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Forecasting with a Global VAR model

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NON-TECHNICAL SUMMARY

The Bank assesses the impact of international conditions on the New Zealand economy using a range of models. Among them, is the Global Vector Autoregressive model (GVAR), which is designed to analyse economic and financial interdependencies between countries. The GVAR is primarily used by the Bank to examine the transmission of global shocks or disturbances to the New Zealand economy. This *Analytical Note* examines to what extent the GVAR can also forecast macroeconomic conditions in New Zealand and its main trading partners.

We test several specifications of the GVAR and calculate out-of-sample forecasts for GDP, inflation, interest rates, exchange rates and equity prices for New Zealand, U.S., China, Australia, Canada and the euro area. We then evaluate whether GVAR forecasts are more accurate than other statistical models and whether the model's GDP forecasts can outperform economists' forecasts published by *Consensus Economics*.

We find that forecasts obtained from simple specifications of the GVAR tend to outperform other simple statistical models of inflation and GDP. The GVAR also outperforms economists' GDP growth forecasts from *Consensus Economics*. These results emphasise the benefits of incorporating international linkages to improve forecast accuracy and suggest that the GVAR is a useful addition to the range of models used by the Reserve Bank to forecast the international economy.

1. Introduction[1]

Global shocks have increasingly become an important feature of domestic monetary policy, with greater spillovers between countries from trade flows and more integrated global capital markets. This had led the Reserve Bank to use a range of economic models to assess the impact of international factors on the New Zealand economy.[2]One such example is the Global Vector Autoregressive model (GVAR), originally proposed in Pesaran et al. (2004) as a coherent global model of the world economy. Initially used as a tool for credit risk analysis, the model has subsequently been used by central banks and academics to answer many questions on international trade and finance (di Mauro et al., 2013). So far, the Reserve Bank is using the GVAR to examine the effect of specific global shocks on the New Zealand economy. In this *Note*, we analyse whether it can also be used for forecasting purposes.

We evaluate the forecast performance of the GVAR across a range of variables, countries and model specifications. For each model and country specification, we generate recursive out-of-sample forecasts from one to eight quarters ahead. First, we test whether GVAR forecasts are more accurate than those of simple univariate autoregressive (AR) models. Second, we investigate whether or not imposing long-run relationships among the underlying variables improves the forecasting performance of the model. Third, we compare the forecasting performance of GVAR with that of a simple vector autoregressive (VAR) model that excludes global variables. Once the baseline GVAR model has been established, we further compare the GDP growth forecasts from this specification with those from *Consensus Economics*.

Our findings suggest that simple specifications of the GVAR generate forecasts that can outperform a variety of other models. The GVAR can also outperform *Consensus* forecasts for GDP growth. Accounting for the long-run relationships among variables, on the other hand, does not provide any additional benefits from a forecasting perspective. The results suggest that the GVAR can be used to produce global growth forecasts for assessing external economic conditions relevant to New Zealand.

2. The GVAR methodology

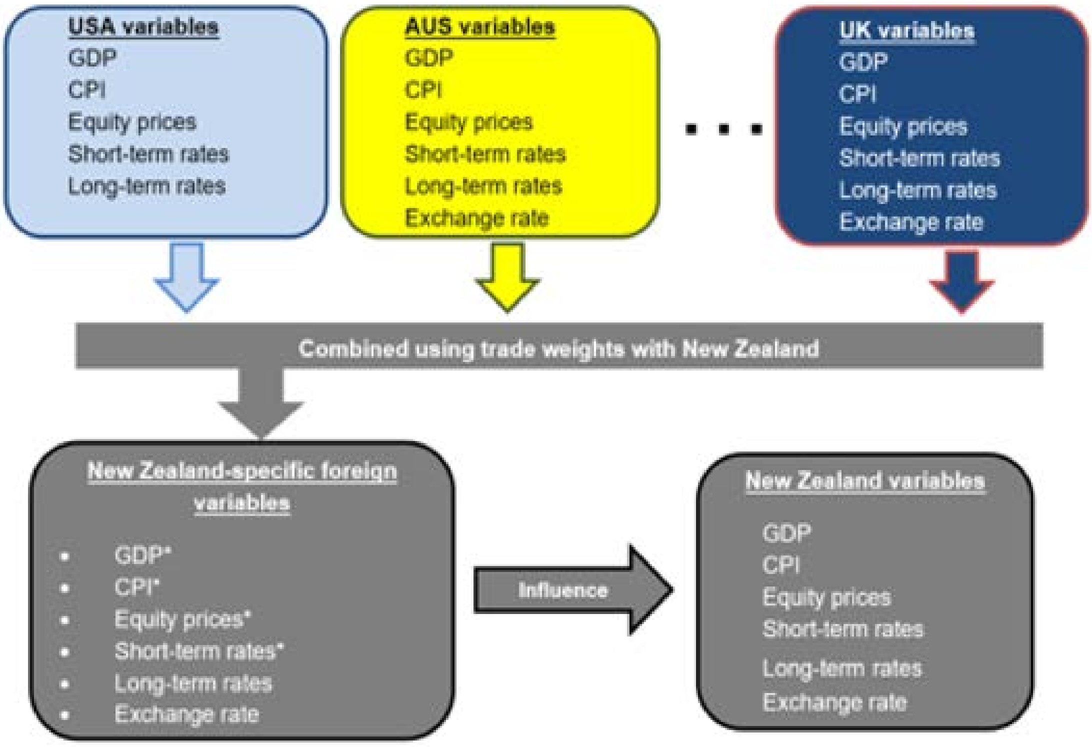
GVAR is a series of small-scale country-specific models that are estimated separately and combined to form a large-scale global VAR model.[3] Each country model includes domestic variables, country-specific foreign variables, and global

