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Asymmetries in Macroeconomic Time Series in Eleven Asian Economies

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Abstract

We investigate business cycle asymmetries in the real GDP of eleven selected Asian economies using nonlinear switching time series models and artificial neural networks. Results based on neural network linearity tests show evidence of business cycle asymmetries in all series. Results based on switching and augmented time series models also reveal business cycle asymmetries in most series studied.

Key words: real GDP growth rates; fat tails; stable distributions; neural networks; out-of-sample forecasts; long memory; nonlinearities; business cycles

JEL classification: C22; C32; C45; C53

1. Introduction

A wide body of empirical literature shows the possible existence of business cycle asymmetries in macroeconomic time series. This hypothesis was tested extensively using macroeconomic time series data from developed countries in conjunction with newly developed modeling techniques. Thus, using univariate time series models, Neftici (1984), Brunner (1992, 1997), Beaudry and Koop (1993), Potter (1995), and others showed that asymmetric business cycle fluctuations do exist in macroeconomic time series. Likewise, employing multivariate time series models, Anderson and Ramsey (2002) and Andreano and Savio (2002) showed existence of business cycle asymmetries in macroeconomic time series. Using artificial neural networks (ANNs), a nonparametric technique involving highly flexible functional forms, Kiani (2005), Kiani et al. (2005), and Kiani (2007) showed existence of business cycle asymmetries in real GDP growth rates from the group of seven (G7) highly industrialized countries of the world.

There are a number of reasons why one would expect to detect business cycle asymmetries in developed or developing countries. For instance, nonlinearities or business cycle asymmetries imply that the affects of expansionary and

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contractionary monetary policy and other shocks on output are not symmetric. Therefore, nonlinearities, if present, would invalidate the measures of the persistence of monetary policy or any other shock on the output of the economy that is anticipated using linear models. Thus, policymakers might not be able to anticipate the impact of a one unit monetary policy shock on output, particularly while implementing a timely policy action for avoiding a downturn in the economy.

A number of studies showed significant evidence of time-varying volatility and outliers in macroeconomic time series data. For example French and Sichel (1993) and Brunner (1992, 1997) demonstrated presence of conditional heteroskedasticity and Blanchard and Watson (1986) showed presence of outliers in the series. Therefore, Granger (1995) recommended testing nonlinearities using a test robust to heteroskedasticity. On the other hand, Balke and Fomby (1994), and Scheinkman and LeBaron (1989) reported weak evidence against linearity in a US macroeconomic time series once outliers were taken into account. This raised awareness that the evidence of nonlinearities reported in a number of studies might be due to the presence of outliers. Tsay (1988) strengthened this idea arguing that linearity could be rejected strictly due to the presence of outliers. However, empirical work shows that the models employed for testing business cycle asymmetries in macroeconomic time series in most studies do not incorporate features to account for time-varying volatility, persistence of the process, or outliers. Exceptions are Bidarkota (2000) and Kiani and Bidarkota (2004), who used nonlinear augmented and switching time series models that take into account time-varying volatility, persistence in the process, and outliers. Inefficient estimation would result when such features are not included in the models that are employed for detecting business cycle asymmetries in macroeconomic time series.

The possible existence of business cycle asymmetries was tested in a number of studies using data from developed countries, especially Canada, the UK, and the US; however, such research is sparse in developing countries and non-existent in Asian countries. This is because the complexity of the models required for testing business cycle asymmetries in macroeconomic time series demands adequate time series data, which is abundant in developed countries but rare in most Asian countries. This makes testing business cycle asymmetries in Asian economies quite challenging. For example, seasonally adjusted quarterly data for most Asian countries simply isn’t available. Therefore, the present research focuses on the 11 of the 50 Asian countries with minimal macroeconomic time series data: Armenia, Indonesia, Iran, Japan, Kazakhstan, Malaysia, Philippines, Russia, Singapore, Thailand, and Turkey. Thus, our sample includes a group of countries that encompass highly developed economies like Japan, fast growing economies like Malaysia, Singapore, and Indonesia, transition economies like Kazakhstan and Russia, and oil rich countries like Iran and Kazakhstan. However, even with the data limitations inherent in the study of this diverse set of countries, we expect that our results will help policymakers in these countries to anticipate the impact of monetary policy or other shocks on output. Taking appropriate policy measures may help to avoid anticipated downturns in these economies.

