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Australian Economic Growth: Non-linearities and International Influences[•]

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Abstract

This paper considers the extent to which fluctuations in Australian economic growth are affected by domestic and overseas economic performance. We investigate the performance of a range of non-linear models versus linear models, comparing the models using Bayes factors and posterior odds ratios. The posterior odds ratios favour non-linear specifications in which fluctuations in economic activity in the US affect Australia's economic performance. Our results suggest that an exogenous negative shock will be more persistent, lead to greater output volatility, and have a greater impact on growth, than a positive shock of equal magnitude.

JEL Codes: F41, C11, C22

Keywords: Business Cycle, Coincident Index, Threshold Autoregression, Bayesian Model Averaging

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1. Introduction

Since the onset of the Asian economic crisis in July 1997, the conventional wisdom has been that since Australia is a small country with a heavy reliance on primary commodity exports, at least some of the impact of the recessions in most East Asian countries must be transmitted to Australia. This perception is perhaps most evident in the recent volatility of the Australian dollar exchange rate, which depreciated by over 7 per cent (in nominal terms) against the $US between May 22 and June 10 1998. The $A later reached an all-time low of 55.5 US cents on August 27, 1998. A large part of the depreciation stemmed from lowered expectations of Australia's growth as the economies representing 60 per cent of its total export market entered severe recessions.

Similarly, the idea that "when the United States sneezes, Australia catches pneumonia" is not new. There have been at least three channels identified by which fluctuations in U.S. markets might affect the Australian economy. Gruen and Shuetrim (1994) document the existence of a long-run equilibrium relationship between U.S. and Australian GDP growth rates. de Roos and Russell (1996) focus on exports as a channel through which U.S. business cycle fluctuations may be transmitted to Australia. These authors also identify a link between the share markets of the United States and Australia, and that share market effects on investment may serve to raise the correlation between the two countries' business cycles. Brooks and Henry (2000) show that a non-linear relationship exists between U.S. and Australian equity markets. In particular, they show that Australian markets are more volatile when the U.S. market is trending downwards.

This paper examines the impact of economic fluctuations on Australia, using the nonlinear threshold regression approach. This framework allows for asymmetry in the effects of exogenous shocks, reflecting the possibility that economic contractions are characterised by fundamentally different behaviour than expansions. We use generalised impulse response functions to trace out the regime-dependent response to positive and negative shocks of a given magnitude.

This paper has five sections. The following section describes the construction of the data. Section three provides a brief overview of threshold regression models. Section four discusses the results of the empirical investigation, while the final section presents a brief summary and some concluding comments.

2. Coincident Indexes

A composite coincident index (or 'coincident index' for short) is used in economic indicator analysis as a proxy for the current 'state of aggregate economic activity.' Such an index is a combination of several time series that one would expect to contain information about the current state of the economy. Examples of such series include industrial production, employment and unemployment, real retail sales, real household income, and real gross domestic product (GDP). Boehm and Summers (1999) provide an overview of the use of coincident (and leading) indexes in forecasting and analysing business cycles. Summers (1997a,b) uses composite coincident indexes in a VAR model to assess the relative importance of international and domestic business cycle fluctuations in Australia and New Zealand.

Several composite coincident indexes of economic activity exist for the United States, including indexes constructed by the Conference Board, the Foundation for International Business and Economic Research (FIBER) and the Economic Cycle Research Institute (ECRI). The latter two institutes also produce indexes for several other countries, including Japan. The coincident index for Australia is produced by the Melbourne Institute. In this paper, we use the U.S. and Japanese indexes constructed by FIBER. The data are monthly and cover the period from March 1970 to May 1998.