[1] The authors wish to thank Christopher Ball, Michael Callaghan, Enzo Cassino, Punnoose Jacob, Adam Richardson, Amber Wadsworth, and staff in the Economics Department for their feedback.
[2] Callaghan, Cassino, Vehbi and Wong (2019)
[3] This section heavily draws on the material presented in GVAR's user manual which can be downloaded from https://sites.google.com/site/gvarmodelling/gvar-toolbox/download

variables (e.g. commodity prices). The country-specific foreign variables are constructed as trade-weighted averages of foreign variables that correspond to the domestic variable in question. After estimating the country-specific models separately, the model is solved simultaneously to form the GVAR model.

The GVAR framework is highly flexible and allows for the economic variables in each country to be affected by all other countries in the model. For example, as shown in Figure 1, New Zealand is affected by New Zealand-specific foreign variables, which are constructed as weighted sums of the variables of other countries. The weights are based on the share of each country in New Zealand's international trade.[4] The countries included in the GVAR account for 90 per cent of world output. Therefore, the GVAR framework adds a complete global dimension to the standard VAR framework.

Figure 1: Schematic representation of the GVAR model for New Zealand



[4] Other weighting schemes, such as financial weighting, are also possible.

2.1 Building a global model: estimation

The first step in constructing a GVAR model is to estimate a country-specific model (ie VARX*)[5] for each country in the model. In its general form, a typical empirical specification for a country $i = 0,1,2, \dots., N$ can be described as:

$$\begin{aligned} x_{it} = a_{i0} + a_{i1}t + \Phi_{i1}x_{i,t-1} + \cdots + \Phi_{ip_i}x_{i,t-p} + \\ \Lambda_{i0}x_{it}^{*} + \Lambda_{i1}x_{i,t-1}^{*} + \cdots + \Lambda_{iq_i}x_{i,t-q}^{*} + \\ \Psi_{i0}g_t + \Psi_{i0}g_{t-1} + \cdots + \Psi_{iq_i}g_{t-q_i} + u_{it} \end{aligned} \quad (1)$$

where x_{it} is a $(k_i \times 1)$ vector of domestic variables for country i in period $t = 0,1,2, \dots, T$; a_{i0} is a $(k_i \times 1)$ vector of constants, t is a $(k_i \times 1)$ vector of deterministic time trends; x_{it}^{*} *and* g_t are $(k_i \times 1)$ vectors of foreign variables (commonly referred to as star variables) and global variables (eg oil prices); u_{it} is a $(k_i \times 1)$ vector of country-specific idiosyncratic shocks and p and q denote the lag lengths for domestic and global variables respectively.

As is evident in equation 1, GVAR allows for very general forms of interdependencies across individual variables within countries since lags of all variables enter individual equations. The reduced-form errors are also allowed to be dependent across countries. By conditioning the domestic variables on weakly exogenous foreign variables, however, the degree of correlation of these errors is reduced. The foreign variables are constructed from the domestic variables to match the international trade pattern of the country under consideration. Each variable in x_{it}^{*} is computed as a weighted average of all countries' corresponding domestic variables with the weights being country-specific, such that

$$x_{it}^{*} = \sum_{j=1}^{N} w_{ij} x_{jt} \quad (2)$$

where w_{ij} , $i,j = 1,2, \dots. N$, are bilateral trade weights, with $w_{ii} = 0$, and $\sum_{j=1}^{N} w_{ij} = 1$. The foreign variables x_{it}^{*} are treated as weakly exogenous given that each economy makes up a relatively small portion of the global economy. The weak exogeneity assumption is the key feature of the GVAR model since it allows country models to be estimated individually and combined at a later stage.

