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The Forecasting and Policy System: stochastic simulations of the core model

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Abstract

Uncertainty in applied macroeconomic policy analysis arises from three distinct sources. The first, often referred to as *model uncertainty*, arises because the models used for policy analysis are simple abstractions of the complex behavioural interactions that occur in an economy. The second source, denoted *shock uncertainty*, arises from unforeseen events that the analysis cannot explicitly factor in *ex ante*. Finally, *starting-point uncertainty* reflects the fact that given data lags and revisions, often it is difficult to assess the current state of the economy. This paper discusses the approach the Reserve Bank has taken to enable its *Forecasting and Policy System* (FPS) to quantify the implications that the typical level of shock uncertainty might be expected have on the analysis of alternative policy actions designed to achieve the objectives of monetary policy.

The technique uses the impulses from an estimated vector autoregression (VAR) model of the New Zealand economy to represent the typical level of shock uncertainty policy must deal with. These impulses are mapped into shocks to key behavioural relationships in the calibrated structural macroeconomic model that lies at the heart of FPS. This approach leads to random disturbances that capture both the serial and cross correlations in the data.

The structural model is then simulated while being randomly subjected to the representative impulses. This exercise builds-up statistical distributions for key macroeconomic variables. The model generated macroeconomic properties are compared to the historical properties of the New Zealand economy. Given the amount of structural change that the New Zealand economy has undergone over the historical sample period, and the functional form of the FPS policy reaction function, *a-priori* one might not expect model generated moments to perfectly replicate historical moments. Nevertheless, the model generated properties appear to be reasonably close to the historical properties of the New Zealand economy.

Sensitivity analysis is also performed to examine the stochastic behaviour of the core model under different characterisations of the shock generating process. Changing the informational structure that the monetary authority has about the shocks, incorporating exogenous disturbances to the policy instrument, and altering the causal ordering of the VAR model, have little impact on the behaviour of the model economy relative to history. However, ignoring the cross-correlations in the data leads to stochastic behaviour of the model economy that is implausible relative to history.

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1 Introduction

The primary goal of the *Forecasting and Policy System* (FPS) modelling project is to aid decision making through the development of a framework to conduct economic analysis in a consistent and theoretically robust manner. The current focus of development for the FPS is to further enhance decision making by factoring in the implications of uncertainty. We can think of this uncertainty as arising from three distinct sources:

- how closely modelled economic relationships capture real world behaviour (model uncertainty);

- the nature and duration of unforeseen events that will influence economic outcomes (shock uncertainty); and

- data that arrives with a considerable time lag, and/or is subject to revision (starting-point uncertainty).

If there are no economic uncertainties, the policy maker can be confident that policy actions lead to desired outcomes. However, uncertainty implies that the link between policy actions and outcomes is far from clear. Given uncertainty, there are a range of outcomes that could possibly occur, many of which may not be consistent with the desired outcome. Quantifying the range of possible outcomes allows the policy maker to be aware of the implications of pursuing certain policy courses. This possible range of outcomes are obviously important for the Reserve Bank to be mindful of given its inflation target objective.

This paper discusses the technique, termed ‘stochastic simulations’, used to incorporate shock uncertainty into policy analysis using FPS.[1] Stochastic simulations quantify the impact that unforeseen shocks can have on tomorrow’s outcomes given today’s policy actions. In doing so, this technique allows decision makers to augment today’s actions to ensure that the outcomes achieved are as close as possible to those desired.

The remainder of this paper is as follows. Section 2 gives a brief description of the core macroeconomic model at the heart of the FPS. Section 3 presents the methodology applied to identify shocks to the core model for use in stochastic simulations, and describes how stochastic simulations are performed. Section 4 presents model-generated moments for macroeconomic variables of interest. These moments are compared to historical moments, and some inferences are drawn about the behaviour of FPS when shock uncertainty is incorporated. In Section 5, the robustness of these inferences to both alternative specifications of the shock identification process, and the information the monetary authority has about the

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[1] A consideration of the other types of uncertainty identified above is part of the Bank’s research agenda, but it is not covered here. See Conway *et al.* (1998), and Drew *et al.* (1998) for applications of model and starting point uncertainties respectively, using techniques similar to those presented here.

shocks, are presented. Finally, in Section 6, results are summarised and avenues of future research are outlined.

2 The FPS core model[2]

The FPS core model describes the interaction of five economic agents: households, firms, government, a foreign sector, and the monetary authority. The model has a two-tiered structure. The first tier is the underlying steady-state structure that determines the long-run equilibrium to which the model will converge. The second tier is the dynamic adjustment structure that traces out how the economy converges towards that long-run equilibrium.

The long-run equilibrium is characterised by a neo-classical balanced-growth path. Along that growth path, consumers maximise utility, firms maximise profits and government achieves exogenously specified targets for debt and expenditures. The foreign sector trades in goods and assets with the domestic economy. Taken together, the actions of these agents determine expenditure flows that support a set of stock equilibrium conditions that underlie the balanced growth path.

The dynamic adjustment process overlaid on the equilibrium structure embodies both "expectational" and "intrinsic" dynamics. Expectational dynamics arise through the interaction of exogenous disturbances, policy actions and private agents' expectations. Policy actions are introduced to re-anchor expectations when exogenous disturbances move the economy away from equilibrium. Because policy actions do not immediately re-anchor private expectations, other real variables in the economy must follow disequilibrium paths until expectations return to equilibrium. To capture this notion, expectations are modelled as a linear combination of a backward-looking autoregressive process and a forward-looking model-consistent process. Modelling expectations in this way partially addresses the critique, initially raised in Lucas (1976), that examining alternative policy actions in reduced form econometric models gives misleading conclusions.[3]

Intrinsic dynamics arise because adjustment is costly. The costs of adjustment are modelled using a polynomial (up to fourth order) adjustment cost framework (see Tinsley (1993)). In addition to expectational and intrinsic dynamics, the behaviour of both the monetary and fiscal authorities also contributes to the overall dynamic adjustment process.

On the supply side, FPS is a single good model. That single good is differentiated in its use by a system of relative prices. Overlaid on this system of relative prices is an

2 See Black *et al*. (1997) for a full account of the FPS.

3 The Lucas critique states that the estimated parameters of reduced-form models are dependent on the policy regimes in place over the estimation period. Consequently, simulating reduced-form models in which behaviour is invariant to policy actions produces misleading policy conclusions. Although FPS has partially addressed the Lucas critique, a more explicit modelling of agents' learning behaviour would be required to address it fully.

inflation process. Although inflation can potentially arise from many sources in the model, fundamentally it is driven by the difference between the economy's supply capacity and the demand for goods and services. Further, the relationship between goods markets disequilibrium and inflation is specified to be asymmetric. Excess demand generates more inflationary pressure than an identical amount of excess supply generates deflationary pressure.

The monetary authority effectively closes the model by enforcing a nominal anchor. Its behaviour is modelled by a forward-looking reaction function that moves the short-term nominal interest rate in response to projected deviations of inflation from an exogenously specified target rate. Although the reaction function is *ad hoc* in the sense that it is not the solution to pre defined optimal control problem as in Svensson (1996), its design is not arbitrary. The forward-looking nature of the reaction function respects the lags in the economy between policy actions and their subsequent implications for inflation outcomes. Further, the strength of the policy response to projected deviations in inflation implicitly embodies the notion that the monetary authority is not single minded in its pursuit of the inflation target. Other factors, such as the variability of its instrument and the real economy, are also of concern.

3 The shock identification process

When the FPS core model is simulated in a 'deterministic mode' single time paths for economic variables are generated. In stochastic simulations, multiple alternative paths are generated; where each alternative path is a function of the randomly generated shocks that impact on key behavioural relationships in the model.

Performing stochastic simulations requires a distribution from which to draw the shocks. In small macroeconometric models, the distributions of the shocks applied to the model are usually based upon the properties of the residuals from the estimated equations. Ideally, systems estimation techniques are employed so that the residuals are based upon the system properties of the model under consideration. For example, see Fillion and Tetlow (1994), and Turner (1996) for applications of this approach. Given the paucity of data in New Zealand, and the size of the model, FPS has been calibrated. Consequently, there are no historical errors from which we can draw shocks to use for stochastic simulations of the model. Instead, a procedure similar to that used in Black, Macklem and Rose (1998) is followed. Essentially, the impulse response functions (IRFs) from an estimated VAR are used to calculate the paths for the shocks appearing in the core model's equations.