In the present work, we investigate whether asymmetries in business cycle fluctuations are present in the real GDP growth rates for these 11 Asian countries using nonlinear time series models that encompass long memory, time-varying volatility, and stable distributions. In addition to employing nonlinear augmented and alternate regime switching models, ANNs are also employed to test business cycle asymmetries in all series. This is because, due to their complexity, some time series models might not be able to identify the type of asymmetries pertinent to a particular type of data series. ANNs were also employed by Kuan and White (1994) and Swanson and White (1995, 1997a, 1997b) in economic time series data. Vishwakarma (1995), Qi (2001), Kiani (2005), Kiani et al. (2005), Kiani and Kastesn (2006), and Kiani (2007) also used ANNs in business cycle research.

The remainder of this study is organized as follows. Section 2 elaborates on ANNs and nonlinear time series models. Estimation results and hypothesis tests are discussed in Section 3. Section 4 presents our conclusions.

2. Empirical Models

We employ nonlinear time series models and ANNs to test for the existence of business cycle asymmetries in macroeconomic time series from 11 Asian countries. The models used in the present work are introduced in this section.

2.1 Artificial Neural Networks

ANNs are based on biological neural networks which represent the human brain's learning and decision-making process. An ANN consists of a number of interconnected elements known as neurons. ANNs are nonlinear, nonparametric models that are independent of the distributions of the underlying data generating processes (White, 1989). ANNs have special characteristics that enable them to learn from examples, and these insights can be employed to solve the problems that were never seen before (Reilly and Cooper, 1990). Consequently, ANNs are able to approximate any continuous function to any desired level of precision (Hornick et al., 1989). However, despite all these qualities, ANNs have been heavily criticized as being "black boxes" since it is difficult to know their functional form since there is a danger of overfitting. Following Kiani (2005), overfitting issues can be obviated by careful construction of neural network architecture. The following equation shows the general form of an ANN employed in the present work:

$$f(x) = sig\left[\alpha_0 + \sum_{j=1}^{n} \alpha_j sig\left(\sum_{i=1}^{k} \beta_{ij} x_i + \beta_{0j}\right)\right] + \varepsilon_t , \tag{1}$$

where n is the number of hidden nodes, k is the number of predictor variables in the network, $sig(x) = 1/(1+e^{-x})$ is a transfer function that can be either a sigmoid (logistic) or a hyperbolic (tangent) cumulative distribution function, α_j represents a vector of parameters or weights that link the hidden node to the output layers' units, the β_{ij} ($i = 1,\ldots,k$ and $j = 1,\ldots,n$) determine a matrix of parameters linking the input to the hidden layers' units, and ε_t denotes the error term.

The ANN model shown in (1) can be used to construct a neural network linearity test. This test was originally proposed by Terasvista et al. (1993) and was employed by Kiani (2005) and others. The test can be described using a linear model and an ANN model. The linear model is:

$$y_t = \pi' w_t + u_t , \tag{2}$$

where $w_t = (1, \tilde{w}_t')'$, $\tilde{w}_t = (y_{t-1}, \ldots, y_{t-p})'$, $\pi = (\pi_0, \ldots, \pi_p)'$, and the u_t are independently distributed $N(0, \sigma^2)$. The residuals from the linear model relative to the ANN are:

$$\hat{u}_t = \pi' w_t + sig\left[\alpha_0 + \sum_{j=1}^{n} \alpha_j sig\left(\sum_{i=1}^{k} \beta_{ij} x_i + \beta_{0j}\right)\right] + \varepsilon_t . \tag{3}$$

The test statistic is constructed from the residuals obtained from (2) and (3):

$$TS = \left[(SSE_1 - SSE_2)/m\right] / \left[SSE_2/(n - p - m - 1)\right], \tag{4}$$

where m is the number of restrictions in the unrestricted model, n is the number of observations in the series, and p is the number of lags in the model. This test statistic is *F*-distributed under the linearity hypothesis with $n - p - m - 1$ and m degrees of freedom. However, this test statistic is approximate because of the nuisance parameter that appears under the alternative hypothesis (Davies, 1977; Andrews, 2001).