The GVAR methodology allows for short and long-run dynamics by imposing co-integration relations. Abstracting from deterministic variables (i.e. constants and trends) and higher order lags, we can rewrite equation 1 using a VARX*(1,1) model as:

$$x_{it} = \Phi_{i1}x_{i,t-1} + \Lambda_{i0}x_{it}^{*} + \Lambda_{i1}x_{i,t-1}^{*} + u_{it} \quad (3)$$

[5] Refers to a vector autoregressive (VAR) model with weakly exogenous variables.

which can be equivalently written in error correction form as:

$$\Delta x_{it} = \alpha_i ECM_{i,t-1} + \Lambda_{i0}\Delta x_{it}^* + u_{it} \quad (4)$$

where

$$ECM_{i,t-1} = \beta_{ix}' x_{i,t-1} + \beta_{ix^*}' x_{i,t-1}^* \quad (5)$$

is the vector of long-run cointegrating relations, also known as the error-correction terms.[6] The individual VARX* models are then consistently estimated using OLS, conditional on a given estimate of β_i and the vector of the representative foreign countries' corresponding variables.

2.2 Building a global model: solving the GVAR

In this step, all the endogenous variables in the global model are solved simultaneously using the estimated country-specific models. Although estimation is done on a country by country basis, the GVAR model is solved for the world as a whole, as all of the variables are endogenous with respect to the global model. The solution of the GVAR is a purely mechanical process and doesn't involve any estimation. The solution methodology, as described in detail in Pesaran et al. (2004), leads to the following GVAR(*p*) model

$$x_t = b_0 + b_1 t + F_1 x_{t-1} + \cdots + F_p x_{t-p} + \epsilon_t \quad (6)$$

where $x_t = (x_{0t}, x_{1t}, \dots, x_{Nt})$ denotes the global vector and $b_0, b_1, F_1, \dots, F_p$ contain the corresponding stacked vectors, which contain the parameter vectors of the country-specific specifications. The solved GVAR model in equation 6 is a standard VAR(*p*) model that is expressed in terms of the domestic variables and can be solved recursively to generate impulse responses, forecast error variance decompositions and conditional/unconditional forecasts as per standard VAR(*p*) frameworks.

2.3 Relevant literature

There is a large body of literature examining the forecast performance of the GVAR model.[7] Pesaran et al. (2009) use the basic GVAR model to investigate the effect of alternative forecast averaging strategies on forecast performance and conclude that averaging forecasts across different GVAR specifications and different estimation windows generally produce better forecasts. Han and Ng (2011) take a similar approach to this paper and estimate a GVAR comprising of the ASEAN-5 countries and compare GVAR forecasts to those from several statistical models. They find that GVAR forecasts tend to be better than forecasts from other statistical models for short-term interest rates and real equity prices. Similarly, Annari et al.

[6] The selection of the rank orders is determined by the trace statistic.
[7] see Chudik and Pesaran (2016)

(2015) examine whether GVAR provides superior forecasts to other models such as a Vector Error Correction model (VECM), a Bayesian VAR (BVAR) model and an Autoregressive model. They find that the forecast performance of a large GVAR is superior to an augmented VECM, especially at longer horizons, although the BVAR model provides the best forecast of output.

3. Empirical analysis

In this section, we describe the data and countries used in our analysis and outline the forecast evaluation strategy we use to evaluate the predictive accuracy of the GVAR.

3.1. Data

To estimate our GVAR, we use quarterly data over 1979Q2-2016Q3[8] covering 27 countries, 8 of which are aggregated as the euro area.[9] Table 1 presents the list of countries and regions included in our GVAR specification, with the 8 euro area countries shown in bold.

Table 1: Countries included in GVAR

Australia	India	Singapore
Austria	Indonesia	**Spain**
Belgium	**Italy**	Sweden
Brazil	Japan	Switzerland
Canada	Korea	Thailand
China	Malaysia	United Kingdom
Chile	**Netherlands**	United States
Finland	Norway	
France	New Zealand	
Germany	Philippines	

Aside from the U.S. model, all country models include the same set of variables-GDP, inflation, equity prices, short- and long-term interest rates, and the exchange rate. The real value of the U.S. dollar is determined outside the U.S. model. Also, all country models also include nominal prices for oil, metal and raw materials. To compute the trade weights for aggregating the country-specific global variables, we

[8] The dataset is an updated version of the '2013 Vintage' available from the GVAR Toolbox webpage (see https://sites.google.com/site/gvarmodelling/data). We have updated the previous vintage using Haver Analytics, Bloomberg and the IMF's Direction of Trade Statistics.
[9] The standard 'off-the-shelf' GVAR model includes 33 countries; however in our framework several countries are excluded due to data quality concerns.