The details of the estimated VAR model are presented in Section 3.1 below. In Section 3.2, the mapping of the VAR's IRF's into shocks to the model's behavioural equations is described. In Section 3.3, the strengths and weaknesses of using the VAR to specify shocks to the core model are discussed. Finally, in Section 3.4, the methodology employed to simulate the model under shock uncertainty is presented.

3.1 The VAR model[4]

To capture the stochastic structure of shocks to the New Zealand macro-economy a six-variable VAR model is estimated. The following variables are included in the VAR:

- foreign demand (*fd*)
- terms of trade (*tot*)
- consumption plus investment ($c + i$)
- price level (*cpi*)
- real exchange rate (z)
- slope of the yield curve (*rsl*)

The foreign demand variable is measured as the total industrial production of the OECD. The terms of trade is calculated as the price of exports divided by the price of imports. Shocks to the sum of consumption and investment are interpreted as the result of shocks in aggregate demand[5]. The price index is measured as the consumer price index excluding interest rate effects and GST.[6] The real exchange rate is calculated using the domestic output deflator, the nominal trade weighted index and trade weighted foreign output deflators. Finally, the slope of the yield curve is measured as the 90 day paper rate minus the five year rate. The yield spread enters the VAR in levels and all other variables are in log levels.

The variables of the VAR and their associated shocks terms are intended to capture the stochastic behaviour of macroeconomic disturbances hitting the New Zealand economy. There are, however, a number of omissions. Perhaps the most notable is shocks to the economy's productive capacity. Initially, an estimate of New Zealand's potential output was also included in the VAR. However, given the short length of the sample period there is insufficient stochastic information in the potential output series to produce sensible shock responses. Despite this omission, innovations in the economy's level of productive capacity will be captured in part by the shock terms of the other variables of the system. Stochastic innovations in the domestic price level, for example, can be partially attributed to temporary aggregate supply shocks.

4 Our thanks to Paul Conway for estimating the standard VAR used for stochastic simulations of FPS, and for technical advice.

5 No long-run restrictions were imposed on the VAR due to data limitations. Despite the lack of restrictions, when the VAR is run-out long enough the roots of the system imply that all variables return to control following the one standard deviation impulses. Hence there are no permanent shocks in the VAR system.

6 GST is a goods and services tax. This tax was initially implemented in 1986 at 10 %. In 1989 GST was increased to 12.5 %.

In the reduced form system of equations, foreign demand and the terms of trade are modelled as block exogenous on the assumption that New Zealand is a small open economy. Lags of the domestic variables do not, therefore, enter into the equations describing these variables. Foreign demand is assumed to be strictly exogenous in that it is only dependant on its own lags. The equation describing the terms of trade includes its own lags and lags of foreign demand. The equations describing the domestic variables and the real exchange rate are identical and contain lags of all the variables of the system. On the basis of modified likelihood ratio tests, the number of lags in the system is set at four. Ljung-Box Q statistics confirm the lack of serially correlated residuals at the 5% level of significance. The reduced form is estimated over the sample period 1985q2 to 1997q2 using the method of seemingly unrelated regressions.

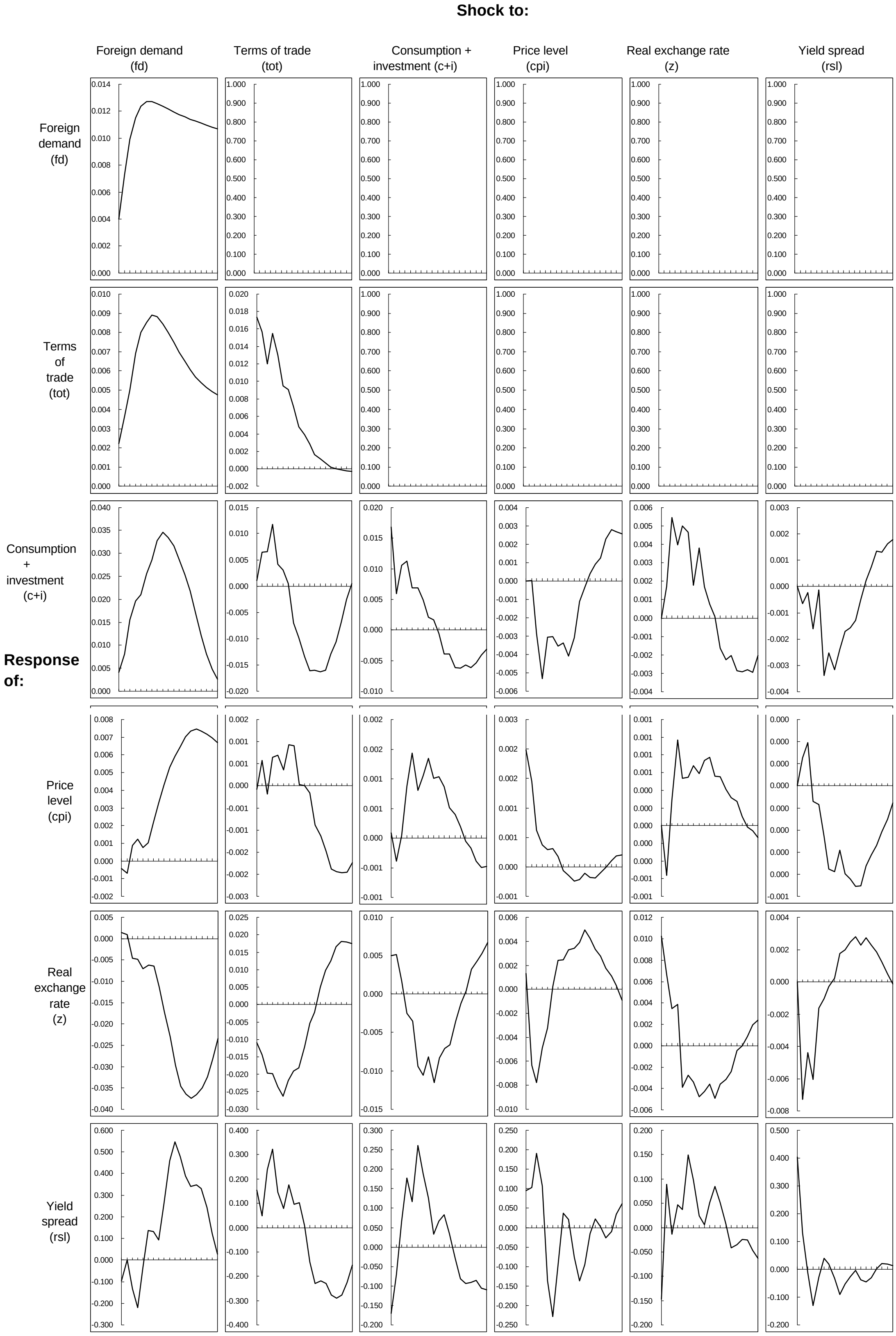
To calculate impulse response functions we identify the moving-average representation of the VAR system by imposing a simple contemporaneous causal ordering. The structure of FPS implies an ordering of $\{fd, tot, c + i, cpi, z, rsl\}$. Foreign demand and the terms of trade are placed causally prior to the domestic variables. This specification extends the assumption of block exogeneity of the foreign sector to the contemporaneous interaction between the variables of the system. In the domestic block, $c + i$ and cpi adjust with a lag to shocks in the real exchange rate and monetary conditions. Finally, the monetary authority is assumed to set monetary policy on the basis of contemporaneous (and historical) information.

As New Zealand is a small open economy, we feel it is quite reasonable for the foreign variables to be causally prior to the domestic variables. Furthermore, the ordering of the domestic variables is standard from a theoretical viewpoint. As a check on the methodology employed, however, the robustness of the stochastic behaviour of FPS to some alternative causal orderings of the domestic variables is examined in Sections 5.