3. Threshold Regressions

The two regime threshold regression model for a univariate time series y_t can be written as

$$y_t = (\phi' x_t + \varepsilon_{1t}) 1_{(z_t \leq \gamma)} + (\theta' x_t + \varepsilon_{2t}) 1_{(z_t > \gamma)} \tag{1}$$

where y_t is a scalar, x_t is a k $\times$1 vector (which includes a constant and may include lagged values of y_t or the other regressors), z_t is a known function of the data and $1_{(.)}$ is an indicator function, taking the value 1 when the condition in parentheses is met. The threshold parameter is γ. The k $\times$1 parameter vector ϕ relates y_t to x_t when $z_t \leq \gamma$ while θ applies in the other regime.

Heteroscedasticity across the regimes can be incorporated in (1) by setting $\mathrm{var}(\varepsilon_{it}) = \sigma_i^2$, *i=1,2*. This model reduces to a standard regression model when $\phi = \theta, \sigma_1^2 = \sigma_2^2$. A special case of equation (1) is the self exciting threshold autoregression (SETAR) in which $x_t = (y_{t-1}, y_{t-2}, ..., y_{t-p})$, the threshold variable $z_t = y_{t-l}$ and l is the unknown delay lag. Henry, Olekalns and Summers (2000), Caner and Hansen (1997), and Potter (1995), *inter alia*, provide examples of this model.

Maximum likelihood estimation of the parameters, ϕ, θ, σ_1^2, σ_2^2, γ and l can be achieved by minimising the residual variance via sequential conditional least squares.[1] Alternatively, Bayesian analysis in this context is particularly attractive because numerous analytical results exist. Specifically, conditional on z_t and γ, and

[1] Hansen (1997) provides further details.

with Normal-Inverted gamma priors on the regime coefficients, the posterior distributions of these coefficients are also Normal-Inverted gamma[2]. The marginal posteriors can be obtained by using a discrete uniform prior on the threshold parameters. Geweke and Terui (1993) and Koop and Potter (1997, 1998) provide further details.

In this paper, we estimate a version of (1) in which is an autoregression of order *p*:

$$y_t = (\mu_1 + \phi(L)y_{t-1} + \varepsilon_{1t})1_{(z_t \leq \gamma)} + (\mu_2 + \theta(L)y_{t-1} + \varepsilon_{2t})1_{(z_t > \gamma)} \qquad (2)$$

here, y_t represents the current state of the Australian economy, measured by the (logarithmic) growth rate of the coincident index of economic activity, or real GDP. The lag operator polynomials $\varphi(L)$ and $\theta(L)$ are both of order *p*. This assumption involves no loss of generality, since differing lag orders or non-consecutive lag coefficients can be incorporated in (2) by allowing some elements of these polynomials to be zero. We model the threshold variable, z_t, as a function of the state of the economy domestically or in either the United States or Japan, as measured by the coincident index for each country. The value of z_t relative to the threshold, γ, determines the regime governing the evolution of Australian activity. Put simply, when z_t lies above the threshold, Australian economic growth is in one regime, while a value of z_t below the threshold puts Australian growth into the other regime. The characteristics of each regime are determined by the estimated parameters governing that regime.

There are three points to note regarding the specification in (2). First, our analysis uses the *growth rates* of the variables under study. Harding and Pagan (1998)

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[2] That is, the regression coefficients have a Normal distribution, while the variances have an inverted gamma distribution.

point out that inferences regarding the *classical* business cycle (i.e., fluctuations in the level of economic activity) are properly made by examination of the growth rates of economic activity. Second, notice that the only way in which US or Japanese economic fluctuations can affect Australia in (2) is through the threshold effect. The specification in (2) is the simplest possible departure from a linear *AR(p)* model (except for a SETAR model). Alternative specifications could include lags of the US or Japanese variables, as is done in Henry and Summers (1999b). We briefly explore a specification of this type below. Third, given that the model is univariate, we do not attempt to distinguish between domestic and external shocks (i.e., we do not attempt to identify any particular source of disturbances, ε_t). Rather, we treat all shocks simply as exogenous.