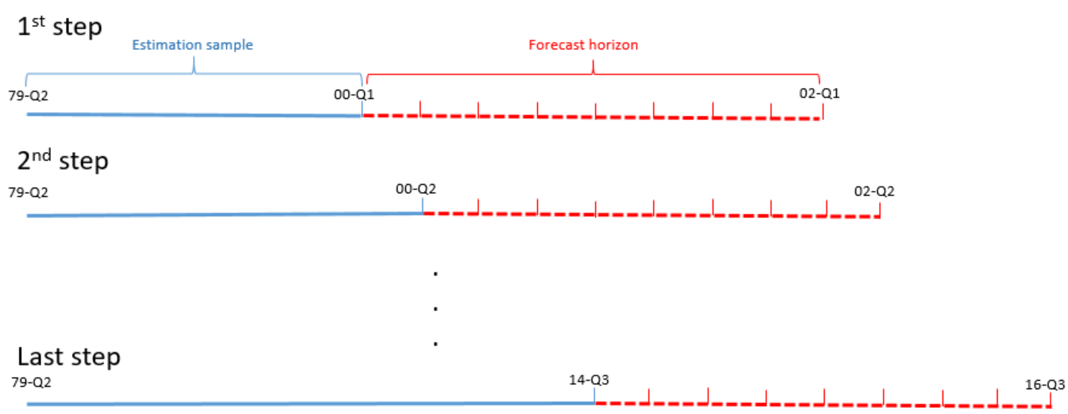
used the three-year-average (2013, 2014, 2015) weights to mitigate the impact of individual yearly movements on the trade weights (see Tables A1 in the appendix).

3.2. Forecast evaluation: methodology

We compare the recursive out-of-sample forecasts for real GDP, inflation, short and long-term interest rates, real exchange rates and real equity prices for New Zealand, U.S., China, Australia, Canada and the euro area. Our benchmark model for evaluating the forecast performance of the GVAR model is an AR(1) model with drift, which is hard-to-beat as a benchmark in the time-series forecasting literature. We then compare our GVAR forecasts for each country with those from a simple VAR model that only includes the domestic variables. Finally, we compare the GVAR's GDP forecasts with those produced by Consensus Economics.

The first estimation sample spans 1979Q2-2000Q1 where we calculate pseudo out-of-sample forecasts for eight forecast horizons (i.e. quarters). Next, we add an observation to the end of the sample (i.e. 1979Q2-2000Q2) and repeat the out-of-sample forecasting exercise. The estimation stops at 2014Q3 to allow for an eight-period forecast from this date, which can be compared to actual data up to 2016Q3. This empirical strategy is shown in Figure 2.

Figure 2: Forecast evaluation methodology



We generate 59 one to eight quarter ahead forecasts of each variable in the GVAR and repeat this process for each of the countries in Table 1. For brevity, we only report the results for New Zealand, U.S., China, Australia, Canada and euro area. We consider six alternative GVAR specifications which are shown in Table 2. We define the specifications in the form of VARX(p,q,c) where p and q refer to the lag orders of the domestic and foreign variables chosen according to AIC criteria and c refers to the number of cointegrating vectors imposed using Johansen cointegration test. The selection of alternative specifications allows us to examine how model complexity affects predictive accuracy.

Table 2: GVAR Specifications

Specification	Domestic Lags (p)	Foreign Lags (q)	Cointegration rank (c)
VARX(1,1,0)	1	1	0
VARX(1,1,1)	1	1	1
VARX(1,1,2)	1	1	2
VARX(2,2,1)	2	2	1
VARX(2,2,2)	2	2	2
GVAR set	AIC	AIC	Auto*

Notes: * Johansen's trace and maximal eigenvalue statistics as set out in Pesaran, Shin and Smith (2000) for models with weakly exogenous I(1) regressors. The final selection of the rank orders is determined by the trace statistic.

We calculate the Root Mean Squared Errors (RMSE) as our metric of predictive accuracy and test whether the differences observed in forecasting accuracy are statistically significant using the Diebold-Mariano test statistic.

4. Forecast evaluation results

In this section, we discuss our main results. The results are presented in Tables 3 and 4 and are reported for forecasting horizons of one, four and eight quarters ahead for the six variables and countries we focus. The RMSEs are expressed in relative terms where a value below one indicates that the GVAR model outperforms the comparative model used.

4.1. Comparisons with an AR(1) model

Table 3 shows the relative RMSEs for the GVAR forecasts relative to the simple AR(1) benchmark. In the case of GDP forecasts, the best predictive accuracy tends to be obtained by the VARX(1,1,0) model which is consistent across all horizons. An exception is the euro area where increasing the number of cointegrating vectors tends to improve forecast accuracy. The VARX(1,1,0) model is also generally the best specification for forecasting short rates, long rates and equity prices although the gains in forecast accuracy in the latter tend to be smaller. In the case of inflation forecasts, the GVAR specifications are consistently worse than the AR benchmark model except for New Zealand where the gains in predictive accuracy of the VARX(1,1,0) model range between 6-19 per cent across one to eight horizons.

