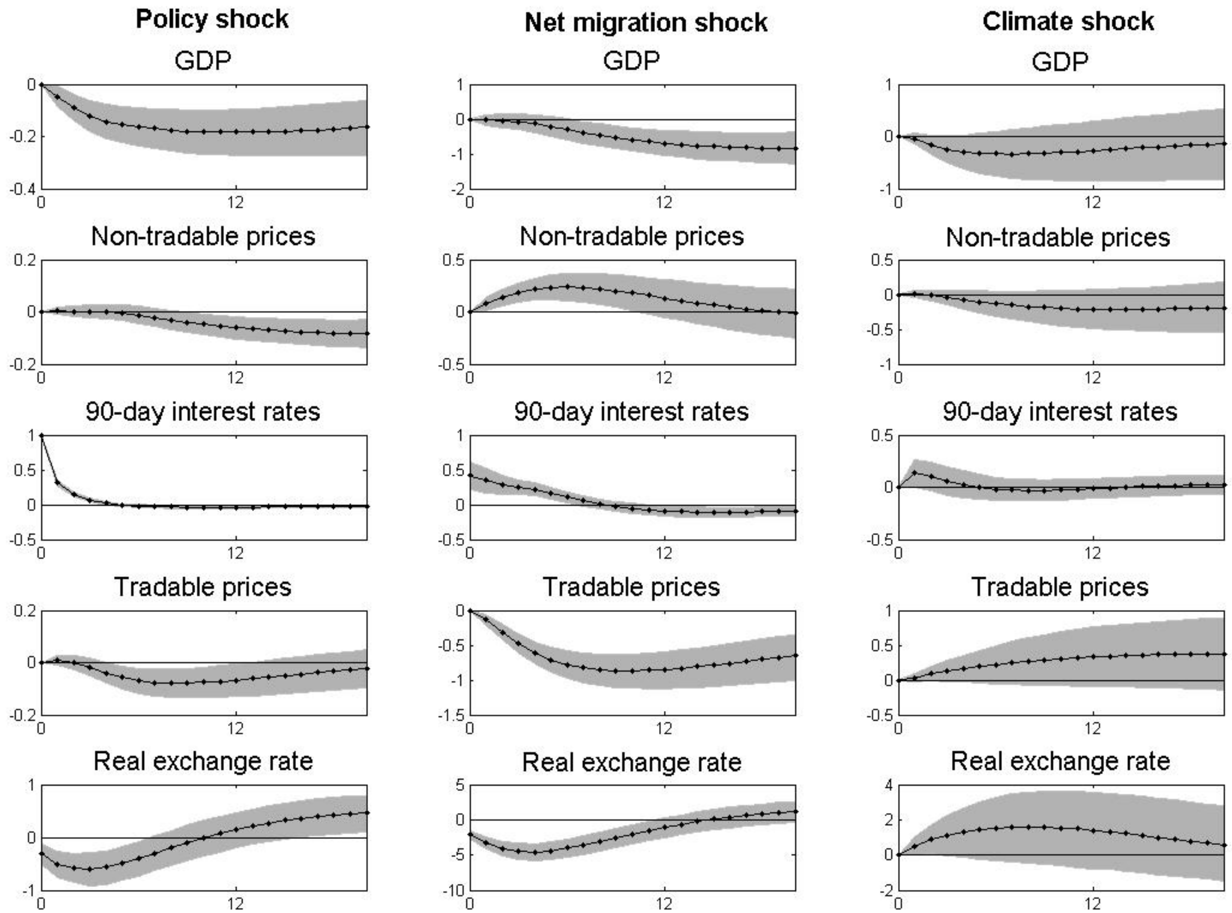


Figure 2
Monetary policy shock

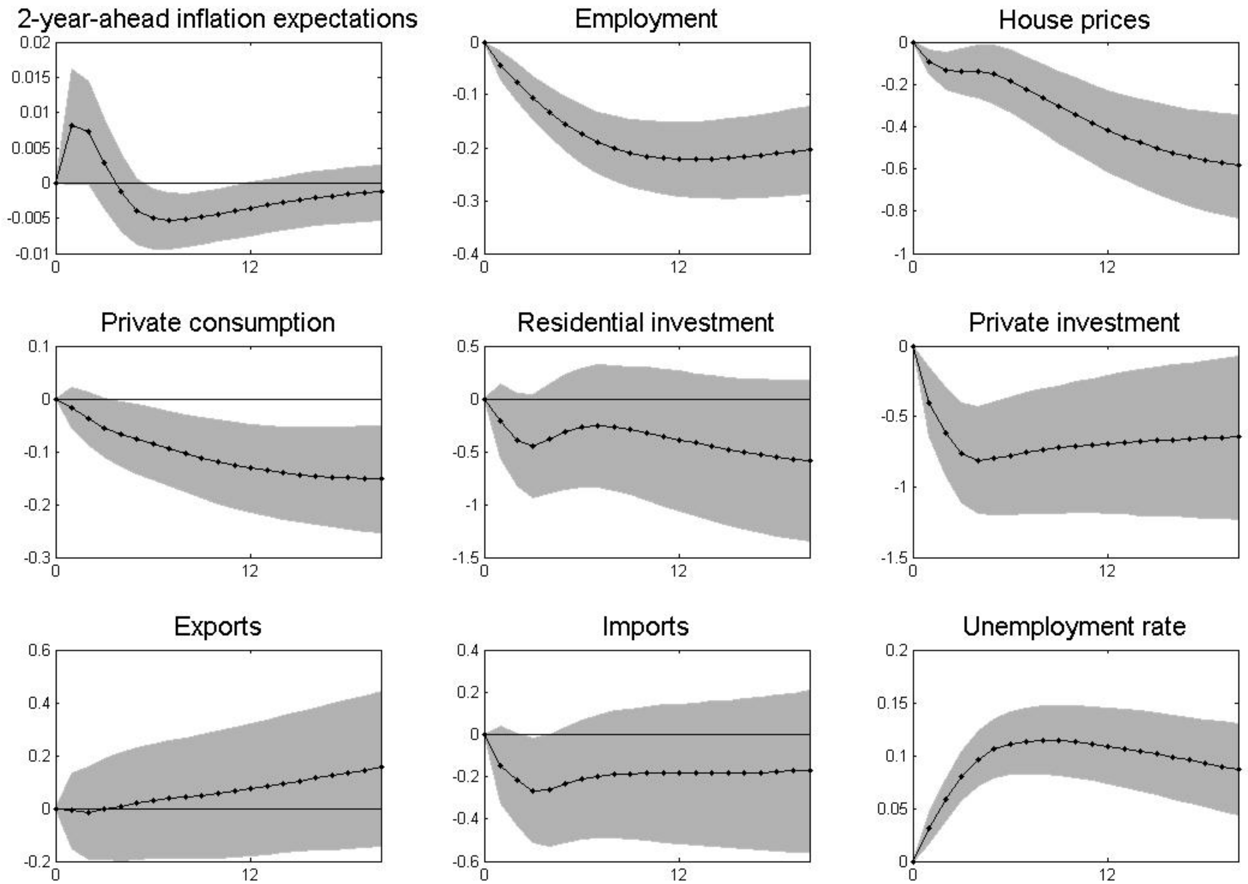


