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Let it be known that as of Sep.14, 2009, materials reported in the following paper were, to our surprise and seriously violating our reprint permission, made into Ch.4 in an e-book edited by the author, entitled "*Business Cycle Fluctuations and Economic Policy*," ISBN 978-1-60741-406-3, published by Nova Science Publishers, Inc. in 2009. In light of his breach of contract and disrespect of the academic code of honor, IJBE will not consider any future manuscript submitted by the author indefinitely.

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Asymmetric Business Cycle Fluctuations and Contagion Effects in G7 Countries

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Abstract

This research studies possible existence of business cycle asymmetries in Canada, France, Germany, Italy, Japan, UK, and US real GDP growth rates. Asymmetries in these countries are modeled using in-sample as well as jackknife out-of-sample forecasts approximated from artificial neural networks. Univariate results show statistically significant evidence of asymmetries in business cycle fluctuations in all the series; this is corroborated with bivariate analysis, which also finds evidence of contagion effects in these countries.

Key words: asymmetries; business cycles; neural networks; nonlinearities; vector autoregressions

JEL classification: C32; C45; E32

1. Introduction

A wide body of empirical research that focused on detecting business cycle asymmetries in economic fluctuations employed US macroeconomic time series to assess the presence of business cycle asymmetries. In this context Beaudry and Koop (1993), Brunner (1992, 1997), and Bidarkota (1999, 2000) found evidence of business cycles asymmetries in US gross national product. Likewise, Neftci (1984) and Ramsey and Rothman (1996) studied US unemployment rates and concluded that asymmetric business cycle fluctuations were present in the series. Similarly, Potter (1995), Anderson and Vahid (1998), and Anderson and Ramsey (2002) showed an existence of business cycle asymmetries in macroeconomic time series. In contrast, Falk (1986), Sichel (1989), Delong and Summers (1986), and Diebold and Rudebusch (1990) were unable to find significant evidence of business cycle asymmetries in the series they studied.

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Nonlinearities imply that the effects of contractionary and expansionary monetary policy and other shocks to output are asymmetric. Therefore, any nonlinearity would invalidate the measures of the persistence of monetary policy or any other shock to output that is based on linear models including those derived from linear vector autoregressions when the underlying data generating process is nonlinear. Policymakers would be interested to know the impact of monetary policy or any other shock to output. Therefore, it is imperative to detect possible nonlinearities in data series so that appropriate forecasting models (linear or nonlinear) are employed to anticipate the impact of shocks to output. Moreover, it would be of interest for macro theorists to know if business cycles are alike. If they are dissimilar, economists would need to come up with new theories of business cycles that take into account underlying country-specific institutional factors. Therefore, the present research focuses on possible existence of business cycle asymmetries in real GDP growth rates in the group of the seven (G7) industrialized countries: Canada, France, Germany, Italy, Japan, the UK, and the US.

A number of studies including Auerbach (1982), Gordon (1986), Kling (1987), Koch and Rasche (1988), Diebold and Rudebusch (1990), Hamilton (1989), Klein (1990), and Estrella and Mishkin (1998) focused on business cycle research; however, only a few studies investigated possible asymmetries in business cycle fluctuations using international data. For example, Andreano and Savio (2002) investigated business cycle asymmetries in G7 countries using Markov switching models but were not able to detect asymmetries in France, Germany, and the UK. Similarly, Kiani and Bidarkota (2004) studied possible business cycle asymmetries in G7 countries but, despite using nonlinear and switching time series models with stable distributions and long memory, were not able to find evidence business cycle asymmetries in French and UK series. Thus the basic question of whether business cycles in G7 countries are alike remains unanswered. Motivated by this shortcoming, the present study uses artificial neural networks (ANN), which are highly flexible nonlinear models that can fit any data series without taking into consideration the distribution of the underlying data generating process.

Neural networks have been applied successfully in many disciplines including business and economics. For example, Kuan and White (1994) and Swanson and White (1995, 1997a, 1997b) employed ANN in economics. Hutchinson et al. (1994), Garcia and Gencay (2000), and Qi and Madala (1999), and Gencay (1999) employed ANN in finance. However, only Vishwakarma (1995), Qi (2001), Kiani (2005), and Kiani et al. (2005) focused on business cycles using ANN. Based on this earlier research, this paper approximates in-sample and jackknife out-of-sample forecasts from neural networks and linear models to construct neural network tests that were originally proposed by Terasvirta et al. (1993) for possible existence of business cycle asymmetries in G7 real GDP growth rates. Moreover, the present analysis is extended to the bivariate framework to reveal further evidence of asymmetric fluctuations, linkages, and spillover effects within these countries.

The remainder of this study is organized as follows. Section 2 includes a brief description of neural network models and underlying tests, and Section 3 presents data sources, hypotheses tests, empirical results on hypotheses tests, and forecast performance of neural network models. Section 4 contains brief conclusions.