The impulse responses of the variables in the VAR to each of the six shocks are presented in Figure 1 below. In all cases the magnitude of the shocks is equal to one standard deviation. The figure should be read vertically; each column shows the response of each variable to a particular shock.

In general, the IRFs accord well with the theory of small open economy macro-dynamics. Consider the effect of a one standard deviation shock to foreign demand. The terms of trade improve and the real exchange rate appreciates, consistent with increased demand for New Zealand exports. Aggregate demand, in the form of consumption plus investment, increases inducing a lagged increase in the price level. The monetary authority reacts to increased inflationary pressure by tightening monetary conditions, causing the yield spread to increase. Increased domestic interest rates exacerbate the appreciation of the real exchange rate. In response to a one standard deviation shock to $c + i$, foreign demand and the terms of trade remain unchanged, given that they are exogenous. The price level increases after two periods, inducing a tightening in monetary conditions. After three quarters the real exchange rate appreciates.

Figure 1: VAR impulse response functions



3.2 Translating VAR impulse response functions into shocks to the core model

In the VAR system, an IRF is generated by applying a 1 standard deviation innovation to a variable. The effect of that impulse is transmitted to all variables in the VAR according to the estimated interrelationships. Given an impulse, the resultant paths for macroeconomic variables in the VAR can be interpreted as deviations from control or equilibrium.

In the FPS model, each behavioural equation has an associated shock term. Deviations from control arising from an impulse to the VAR are added to the control levels of the behavioural variable in the model with the closest economic match to the associated VAR variable. The model is then simulated with the behavioural variables concerned defined to be exogenous and shock terms on the behavioural equations defined to be endogenous. The simulations then solve for the additive shock term that is necessary to get the behavioural equation to replicate the VAR impulse response path. This exercise is repeated for all of the VAR's IRFs.

The simulations run to back out the shocks are performed quarter-by-quarter as only the contemporaneous and lagged information of the IRF is added to the levels of the relevant variables. That is, in solving for the shocks, model agents never see the future path of the VAR impulse. Given the amount of uncertainty that exists in the real world, we feel this informational assumption closely reflects the amount of information agents have at their disposal. Further, the simulations are run to replicate the first four quarters of the VAR impulse only. This reflects the fact that what are required are proxies for the purely exogenous impulses that are hitting the economy. Some of the VAR's impulse response paths will undoubtedly embody the effects of historical policy responses to these disturbances. However, given the lags with which policy affects the economy, it is assumed that the first four quarters of the IRFs are largely free of policy actions. As such, when solving for the shocks required to replicate the VAR's IRFs over the first four quarters, the FPS policy reaction function is turned-off. This ensures that the shocks generated are independent of the functional form of the FPS reaction function.[7] Finally, note that in most of the stochastic simulation experiments run in this paper the IRF arising from an impulse to the policy instrument is ignored. This reflects uncertainty as to precisely how these impulses should be interpreted (see Evans and Kuttner (1998) for an informed discussion of this issue).

The shocks required to induce FPS to replicate the IRFs are serially and cross correlated. To capture this in a way such that the stochastic simulations can be implemented by drawing from a normal(0,1) distribution, the shock terms that appear in the behavioural equations in the model are re-written to capture all these interrelationships. A "shock model" is then used to generate vector of shocks that are applied to the model in the stochastic simulations.

An example is provided here to illustrate how this works. Suppose that there are only two variables used in the VAR system, X1 and X2, where an impulse to X1 does not affect X2 but an impulse to X2 affects both itself and X1. The impulses to the system

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7 This issue is crucial when the subject of investigation is the stochastic behaviour of the model economy under alternative policy rules. For example, see Drew *et al.* (1998).

are mapped to the behavioural FPS variables x_1 and x_2 that have associated shock terms x_1_shk and x_2_shk. This example assumes that the model is then solved to replicate the VAR system for two quarters only.

Truncated after two quarters, the vector of shock required for the model to replicate the paths arising from the IRFs are:

1) Impulse to X1

$x_1\_shk = \{\alpha^1_{1,1}, \alpha^1_{1,2}, 0, 0\}$

$x_2\_shk = \{0, 0, 0, 0\}$

2) Impulse to X2

$x_1\_shk = \{\alpha^2_{1,1}, \alpha^2_{1,2}, 0, 0\}$

$x_2\_shk = \{\alpha^2_{2,1}, \alpha^2_{2,2}, 0, 0\}$

where $\alpha^i_{j,t}$ is the numerical solution for the value of the shock term at time *t*, given the effect the IRF *i* has on the behavioural variable *j*.

Let ε^i_t be a single period random number at time *t*. If this random number equals one, then it will generate the shock path required to replicate the IRF with the shock structure coded in the behavioural equation as follows:

$$x_1\_shk_t = \alpha^1_{1,1}*\varepsilon^1_t + \alpha^1_{1,2}*\varepsilon^1_{t-1} + \alpha^2_{2,1}*\varepsilon^2_t + \alpha^2_{2,2}*\varepsilon^2_{t-1}$$

$$x_2\_shk_t = 0*\varepsilon^1_t + 0*\varepsilon^1_{t-1} + \alpha^2_{2,1}*\varepsilon^2_t + \alpha^2_{2,2}*\varepsilon^2_{t-1}$$

Essentially, the methodology rewrites the shock terms in the behavioural equations to capture all the impulses in the VAR system. The shock paths required to replicate IRF_i for 2 quarters will be generated when the random number ε^i_t takes the value one.

Extending the above example to replicate the VAR in this paper is relatively simple. There are five shock terms that are rewritten rather than two. Any individual shock term *j* appearing in a behavioural equation is represented by:

$$x\_shk_{j,t} = \sum_{i=1}^{5}\sum_{k=0}^{3} a^i_{j,k+1} e^i_{t-k}$$

3.3 Strengths and weaknesses of the VAR approach

Using the VAR to identify shocks to the structural model has several attractive features. First, if the VAR is viewed as a reasonably complete representation of the economy, then it should capture most of the key disturbances. Secondly, the VAR approach leads to shock terms that capture both the serial and cross correlations in the data; hence there is no need to assume independence. This is viewed as an advantage as the shocks are not interpreted as deep structural shocks, but rather as summary measures of all the disturbances impacting on the economy at a micro level. In general, deep structural disturbances have wide-ranging implications and thus summary shocks should not be expected to be independent.

There are also limitations of the VAR approach. As stated above, because we were unable to include a measure of the supply side, the VAR captures only temporary disturbances. Secondly, the VAR's impulse response functions are likely to depend not only upon deep structural disturbances to micro markets, but also upon:

- the policy regimes in place over the estimation period, and

- adjustment in the New Zealand economy attributable to the economic reform program.

Because of these factors, the Lucas critique becomes relevant.[8] Using only the first four quarters of the impulse response paths partially addresses the issue of the influence of policy. Furthermore, turning off the model's reaction function to solve for the required shock terms ensures that these shocks are not influenced by the base-case reaction function used in the model. The sample period used to estimate the VAR has been restricted to try to mitigate, to the extent possible, the influence of major structural change. For example, in Conway (1998), the opening up of the New Zealand economy that occurred in the 1980s is shown to have had a significant impact on the degree to which foreign business cycle developments impact upon the New Zealand economy. The sample period over which the VAR used here has been estimated excludes most of the period during which the New Zealand economy was considerably less open.

3.4 Generating stochastic simulations

It is convenient to write the full set of behavioural shocks applied to the model in stochastic simulations as:

$\mathbf{X}_t = \mathbf{A}\mathbf{E}_t$

where:

$\mathbf{X}_t$ is a vector of the shock terms in the behavioural equations at time t

$\mathbf{A}$ is a matrix of the $\alpha^i_{j,t}$ coefficients

$\mathbf{E}_t$ is a vector of the ε^i_t random variables that exist from time t-3 to t.
This matrix can be decomposed into four sub-vectors $\mathbf{e}_{t-i}$ where i = 0 to 3. Each $\mathbf{e}_{t-i}$ is a vector of the random numbers drawn at time $t-i$.