Figure 3
Monetary policy shock: production GDP

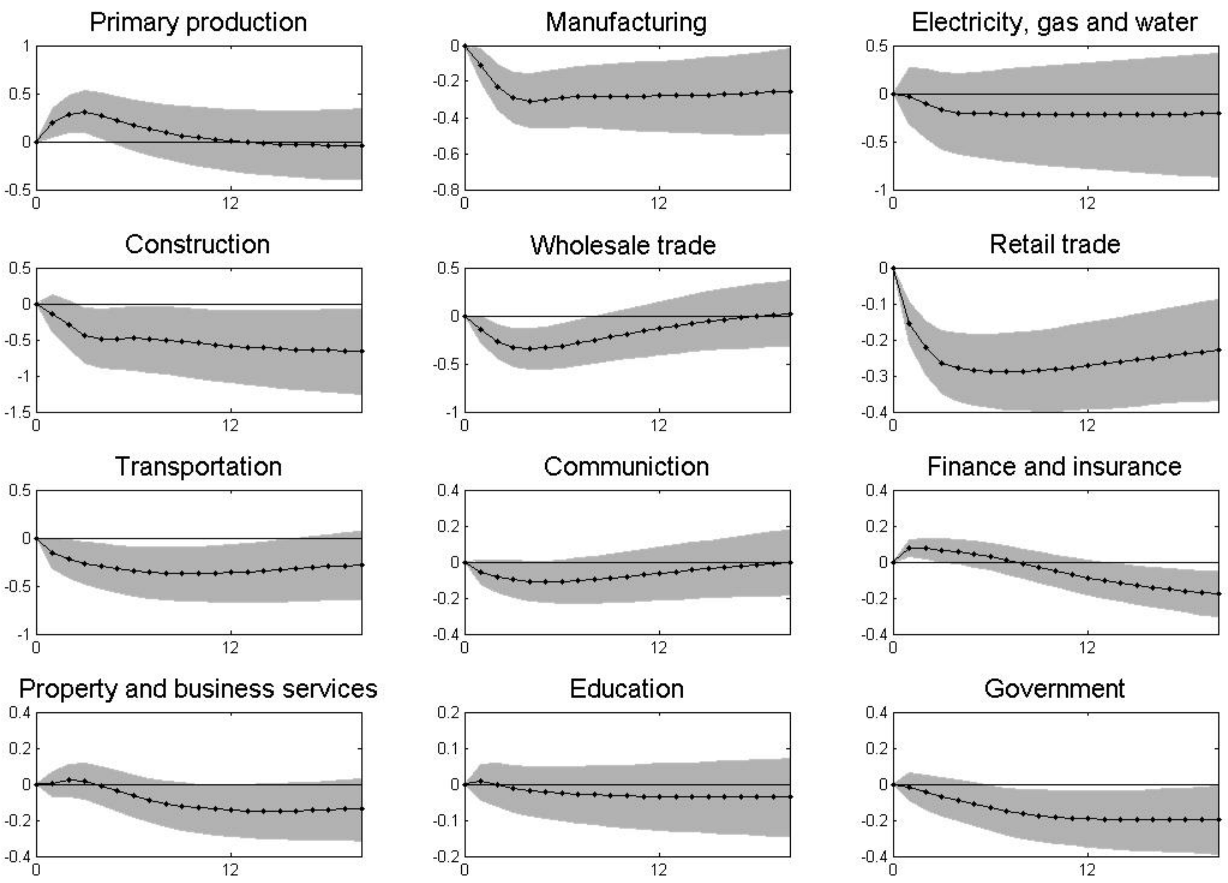


Figure 4