2. Empirical Model: Artificial Neural Network

ANNs represent an artificial intelligence technology that mimics the human brain's learning and decision-making process. The ability to process information makes ANNs powerful computational devices that can learn from examples and generalize these learning to solve problems never seen before (Reilly and Cooper, 1990). ANNs are nonlinear, nonparametric statistical methods that are independent of the distributions of the underlying data generating processes (White, 1989b). The present research employs ANNs to investigate possible existence of business cycle nonlinearities in G7 real GDP growth rates using in-sample forecasts approximated from ANNs that are extensions of those in Kiani and Bidarkota (2004). Likewise, this analysis is extended to neural network tests using a bivariate framework that is constructed using in-sample and jackknife out-of-sample approximations from neural networks to investigate the behavior of these models out-of-sample and to investigate spillover and contagion effects within the G7 countries.

Quenouille (1949) used jackknife re-sampling to reduce the bias in estimators, and Tuckey (1958) employed jackknife re-sampling to estimate variances. Wu (1990) introduced the sub-sample jackknife technique, which was also used by Politis and Romeo (1994). Later, Politis et al. (1997), Ziari et al. (1997), and Kiani et al. (2005) also used this re-sampling technique. In the sub-sample jackknife, more than one observation is dropped to estimate out-of-sample forecasts of the remaining $m = n - d$ observations, where n is the total number of observations and $d = 2, \ldots, n-1$.

2.1 Neural Network Linearity Test

The model for constructing neural network linearity test due to Terasvirta et al. (1993) is based on a neural network model similar to that presented here. Although this model is constructed to work with lagged exogenous variables from more than one series, it can be restricted to contemporaneous independent and lagged variables from a single series. A general form of the neural network linearity test is:

$$y_t = \pi' w_t + u_t , \tag{1}$$

$$\hat{u}_t = \pi' w_t + \sum_{j=1}^{k} \theta_{0j} \psi\left(\gamma_j' w_t\right) + v_t , \tag{2}$$

where:

$$u_t \sim N(0, \sigma^2), \quad w_t = (1, \tilde{w}_t')', \quad \tilde{w}_t = (y_{t-1}, \ldots, y_{t-p}, x_{t-1}, \ldots, x_{t-p})' ,$$

$$\pi = (\pi_0, \ldots, \pi_p)' ,$$

$$\psi(\gamma' w_t) = \left(1 + \exp(-\gamma' w_t)\right)^{-1} ,$$

and π_0 is an intercept. Equation (2) shows a nonlinear neural network model that nests the linear model shown in (1). Under normality conditions, the test statistic for this test is distributed approximately $F(m, n-p-m-1)$. The distribution of this test statistic is approximate due to the nuisance parameter appearing under the alternative hypothesis (see Davies, 1977; Andrews, 2001). The test statistic is:

$$TS = \frac{(SSE_1 - SSE_2)/m}{SSE_2/(n-p-m-1)}, \tag{3}$$

where m denotes the number of restrictions, n the number of observations, and p the number of lags in the linear and ANN models.

We consider in-sample forecasts from ANN in conjunction with linear models to construct neural network linearity test statistic, which is calculated using (3) for each of the real GDP series. We also consider neural network linearity tests constructed from jackknife out-of-sample forecasts using linear models and ANN.

While neural network linearity test are constructed using in-sample forecasts from the G7 real GDP series using univariate linear models and neural networks, the present study also considers constructing neural network linearity tests from in-sample and jackknife out-of-sample forecasts from bivariate linear models in conjunction with ANN. The rational for this extension is to find additional evidence of business cycle asymmetries (if any) and to consider linkages, spillovers, and contagion effects across countries. These types of linkages were also discussed in Anderson and Ramsay (2002) in a bivariate framework for Canadian and US time series.

A general form of a bivariate vector autoregression (VAR) model is:

$$y_t = \alpha_1 + \sum_{i=1}^{p} \beta_{1i} y_{t-i} + \sum_{i=1}^{p} \beta_{2i} x_{t-i} + e_{1t}, \tag{4}$$

$$x_t = \delta_1 + \sum_{j=1}^{p} \gamma_{1j} y_{t-j} + \sum_{j=1}^{p} \gamma_{2j} x_{t-j} + e_{2t}, \tag{5}$$

where y_t and x_t are contemporaneous whereas y_{t-p} and x_{t-p} are lagged real GDP growth rates. For example, let CAFR denote a bivariate VAR model that comprises of the series for Canada and France for all $p \geq 1$. The CAFR bivariate model consists of (4) and (5). These equations are employed to construct two separate neural network linearity tests.