Finally, the GVAR can outperform the AR model for forecasting the real exchange rate although the gains in predictive accuracy tend to be smaller. The results also suggest that accounting for the long-run relationships via cointegration does not provide any additional benefits from a forecasting perspective. This is in line with the findings of Duy and Thoma (1998) who show that models with fewer restrictions and those with estimated cointegrating restrictions tended to have a poorer forecasting performance than their more restricted counterparts. An alternative strategy would be to impose meaningful overidentifying restrictions that are in accordance with theoretical priors (see Assenmacher-Wesche and Pesaran, 2008).

Table 3: RMSEs of GVAR relative to the AR model

		New Zealand			U.S.			AUS		
Specification	Variables	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8
VARX(1,1,0)	r	0.81*	0.79**	0.71**	1.02	0.91	0.92	1.08	1.08	0.97
	lr	0.91	0.93	0.92	0.92*	0.93	0.92	0.91*	0.97	0.95
	y	0.95	1.01	0.96	0.93*	0.91*	0.91	1	0.93*	0.92*
	eq	1.02	1.06	1.08	1	1	0.98	0.92	0.98	0.97
	ep	0.98	0.97	0.94*	-	-	-	0.99	0.95	0.93*
	dp	0.94	0.87	0.81	1.19	1.17	1.14	1.13	1.1	1
VARX(1,1,1)	r	1.35	0.98	0.87	1.02	0.94	0.96	1.34	1.11	1.05
	lr	0.91	0.95	0.98	1.02	1.05	1.04	0.93	1.06	1.08
	y	1.02	1.12	1.07	1.02	1.02	1.02	1.06	0.93	0.88
	eq	1.12	1.18*	1.29*	1.05	1	0.99	0.98	1.03	1.04
	ep	0.98	0.97	0.96	-	-	-	1.01	0.99	1
	dp	0.97	0.92	0.91	1.18	1.14	1.18	1.15	1.11	1.07
VARX(1,1,2)	r	1.77***	1.17	1	1.12	0.99	0.95	1.42	1.35	1.31
	lr	1.10	1.02	0.97	1.17	1.11	0.98	1.05*	1.22*	1.21
	y	1.06	1.13	1.12	1.07	1.12	1.13	1	0.93*	0.86*
	eq	1.02	1.09	1.17	1.08	1.05	1.08	1.04	1.01	0.99
	ep	0.99	0.93	0.89*	-	-	-	1.04	1.02	1.03
	dp	1.16	1.09	0.98	1.21	1.13	1.13	1.08**	1.01	0.95
VARX(2,2,1)	r	1.87**	1.17	1.13	1.32	0.83	0.8	2.56***	1.5	1.38
	lr	1.42**	1.23	1.24	1.14	1.13	1.03	1.26	1.29**	1.36*
	y	1.07	1.13	1.08	1.01	1.02	1.03	1.45**	1.32	1.22
	eq	1.30***	1.34**	1.41**	1.09*	1.03	1.01	1.13	1.11	1.10
	ep	1.04	0.95	0.91	-	-	-	1.08	0.99	0.96
	dp	1.45**	1.40***	1.44**	1.19*	1.06	1.09	1.17**	1.13	1.08
VARX(2,2,2)	r	1.95***	1.17	1.03	1.41	0.94	0.87	2.63***	1.5	1.31
	lr	1.52**	1.05	1	1.12	1.01	0.88	1.18	1.16	1.17
	y	1.13	1.1	1.02	1.02	1.07	1.07	1.56***	1.42*	1.35
	eq	1.35***	1.48***	1.55**	1.10	1.03	1.03	1.15	1.09	1.08
	ep	1.05	0.93	0.85***	-	-	-	1.10	0.97	0.89**
	dp	1.42**	1.35***	1.32	1.21***	1.07	1.1	1.24*	1.21**	1.13
GVAR set	r	1.59	0.99	0.94	1.24	0.95	0.92	1.97**	1.92***	1.99***
	lr	1.31**	1.24	1.41**	1.06	1.13	1.11	1.16	1.27*	1.43**
	y	1.07	1.16	1.14	0.92	0.95	1.01	1.52**	1.44***	1.48***
	eq	1.18	1.44***	1.62***	0.99	1	0.99	1.04	1.14	1.17
	ep	0.98	1.01	0.96	-	-	-	1.09	1.02	1.09
	dp	1.11	1.08	1.08	1.20**	1.06	1.06	1.06	0.98	0.95

Notes: * is 10% level of significance, ** is significant at the 5% level and *** is significant at the 1% level of Diebold-Mariano test that forecast differs from the benchmark. h: forecast horizon in quarters, r: short-term interest rate, lr: long-term interest rate, y: real GDP, eq: real equity price, ep: real exchange rate, dp: inflation. Green cells indicate that the GVAR's forecasting accuracy is better than the AR benchmark. Red cells indicate that the forecasting accuracy of the AR model is as good as or better than the GVAR.