Net migration shock

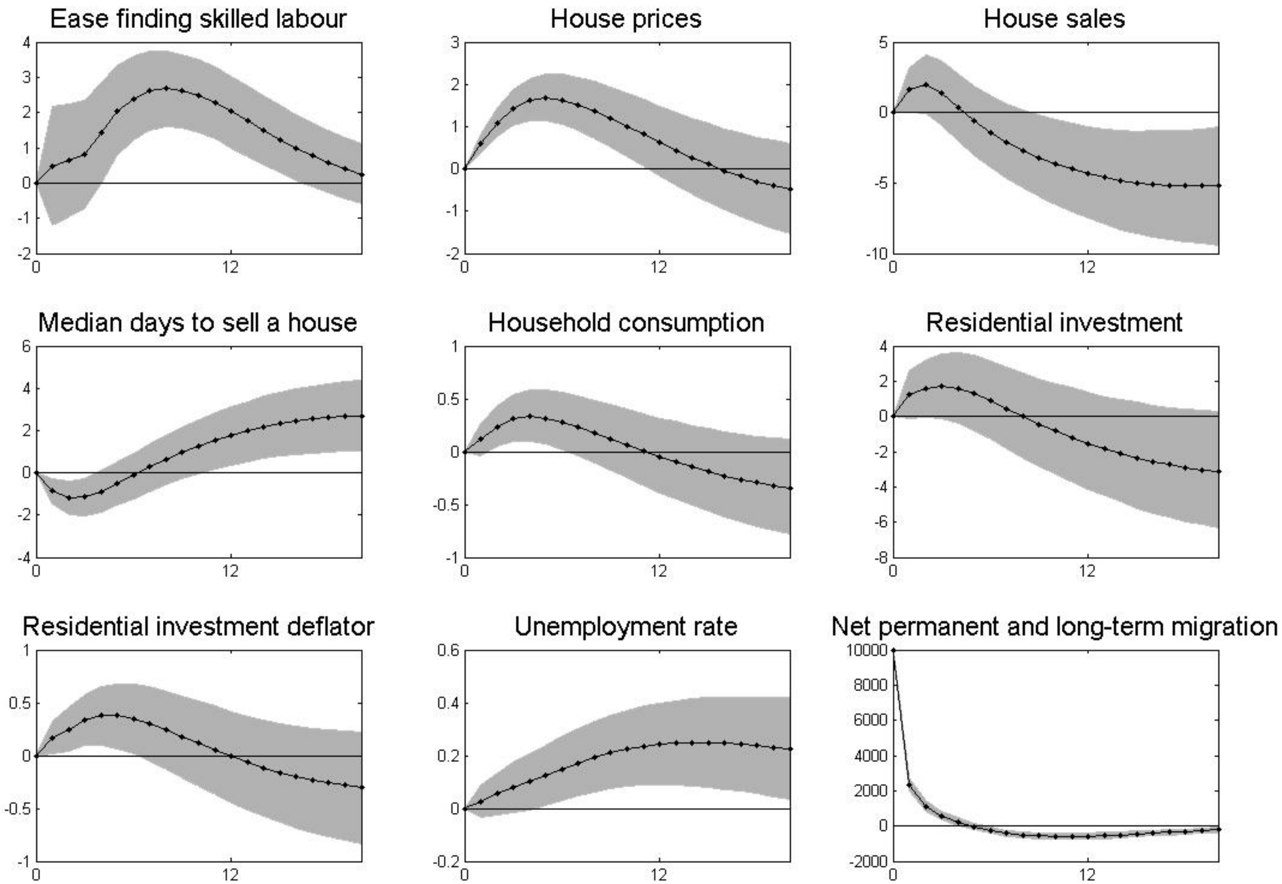
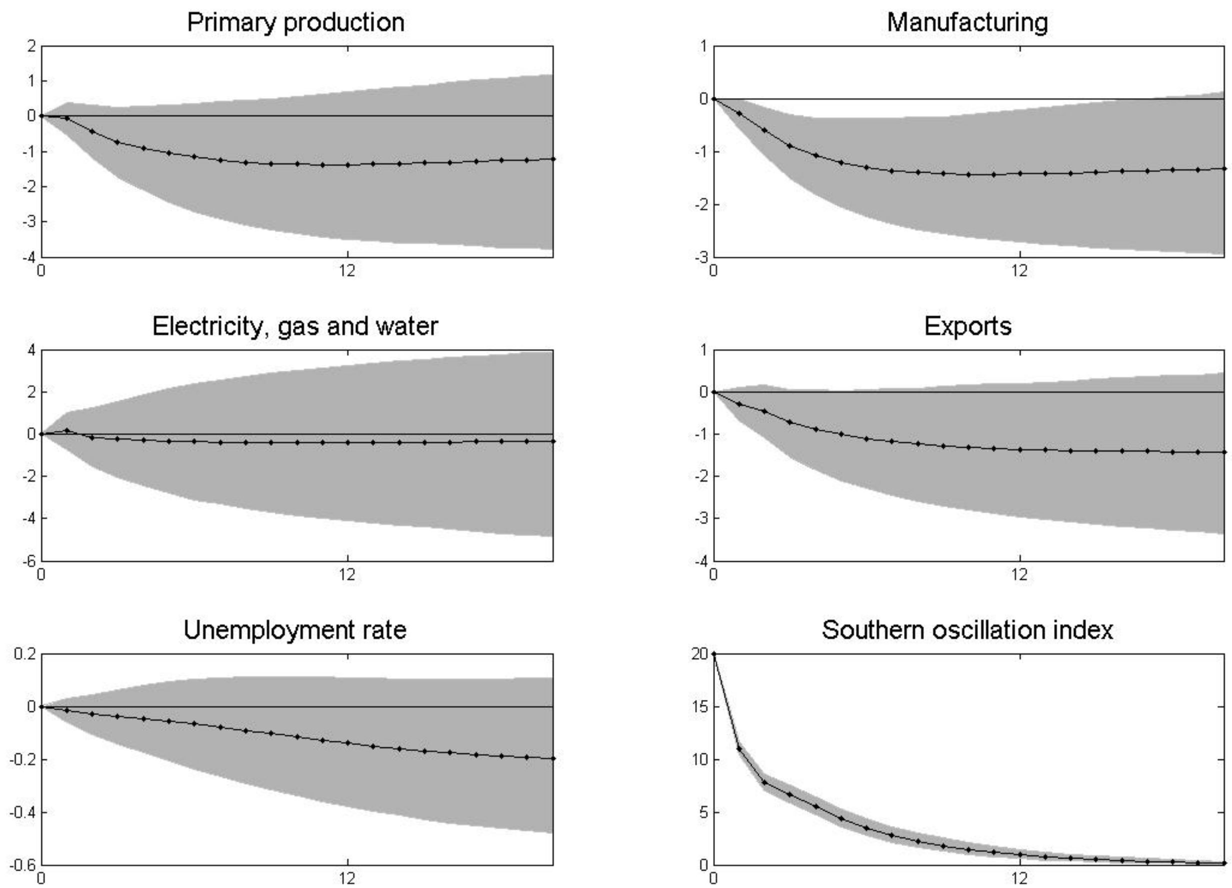