In the first part of neural network linearity test, the CAFR model is estimated to recover residuals $\hat{\mu}_i$, $i = 1, 2$, and construct the residual sum of squares RSS_i, $i = 1, 2$, for each equation. This process is repeated for each of the $C_7^2 = 21$ bivariate models. The residual sums of squares are then used to construct neural network linearity tests.

In the second part of the bivariate neural network linearity test, in-sample forecasts from ANN are approximated using (2) with residuals $\hat{u}_i$, $i = 1, 2$, from each VAR equation employed as endogenous variables and lagged real GDP growth rates ($y_{t-1}, \ldots, y_{t-k}$, $x_{t-1}, \ldots, x_{t-k}$, $k \geq 0$)) as exogenous variables. From this part of the test, the residuals $\hat{v}_i$, $i = 1,2$, and the sum of squared residuals SSE_i, $i = 1,2$, are calculated from each neural network model approximated. Finally, test statistics are calculated as:

$$TS = \frac{(RSS_i - SSE_i)/m}{SSE_i/(n - p - m - 1)}, \tag{6}$$

where RSS_i, $i = 1,2$, are residual sums of squares from the first part and SSE_i, $i = 1,2$, are squared residual sums from the second part of the neural network linearity test. In addition to using in-sample forecasts from linear models and ANN, jackknife out-of-sample forecasts are also employed to construct neural network linearity tests for all series.

To avoid getting stuck at local optima, a genetic algorithm (GA) is employed with a couple of random starts to obtain the best parameter vector for neural network approximations. This is considered to be a reliable estimation algorithm but is very slow. Therefore, GA is employed in conjunction with fminsearch, which is an optimizing routine from MATLAB that employs simplex algorithm. The combination of these algorithms worked satisfactorily. After its applications in biology and engineering, the GA was employed in operations research by Goldberg (1989). Economic application was considered by Axelord (1987), Marimon et al. (1990), and Dorsey and Mayer (1995).

3. Empirical Results

3.1 Data Sources

Quarterly real GDP for G7 countries were obtained from the November 2006 version of the International Financial Statistics (IFS) CD-ROM. The dataset spans first quarter 1957 to second quarter 2006 for all countries except for France, for which the data starts in first quarter 1965, and Germany and Italy for which the data starts in first quarter 1960. Table 1 summarizes sample lengths.

Table 1. Data Description

	Canada	France	Germany	Italy	Japan	UK	US
Start	1957:1	1970:1	1960:1	1970:2	1957:1	1957:1	1957:1
Length	197	165	185	185	197	197	197

Figures 1-7 illustrate real GDP growth rates for each country. The breaks shown in Figures 2 and 4 for France and Italy are because the IFS joined the two series that are expressed at base prices of two different reference years and refer to two different systems of national accounts. The break shown for Germany in Figure 3 occurred at reunification.