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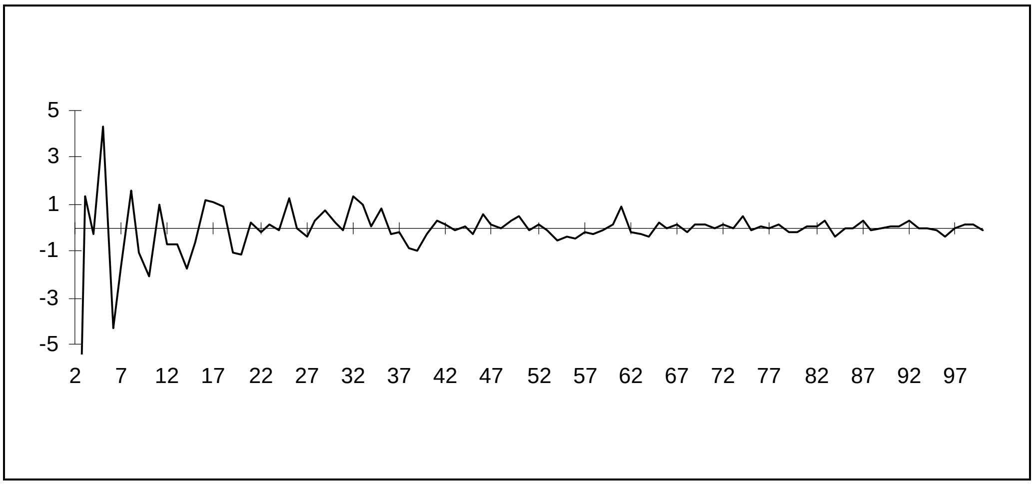
8 This problem also arises in structural macroeconometric models, as identifying regime shift in policy, and modelling structural change in general, has proved very difficult. For further information, see Qin (1997) for a critique on the main econometric research strategies being applied to model structural change.

Stochastic simulations of the model are generated using the following procedure. First, elements of the vector $\mathbf{e}_t$ are drawn from a standard normal distribution. Given this vector of random impulses a "shock model" solves for the shock vector $\mathbf{X}_t$. The model is then simulated with this shock vector exogenous and all the behavioural variables endogenous. This counts as one "iteration" of the model. A single "draw" consists of simulating the model for 100 iterations, where in each iteration a new vector for $\mathbf{X}_t$ is generated given the historical and contemporaneous stochastic iid impulses in $\mathbf{E}_t$. This exercise is repeated for 100 draws, so the total number of simulations run for an experiment is 10,000. Furthermore, the drawing of the iid random numbers are seeded so that for each set of 100 draws, an identical battery of shocks are generated.

Distributions for variables of interest are built up by averaging across time and across draws. In each draw, the first 5 years of the simulations are discarded. This alleviates any possible bias that may arise from starting the stochastic simulations from a deterministic equilibrium (see Bryant *et al* (1995) for further discussion on this issue). Furthermore, we have found that the averaging process across draws does not stabilise until roughly 70 draws have been conducted. Figure 2 illustrates how the percent change in the standard deviation of output evolves as the number of draws increases. For fewer than 30 draws, this statistic is very volatile.[9]

Figure 2: Percent change in the standard deviation of output



In each quarter the shocks are applied, the monetary authority sees the contemporaneous cross correlation effects only, and sets policy based on this information. One can argue that the inflation control problem in this exercise is reasonably realistic as the information that the monetary authority has about the shocks is close to the information real-world authorities have at their disposal. In section 5, however, alternative information structures are considered to examine the robustness of our standard assumption.

9 Typically, stochastic simulation studies in the past using models in a generic vein to FPS have conducted roughly 20 draws (for example see Bryant *et al.* (1995)). Principally, this has been because the computing time required. With the ongoing rapid advances in computing technology this constraint has become less binding.

4 The stochastic behaviour of FPS under shock uncertainty

A temporary shock applied to the FPS core model, such as a shock to aggregate demand, will force endogenous model variables away from their respective equilibrium paths. The expectational, intrinsic and policy dynamics calibrated into the model determine how quickly these paths return to equilibrium. The time taken to re-equilibrate has been calibrated to reflect the business cycle properties of the New Zealand economy.[10]

Under stochastic simulations, new shocks are applied in every quarter and, consequently, model variables never permanently return to their equilibrium paths. Instead, they fluctuate about their respective equilibrium paths. All model variables are stationary because abstracting from growth means that there are no stochastic trends in the equilibrium paths.

Historical data for macroeconomic variables of interest, including: output and the components of output, the real exchange rate, inflation, nominal interest rates, and the terms of trade are all non-stationary over the time period that the VAR was estimated. In order to compare model generated outcomes to the historical data meaningfully, the historical data must be rendered stationary.

Given that the real model endogenous variables fluctuate about equilibrium paths at business cycle frequencies and above, our *a-priori* preference is to apply a filter that removes the trend component in this data only. However, there is no real consensus in the literature on what is the most appropriate filtering process to apply. For example, Cogley and Nason (1995) show that the commonly used Hodrick-Prescott filter can induce spurious correlations in the data at business cycle frequencies.[11] For the components of demand, a common way to address this problem is to express the components as ratios-to-output. However, in the New Zealand context this is not so straight forward as there are significant trends in the data when it expressed relative to output, particularly in exports and imports following the deregulation of the economy over the 1980s. The demand component ratios are de-trended using a simple linear time trend to address this problem.[12] The fourth difference operator was also used to measure the data in terms of its annual growth rate. These approaches were also used to de-trend the real exchange rate and the terms of trade which also exhibit significant drift over much of the sample period.

With aggregate output itself, two filters were applied. The first is the fourth difference operator, and the second is a multivariate filtering technique used by the Bank to identify potential output, as outlined in Conway and Hunt (1997). This filter decomposes actual output into its trend and cycle components by augmenting an HP

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[10] See Black et al. (1997) for a full description of the calibration of the FPS core model.

[11] See Baxter and King (1995), Harvey and Jaeger (1993), and Canova (1998) for alternative approaches to isolating the business frequency content in the data.

[12] Although applying a linear time trend to the data does not entirely escape the filtering problem, it is of second order compared to applying a business cycle filter to the data itself.

filter with conditioning information including: past inflation, labour market conditions, and a survey measure of capacity utilisation.

Nominal interest rates and inflation trend significantly downwards from the mid-1980s into the early 1990s, as would be expected following dis-inflation in the industrialised world over this time. To account for this problem, the historical standard deviations for CPI inflation, nominal interest rates, and the yield spread are presented over the whole historical sample, and from 1990 onwards to coincide with the adoption of formal inflation targets by the Reserve Bank.

Table 1 below presents results for historical and model-generated standard deviations. Standard errors of the model-generated standard deviation are in brackets. The model-generated standard deviations are not significantly different from the historical standard deviations at the 95% level of confidence for the terms of trade, aggregate demand, and its components (expressed as ratios-to-output). This is also the case for all components of demand expressed as annual rates of change, except for exports which are less variable than they were historically.

The model-generated output gap exhibits more variability than that of the historical data, while inflation variability is lower, even compared to post 1990. We do not see this result as problematic, as it is consistent with the model's reaction function responding more vigorously to inflation deviations from target than historical policy may have done. This is suggested by the volatility in the yield spread being higher than the historical yield spread over both samples examined (significantly so for the post-1990s). Nominal interest rate volatility is also significantly higher than over the historical inflation targeting period. In contrast, although not significant, the real exchange rate exhibits more volatility over history. This result is also consistent with the Bank relying more heavily on the exchange rate channel to control inflation in the past.[13]

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13 See Grimes and Wong (1994) for a description of this approach to inflation control.