Figure 5
Climate shock



7 Summary and conclusion

This paper analysed a large BVAR for New Zealand. We extended the work of Banbura *et al* (2007) by adding a co-persistence prior, and by generalising the algorithm for determining the tightness of the Bayesian prior to the case where restrictions on lags are imposed.

We found that our large BVAR produces relatively good forecasts of real GDP, tradable and non-tradable prices, 90-day rates and the real exchange rate compared with a range of other time series models, and reasonable impulse responses to a monetary policy shock, a net migration shock, and a climate shock. Overall, we find that the large BVAR is a useful tool for analysing shock transmission in a data-rich environment.

References

Banbura, M, D Gianonne, and L Reichlin (2007), "Bayesian VARs with Large Panels," *Centre for Economic Policy Research (CEPR), Discussion paper*, 6326.

Bernanke, B, J Boivin, and P S Eliasz (2005), "Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach," *The Quarterly Journal of Economics*, 120(1), 387–422.

Boivin, J and M Giannoni (2008), "Global forces and monetary policy effectiveness," *National Bureau of Economic Research*, *Working Paper*, 13736.

Buckle, R A, K Kim, H Kirkham, N McLellan, and J Sharma (2007), "A structural VAR business cycle model of a volatile small open economy," *Economic Modelling*, 24, 990–1017.

Christiano, L J, M Eichenbaum, and C Evans (2005), "Nominal rigidities and the dynamic effects of a shock to monetary policy," *Journal of Political Economy*, 113(1), 1–45.

Coleman, A and J Landon-Lane (2007), "Housing markets and migration in New Zealand, 1962-2006," *Reserve Bank of New Zealand*, *Discussion paper*, 2007/12.

Cushman, D O and T Zha (1997), "Identifying monetary policy in a small open economy under flexible exchange rates," *Journal of Monetary Economics*, 39, 433–48.

De Mol, C, D Gianonne, and L Reichlin (2008), "Forecasting using a large number of predictors: Is Bayesian regression a valid alternative to Principal Components?" *Journal of Econometrics*, forthcoming.

Del Negro, M and F Schorfheide (2004), "Priors from general equilibrium models for VARs," *International Economic Review*, 45(2), 643–73.

Diebold, F X and R S Mariano (1995), "Comparing predictive accuracy," *Journal of Business and Economic Statistics*, 13(3), 253–63.

Doan, T, R Litterman, and C Sims (1984), "Forecasting and conditional projections using realistic prior distributions," *Econometric Reviews*, 3, 1–100.

Forni, M, M Hallin, M Lippi, and L Reichlin (2000), "The generalized factor model: Identification and estimation," *Review of Economics and Statistics*, 82, 540–554.

Forni, M, M Hallin, M Lippi, and L Reichlin (2005), "The generalized factor model: one-sided estimation and forecasting," *Journal of the American Statistical Association*, 100(471), 830–840.

Haug, A A and C Smith (2007), “Local linear impulse responses for a small open economy,” *Reserve Bank of New Zealand*, *Discussion paper*, 2007/09.

Kadiyala, K R and S Karlsson (1997), “Numerical methods for estimation and inference in Bayesian VAR-models,” .

Litterman, R (1986), “Forecasting with bayesian vector autoregressions - five years of experience,” *Journal of Business and Economic Statistics*, 4, 25–38.

Newey, W K and K West (1987), “A simple, positive semidefinite, heteroskedasticity and autocorrelation consistent covariance matrix,” *Econometrica*, 55, 703–708.

Robertson, J C and E W Tallman (1999), “Vector autoregressions: forecasting and reality,” *Federal Reserve Bank of Atlanta*, *Economic Review*, 4–18.

Sims, C A (1993), “A nine-variable probabilistic macroeconomic forecasting model,” in *Business Cycles, Indicators, and Forecasting*, eds J H Stock and M W Watson, University of Chicago Press, Chicago.

Sims, C A and T Zha (1998), “Bayesian methods for dynamic multivariate analysis,” *International Economic Review*, 39(4), 949–968.