We estimate several versions of (2), using the Bayesian approach of Koop and Potter (1998). Besides varying the country represented by the threshold variable (Australia, Japan or the US), we also study different forms of the threshold function. For example, let $y_t = 100 \times \left(\ln CI_t^{AU} - nCI_t^{AU}\right)$ and $z_t = 100 \times \left(\ln CI_t^{US} - nCI_t^{US}\right)$ be the growth rates of Australian and US Coincident Indexes, respectively. We use three different specifications for the threshold variable: z_t itself (US growth), Δz_t (the *change* in US growth over the past quarter), and $\left(z_t - z_{t-l}\right)/l$ (the average change in US growth over the past l quarters). Note that the last two specifications are identical in the case of $l=1$. We refer to these models as the current growth (G), change in growth (CG), and average change (AC) models, respectively. We estimate both hetero-and homoscedastic versions of these models, denoting the latter by appending an ‘H’ to the model abbreviation (so CGH is the homoscedastic change in growth model).

Bayes Factors and Priors

A major advantage of the Bayesian approach used in this paper is that competing models (even non-nested ones) can easily be compared using Bayes factors. Given a data set *D*, the Bayes factor (*BF*) for comparing two models *A* and *B* is computed as:

$$BF = \frac{pr(D \mid A)}{pr(D \mid B)} \tag{3}$$

which is the ratio of the marginal probability of the data under model *A* to its marginal probability under model *B*. Another way of writing the Bayes factor is in terms of the prior and posterior odds ratios of the two models:

$$BF = \frac{pr(A \mid D)/\, pr(A)}{pr(B \mid D)/\, pr(B)} \tag{4}$$

In this expression, the prior odds in favour of model *A* are given by *pr(A)/pr(B)*. In the case of both models being equally likely *a priori*, the Bayes factor is just the posterior odds in favour of model *A.* Kass and Raftery (1995) provide a general discussion of Bayes factors, while Koop and Potter (1998) present an application similar to the one in this paper.

Note that quantities such as $pr(D \mid A)$ in (3) require the integration of the posterior distribution of model A's parameters over the relevant parameter space. These integrals are intractable in most cases, and must be computed numerically or by Monte Carlo methods. In the present case however, analytical results for the Bayes factors exist, which simplifies the computations considerably. See Koop and Potter (1997, 1998) for details.

The prior distributions we use are proper (i.e., they integrate to one), but are designed to be diffuse relative to the likelihood function. The need for proper priors in model comparisons of this kind is explained in Koop and Potter (1998), and is due to the fact that the Bayes factors have an inherent bias towards the more parsimonious linear models. A completely non-informative prior drives this bias to its extreme; all posterior probability will be allocated to the linear model.

Our priors are very similar to those used by Koop and Potter (1998). Specifically, we use Normal priors on all the regression coefficients (i.e., the elements of $\phi(L)$ and $\theta(L)$ in (2)). All of these distributions have mean zero. Since the model is in growth rates, this prior is centred on a random walk representation for the (log) level of the Australian coincident index. The prior variances for these coefficients are unity for the first lag, 0.8 for the second, 0.64 for the third, and so on. The prior on the constant term is $N(0,4)$.

The prior on the regime-specific variances σ_i^2 is inverted-gamma with mean 1 and 3 degrees of freedom. This value for the degrees of freedom parameter is the lowest (i.e., most diffuse) which ensures the existence of the first two moments of the posterior distributions of the regime coefficients. The mean and standard deviation of the monthly (logarithmic) growth rates in the Australian coincident index over our sample period are 0.238 and 0.739 per cent, respectively. This suggests that our priors are reasonable.

The prior for the threshold variable is flat (i.e., uniform) over the observed range of the data, while the delay lag prior is also uniform, from 1 to the lag length estimated for each model.[3]

4. Empirical Results

In the first stage of our analysis, we estimated (2) allowing for up to twelve lags, giving a total of 252 models for the Australian coincident index (six nonlinear

[3] Although the threshold variable is in principle continuous, in practice it is discrete (i.e., we only observe a discrete subset of values for Australian economic growth). Koop and Potter (1998) explain the effect of this on the computation of the marginal likelihoods and Bayes factors.