Figure 1. Canada Real GDP Growth Rates

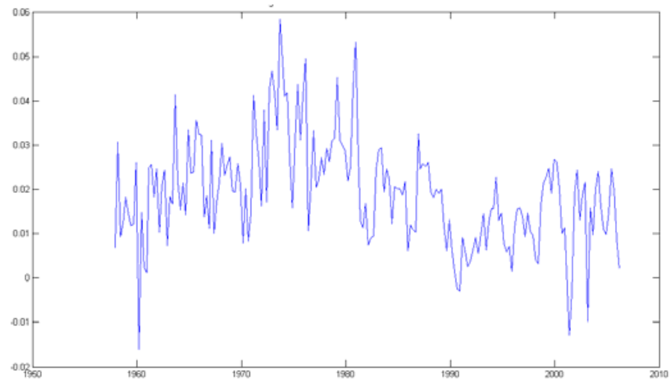


Figure 2. France Real GDP Growth Rates

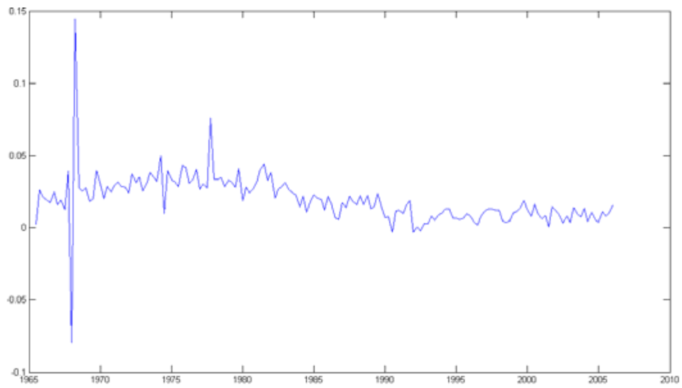


Figure 3. Germany Real GDP Growth Rates

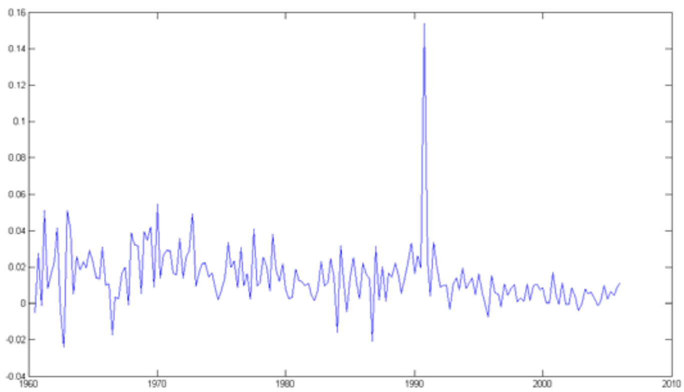


Figure 4. Italy Real GDP Growth Rates

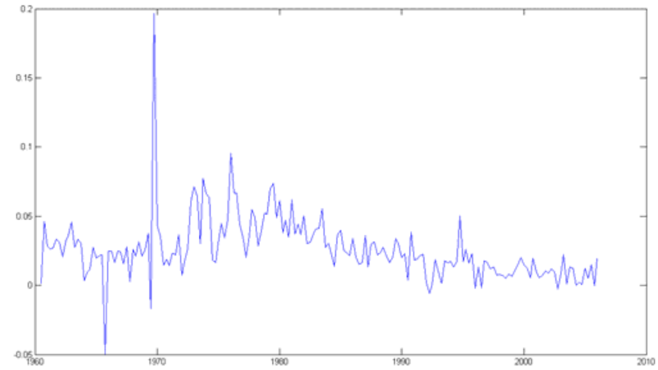


Figure 5. Japan Real GDP Growth Rates

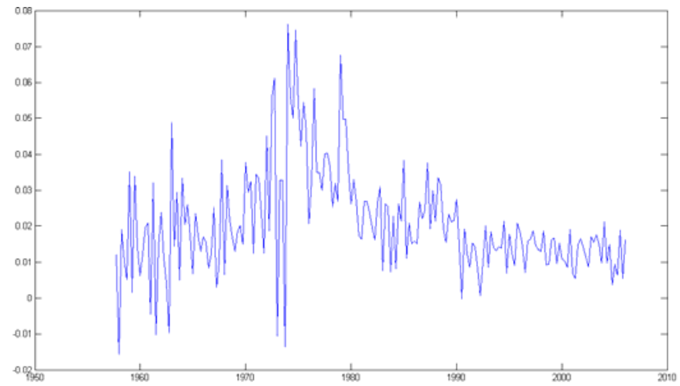


Figure 6. UK Real GDP Growth Rates

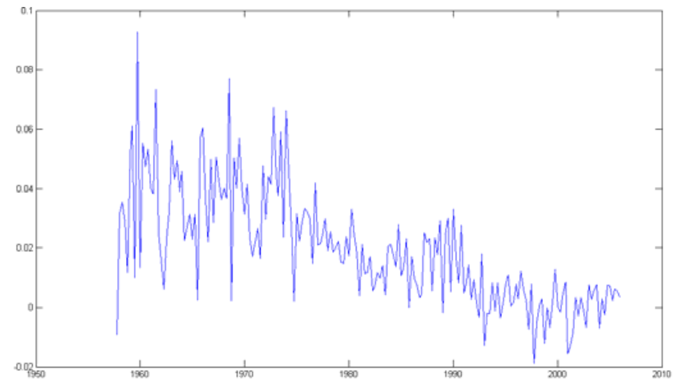
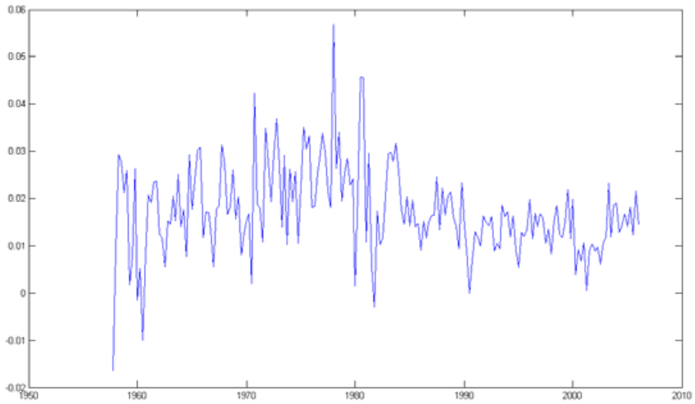


Figure 7. US Real GDP Growth Rates



3.2 Preliminary Data Analysis

Preliminary data analysis revealed that skewness and excess kurtosis are statistically significant with fat tails in all series, though significance is marginal for Japan. The Jarque-Bera test rejects normality for all countries except Canada. The augmented Dicky-Fuller test indicates unit roots in levels (with constant and time trend) for all countries but not in growth rates (with constant only). The only exception is Japan for which the test fails to reject unit roots in growth rates with a constant term only but does reject with constant and time trend. The Goldfeld-Quandt test fails to reject homoskedasticity in all countries and the Lagrange multiplier test detects autoregressive conditional heteroskedasticity only in Japan.