Neural network linearity tests are constructed using in-sample forecasts from linear models and approximations from ANNs. Therefore, in addition to constructing the test statistic in (4) using in-sample forecasts for all series, neural network linearity tests are repeated for all series using jackknife out-of-sample approximations from the ANNs and forecasts from their linear counterparts. This involves in-sample and jackknife out-of-sample forecasts from the linear model and in-sample and jackknife out-of-sample approximations from the ANN that is eventually employed to construct neural network linearity tests. Further, to construct neural network linearity tests using jackknife out-of-sample forecasts, we employ the sub-sample jackknife re-sampling technique proposed by Wu (1990) and extended by Politis and Romano (1994). The sub-sample jackknife was also used by Politis et al. (1997) and Ziari et al. (1997).

2.2 Non-Linear Time Series Models

In this study we use two classes of time series models to detect business cycle asymmetries: the CDR-augmented model and the SETAR-switching model (defined below). Each class is further sub-divided into three types, with Model 1 incorporating stable distributions, conditional heteroskedasticity, and fractional differencing, Model 2 obtained by restricting fractional differencing in Model 1, and

Model 3 obtained by imposing heteroskedasticity on Model 2. These models are described below.

2.3 CDR-Augmented Models

Beaudry and Koop (1993) initially recommended this type of model and proposed an ad hoc nonlinear term to capture nonlinearity in a standard autoregressive moving average (ARMA) model assuming that errors are normally distributed. The most general form of this model that incorporates stable distributions, conditional heteroskedasticity, and long memory was also employed by Kiani and Bidarkota (2004), where errors were assumed to follow a more general stable distribution:

$$\Phi(L)(1-L)^d(\Delta y_t - \mu) = [\Omega(L)-1]CDR_t + \varepsilon_t\,, \tag{5a}$$

$$\begin{aligned} &\varepsilon_t \mid I_{t-1} \sim z_t c_t\,, \\ &z_t \overset{iid}{\sim} S_\alpha(0,1)\,, \\ &c_t^\alpha = b_1 + b_2 c_{t-1}^\alpha + b_3 \mid \varepsilon_{t-1} \mid^\alpha\,, \end{aligned} \tag{5b}$$

where $\Delta y_t \equiv 100 \times \Delta(\ln GDP_t)$ is the GDP growth rate, μ is its unconditional mean, and d is the differencing parameter. The nonlinear term, defined as the current depth of recession $CDR_t = \max\{y_{t-j}\}_{j\geq 0} - y_t$, measures the gap between the current level of output and the economy's historical maximum level. This term is designed to permit recessions to be more or less persistent than expansions depending on the parameter estimates. The polynomial $\Omega(\cdot)$ is of order r and polynomial $\Phi(\cdot)$ is of order p in the lag operator L, with $\Omega(0) = \Phi(0) = 1$.

A random variable X will have a symmetric stable distribution $S_\alpha(\delta, c)$ if its log characteristic function can be expressed as $\ln E\left[\exp(iXt)\right] = i\delta t - \mid ct \mid^\alpha$. Here $c \in [0,\infty]$ is the scale parameter, $\delta \in [-\infty,\infty]$ is the location parameter, and $\alpha \in [0,2]$ is the characteristic exponent governing the tail behavior, small values of which correspond to thicker tails. However, when $\alpha = 2$ in (5b), a normal GARCH (1, 1) process results. On the other hand, when $d = 0$ we get a unit root in y_t, but with $d = -1$, y_t becomes integrated of order zero. ARFIMA models with long memory are defined in terms of the rate of decay of their autocovariances, so the extension of these models to infinite variance stable shocks is not immediate.

A stationary casual and invertible solution to an ARFIMA model with Gaussian errors requires $\mid d \mid < 0.5$ (Brockwell and Davis, 1991). On the other hand, according to Kokoszka and Taqqu (1995), an MA (∞) representation of an ARFIMA model with stable shocks requires $\alpha(d-1) < -1$. Therefore, d needs to be positive when $\alpha > 1$. In addition, $\alpha > 1$ and $\mid d \mid < (1 - 1/\alpha)$ are necessary for the ARFIMA model to be a solution to an AR (∞) process. Consequently, α and d are restricted within these limits.

When $\Omega(L) = 1$, equation (5a) reduces to an AR model with non-integer differencing. This is because it nests AR models, and as such the likelihood ratio (LR) test statistic can be used to test the non-linear term governing the conditional mean dynamics. However, when the autoregressive lag order p is 0, r is 1, and ω_1 is 0 we obtain a random walk model with drift. Nevertheless, a positive ω_1 implies that negative shocks are less persistent, whereas a negative ω_1 implies that positive shocks are less persistent.