Stock, J H and M W Watson (1999), “Forecasting inflation,” *Journal of Monetary Economics*, 44(2), 293–335.

Stock, J H and M W Watson (2002), “Macroeconomic forecasting using diffusion indexes,” *Journal of Business and Economic Statistics*, 20(2), 147–62.

Stock, J H and M W Watson (2005), “Implications of Dynamic Factor Models for VAR Analysis,” *National Bureau of Economic Research*, *Working Paper*, 11467.

Waggoner, D F and T Zha (2003), “A Gibbs sampler for structural vector autoregressions,” *Journal of Economic Dynamics and Control*, 28, 349–366.

Zha, T (1999), “Block recursion and structural vector autoregressions,” *Journal of Econometrics*, 90, 291–316.

Appendices

A Data

A.1 Data key

Transform		
	0	level
	1	log level (multiplied by 100)
Prior		
	1	Random Walk
	0	White Noise
Speed		
	S	Slow
	F	Fast
	r	Shock
	[MP,NM,C]	[Monetary policy, Net Migration, Climate]

Identifier	Description	Transform	Prior	[MP, NM, C]
AFFM	Real GDP – Agriculture, Fishing, forestry and mining	1	1	[S, S, S]
MAN	Real GDP – Manufacturing	1	1	[S, S, S]
EGW	Real GDP – Electricity, gas and water	1	1	[S, S, S]
CON	Real GDP – Construction	1	1	[S, S, S]
WHOL	Real GDP – Wholesale trade	1	1	[S, S, S]
RET	Real GDP – Retail trade	1	1	[S, S, S]
TRAN	Real GDP – Transport, storage	1	1	[S, S, S]
COM	Real GDP – Communications	1	1	[S, S, S]
FIN	Real GDP – Finance and insurance	1	1	[S, S, S]
PROP	Real GDP – Property and business services	1	1	[S, S, S]
EDN	Real GDP – Education, health, cult, recr, pers and other services	1	1	[S, S, S]
GOV	Real GDP – General government services	1	1	[S, S, S]
UNA	Real GDP – Unallocated	1	1	[S, S, S]
AFFMP	GDP deflator – Agriculture, Fishing, forestry and mining	1	1	[S, S, S]
MANP	GDP deflator – Manufacturing	1	1	[S, S, S]
EGWP	GDP deflator – Electricity, gas and water	1	1	[S, S, S]
CONP	GDP deflator – Construction	1	1	[S, S, S]
WHOLP	GDP deflator – Wholesale trade	1	1	[S, S, S]
RETP	GDP deflator – Retail trade	1	1	[S, S, S]
TRANP	GDP deflator – Transport, storage	1	1	[S, S, S]
COMP	GDP deflator – Communications	1	1	[S, S, S]
FINP	GDP deflator – Finance and insurance	1	1	[S, S, S]
PROPP	GDP deflator – Property and business services	1	1	[S, S, S]
EDNP	GDP deflator – Education, health, cult, recr, pers and other services	1	1	[S, S, S]
NCP	Real GDP – Private consumption	1	1	[S, S, S]
NCPD	Real GDP – Private consumption (durables)	1	1	[S, S, S]
NCPND	Real GDP – Private consumption (non-durables)	1	1	[S, S, S]
NCPS	Real GDP – Private consumption (services)	1	1	[S, S, S]

– continued from previous page

Identifier	Description	Transform	Prior	[MP, NM, C]
NCG	Real GDP – Government consumption	1	1	[S, S, S]
NIP	Real GDP – Private investment	1	1	[S, S, S]
NIMP	Real GDP – Market Investment Plant and Machinery	1	1	[S, S, S]
NIMTE	Real GDP – Market Investment Transport	1	1	[S, S, S]
NIMNR	Real GDP – Market Investment Non-Residential	1	1	[S, S, S]
NITIA	Real GDP – Total Investment - Intangible Assets	1	1	[S, S, S]
NIPD	Real GDP – Private investment (dwellings)	1	1	[S, S, S]
NIG	Real GDP – Government investment	1	1	[S, S, S]
X	Real GDP – Exports	1	1	[S, S, S]
M	Real GDP – Imports	1	1	[S, S, S]
NVI	Real GDP – Change in stocks	0	0	[S, S, S]
NCPP	GDP deflator – Private consumption	1	1	[S, S, S]
NCPDP	GDP deflator – Private consumption (durables)	1	1	[S, S, S]
NCPNDP	GDP deflator – Private consumption (non-durables)	1	1	[S, S, S]
NCPSP	GDP deflator – Private consumption (services)	1	1	[S, S, S]
NCGP	GDP deflator – Government consumption	1	1	[S, S, S]
NIPP	GDP deflator – Private investment	1	1	[S, S, S]
NIMPP	GDP deflator – Market Investment Plant and Machinery	1	1	[S, S, S]
NIMTEP	GDP deflator – Market Investment Transport	1	1	[S, S, S]
NIMNRP	GDP deflator – Market Investment Non-Residential	1	1	[S, S, S]
NITIAP	GDP deflator – Market Investment Intangible Assets	1	1	[S, S, S]
NIPDP	GDP deflator – Private investment (dwellings)	1	1	[S, S, S]
NIGP	GDP deflator – Government investment	1	1	[S, S, S]
NXSP	GDP deflator – Exports of services	1	1	[S, S, S]
Y	Real GDP – Total production	1	1	[S, S, S]
NGDE	Real Gross Domestic Expenditure	1	1	[S, S, S]
TBC	Current account balance	0	1	[S, S, S]
U	Unemployment rate (HLFS)	0	1	[S, S, S]