3.3 Estimation Results

Table 2 shows test statistics for neural network linearity tests that are constructed from in-sample and jackknife out-of-sample forecasts from univariate linear models and neural networks. Column 2 shows test statistics for neural network linearity tests, and column 5 shows test statistics for neural network linearity tests constructed using jackknife out-of-sample forecasts from linear models and neural networks. Root mean squared errors (RMSEs) for in-sample and jackknife out-of-sample forecasts are also shown in this Table.

Table 3 shows test statistics for neural network linearity tests that are based on in-sample as well as jackknife out-of-sample forecasts from bivariate linear models and neural networks. In this Table column 2 and 5 show test statistics computed from all the bivariate linear models in conjunction with the relevant neural networks for Canada, France, Germany, Italy, Japan, UK, and US real GDP growth rates. Relevant p-values for each of the test statistic are juxtaposed in the subsequent column in the same row. The Table also show root mean squared errors (RMSEs) for in-sample and jackknife out-of-sample forecasts that are shown in columns 4 and

7 respectively for all the models estimated for Canada, France, Germany, Italy, Japan, UK, and US real GDP growth rates.

Table 2. Neural Network Tests with Univariate Linear Models

	In-Sample Forecasts			Jackknife Out-of-Sample Forecast		
Model	**Test Statistic**	**P-Value**	**RMSE**	**Test Statistic**	**P-Value**	**RMSE**
Canada	280.8325	< 0.001	0.1404	41.4805	< 0.001	0.2918
France	2428.0671	< 0.001	0.1568	520.4057	< 0.001	0.3247
Germany	380.9606	< 0.001	0.2169	191.1076	0.0003	0.2905
Italy	672.8380	< 0.001	0.2687	218.7765	0.0226	0.4444
Japan	209.5664	< 0.001	0.1793	36.6850	< 0.001	0.3405
UK	202.0907	< 0.001	0.2201	59.7420	< 0.001	0. 3512
US	346.0786	< 0.001	0.1247	52.9753	0.0080	0. 2641

3.4 Hypotheses Tests

The chief hypothesis of this study is linearity versus the alternative hypothesis of nonlinearity to test for the existence of asymmetries in G7 real GDP growth rates. The linearity hypothesis is based on the test statistic that is constructed from in-sample forecasts approximated from neural network models with its linear and bivariate linear counterparts for all the growth rate series. The linearity hypothesis is also tested using jackknife out-of-sample forecasts from linear models and approximations from relevant ANNs for all models for each series.

The test statistic calculated using (3) for each series is distributed $F(m, n-p-m-1)$ under the null hypothesis of linearity when considering the neural network linearity test using univariate linear models. The neural network linearity tests in conjunction with bivariate linear models are constructed for in-sample and jackknife out-of-sample forecasts for each model estimated using (6).

3.5 Hypothesis Test Results

All the neural network test statistics presented in Table 2 are statistically significant at the 5% level. These results indicate that there is an evidence of business cycle asymmetries in the real GDP growth rates of all the G7 countries.

While the objective of the present study is to assess the existence of business cycle asymmetries in the G7 series, contagion effects in G7 countries in bivariate frameworks are also examined. Inclusion of such tests in this analysis is intended to test additional evidence of nonlinearities in all series in addition to exploring contagion effects and to observe how one country's business cycle may affect the magnitude of business cycle fluctuation in another country. For example, for the bivariate CAUS2 model, the neural network linearity test statistic shown in Table 2 indicates that the US business cycle is not affected much when the Canadian GDP series is included in the model; however, the CAUS1 test statistic shows that