Table 1: Historical and model-generated standard deviations

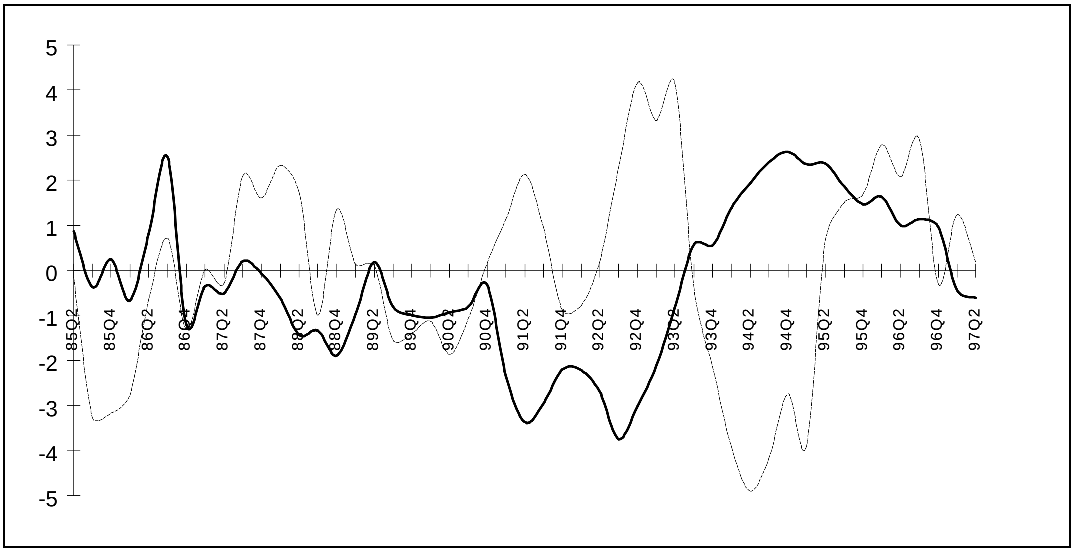
VARIABLE	HISTORY		MODEL
Standard deviations coefficient for annual percent changes in macro variables			
Y	2.5		3.70 (0.60)*
C	4.1		3.85 (0.65)*
I	12.4		14.34 (2.42)*
c+I	4.7		5.88 (0.96)*
G	3.2		3.69 (0.70)*
x	5.0		2.50 (0.36)
m	6.8		5.42 (0.84)*
z	7.4		5.62 (0.93)*
tot	4.6		4.66 (0.64) *
Standard deviations coefficient of macro variables			
ygap	1.7		2.80 (0.44)
c/y	1.2		0.86 (0.25)*
i/y	1.1		1.24 (0.17)*
(c+I)/y	1.9		1.54 (0.25)*
g/y	1.5		1.56 (0.32)*
x/y	1.0		0.9 (0.15)*
m/y	1.1		1.32 (0.34)*
z	4.9		4.87 (0.95)*
tot	4.3		3.70 (0.5) *
	85q2 to 97q2	*90q1 to 97q2*	
rsl	2.0	1	2.2 (0.36)*a
rn	5.7	2.7	3.11(0.50)*b
p_4	3.9	1.2	1.04 (0.17)*b

*Indicates that model standard deviations are not significantly different from historical standard deviations at the 95% level of confidence. *a and *b indicate that the standard deviations are not significantly different from the historical sample standard deviations from 85q2 to 97q2 and 90q1 to 97q2 respectively. Note that the *tot* variable is measured in domestic price terms.

The analysis so far suggests that the technique employed does result in model-generated moments that are reasonably close to the historical moments. However, early criticism of the real business cycle (RBC) literature centred upon the fact that ‘matching moments’ was not sufficient to ensure that models under consideration could also generate business cycles that actually ‘looked like’ historically observed cycles (see King *et al*. (1988)). In figure 3a below the time series paths of output relative to potential over history and from one draw is presented. It is seen that both the amplitude and length of the model cycle is not too dissimilar from the historical cycle.

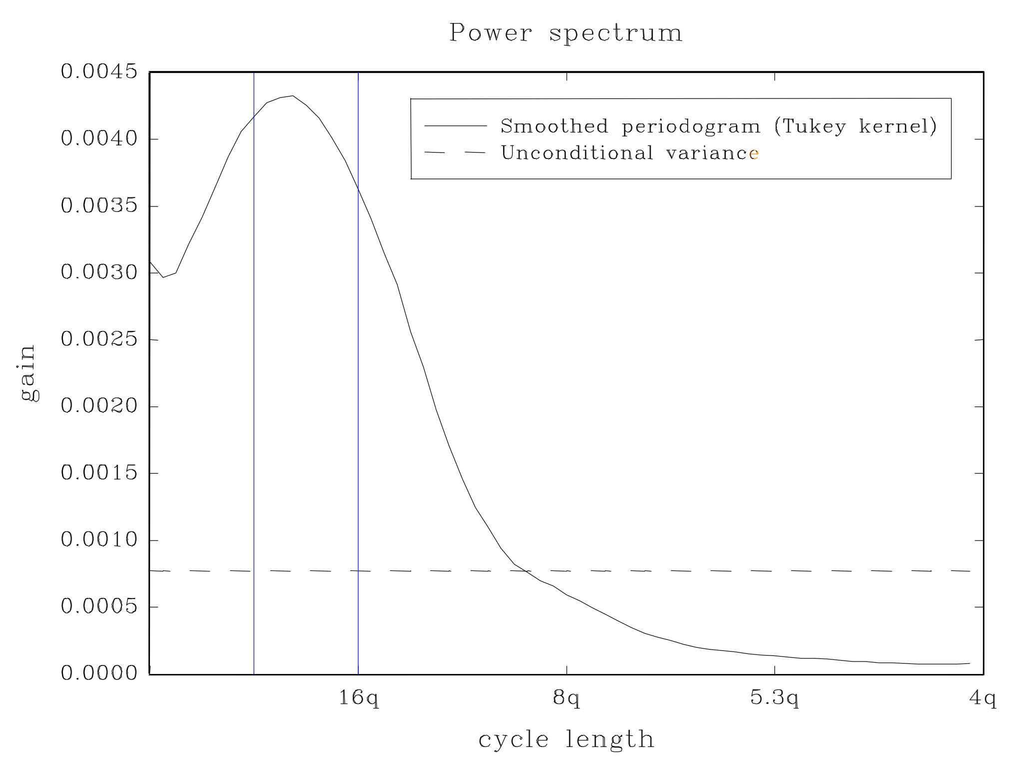
A technique commonly employed to analyse the business cycle properties of the data more formally is spectral analysis. This technique allows us to represent the business cycle in the frequency domain. However, in the New Zealand context examining cycles using spectral analysis is difficult simply because it requires a long span of data. New Zealand production-based GDP does not exist before 1982q3, and over much of the sample where data does exist the business cycle is ‘muddied’ with the effects of the reform program. Due to these problems we were unable to generate a plausible power spectrum of the historical output cycle. *A-priori*, however, in concordance with NBER definitions we would expect that the cyclical component of GDP displays cycles with an average duration somewhere between 4 and 6 years. The frequency domain representation of the model generated business cycle for output is shown in figure 3b below. Most of the power of the series is observed to lie between 16 and 32 quarters.[14] The length of model generated cycles thus conform to standard NBER definitions. To a large extent, the ability of the model to generate plausible business cycle properties reflects the way that the model properties were calibrated using an eclectic mix of matching properties and matching moments suggested by a range of empirical evidence. In contrast, many RBC models were calibrated relying primarily on matching moments techniques.

Figure 3a: Historical business cycle (solid) and model generated business cycle from one draw (dashed)



[14] Our thanks to Alasdair Scott for assistance with the spectral analysis. Note that the stochastically-generated output gap is strictly stationary; hence the positive gain observed at frequencies near zero in the power spectrum is spurious. See Hamilton (1994), Chapter 6, for a good treatment on spectral analysis.

Figure 3b: Frequency domain representation of the model-generated business cycle



In summary, data limitations aside, most model-generated standard deviations are not significantly different from the historical outcomes. Where most differences arise, they can be explained by the reaction function in FPS responding more vigorously to inflation deviations from target than over history. Furthermore, model-generated business cycles 'look like' how we might expect business cycles to appear. This gives us some confidence that the methodology used to examine the stochastic behaviour of the model economy is capturing the salient features of variability in the historical data. The robustness of these conclusions to other specifications of the shock generating process is examined next.