– continued from previous page

Identifier	Description	Transform	Prior	[MP, NM, C]
LHEMP	Total employed (HLFS)	1	1	[S, S, S]
LHPR	Labour force participation rate (HLFS)	0	1	[S, S, S]
LLISTOX	Labour cost index – total salary and wages (LCI)	1	1	[S, S, S]
LNMIGPWA	Net long-term migration of the working age population (HLFS)	0	0	[S, r, S]
LSTMNAA	Net short-term migration of the working age population (HLFS)	0	0	[S, S, S]
EBEGBO	Business opinion (QSBO)	0	0	[S, S, S]
EBEASPN	Expected selling price next quarter (QSBO)	0	0	[S, S, S]
EBEACN	Expected costs next quarter (QSBO)	0	0	[S, S, S]
EBECU	Capacity utilisation (QSBO)	0	0	[S, S, S]
EBEDTAN	Domestic trading activity – next quarter (QSBO)	0	0	[S, S, S]
EBEPRFN	Profitability next quarter – (QSBO)	0	0	[S, S, S]
EBEFLU	Ease finding unskilled labour (QSBO)	0	0	[S, S, S]
EBEFLS	Ease finding skilled labour (QSBO)	0	0	[S, S, S]
EWMC	Consumer confidence (Westpac McDermott Miller)	0	0	[S, S, S]
ERCPI2	Expected inflation – 1 year ahead (RBNZ survey of expectations)	0	0	[S, S, S]
ERCPI3	Expected inflation – 2 year ahead (RBNZ survey of expectations)	0	0	[S, S, S]
PQHPI	House prices (QVNZ)	1	1	[S, S, S]
AHSALEDZ	House sales (REINZ)	1	1	[S, S, S]
AHDAYSALZ	Median days to sell a house (REINZ)	0	1	[S, S, S]
IEQNZMNZD	Real New Zealand equity prices (Datastream) – deflated using the CPI	1	1	[F, F, S]
TDOT	CPI – Tradables, excluding petrol	1	1	[S, S, S]
NTDOT	CPI – Non-tradables, excluding shift to HNZ rents in 2001Q1	1	1	[S, S, S]
PTGAS	CPI – Petrol	1	1	[S, S, S]
CPIDOT	CPI – Headline	1	1	[S, S, S]
RN	90-day bank bill rate	0	0	[r, F, S]
RNL	10 year bond yield	0	0	[F, F, S]
Z	Real trade-weighted exchange rate (RBNZ)	1	1	[F, F, S]
MM1	Monetary aggregate – M1	1	1	[F, F, S]

– continued from previous page

Identifier	Description	Transform	Prior	[MP, NM, C]
MM3	Monetary aggregate – M3 minus M2	1	1	[F, F, S]
ASOI	Southern Oscillation Index (NIWA)	0	0	[S, S, r]
PXG	World price of exported goods (GDP deflator expressed in world prices)	1	1	[S, S, S]
PM	World price of imports (GDP deflator expressed in world prices)	1	1	[S, S, S]
IWCPI	World CPI – 5 country trade-weighted average	1	1	[S, S, S]
IWGDPZ	World GDP – 12 country trade-weighted average	1	1	[S, S, S]
RROW	World 90-day interest rate (80-20 weighted average of US and Australian rates)	0	0	[S, S, S]
RNLROW	World 10 year interest rate (80-20 weighted average of US and Australian rates)	0	0	[S, S, S]
PCROWO	World oil price (Dubai: expressed in US dollars)	1	1	[S, S, S]
IEQWLDM	Real world equity price index (Datastream) – deflated using world CPI	1	1	[S, S, S]