Table 3. Neural Network Tests with Bivariate Linear Models

	In-Sample Forecasts			Jackknife Out-of-Sample Forecast		
Model	**Test Statistic**	**P-Value**	**RMSE**	**Test Statistic**	**P-Value**	**RMSE**
CAFR1	270.1986	< 0.001	1.0292	16.4824	< 0.001	0.3735
CAFR2	2332.0594	< 0.001	0.4591	33.2566	< 0.001	1.2228
CAGR1	265.5669	< 0.001	1.1298	5.6772	0.0003	0.4257
CAGR2	307.3003	< 0.001	0.8458	2.9238	0.0226	0.8345
CAIT1	260.8549	< 0.001	0.1218	8.4628	< 0.001	0.4107
CAIT2	736.0613	< 0.001	0.2289	15.2931	< 0.001	1.2066
CAJP1	273.4044	< 0.001	1.1353	3.5625	0.0080	0.4504
CAJP2	205.0926	< 0.001	1.1700	3.3339	0.0117	0.5027
CAUK1	280.1213	< 0.001	1.1268	21.8905	< 0.001	0.3857
CAUK2	242.9319	< 0.001	1.1096	6.2060	0.0001	0.5817
CAUS1	286.7682	< 0.001	0.1182	15.4751	< 0.001	0.4037
CAUS2	316.0419	< 0.001	1.0988	8.2575	0.0001	0.4279
FRGR1	2017.3321	< 0.001	0.4850	39.5745	< 0.001	1.1219
FRGR2	290.9946	< 0.001	0.7832	16.2750	0.9964	0.8074
FRIT1	983.0594	< 0.001	0.6914	35.3386	< 0.001	1.0014
FRIT2	530.1332	< 0.001	0.1829	20.6363	< 0.001	1.2042
FRJP1	2160.8583	< 0.001	0.4770	48.6139	< 0.001	1.1151
FRJP2	199.4415	< 0.001	1.0736	0.0185	0.9993	0.4730
FRUK1	2139.9850	< 0.001	0.4794	56.9604	< 0.001	1.0577
FRUK2	255.1859	< 0.001	0.9347	2.0882	0.0843	0.5425
FRUS1	2221.8645	< 0.001	0.4704	54.8573	< 0.001	1.0666
FRUS2	339.6425	< 0.001	0.1197	6.3342	0.0843	0.3880
GRIT1	301.3993	< 0.001	0.8540	6.9836	< 0.001	0.7881
GRIT2	735.5024	< 0.001	0.6535	16.3525	< 0.001	1.1293
GRJP1	301.7980	< 0.001	0.8540	4.1894	0.5239	0.7702
GRJP2	193.2506	< 0.001	1.1915	2.9310	0.0221	0.4795
GRUK1	313.5724	< 0.001	0.8372	7.3175	< 0.001	0.7536
GRUK2	241.2715	< 0.001	1.0500	18.1193	< 0.001	0.4684
GRUS1	377.9493	< 0.001	0.7678	15.6002	< 0.001	0.7434
GRUS2	307.2726	< 0.001	1.0590	19.0447	< 0.001	0.1139
ITJP1	788.0186	< 0.001	0.6316	29.3709	< 0.001	1.0908
ITJP2	199.9694	< 0.001	1.1673	1.8838	0.1153	0.4927
ITUK1	661.9456	< 0.001	0.6871	17.9637	< 0.001	0.5019
ITUK2	250.8894	< 0.001	3.7961	17.9637	< 0.001	0.5019
ITUS1	667.8976	< 0.001	0.6848	19.7459	< 0.001	1.1672
ITUS2	332.7416	< 0.001	1.0189	12.6557	< 0.001	0.3922
JPUK1	169.5096	< 0.001	1.3045	3.4933	0.0090	0.5052
JPUK2	184.0335	< 0.001	1.2437	5.4035	0.0004	0.5915
JPUS1	185.8725	< 0.001	1.2511	13.8287	< 0.001	0.5219
JPUS2	306.3379	< 0.001	1.0978	7.2141	< 0.001	0.4275
UKUS1	180.6804	< 0.001	1.2559	10.3327	< 0.001	0.5658
UKUS2	294.7611	< 0.001	1.1199	4.8548	0.0010	0.4380

inclusion of the US series in the bivariate model for Canada reduces the magnitude of test statistic, indicating that the US economy has a more pronounced impact on Canadian business cycles. This can be attributable to the fact that despite the size of their economies, these neighbors depend heavily on each other's products. For example, about 84% of Canada's exports are sent to the US and 57% of Canada's imports come from the US. Similarly, about 13% of US imports come from Canada and 23% of US exports go to Canada. Similarly, using test statistics for the remaining bivariate models shown in the Table, one can analyze the bidirectional impact between Canada and France, Germany, Italy, Japan, and the UK. The impact of business cycle fluctuations among other G7 countries can also be analyzed in a similar manner.

Neural network nonlinearity tests to detect business cycle nonlinearities using in-sample forecasts from neural networks with univariate linear and bivariate linear models show evidence of asymmetries in all the series. Similarly, neural network nonlinearity tests constructed from jackknife out-of-sample forecasts from neural networks and its linear counterparts also show evidence of business cycle asymmetries in all real GDP growth series. However, using jackknife out-of-sample forecasts, the neural network linearity tests fail to reject the linearity hypothesis in 4 out of 40 cases at 10% level of significance, and in 6 out of 40 cases at 5% level of significance.

3.6 Forecast Performance of Neural Network Models

Figures 8 to 14 show plots of in-sample forecasts for the G7 countries from linear models and ANNs against real GDP growth rates for each country. Comparing linear versus ANN forecasts, these figures show that neural network models explain data series better than linear models for real GDP growth rates.