5 Sensitivity analysis

The results presented in Table 1 show the performance of the FPS model economy under one specification of the shock identification process. In this section alternative specifications are considered, including:

- the imposition of shocks to the policy instrument

- removing the cross-correlation structure amongst disturbances estimated from the VAR

- changing the causal ordering of some of the domestic variables in the VAR

Furthermore, the information the monetary authority has about the shocks is also altered to consider:

- the implication of the monetary authority also understanding the serial correlation structure of the shocks

- the implication of the monetary authority observing the shocks one quarter after they hit the economy

To evaluate the performance of the model economy under the alternative specifications of the shock process, root mean squared deviations (RMSDs) of output, inflation, interest rates, and the exchange rate are compared.[15] Significance tests are conducted by constructing *t-test* statistics to examine the hypothesis that differences between the RMSDs over the draws are not significantly different from zero. These results are presented in Table 2.

Also presented for each alternative specification of the shock identification process are the moments relative to history. Model-generated standard deviations are often not significantly different from history, although alternative characterisations of the shock process do result in behaviour of the model economy that is significantly different from the standard characterisation discussed in Section 4.[16]

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15 RMSDs are calculated rather than SDs because in a model with a non-linear Phillip's curve such as FPS, under stochastic simulations the long-run average outcome for output will be less than the deterministic level of potential output, and the average outcome for inflation will be above target. RMSDs penalise deviations from the control solution for model variables, and hence 'reward' outcomes that are closer to the control solution. See Laxton *et al.* (1994) for further elaboration on this point.

16 The impulses drawn from a standard normal distribution are seeded so that for all specifications considered, in any single draw an identical battery of impulses are generated. The difference between outcomes for a single draw is then a function of the size of the shocks, or the information the monetary authority has about the shocks. In this paper we have found that over 100 draws, the average RMSD statistics can be quite close. However, as the differences between the draws are mostly in one direction the hypothesis that the difference between the statistics is not significantly different from zero is rejected. In actual history there is only one 'draw', and hence one set of statistics of interest. If a historical statistic of interest lies within +/- 2 standard deviations of the mean of the model generated statistic, then the hypothesis that the historical statistic is not significantly different from the model generated statistic is not rejected.

Table 2: Results of Sensitivity Analysis

Shock identification process	**STATISTIC**			
	rmsd y	*rmsd* p	*rmsd rn*	*rmsd z*
Standard	2.80	1.09	3.12	5.03
Including rsl shocks	2.85	1.11	3.22	5.23
	(-1.83)	(-0.1)	(-3.40)*	(-6.04)*
no cross correlation	1.75	1.04	2.74	2.36
structure	(28.0)*	(2.8)*	(5.9)*	(40.0)*
causal ordering	2.75	1.08	3.06	4.93
alternative 1	(1.15)	(0.19)	(1.07)	(1.0)
causal ordering	2.73	1.07	3.05	4.95
alternative 2	(1.28)	(1.53)	(1.15)	(0.95)
causal ordering	2.83	1.08	3.12	5.04
alternative 3	(-1.05)	(0.91)	(-0.04)	(-0.11)
causal ordering	2.79	1.07	3.06	4.88
alternative 4	(0.19)	(1.5)	(1.5)	(2.15)*
causal ordering	2.80	1.05	3.00	4.84
alternative 5	(0.07)	(1.95)	(2.12)*	(2.0)*
monetary authority has	2.56	0.99	2.57	5.24
more information	(14.7)*	(10.8)*	(18.0)*	(-6.8)*
monetary authority has	2.87	1.16	3.08	5.12
less information	(-10.0)*	(-25.0)*	(4.0) *	(-15.8)*

* Indicates that model standard deviations are significantly different from the model standard deviations using the standard characterisation of the shock process at the 95% level of confidence.

5.1 The imposition of shocks to the policy instrument

As noted in section 2, impulses to the policy instrument are ignored for the standard shock identification process. This reflects uncertainty as to the precise interpretation of these impulses. In the real world, the policy instrument may in fact be subject to other innovations in addition to monetary policy actions, for example, changes in the term premium. To examine the implications of non-policy shocks shifting the instrument, the simulations are re-run with an exogenous shock to the policy instrument as defined by the VAR's IRF. However, the shocks are restricted to being only half the standard deviation estimate. In our opinion, this is a reasonable upper bound on the proportion of instrument shocks in the VAR that may reflect non-policy factors.

A-priori, the imposition of non-policy shocks should make the inflation control problem harder for the monetary authority as policy settings will also embody exogenous disturbances. However, the results presented in Table 2 illustrate that the RMSD of inflation is trivially different from the case where there are no disturbances to the instrument. The RMSD of the nominal interest rate does significantly increase, as does the RMSD of the exchange rate. However, despite this increase policy is still 'right' often enough to not significantly deteriorate the monetary authority's ability to control inflation.

The results presented in Table 2b illustrate that the increases in the RMSDs and standard deviations of the interest rate and the exchange rate are economically trivial in comparison to their behaviour historically. Thus incorporation of exogenous shocks to the policy instrument does not qualitatively alter the stochastic performance of the model economy.

5.2 No cross correlation in disturbances

In the standard characterisation of the shock generating process, the translation of the IRFs to shocks to the core model captures both the serial and cross correlations arising from the impulses. This is seen as a strength of the VAR approach. To examine the impact of ignoring the cross correlations, the stochastic simulations are re-run retaining the serial correlation structure, but not the cross correlation structure.

A-priori, removing the cross correlations should make the control problem easier for the monetary authority as there are fewer shocks to the behavioural equations. The results in Table 2 illustrate that the RMSD of all macro variables considered are all significantly lower than in the standard implementation. Furthermore, the decrease in the standard deviations of the macro variables considered is so large that this characterisation of the shock generating process renders stochastic behaviour of the model economy that is implausible relative to history. In Table 2b, although the standard deviation of the annual percentage change in output itself is not significantly different from the historical estimate, those of the components of demand are all significantly lower than the historical standard deviations. Furthermore, the standard deviation of the exchange rate is only about 1/3 the size it is over history. Finally, although not significantly different from history over the 1990s, the standard deviation of inflation is low. From a conservatism perspective, it would seem better to assume that the inflation control problem is harder rather than easier.

Table 2b: Historical and model-generated standard deviations for alternative characterisations of the shock process

VARIABLE	HISTORY		MODEL				
			standard	**shocks to policy**	**no cross correlation**	**authority knows more**	**authority knows less**
Standard deviations coefficient for annual percent changes in macro variables							
y	2.5		3.70 (0.60)*	3.80 (0.60)*	2.03 (0.30)*	3.50 (0.60)*	3.73 (0.60)*
c	4.1		3.85 (0.65)*	3.90 (0.66)*	2.32 (0.36)	3.55 (0.62)*	3.93 (0.66)*
I	12.4		14.34 (2.42)*	14.35 (2.40)*	7.93 (1.0)	15.36 (2.82)*	14.20 (2.40)*
c+i	4.7		5.88 (0.96)*	5.89 (0.95)*	3.28 (0.45)	5.86 (1.02)*	5.86 (0.95)*
g	3.2		3.69 (0.70)*	3.73 (0.74)*	2.10 (0.41)	3.35 (0.67)*	3.80 (0.74)*
x	5.0		2.50 (0.36)	2.50 (0.36)	2.48 (0.33)	2.29 (0.34)	2.50 (0.37)
m	6.8		5.42 (0.84)*	5.5 (0.86)*	3.14 (0.40)	5.85 (0.97)*	5.37 (0.82)*
z	7.4		5.62 (0.93)*	5.64 (0.94)*	2.18 (0.32)	5.83 (0.90)*	5.74 (0.94)*
tot	4.6		4.66 (0.64)*	4.68 (0.64)*	5.10 (0.68)*	4.46 (0.60)*	4.66 (0.64)*
Standard deviations coefficient of macro variables							
ygap	1.7		2.80 (0.44)	2.88 (0.45)	1.6 (0.3)*	2.56 (0.42)*	2.86 (0.46)
c/y	1.2		0.86 (0.25)*	0.87 (0.25)*	1.0 (0.14)*	0.99 (0.25)*	0.87 (0.25)*
i/y	1.1		1.24 (0.17)*	1.24 (0.17)*	0.9 (0.19)*	1.22 (0.19)*	1.23 (0.17)*
(c+I)/y	1.9		1.54 (0.25)*	1.57 (0.24)*	0.8 (0.08)	1.69 (0.23)*	1.53 (0.24)*
g/y	1.5		1.56 (0.32)*	1.57 (0.33)*	0.7 (0.17)	1.38 (0.28)*	1.62 (0.33)*
x/y	1.0		0.9 (0.15)*	0.9 (0.16)*	0.8 (0.15)*	0.81 (0.14)*	0.9 (0.16)*
m/y	1.1		1.32 (0.34)*	1.33 (0.34)*	0.8 (0.18)*	1.47 (0.39)*	1.33 (0.34)*
z	4.9		4.87 (0.95)*	4.87 (0.95)*	4.02 (0.58)*	5.07 (0.97)*	4.95 (0.95)*
tot	4.3		3.70 (0.5)*	3.70 (0.51)*	2.22 (0.49)	3.56 (0.50)*	3.70 (0.51)*
	85q2 to 97q2	*90q1 to 97q2*					
rsl	2.0	1	2.2 (0.36)*a	2.31 (0.37)*a	1.88 (0.42)*a	1.93 (0.29)*a	2.21 (0.37)*a
rn	5.7	2.7	3.11 (0.50)*b	3.19 (0.53)*b	2.7 (0.61)*b	2.56 (0.40)*b	3.08 (0.53)*b
p_4	3.9	1.2	1.04 (0.17)*b	1.06 (0.19)*b	0.99 (0.17)*b	0.97 (0.15)*b	1.11 (0.19)*b