Table 3: RMSEs of GVAR relative to the AR model (continued)

		Canada			China			Euro Area		
Specification	Variables	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8
VARX(1,1,0)	r	0.92	0.95	0.89	1.20*	1.08	1.04	1.03	1.01	0.97
	lr	0.92	0.94	0.84***	-	-	-	0.95	0.95***	0.92***
	y	0.94	0.86***	0.82**	0.94	0.96*	0.92***	0.92*	0.94	0.96
	eq	0.99	0.95	0.93	-	-	-	1.01	1.02	1.03
	ep	0.99	0.95	0.93	0.79***	0.77***	0.78***	0.96	0.98	0.99
	dp	1.12***	1.14*	1.13	1.07	1.08*	1.11	1.06	1.09	1.07
VARX(1,1,1)	r	0.96	1.02	0.98	1.76	1.25	1.19	0.83	0.73*	0.83
	lr	1.11	1.07	0.95	-	-	-	1.01	1.18	1.18
	y	1.03	0.95	0.93	1.04	1.04	1	0.83	0.92	1.05
	eq	1.02	0.97	0.97	-	-	-	1.06	1.08	1.17*
	ep	1	0.92	0.91	0.77***	0.71*	0.68**	0.99	1.04	1.08
	dp	1.09	1.12	1.10	1.05	1.14**	1.14	1.03	1.09	1.09
VARX(1,1,2)	r	1.24	1.19	1.05	1.76	1.35	1.41***	0.84	0.67*	0.73*
	lr	1.64***	1.56**	1.33	-	-	-	1.23**	1.44**	1.39
	y	1.1	1.06	1.01	1.21***	1.32***	1.30	0.84	0.90	0.99
	eq	1	0.97	0.97	-	-	-	0.99	0.99	1.01
	ep	0.98*	0.93	0.92	0.74**	0.72	0.72*	1.05**	1.31***	1.48***
	dp	1.09	1.10	1.04	1.05	1.21*	1.26	1	1.04	1.02
VARX(2,2,1)	r	1.22	0.82	0.77	1.77	1.42*	1.29	1.06	0.76	0.77
	lr	1.61**	1.44**	1.21	-	-	-	1.16**	1.22	1.06
	y	1.06	0.93	0.96	1.2	1.07	1.02	0.94*	0.92	1.05
	eq	1.11**	1.11*	1.09	-	-	-	1.26**	1.31*	1.44*
	ep	1.05	0.99	0.95	1.02	0.69**	0.63***	0.92	1.10	1.17
	dp	1.28*	1.17	1.18	1.06	1.10*	1.14**	1.07	1.08	1.09
VARX(2,2,2)	r	1.34	0.89	0.81	1.80	1.42***	1.40**	1.08	0.80	0.77
	lr	1.60**	1.36**	1.07	-	-	-	1.16*	1.10	0.94
	y	1.10	0.96	1.02	1.27*	1.34***	1.34***	0.93*	0.90	1.04
	eq	1.11	1.14***	1.15*	-	-	-	1.18*	1.26*	1.41*
	ep	1.06	1.03	0.99	1.29	1.04	0.94	0.99	1.18***	1.32***
	dp	1.19*	1.06	1.04	1.18*	1.40***	1.68***	1.10**	1.17**	1.29*
GVAR set	r	1.25	1.08	0.98	1.95	1.46	1.48***	0.89	0.79	0.90
	lr	1.46***	1.47***	1.24	-	-	-	1.14	1.33**	1.46**
	y	0.95	0.91	0.93	1.21**	1.29*	1.26	0.83	0.89	1.12
	eq	0.99	1.04	1.07	-	-	-	1.06	1.33**	1.54***
	ep	1.06	1	1	0.89	0.89	0.99	0.88	1.13*	1.21**
	dp	1.09	1.10	1.10	1.05	1.23**	1.33**	1.03	1.12	1.22

4.2. Comparisons with a VAR with domestic variables

For this comparison, we first estimate a VAR model which comprises of only the domestic variables relevant for each of the six countries. We estimate the model using OLS and select the appropriate lag lengths based on Bayesian Information Criteria. We then generate forecasts from the VAR by following the same strategy outlined in Section 3.2. The results are presented in Table 4. We can see that the GVAR model, to a large extent, has produced smaller forecast errors than the simple VAR model.