Table 3 shows in-sample RMSE computed from in-sample and jackknife forecasts from neural network models for all series. Comparing RMSE from in-sample to jackknife out-of-sample forecasts for Canada, for example, we find that jackknife out-of-sample forecast performance of neural network models is not superior to in-sample forecasts from neural networks.

3.7 Discussion

The study results on nonlinearity for the US are in line with Bidarkota (2000) and Andreano and Savio (2002). Similarly, results on nonlinearity for Canada, Germany, Italy, Japan, and the US are in line with Kiani and Bidarkota (2004). This shows that evidence against linearity for US is robust across samples and testing approaches. Neural network models outperform the traditional statistical tests for remaining nonlinearities, an observation that is also consistent with previous studies (Terasvirta et al., 1993). However, in-sample forecast performance of neural network models is superior to univariate linear models (Kiani et al., 2005). Additionally, the effects of one country's business cycle fluctuations on another country in the bivariate framework can be viewed as business cycle linkages or contagion effects due to trade and other linkages. For example, the size of an economy and magnitude of trade appear to be two important factors in determining a high or low magnitude of business cycle linkages or contagion effects between any two countries in a bivariate framework.

Figure 8. Canada Linear Model versus Neural Network Predictions

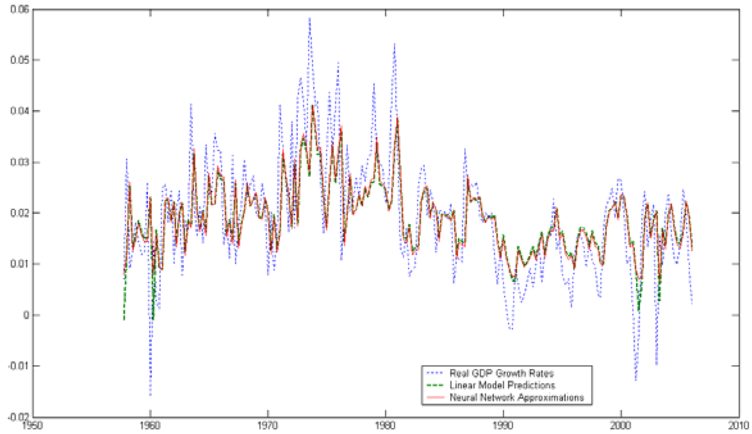


Figure 9. France Linear Model versus Neural Network Predictions

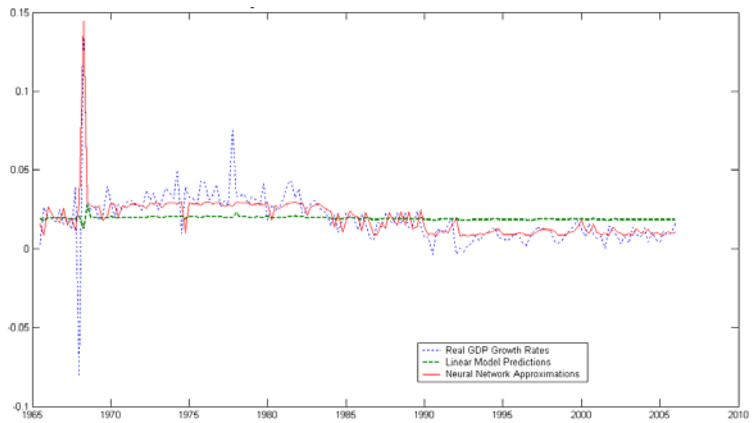


Figure 10. Germany Linear Model versus Neural Network Predictions

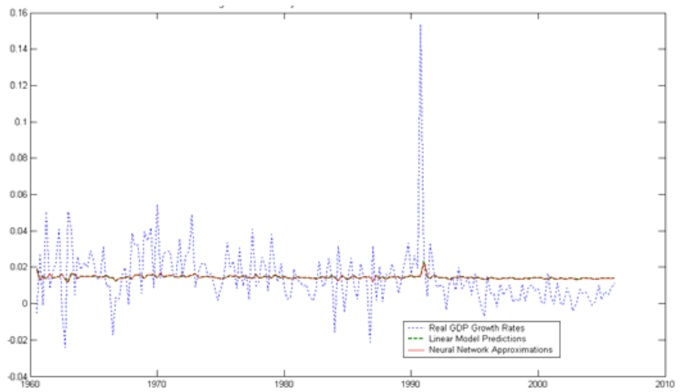


Figure 11. Italy Linear Model versus Neural Network Predictions

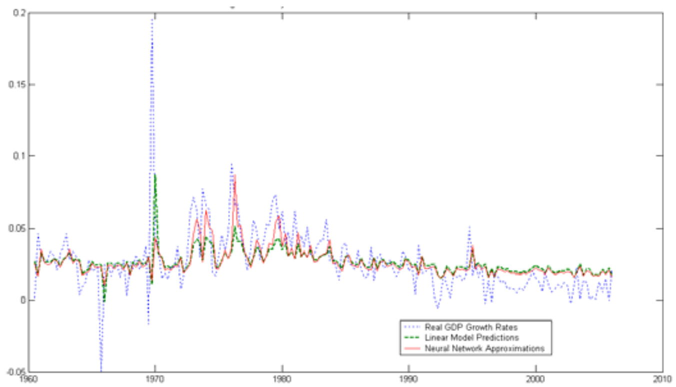