B Impulse responses

	Monetary policy				Net Migration				Climate			
Identifier/horizon	0	4	8	20	0	4	8	20	0	4	8	20
ERCPI2	0.00	-0.02	-0.02	0.00	0.00	-0.07	-0.04	0.00	0.00	0.00	0.00	0.01
ERCPI3	0.00	0.00	-0.01	0.00	0.00	-0.03	-0.01	0.00	0.00	0.00	0.00	0.00
EBEGBO	0.00	-0.05	0.51	0.27	0.00	-2.40	-0.68	0.70	0.00	1.19	1.42	0.07
EBEASPN	0.00	-1.07	-0.25	0.04	0.00	-2.48	-1.18	0.36	0.00	-0.35	0.13	0.11
EBEACN	0.00	-0.88	-0.31	-0.04	0.00	-2.23	-0.64	0.31	0.00	-0.17	-0.04	0.04
EBEPRFN	0.00	-0.30	0.00	0.14	0.00	-1.11	-1.45	0.10	0.00	-0.09	0.51	0.25
EBEDTAN	0.00	-0.81	0.00	0.16	0.00	-2.88	-1.70	0.37	0.00	0.59	0.95	0.24
EWMC	0.00	-0.44	-0.25	0.01	0.00	-0.49	-1.29	-0.54	0.00	-0.53	0.14	0.59
EBEFLU	0.00	1.30	0.65	0.00	0.00	1.14	2.24	0.25	0.00	1.08	0.34	-0.41
EBEFLS	0.00	1.61	0.73	-0.08	0.00	1.43	2.68	0.23	0.00	1.08	0.23	-0.56
EBECU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AFFM	0.00	0.28	0.09	-0.10	0.00	0.40	0.03	-0.94	0.00	-0.90	-1.31	-1.22
MAN	0.00	-0.29	-0.28	-0.28	0.00	0.06	-0.51	-1.18	0.00	-1.09	-1.40	-1.33
EGW	0.00	-0.21	-0.23	-0.24	0.00	0.44	0.13	-0.54	0.00	-0.30	-0.41	-0.35
CON	0.00	-0.45	-0.48	-0.69	0.00	0.30	-0.64	-2.77	0.00	-1.57	-2.03	-1.59
WHOL	0.00	-0.33	-0.24	0.02	0.00	-1.07	-0.82	0.34	0.00	0.45	0.84	1.13
RET	0.00	-0.27	-0.29	-0.24	0.00	-0.15	-0.44	-0.60	0.00	-0.11	-0.05	0.16
TRAN	0.00	-0.29	-0.37	-0.31	0.00	-0.39	-0.81	-0.92	0.00	-0.57	-0.58	-0.36
COM	0.00	-0.10	-0.10	-0.02	0.00	-0.31	-0.42	-0.44	0.00	-0.51	-0.56	-0.45
FIN	0.00	0.06	-0.01	-0.17	0.00	0.08	-0.21	-0.99	0.00	0.07	0.10	0.27
PROP	0.00	-0.01	-0.11	-0.15	0.00	-0.55	-0.99	-1.34	0.00	0.04	0.14	0.47
EDN	0.00	-0.02	-0.03	-0.04	0.00	0.06	-0.02	-0.21	0.00	0.03	0.04	0.12
GOV	0.00	-0.10	-0.18	-0.22	0.00	0.23	0.01	-0.26	0.00	-0.49	-0.63	-0.62
UNA	0.00	-0.35	-0.37	-0.25	0.00	0.20	-0.31	-0.81	0.00	-0.77	-0.82	-0.42
AFFMP	0.00	-0.47	-0.43	-0.03	0.00	-2.53	-2.58	-0.18	0.00	-0.64	-0.77	-1.00
MANP	0.00	-0.16	-0.17	0.02	0.00	-0.95	-0.92	0.12	0.00	-0.18	-0.24	-0.38
EGWP	0.00	0.04	-0.26	-0.19	0.00	-2.59	-2.95	-2.67	0.00	0.19	0.91	1.91
CONP	0.00	-0.09	-0.16	-0.18	0.00	-0.17	-0.22	-0.26	0.00	-0.06	-0.15	-0.16
WHOLP	0.00	-0.30	-0.33	-0.15	0.00	-1.29	-1.43	-0.46	0.00	-0.01	-0.01	-0.05
RETP	0.00	-0.06	-0.09	-0.03	0.00	-0.62	-0.72	-0.38	0.00	-0.04	-0.02	0.00
TRANP	0.00	-0.10	-0.15	-0.12	0.00	-0.56	-0.73	-0.42	0.00	-0.01	-0.05	-0.09
COMP	0.00	-0.04	-0.13	-0.20	0.00	-0.07	-0.32	-0.50	0.00	-0.78	-1.15	-1.30
FINP	0.00	-0.09	-0.01	0.07	0.00	0.14	0.31	0.44	0.00	0.02	0.03	0.00
PROPP	0.00	0.03	-0.02	-0.10	0.00	0.36	0.37	-0.03	0.00	0.22	0.24	0.31
EDNP	0.00	-0.06	-0.06	-0.07	0.00	-0.10	-0.12	-0.14	0.00	0.06	0.03	0.04
NGDE	0.00	-0.15	-0.19	-0.25	0.00	0.17	-0.08	-0.77	0.00	-0.24	-0.22	0.07
LHEMP	0.00	-0.13	-0.20	-0.21	0.00	-0.10	-0.30	-0.57	0.00	-0.08	-0.08	0.10
LHPR	0.00	-0.02	-0.05	-0.06	0.00	-0.10	-0.14	-0.18	0.00	-0.09	-0.12	-0.10
LLISTOX	0.00	0.02	0.01	-0.03	0.00	0.03	0.02	-0.09	0.00	-0.03	-0.05	-0.05
PQHPI	0.00	-0.13	-0.26	-0.60	0.00	1.63	1.37	-0.49	0.00	-0.63	-0.88	-0.57
AHSALEDZ	0.00	0.42	0.03	-0.11	0.00	0.32	-2.68	-5.20	0.00	-0.56	0.05	1.61
AHDAYSALZ	0.00	0.31	0.52	0.76	0.00	-0.88	0.63	2.70	0.00	0.67	0.62	-0.13
TBC	0.00	-7.75	-12.35	-8.57	0.00	-5.33	-45.22	-33.29	0.00	68.60	83.77	83.24
Y	0.00	-0.14	-0.18	-0.19	0.00	-0.14	-0.46	-0.84	0.00	-0.29	-0.33	-0.14
NCP	0.00	-0.07	-0.11	-0.16	0.00	0.33	0.18	-0.34	0.00	0.13	0.20	0.43
NCPND	0.00	-0.11	-0.15	-0.21	0.00	0.11	-0.09	-0.56	0.00	-0.05	-0.03	0.14
NCPD	0.00	-0.14	-0.25	-0.34	0.00	0.25	-0.37	-1.32	0.00	-0.26	-0.11	0.46
NCPS	0.00	-0.10	-0.12	-0.11	0.00	0.15	0.01	-0.26	0.00	0.21	0.33	0.52
NCG	0.00	0.07	0.08	0.01	0.00	0.15	0.36	0.30	0.00	-1.18	-1.52	-1.72
NIMP	0.00	-0.93	-0.79	-0.35	0.00	-0.64	-0.80	-0.07	0.00	0.31	0.67	1.19
NIMTE	0.00	-0.57	-0.91	-0.51	0.00	-2.82	-3.96	-3.21	0.00	1.11	2.75	5.22
NIMNR	0.00	-1.42	-1.90	-1.66	0.00	-4.38	-5.79	-6.13	0.00	0.30	0.76	2.04
NITIA	0.00	-0.53	-0.27	-0.21	0.00	0.08	0.64	-0.11	0.00	7.58	9.95	11.30
NIPD	0.00	-0.34	-0.26	-0.64	0.00	1.58	-0.02	-3.13	0.00	-2.02	-2.37	-1.64
NIP	0.00	-0.80	-0.74	-0.67	0.00	0.09	-0.67	-1.71	0.00	-0.44	-0.29	0.46
NIG	0.00	0.43	-0.15	-0.75	0.00	-1.03	-2.33	-5.84	0.00	0.66	1.14	2.62
X	0.00	0.03	0.06	0.13	0.00	0.02	-0.18	-0.18	0.00	-0.89	-1.24	-1.42
M	0.00	-0.25	-0.20	-0.22	0.00	0.80	0.72	0.17	0.00	-1.08	-1.17	-0.84
NVI	0.00	-7.31	-0.66	1.51	0.00	-0.19	-5.98	0.91	0.00	-1.11	2.79	2.73
NCPP	0.00	-0.02	-0.05	-0.06	0.00	-0.14	-0.15	-0.14	0.00	-0.10	-0.15	-0.17
NCPNDP	0.00	-0.01	-0.03	-0.02	0.00	-0.23	-0.19	0.03	0.00	-0.31	-0.43	-0.54
NCPDP	0.00	-0.10	-0.14	-0.04	0.00	-0.63	-0.87	-0.55	0.00	0.25	0.40	0.54
NCPSP	0.00	0.01	-0.04	-0.15	0.00	0.30	0.25	-0.27	0.00	-0.02	-0.08	-0.04
NCGP	0.00	-0.07	-0.08	-0.07	0.00	-0.08	-0.09	-0.06	0.00	0.02	0.03	0.06
NIMPP	0.00	-0.23	-0.19	0.04	0.00	-1.20	-1.20	-0.08	0.00	0.22	0.27	0.07
NIMTEP	0.00	-0.02	-0.12	-0.15	0.00	-1.58	-1.92	-0.93	0.00	-0.80	-0.55	-0.05
NIMNRP	0.00	-0.03	-0.11	-0.13	0.00	0.04	-0.03	-0.26	0.00	0.05	-0.05	-0.06
NITIAP	0.00	-0.04	-0.16	-0.21	0.00	-0.41	-0.78	-0.98	0.00	-0.01	-0.02	0.13
NIPDP	0.00	-0.13	-0.22	-0.28	0.00	0.38	0.24	-0.30	0.00	0.08	0.02	0.18
NIPP	0.00	-0.11	-0.14	-0.08	0.00	-0.44	-0.50	-0.16	0.00	0.09	0.08	0.08
NIGP	0.00	-0.20	-0.27	-0.09	0.00	-0.93	-0.96	-0.05	0.00	0.03	0.13	0.21
NXSP	0.00	-0.05	-0.07	-0.02	0.00	-0.15	-0.08	0.19	0.00	0.06	-0.08	-0.25
U	0.00	0.10	0.12	0.09	0.00	0.10	0.19	0.23	0.00	-0.05	-0.09	-0.20