Table 4: RMSEs of GVAR relative to the VAR(p) model

	New Zealand			U.S.			Australia		
Variables	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8
r	0.60***	0.43	0.38	0.72*	0.56	0.71	1.03*	0.53	0.45
lr	0.62	0.44	0.36	0.72	0.55*	0.73	0.80	0.53	0.46
y	0.84*	0.67	0.71	0.95	0.70**	0.73	0.65**	0.57	0.55
eq	0.91	0.59	0.54	0.89	0.64	0.61	0.82	0.64	0.69
ep	1.01	0.68	0.64				0.87	0.66	0.64
dp	0.79***	0.83	0.71	1.01**	1.34	1.6	0.95***	1.01	0.91
	Canada			**China**			**Euro Area**		
	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8	h = 1	h = 4	h = 8
r	0.53***	0.48	0.60	0.74***	0.50	0.39	1.14	0.75	0.7
lr	0.51	0.42	0.49				0.76	0.58	0.49
y	1.01	0.62	0.60	1.12	0.77	0.69	0.93	0.79	0.81
eq	0.77	0.58	0.72				0.93	0.67	0.62
ep	0.92	0.68	0.65	1.14	0.71	0.61	0.93	0.73	0.64
dp	0.89***	1.07	1.08	1.02***	0.72	0.63	1.00	0.88	0.81

Notes: See Table 3 for details.

4.3. Comparisons with Consensus forecasts

Consensus Economics conducts a monthly survey of organizations and publishes their forecasts of macroeconomic variables such as GDP growth, inflation and interest rates. Regarding their GDP forecasts, each forecaster reports their projections for the current and next year's annual GDP growth. Using these two sets of projections and the methodology in Greig, Rice, Vehbi and Wong (2018), we construct a one-year ahead forecast measure as the weighted average of each forecaster's current and next year forecasts.[10] We then compare these one-year-ahead forecasts with the corresponding GVAR forecasts using similar forecast evaluation strategy outlined in previous sections.[11]

The results are shown in Table 5, where a number less than 1 implies the model specification is more accurate than the *Consensus* forecasts. For the VARX(1,1,0) specification, the one-year ahead growth forecasts from GVAR are more accurate than those of the *Consensus* for the cases of Canada, Australia and China and the results are statistically significant. For Australia, the VARX(1,1,0) , VARX(1,1,1) and VARX(1,1,2) specifications also produce relatively better forecast accuracy than those of the *Consensus*. The results, however, are less promising for the cases of New Zealand and the U.S. where the specifications generally perform as good as (U.S.) or worse than the *Consensus* forecasts.

[10] The *Consensus* weighting scheme is as follows: $F = \left(\frac{13-m}{12}\right) F_c + (\frac{m-1}{12}) F_n$ Where F_c is the current year forecasts and F_n is the next years forecast.
[11] We exclude the euro area from this comparison as we do not have access to the *Consensus Economics* forecasts for the euro area.

Table 5: RMSE Ratios of various GVAR specifications relative to Consensus

Specifications	Canada	NZ	Australia	U.S.	China
VARX(1,1,0)	0.91*	0.99	0.85***	1	0.85*
VARX(1,1,1)	0.94	1.11*	0.85**	1.07	0.92
VARX(1,1,2)	1.02	1.12**	0.85**	1.12	1.23***
VARX(2,2,1)	0.94	1.16**	1.26*	1	0.87
VARX(2,2,2)	0.98	1.07	1.31***	1.05	1.12
GVAR (set)	0.84*	1.14	1.57**	0.95	1.23*

Notes: See Table 3 for details

5. Conclusion

In this *Analytical Note*, we introduce the GVAR and evaluate its predictive accuracy by conducting a series of out-of-sample forecast comparisons. Our empirical findings show that a relatively simple GVAR model is able to outperform a variety of benchmark models across several countries and forecast horizons. GVAR forecasts are generally superior to those obtained from a simple VAR specification comprising only domestic variables. Further, GVAR can outperform *Consensus* forecasts for GDP growth for several countries. The results suggest that using international linkages between economies will improve forecast performance when the model is specified in a parsimonious way. Therefore, the GVAR is a useful addition to the range of models used by the RBNZ to forecast the international economy.

REFERENCES

Annari De Waal, Reneé Van Eyden and Rangan Gupta (2015). “Do we need a global VAR model to forecast inflation and output in South Africa?”, Applied Economics, 47:25, 2649-2670.

Assenmacher-Wesche, K. and Pesaran, M.H. (2008). “A VECX* Model of the Swiss Economy”, Cambridge Working Papers in Economics 0809, Faculty of Economics, University of Cambridge.

Callaghan, M., Cassino, E., Vehbi, T., Wang, B. (2019). “Opening the toolbox: how does the RBNZ analyse the world?”, RBNZ Bulletin forthcoming.

Chudik Alexander and Pesaran, M.H. (2016). "Theory And Practice of GVAR Modelling", Journal of Economic Surveys, Wiley Blackwell, vol. 30(1), pages 165-197, February.

di Mauro, Filippo and Pesaran, M.H. (2013). “The GVAR Handbook: Structure and Applications of a Macro Model of the Global Economy for Policy Analysis”, Oxford University Press.

Duy, Timothy A. and Thoma, Mark A., (1998). “Modelling and Forecasting Cointegrated Variables: Some Practical Experience”, Journal of Economics and Business, Elsevier, vol. 50(3), pages 291-307, May.