TAR(p) models plus the linear AR(p) for p=1,...,12, with thresholds in the US, Japanese or Australian coincident index). The posterior probabilities of the various models are shown in tables 1. In addition to reporting the posterior probability for a particular model, the entries in each column can be added to give the marginal probability of each model across all lag lengths. This probability is shown in the row labelled “Marginal.” The evidence in favour of the linear AR model can be assessed by comparing the sum of the first six columns (i.e., integrating over the various nonlinear models and lag lengths) with the sum of the last column (integrating over lag lengths for the linear model). Since none of the models has a higher *a priori* likelihood than any other, the Bayes factor for one model relative to another is obtained simply by computing the ratio of the respective posterior probabilities.

Table 1 shows the posterior probabilities for the various models in turn. Panel A displays the results when the Japanese coincident index is the threshold variable, Panel B reports the results with the US coincident index in that role, and Panel C presents the results from the SETAR model. There is a good deal of evidence that fluctuations in the Japanese economy have a nonlinear effect on the Australian economy. Over one third of the posterior probability is assigned to one nonlinear model, the homoscedastic average change (*AH*) model with 2 lags. The heteroscedastic version of this model receives a further 9 per cent probability, for a total of 45.7 per cent probability allocated to the 2-lag average change model. The linear model with the highest probability is an *AR(3)*, which receives about 11 per cent posterior probability. Overall, the posterior odds in favour of a nonlinear model are 2.24 to one (69.2 per cent to 30.8 per cent). If we concentrate on the models with the highest probability in each class (linear vs. nonlinear), the odds are 3.39 in favour of the *AH(2)* relative to the *AR(3)* .

The evidence for a nonlinear influence of the US on Australia is much stronger. Panel B of Table 1 shows that over 99 per cent posterior probability is allocated to the two versions of the G model, in which the threshold variable is lagged US economic growth. No linear model receives as much as 0.1 per cent probability, and the odds in favour of a nonlinear model are 587 to one. Panel C shows that the SETAR model is not supported by the data. Linear models attract 92% posterior probability, with the AR(3) model being the most likely.

In Table 2 we compare across the various models. In addition to the various threshold and univariate AR models discussed previously, we also present results from a linear model which includes lags of both the US and Japanese coincident indexes. We refer to this as the 'VAR model' as it represents the 'Australia equation' from a three-variable vector autoregression. When the threshold is set in the growth rate of the US coincident index almost all the posterior probability (99.48%) is allocated to the 2 lag model and its homoscedastic counterpart. The remaining probability is spread across various models in the Japanese coincident index and the linear models. In particular, notice that the 'VAR' model, allowing lags of the US and Japanese coincident indexes to affect Australian growth directly, receives virtually no posterior support.

Based upon the results in Tables 1 and 2 we consider the two lag model with the threshold set by the growth of the US economy to be (overwhelmingly) the most likely out of the set of models considered.

Parameter estimates for the *A(2)* model are presented in table 3. In addition to the posterior mean and standard deviation of each parameter we present the maximum likelihood estimate of the parameter and the associated asymptotic standard error. When we evaluate the growth rates across regimes based on the posterior mean estimates, a clear asymmetry emerges. When growth in the US economy is below the threshold (-0.1247 per cent per month), the Australian economy contracts, on average, by 0.6031 per cent per month. On the other hand, when US growth is above the threshold, the estimated expansion in the Australian economy is 0.3892 per cent per month.[4] Furthermore, the contractionary regime displays relatively higher volatility than the expansionary regime, as is clear from the estimates of the regime-specific residual variances. Thus, not only does 'Australia catch a cold when the US sneezes,' uncertainty about the health of the Australian economy increases following a negative shock. However, notice that a contraction in the US coincident index is not sufficient to cause Australia to enter the low-growth, high-variance regime; the contraction in the US economy must exceed the threshold for this to occur. To continue the analogy, a 'mere sniffle' in the US may not be contagious.