Existence of nonlinearities means that the impulse response mechanism is nonlinear, although innovations are symmetric. Alternate nonlinearities would result when innovations are asymmetric and the impulse transmission mechanism is also nonlinear. However, the nonlinear propagation mechanism and asymmetric innovations cannot be disentangled from each other when both exist. Therefore, in the present work we investigate asymmetries in the conditional mean regardless of their source.

2.4 SETAR-Switching Models

Potter (1995) introduced the self-exciting threshold autoregressive (SETAR) switching model that governs switching between two regimes defined in terms of the observed series y_t. A modified version of this model that includes features to account for long memory, conditional heteroskedasticity, and stable distribution was employed by Bidarkota (2000) and Kiani and Bidarkota (2004); we consider this modified version in the present work. The most general form of this model estimated within this class of models is shown for regimes 1 and 2. In regime 1:

$$(1-\phi_1 L-\phi_2 L^2)(1-L)^d(\Delta y_t-\mu_1)=\varepsilon_t\,, \tag{6a}$$

$$\varepsilon_t \mid I_{t-1} \sim z_t c_t\,,$$

$$z \overset{iid}{\sim} S_\alpha(0,1)\,, \tag{6b}$$

$$c_t^\alpha = b_1 + b_2 c_{t-1}^\alpha + b_3 \mid \varepsilon_{t-1} \mid^\alpha .$$

In regime 2:

$$(1-\phi_3 L-\phi_4 L^2)(1-L)^d(\Delta y_t-\mu_2)=\varepsilon_t\,, \tag{6c}$$

$$\varepsilon_t \mid I_{t-1} \sim z_t \gamma c_t\,,$$

$$z \overset{iid}{\sim} S_\alpha(0,1)\,, \tag{6d}$$

$$c_t^\alpha = b_1 + b_2 c_{t-1}^\alpha + b_3 \mid \varepsilon_{t-1}/\gamma \mid^\alpha .$$

In this model, switching behavior between the two regimes is governed by the term $\Delta y_{t-d} > r$, where y_t is log real GDP, d is the delay parameter, and r is the threshold parameter. Therefore, $\Delta y_{t-2} > 0$ yields regime 1 and $\Delta y_{t-2} \le 0$ yields regime 2.

2.5 Estimation Issues

As noted above, Beaudry and Koop (1993) incorporated an ad hoc nonlinear term in a standard ARMA model to capture nonlinearities in the data with the assumption that the errors are normally distributed. Later Bidarkota (1999, 2000), and Kiani and Bidarkota (2004) also used an ad hoc nonlinear term in a standard ARMA model assuming that the errors come from a more general stable family. In estimating such a complex nonlinear model, we follow Kiani and Bidarkota (2004), who employed a computational algorithm due to McCulloch (1996, 1998) to obtain stable densities for maximum likelihood (ML) estimation of the models that works well when the errors are symmetric stable. However, the full information ML method due to Sowell (1992a) works accurately only when the errors are independently normally distributed. The present work uses more complicated non-normal conditionally heteroskedastic models; therefore, we employ the conditional sum of squares (CSS) estimation method discussed in Box and Jenkins (1976) and first used by Hosking (1984). In their research, Baillie et al. (1996) found that the CSS procedure is asymptotically equivalent to the full information ML estimation, which works better even for more complex models like those considered in the present work since ML estimation of mixed ARMA models with stable errors poses a challenge. Therefore, like Kiani and Bidarkota (2004), we employ the Whittle estimator due to Mikosch et al. (1995) and minimum dispersion estimators due to Brockwell and Davis (1991).

When approximating ANNs, we observed that convergence was difficult to achieve because of the linear model nested in the ANN specifications, which is necessary to construct the neural network linearity test. To overcome this difficulty, the genetic algorithm (GA) was selected as an estimation algorithm to approximate an ANN. The GA was initially employed by De Jong (1975) for mathematical optimization. Thereafter, Goldberg (1989) employed GA in biology, engineering, and operations research. However, the first economic application of GA was implemented due to Axelord (1987). Later, Marimon et al. (1990) and Dorsey and Mayer (1995) used GA in economics.