Figure 12. Japan Linear Model versus Neural Network Predictions

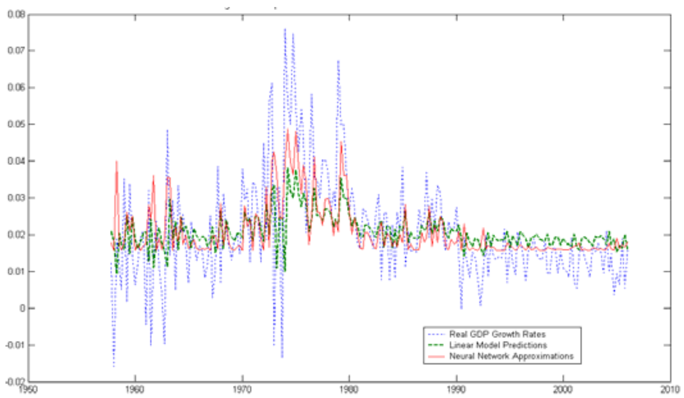


Figure13. UK Linear Model versus Neural Network Predictions

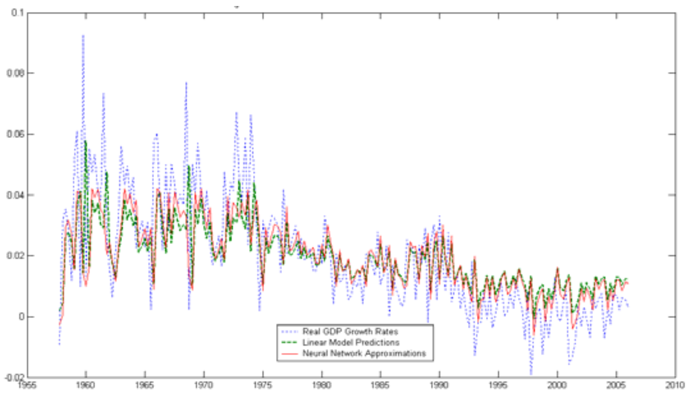
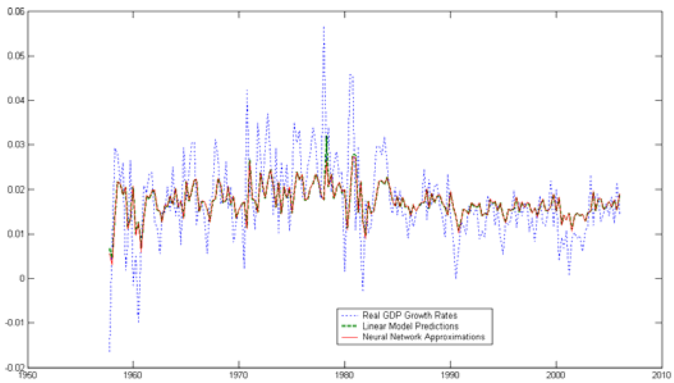


Figure 14. US Linear Model versus Neural Network Predictions



4. Conclusions

This study considers neural networks with univariate linear models and bivariate VARs to assess business cycle asymmetries in G7 real GDP growth rates. Possible business cycle asymmetries in all series are studied using in-sample and jackknife out-of-sample forecasts that are approximated from neural networks and their linear counterparts. The results based on in-sample forecasts show robust evidence of asymmetries in business cycle fluctuations in all the countries. In addition, the results based on jackknife out-of-sample forecasts strengthen the evidence of asymmetries. These results show that the impact of monetary policy or other shocks to GDP in these countries cannot be accurately predicted by linear models.

Our findings suggest that in-sample forecasts from neural networks are superior to out-of-sample forecasts from neural networks in a jackknife framework. In addition, results from bivariate analysis show spillover and contagion effects among

G7 countries; these effects may or may not be due to trade. For example, trade Canada-US linkages, supported by geographic proximity and NAFTA, help to explain the observed dependence structure between their business cycles. However, it might be premature to assume that all linkages across countries are based on trade; other historical or political considerations may be as or more important.

Future research may employ additional models and tests to explore the role of trade and other linkages on economic fluctuations within these economies.

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