Greig, L., Rice, A., Vehbi, T. and Wong, B. (2018). “Measuring Uncertainty and Its Impact on a Small Open Economy”, Australian Economic Review, The University of Melbourne, Melbourne Institute of Applied Economic and Social Research, vol. 51(1), pages 87-98, March.

Han, Fei; Ng, Thiam Hee. (2011). “ASEAN-5 Macroeconomic Forecasting Using a GVAR Model”, ADBI working paper, No.76.

Pesaran M.H., Til Schuermann and L. Vanessa Smith (2009). “Forecasting Economic and Financial Variables with Global VARs”, International Journal of Forecasting, Volume 25, Issue 4.

Pesaran M.H., Til Schuermann and Scott M Weiner (2004). “Modeling Regional Interdependencies Using a Global Error-Correcting Macroeconometric Model”, Journal of Business and Economic Statistics, 22:2, 129-162.

Appendix

Table A1: Trade weights (2013-2015 average)

`	Australia	Brazil	Canada	China	Chile	India	Indonesia	Japan	Korea	Malaysia	Norway	New Zealand	Philippines	Singapore	Sweden	Switzerland	Thailand	UK	U.S.	Euro Area
Australia	0.00	0.01	0.00	0.05	0.01	0.03	0.04	0.06	0.04	0.04	0.00	0.18	0.01	0.04	0.01	0.01	0.05	0.01	0.01	0.01
Brazil	0.00	0.00	0.01	0.03	0.08	0.03	0.01	0.01	0.02	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.03	0.03
Canada	0.01	0.02	0.00	0.02	0.02	0.02	0.01	0.02	0.01	0.00	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.02	0.24	0.02
China	0.32	0.27	0.09	0.00	0.30	0.19	0.18	0.29	0.33	0.19	0.07	0.23	0.18	0.18	0.06	0.07	0.20	0.10	0.23	0.18
Chile	0.00	0.03	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01
India	0.03	0.04	0.01	0.03	0.03	0.00	0.06	0.01	0.03	0.04	0.00	0.01	0.01	0.04	0.01	0.05	0.03	0.02	0.03	0.03
Indonesia	0.03	0.01	0.00	0.03	0.00	0.05	0.00	0.04	0.03	0.05	0.00	0.02	0.04	0.10	0.00	0.00	0.05	0.00	0.01	0.01
Japan	0.14	0.04	0.03	0.12	0.08	0.04	0.14	0.00	0.12	0.12	0.02	0.08	0.19	0.07	0.02	0.02	0.18	0.02	0.08	0.04
Korea	0.07	0.04	0.01	0.12	0.06	0.05	0.08	0.08	0.00	0.05	0.00	0.05	0.07	0.07	0.01	0.01	0.04	0.02	0.04	0.03
Malysia	0.04	0.01	0.00	0.04	0.00	0.04	0.07	0.04	0.03	0.00	0.00	0.04	0.04	0.16	0.00	0.01	0.08	0.01	0.02	0.01
Norway	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.13	0.00	0.00	0.04	0.00	0.03
New Zealand	0.04	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00
Phillipines	0.01	0.00	0.00	0.02	0.00	0.00	0.02	0.02	0.02	0.02	0.00	0.01	0.00	0.02	0.00	0.00	0.03	0.00	0.01	0.01
Singapore	0.05	0.01	0.00	0.03	0.00	0.04	0.14	0.03	0.04	0.17	0.01	0.04	0.09	0.00	0.00	0.02	0.06	0.01	0.02	0.02
Sweden	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.01	0.06
Switzerland	0.01	0.02	0.01	0.01	0.01	0.06	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.02	0.05	0.02	0.10
Thailand	0.04	0.01	0.00	0.03	0.01	0.02	0.06	0.05	0.02	0.07	0.00	0.03	0.06	0.04	0.01	0.01	0.00	0.01	0.02	0.01
UK	0.02	0.02	0.03	0.03	0.01	0.04	0.01	0.02	0.02	0.01	0.20	0.04	0.01	0.02	0.09	0.11	0.02	0.00	0.04	0.20
U.S.	0.09	0.21	0.73	0.23	0.21	0.17	0.09	0.20	0.17	0.11	0.06	0.13	0.15	0.12	0.07	0.12	0.12	0.14	0.00	0.20
Euro Area	0.09	0.24	0.07	0.17	0.15	0.19	0.08	0.10	0.10	0.10	0.48	0.11	0.12	0.10	0.56	0.53	0.09	0.52	0.18	0.00

Notes: The trade share of country *i* with respect to country *j* is defined as the sum of country *i*'s imports from country *j* and exports to country *j* divided by the sum of country *i*'s total imports and exports They are displayed in columns by country such that a column sums to one.
Source: International Monetary Fund (IMF), Direction of Trade Statistics.