The GA is one of the most reliable estimation algorithms for estimating any nonlinear functional form, including ANNs, but it is notoriously slow. Therefore, to speed up the estimation process and to increase the probability for obtaining global a minimum of the negative likelihood, the estimation process was initiated with several random starts. Therefore, the parameter vector that had the smallest sum of squares error was chosen to run GA for up to 50,000 iterations. Thereafter, the parameter vector obtained from GA that had the smallest sum of squared errors was used as the starting condition for Matlab's *fminsearch* algorithm, an implementation of the Nelder-Mead simplex algorithm.

3. Empirical Results

3.1 Data Sources and Specification Search

We work with quarterly real GDP growth rate series obtained from DataStream. Table 1 provides additional details about the data used for each country included in the study.

Table 1. Data Description

Countries	Data Span	Number of Observations	Frequency
Armenia	1994Q4–2004Q1	37	Quarterly
Indonesia	1990Q1–2004Q1	56	Quarterly
Iran	1988Q1–2000Q1	48	Quarterly
Japan	1980Q1–2004Q2	97	Quarterly
Kazakhstan	1994Q1–2004Q1	40	Quarterly
Malaysia	1991Q1–2004Q1	52	Quarterly
Philippines	1981Q1–2004Q2	93	Quarterly
Russia	1993Q3–2004Q1	42	Quarterly
Singapore	1984Q3–2004Q2	79	Quarterly
Thailand	1993Q1–2004Q2	45	Quarterly
Turkey	1987Q1–2003Q4	67	Quarterly

A wide-ranging specification search was performed for each country for Models 1 through 3 for each class of model (i.e., CDR-augmented and SETAR-switching models). However, in the CDR-switching model is constrained to three lag orders of the autoregression for parsimony, and in the SETAR-switching models the search was performed with the autoregressive lag polynomials in the two regimes restricted to be of orders (3,3), (2,2), (1,1), or (0,0). Table 2.1 shows specification search results for the CDR-augmented models and Table 3.1 shows specification search results for the SETAR-switching models.

Table 2.1 Specification Search Results for CDR-Augmented Models

Countries	Model 1	Model 2	Model 3
Armenia	(3, 3)	(3, 2)	(3, 3)
Indonesia	(3, 3)	(3, 2)	(3, 3)
Iran	(1, 3)	(3, 3)	(3, 3)
Japan	(3, 3)	(3,3)	(3, 3)
Kazakhstan	(3, 2)	(3, 2)	(3, 2)
Malaysia	(3, 3)	(3, 3)	(3, 3)
Philippines	(3, 1)	(3, 1)	(3, 0)
Russia	(3, 2)	(3, 2)	(3, 3)
Singapore	(2, 3)	(3, 3)	(3, 3)
Thailand	(3, 3)	(2, 3)	(3, 1)
Turkey	(3, 0)	(3, 1)	(3, 2)

Table 2.2 Log Likelihood Results for CDR-Augmented Models

Countries	Model 1	Model 2	Model 3
Armenia	−170.097	−170.363	−172.682
Indonesia	−328.901	−333.238	−336.870
Iran	−197.312	−288.447	−288.465
Japan	−610.483	−615.045	−618.194
Kazakhstan	−231.292	−231.611	−231.659
Malaysia	−312.175	−312.246	−312.689
Philippines	−481.887	−481.979	−482.579
Russia	−170.176	−240.122	−240.228
Singapore	−470.992	−472.286	−488.767
Thailand	−266.273	−268.049	−268.537
Turkey	−290.408	−290.820	−291.728

Table 3.1 Specification Search for SETAR-Switching Models

Countries	Model 3	Model 2	Model 1
Armenia	(3, 3)	(3, 3)	(3, 3)
Indonesia	(1, 1)	(1, 1)	(2, 2)
Iran	(3, 3)	(3, 3)	(3, 3)
Japan	(2, 2)	(2, 2)	(1, 1)
Kazakhstan	(3, 3)	(3, 3)	(3, 3)
Malaysia	(3, 3)	(3, 3)	(3, 3)
Philippines	(3, 3)	(3, 3)	(3, 3)
Russia	(3, 3)	(3, 3)	(3, 3)
Singapore	(3, 3)	(3, 3)	(3, 3)
Thailand	(3, 3)	(3, 3)	(3, 3)
Turkey	(2, 2)	(2, 2)	(2, 2)

3.2 Hypotheses Tests

Two types of hypotheses are tested in the present work; we first apply the neural network linearity test then test linearity in the conditional mean using nonlinear time series models. Both hypotheses tests are described in this section.