In a non-linear model the impulse responses will depend upon the initial condition, the magnitude of the shock and the sign of the shock (see Koop, Pesaran and Potter, 1996). Table 4 presents generalised impulse responses (GIRFS) to positive and negative shocks of magnitude 2. The asymmetric response to shocks is clear, with negative shocks taking much longer to die out than positive shocks in all three cases. That is, irrespective of the economy's initial conditions, the effects of a negative shock will be more persistent than those of a positive shock of equal size.

5. Summary and Conclusions

This paper has examined the extent to which domestic and overseas economic fluctuations may have non-linear effects on the growth rate of the Australian economy. Using Bayesian methods, we compare models in which Australian economic growth is influenced by purely domestic factors, or by economic

[4] At the maximum likelihood estimates, the growth rates are –0.137 and 0.2067 in regimes 1 and 2,

fluctuations in Japan or the United States. There is considerable evidence that fluctuations in the American economy have a nonlinear effect on Australia. The rejection of the linear model in favour of the non-linear model in US growth has important implications. The analysis casts a new light on the Gruen and Sheutrim (1994) result, and while our analogy to contagion between the US and Australia appears valid, the evidence suggests that the dynamics of this interrelation are highly non-linear. In particular the effects of a positive and negative shock are markedly different for Australian growth. The impulse response to a negative shock is larger than to a positive shock of equal magnitude. Hence when "when the U.S. sneezes, Australia catches pneumonia" may only be part of the story. News that the US has not sneezed does not imply that Australia is necessarily healthy.

Our analysis was largely a model comparison exercise. The results of the empirical work raise many questions. Our results provide strong evidence in favour of the non-linear model as a characterisation of the data generating process underlying Australian growth. Pagan (1997) and Harding and Pagan (1999) raise concerns about the ability of univariate non-linear models to reproduce certain key features of the data. While we are mindful of these concerns, it seems clear that a strictly linear model is an inappropriate specification. Furthermore, in addition to the fact that our simple non-linear specification fits the data better than a linear model, our approach allows external economic fluctuations to have a direct influence on Australia's economy.

We have presented some evidence that the non-linear model continues to be overwhelmingly preferred over the 'Australian equation' in a three-variable VAR. This lack of support for the 'VAR model' is surprising. We believe further work on

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respectively. The corresponding variances are 0.4595 and 0.4408.

such models, using systems-based versions of the methods presented here, is needed in order to determine the reasons for the relatively poor performance of standard VARs.

The overwhelming evidence in this paper suggests that the mechanism which propagates business cycle shocks to Australia is non-linear. Large negative shocks (ie, those which occur when US growth is below the threshold) are more persistent, lead to greater uncertainty, and have a greater impact on Australia's growth rate than positive shocks of an equal magnitude.

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Table 1: Posterior Model Probabilities, by Model