– continued from previous page

	Monetary policy				Net Migration				Climate			
TDOT	0.00	-0.04	-0.08	-0.03	0.00	-0.61	-0.85	-0.65	0.00	0.16	0.26	0.37
NTDOT	0.00	0.00	-0.03	-0.08	0.00	0.22	0.22	-0.01	0.00	-0.08	-0.17	-0.19
CPIDOT	0.00	-0.02	-0.04	-0.05	0.00	-0.16	-0.20	-0.18	0.00	-0.07	-0.12	-0.13
PTGAS	0.00	-0.56	-0.46	-0.11	0.00	0.63	1.21	1.23	0.00	-2.49	-3.60	-4.68
LSTMNAA	0.00	-34.30	-25.13	8.20	0.00	-248.94	-176.94	5.66	0.00	-12.17	10.29	19.78
LNMIGPWA	0.00	-18.78	-118.72	-21.99	10000.00	238.20	-509.40	-218.68	0.00	-191.32	-69.02	118.87
IWGDPZ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IWCPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PXG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RROW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RNLROW	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IEQWLDM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ASOI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.00	5.48	2.25	0.16
PCROWO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RN	1.00	0.02	-0.03	-0.02	0.42	0.22	0.01	-0.09	0.00	0.03	-0.03	0.03
RNL	0.41	0.02	0.00	-0.01	0.16	0.10	0.02	-0.04	0.00	-0.02	-0.02	0.02
Z	-0.43	-0.72	-0.34	0.43	-2.12	-4.60	-3.07	1.19	0.00	1.31	1.59	0.56
MM1	-0.63	-0.89	-0.86	-0.75	-0.25	-0.44	-0.93	-1.18	0.00	-0.26	-0.11	0.23
MM3	1.21	1.22	1.04	0.70	3.14	3.20	2.36	0.86	0.00	-0.19	-0.36	-0.10
IEQNZMNZD	0.48	0.54	0.60	0.45	0.14	1.12	1.14	0.24	0.00	-0.01	-0.13	0.09