*Indicates that model standard deviations are not significantly different from historical standard deviations at the 95% level of confidence. *a and *b indicate that the standard deviations are not significantly different from the historical sample standard deviations from 85q2 to 97q2 and 90q1 to 97q2 respectively. Note that the *tot* variable is measured in domestic price terms.

5.3 Alternative causal orderings of domestic variables in the VAR system

As outlined in section 3.1, to calculate IRFs the moving-average representation of the VAR system is identified by imposing a simple contemporaneous causal ordering. The structure of FPS implies an ordering of {*fd*, *tot*, *c* + *i*, *cpi*, *z*, *rsl*}. In this section, the stochastic behaviour of FPS under alternative causal orderings of the VAR is examined. We maintain the assumptions that foreign variables are not affected by domestic variables, and that the policy instrument is the most endogenous variable in the system. The alternative causal orderings examined are then:

1. {*fd*, *tot*, *c* + *i*, *z*, *cpi*, *rsl*}
2. {*fd*, *tot*, *z*, *c* + *i*, *cpi*, *rsl*}
3. {*fd*, *tot*, *z*, *cpi*, *c* + *i*, *rsl*}
4. {*fd*, *tot*, *cpi*, *c* + *i*, *z*, *rsl*}
5. {*fd*, *tot*, *cpi*, *z*, *c* + *i*, *rsl*}

The resultant RMSDs of output, inflation, the real exchange rate, and the interest rate under the alternative causal orderings are presented in Table 2. The standard deviations relative to history are contained in Table 2c. The results in Table 2 illustrate that relative to the performance of the model economy under the standard causal ordering, the alternative causal orderings have lower RMSDs, except for ordering 3. However, most of the RMSD statistics are not significantly different from those under the standard causal ordering. The exceptions are the real exchange rate for orderings 4 and 5, and the interest rate for ordering 5, all of which are significantly lower. Examining model-generated standard deviations relative to history in Table 2c shows that the qualitative stochastic behaviour of the model economy under the alternative causal orderings is essentially unaltered. Relative to history, most model-generated standard deviations are not significantly different from the historical outcome. The exception is for the standard deviation of the annual rate of change in the real exchange rate under orderings 1, 2 and 4, all of which are all significantly lower than the historical outcome. However, under these alternative causal orderings the standard deviation of the real exchange rate relative to equilibrium is not significantly different from the historical outcome.

When the causal ordering of the VAR is altered, both the auto and cross-correlations of the IRFs are changed for the variables re-ordered. Figure 4 contains graphs of the impulse responses under all the causal orderings considered. The results of this sensitivity analysis are comforting as they suggest that the stochastic behaviour of the FPS model is robust to these alternative orderings. Furthermore, it illustrates that moments generated under stochastic simulations reflect the properties of the model, and not simply the properties of the VAR.

Figure 4: VAR impulse response functions under alternative causal orderings

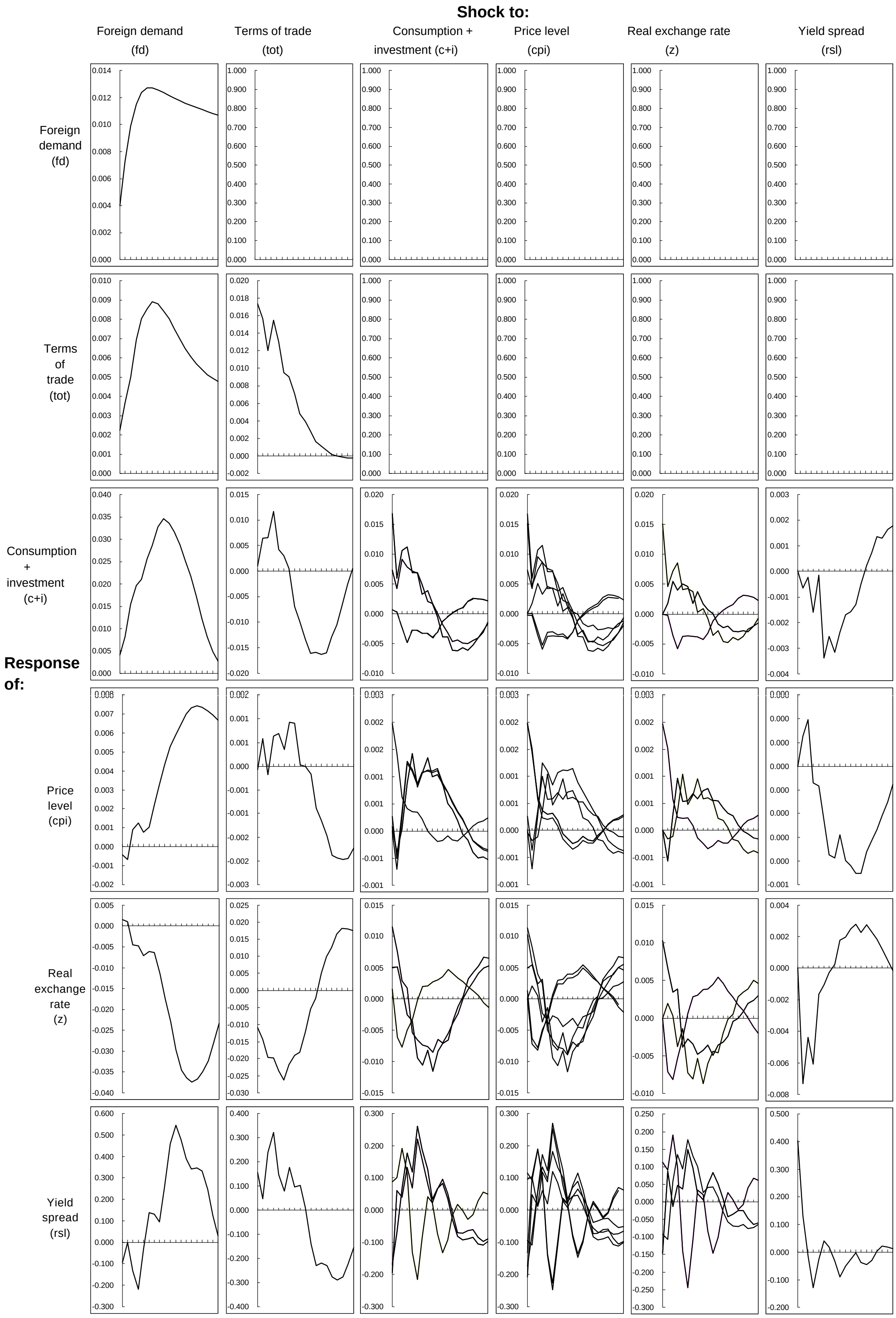

Table 2c: Historical and model-generated standard deviations with alternative causal orderings