Panel A. Threshold in Japanese Coincident Index							
Lags	G	GH	M	MH	A	AH	AR
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0098	0.0403	4.6578	18.2393	9.3157	36.4786	6.1871
3	0.0169	0.0278	0.0053	0.0074	0.0080	0.0112	10.7684
4	0.0204	0.0906	0.0058	0.0112	0.0077	0.0150	4.7634
5	0.0006	0.0028	0.0027	0.0095	0.0033	0.0119	5.8652
6	0.0001	0.0002	0.0118	0.0165	0.0142	0.0198	2.6370
7	0.0151	0.0384	0.0005	0.0016	0.0006	0.0018	0.4674
8	0.0000	0.0001	0.0012	0.0002	0.0013	0.0002	0.0852
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0490
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0170
11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0047
12	0.0000	0.0000	0.0000	0.0001	0.0000	0.0001	0.0320
Marginal	0.0629	0.2003	4.6851	18.2859	9.3509	36.5386	30.8764
Panel B. Threshold in US Coincident Index							
Lags	G	GH	M	MH	A	AH	AR
1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	29.1249	70.6456	0.0001	0.0001	0.0000	0.0001	0.0343
3	0.0243	0.0234	0.0000	0.0003	0.0001	0.0004	0.0597
4	0.0009	0.0019	0.0000	0.0000	0.0000	0.0000	0.0264
5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0325
6	0.0001	0.0001	0.0000	0.0023	0.0000	0.0000	0.0146
7	0.0000	0.0000	0.0006	0.0000	0.0007	0.0027	0.0026
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0005
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0003
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Marginal	29.1502	70.6711	0.0007	0.0027	0.0008	0.0032	0.1712
Panel C. Threshold in AUS Coincident Index (SETAR)							
Lags	G	GH	M	MH	A	AH	AR
1	0.0002	0.0000	0.0007	0.0027	0.0000	0.0000	0.0000
2	2.1895	1.4943	0.5233	0.7336	0.3048	1.0113	27.9538
3	0.1634	0.4271	0.0421	0.2026	0.0291	0.1344	39.2646
4	0.0015	0.0016	0.0023	0.0106	0.0087	0.0389	12.5014
5	0.0023	0.0036	0.0007	0.0030	0.0024	0.0047	10.0440
6	0.0001	0.0002	0.0000	0.0001	0.0009	0.0038	2.6253
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.2402
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0203
9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0051
10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0007
11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002
Marginal	2.3569	1.9268	0.5691	0.9525	0.3458	1.1931	92.6557

Table 2: Posterior Model Probabilities- All Models

Panel A. Threshold in Japanese Coincident Index

Lags	G	GH	M	MH	A	AH
1	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.03	0.10	0.05	0.20
3	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00
7-12	0.00	0.00	0.00	0.00	0.00	0.00

Panel B. Threshold in US Coincident Index

Lags	G	GH	M	MH	A	AH
1	0.00	0.00	0.00	0.00	0.00	0.00
2	29.11	70.60	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00
7-12	0.00	0.00	0.00	0.00	0.00	0.00

Panel C. Threshold in AUS Coincident Index (SETAR)							Linear Models	
Lags	G	GH	M	MH	A	AH	AR	VAR
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.04
3	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00
6	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
7-12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 3. Parameter estimates, Threshold in US Coincident Index

Parameter	Posterior Mean	Posterior SD	MLE	Asymptotic SE
μ_1	-0.1892	0.0848	-0.0470	0.1004
ϕ_1	0.2522	0.1041	0.1061	0.1201
ϕ_2	0.4341	0.1111	0.5509	0.1152
σ_1	0.4937	0.0565	0.4595	--
μ_2	0.2789	0.0481	0.1322	0.0737
θ_1	0.0553	0.0603	0.1611	0.0932
θ_2	0.2281	0.0587	0.2444	0.0916
σ_2	0.3942	0.0251	0.4408	--
γ	-0.1247	--	-0.1037	--

Table 4. Generalised Impulse Response Functions, Threshold in US Coincident Index

History	Fast Increase		Fast Decrease		No Change	
Horizon/Shock	+2	-2	+2	-2	+2	-2
0	1.3465	-1.3465	1.3148	-1.3148	1.3269	-1.3269
1	0.1371	-0.4423	0.1723	-0.3991	0.1801	-0.4208
2	0.4558	-0.5878	0.5013	-0.5846	0.4851	-0.5898
3	0.1387	-0.3212	0.1728	-0.3045	0.1668	-0.3189
4	0.1998	-0.3058	0.2352	-0.3041	0.2194	-0.3091
5	0.1019	-0.2069	0.1261	-0.2013	0.1138	-0.2075
6	0.1029	-0.1776	0.1275	-0.1765	0.1150	-0.1801