VARIABLE	HISTORY		MODEL					
			standard	alternative causal orderings 1	2	3	4	5
Standard deviations coefficient for annual percent changes in macro variables								
y	2.5		3.70 (0.60)*	3.65 (0.62)*	3.66 (0.60)*	3.71 (0.58)*	3.70 (0.55)*	3.69 (0.57)*
c	4.1		3.85 (0.65)*	3.79 (0.65)*	3.78 (0.63)*	3.85 (0.61)*	3.83 (0.57)*	3.85 (0.58)*
i	12.4		14.3 (2.42)*	14.3 (2.42)*	14.4 (2.32)*	14.5 (2.40)*	14.6 (2.16)*	14.6 (2.20)*
c+i	4.7		5.88 (0.96)*	5.83 (0.97)*	5.85 (0.94)*	5.91 (0.93)*	5.92 (0.86)*	5.94 (0.87)*
g	3.2		3.69 (0.70)*	3.57 (0.74)*	3.57 (0.75)*	3.70 (0.68)*	3.70 (0.66)*	3.68 (0.65)*
x	5.0		2.50 (0.36)	2.43 (0.41)	2.43 (0.39)	2.46 (0.35)	2.45 (0.39)	2.44 (0.41)
m	6.8		5.42 (0.84)*	5.45 (0.80)*	5.47 (0.80)*	5.44 (0.86)*	5.53 (0.76)*	5.53 (0.76)*
z	7.4		5.62 (0.93)*	5.53 (0.80)	5.60 (0.82)	5.65 (0.91)*	5.45 (0.77)	5.43 (0.77)
tot	4.6		4.66 (0.64)*	4.68 (0.66)*	4.68 (0.66)*	4.65 (0.65)*	4.70 (0.64)*	4.66 (0.64)*
Standard deviations coefficient of macro variables								
ygap	1.7		2.80 (0.44)	2.75 (0.48)	2.74 (0.45)	2.82 (0.43)	2.79 (0.41)	2.80 (0.44)
c/y	1.2		0.86 (0.25)*	0.87 (0.25)*	0.90 (0.23)*	0.88 (0.21)*	0.89 (0.20)*	0.88 (0.18)*
i/y	1.1		1.24 (0.17)*	1.24 (0.17)*	1.25 (0.18)*	1.26 (0.17)*	1.27 (0.17)*	1.27 (0.16)*
(c+i)/y	1.9		1.54 (0.25)*	1.55 (0.26)*	1.56 (0.25)*	1.56 (0.25)*	1.57 (0.22)*	1.57 (0.22)*
g/y	1.5		1.56 (0.32)*	1.51 (0.31)*	1.48 (0.31)*	1.56 (0.32)*	1.53 (0.31)*	1.52 (0.33)*
x/y	1.0		0.9 (0.15)*	0.88 (0.17)*	0.88 (0.16)*	0.9 (0.16)*	0.88 (0.14)*	0.88 (0.16)*
m/y	1.1		1.32 (0.34)*	1.32 (0.34)*	1.31 (0.33)*	1.33 (0.34)*	1.31 (0.33)*	1.29 (0.31)*
z	4.9		4.87 (0.95)*	4.75 (0.84)*	4.78 (0.85)*	4.87 (0.91)*	4.71 (0.82)*	4.68 (0.81)*
tot	4.3		3.70 (0.5)*	3.72 (0.5)*	3.71 (0.5)*	3.70 (0.5)*	3.72 (0.5)*	3.72 (0.54)*
	85q2 to 97q2	*90q1 to 97q2*						
rsl	2.0	1	2.2 (0.36)*a	2.17 (0.38)*a	2.15 (0.39)*a	2.2 (0.38)*a	2.16 (0.35)*a	2.12 (0.38)*a
rn	5.7	2.7	3.11 (0.50)*b	3.07 (0.53)*b	3.05 (0.55)*b	3.11(0.52)*b	3.06 (0.49)*b	3.00 (0.53)*b
p_4	3.9	1.2	1.04 (0.17)*b	1.04 (0.15)*b	1.02 (0.15)*b	1.04 (0.17)*b	1.03 (0.16)*b	1.02 (0.15)*b

*Indicates that model standard deviations are not significantly different from historical standard deviations at the 95% level of confidence. *a and *b indicate that the standard deviations are not significantly different from the historical sample standard deviations from 85q2 to 97q2 and 90q1 to 97q2 respectively. Note that the *tot* variable is measured in domestic price terms.

5.4 The monetary authority has more information

In the standard shock identification process, the monetary authority sees all the shocks contemporaneously but does not see the serial correlation. It is perhaps naïve to assume the monetary authority knows the shocks hitting the economy in the current period. However, it may also be naïve to assume that they will not gain more information about other dimensions of the shock generating process as time passes. Incorporating realistic learning mechanism is outside the scope of this paper. However, examining the implications of full learning is possible by allowing the monetary authority to see the full auto and cross-correlation structure of the shocks. This effectively makes the control problem easier as the monetary authority makes fewer policy ‘errors’. Table 2 contains the results of this experiment. The RMSDs of all macro variables are lower than in the standard implementation. However, in Table 2b it is seen that the model-generated standard deviations are not substantially different relative to history relative to the standard specification. Hence, allowing the monetary authority to see the full shock structure does not change our qualitative conclusions reached in Section 4. Conceptually however, the informational assumptions inherent in this experiment are somewhat unpalatable. From a conservatism perspective, it would seem better to assume the monetary authority has less information than more.

5.5 The monetary authority has less information

The flip-side of the previous sensitivity experiment is to examine what occurs when the monetary authority has less information about the shocks. Specifically, the implications of the monetary authority seeing the shocks one quarter after they occur are examined. Arguably, this is more realistic, as in New Zealand most macro data is released quarterly only with a considerable lag and hence the monetary authority often does not learn about shocks until after they have occurred. This effectively makes the control problem harder as the monetary authority makes more policy ‘errors’. This is seen in Table 2, where the RMSDs of all macro variables aside from the nominal interest rate is higher than in the standard implementation. However, as in the case of the monetary authority having more information about the shocks, the stochastic behaviour of the economy relative to history is not substantively different than that of the standard shock specification. This can be seen in the final column of Table 2b.

6 Summary and agenda for future research

This paper presents the stochastic behaviour of the FPS model under shock uncertainty. As FPS is a calibrated structural macro model there are no historical residuals that can be used for stochastic simulations. Instead, representative historical impulses are derived from an estimated VAR model. These impulses are then mapped into shocks to the corresponding behavioural equations in the FPS model. The model is then simulated quarter-by-quarter with unanticipated randomly generated shocks hitting every quarter.

Under stochastic simulations, most model-generated standard deviations are not significantly different from the historical standard deviations of the New Zealand economy. Differences that arise can largely be explained by the reaction function in FPS responding more vigorously to control inflation than may have been the case historically. This provides some assurance that the methodology employed does capture the salient features of the stochastic properties of the New Zealand economy. The robustness of these conclusions to other specifications of the shock generating process is examined. Adding non-policy shocks to the policy instrument, changing the causal ordering of the VAR, and affording the monetary authority more or less information do not materially alter the model's ability to replicate variability observed in the historical data. When the cross-correlation in the IRFs are ignored, however, the macro variability of the model economy is too low relative to history.

Our future research agenda will be to provide more robustness testing of the behaviour of FPS under shock uncertainty. There are two main research strands to be pursued in this respect. Firstly, in evaluating model-generated moments relative to history it is necessary to render historical data stationary. This necessitates filtering the historical data. What constitutes the correct filter(s) to apply is an open question. Secondly, effort is being directed towards building a more complete representation of historical shocks than that offered by the VAR described in this paper. In particular we are most interested in incorporating a measure of the supply side, and extending the foreign block of the VAR by incorporating foreign inflation and the responses of foreign monetary authorities.

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