The first hypothesis test relates to the neural network linearity tests that are constructed from in-sample forecasts from linear models and neural networks that nest the relevant linear model. In addition to the linearity tests constructed from in-sample forecasts, neural networks linearity tests are also constructed using jackknife out-of-sample forecasts from the linear models and neural networks. In both cases, the null hypothesis is linearity in the series under consideration.

Table 3.2 Log Likelihood for SETAR-Switching Models

Countries	Model 1	Model 2	Model 3
Armenia	−165.354	−164.058	−212.835
Indonesia	−328.305	−333.852	−333.599
Iran	−279.308	−280.193	−280.809
Japan	−603.364	−613.895	−614.997
Kazakhstan	−222.850	−223.108	−223.364
Malaysia	−298.136	−299.004	−302.221
Philippines	−470.023	−470.069	−472.862
Russia	−234.024	−234.601	−233.799
Singapore	−1073.283	−1077.185	−1096.431
Thailand	−256.499	−257.169	−256.778
Turkey	−328.105	−340.519	−349.057

The second hypothesis test is linearity in conditional mean based on the LR test statistic constructed from the forecasts obtained from the two versions (restricted and unrestricted) of SETAR-switching models. According to the null hypothesis of linearity, the unconditional means (μ_1 and μ_2) in the two regimes, and the corresponding autoregressive coefficients in the two regimes, need to be equal with the scale ratio (γ) equal to 1. If linearity is not rejected, we do not find evidence for more than one regime. However, if linearity is rejected, we would have evidence of two distinct regimes. On the other hand, for the CDR-augmented models, the asymptotic distribution for the test of a nonlinear CDR_t term in (5a) is non-standard, especially when the response variable is non-stationary (Hess and Iwata, 1977; Kiani and Bidarkota, 2004). Therefore, linearity in the conditional mean based on these models is not entertained.

Table 4. LR Tests for Linearity Based on SETAR-Switching Models

Countries	Model 1	Model 2	Model 3
Armenia	80.2763 (0.000)	0.3346 (0.953)	—
Indonesia	8.8074 (0.003)	10.6737 (0.001)	8.2574 (0.016)
Iran	6.9144 (0.074)	5.3171 (0.149)	4.3048 (0.230)
Japan	6.8447 (0.032)	—	12.8338 (0.000)
Kazakhstan	5.1335 (0.162)	5.1803 (0.159)	4.6728 (0.197)
Malaysia	10.9769 (0.011)	10.9790 (0.011)	6.6203 (0.085)
Philippines	15.4785 (0.001)	15.5929 (0.001)	10.1706 (0.001)
Russia	0.2418 (0.970)	0.8036 (0.848)	2.0993 (0.552)
Singapore	1214.6804 (0.000)	—	—
Thailand	3.4166 (0.331)	2.5088 (0.473)	8.5703 (0.035)
Turkey	—	—	26.3381 (0.000)

Notes: P-values are in parentheses. "—" denotes that the nonlinear time series models failed to converge.

3.3 Results of Hypotheses Tests

LR test statistics are reported in Table 4; corresponding p-values are in parentheses. Results for neural network linearity tests based on in-sample and jackknife out-of-sample forecasts are reported in Tables 5.1 and 5.2.

Table 5.1 Neural Network Linearity Tests for In-Sample Forecasts

Countries	Test Statistics	P-values
Armenia	393.502	< 0.0001
Indonesia	71.662	< 0.0001
Iran	108.912	< 0.0001
Japan	109.722	< 0.0001
Kazakhstan	59.121	< 0.0001
Malaysia	64.148	< 0.0001
Philippines	268.639	< 0.0001
Russia	34.304	< 0.0001
Singapore	1049.931	< 0.0001
Thailand	63.222	< 0.0001
Turkey	186.245	< 0.0001

Notes: Neural network test results are approximated from in-sample and jackknife out-of-sample forecasts from linear and neural network models.

Table 5.2 Neural Network Linearity Tests for Jackknife Out-of-Sample Forecasts

Countries	Test Statistics	P-values
Armenia	22.237	< 0.0001
Indonesia	0.517	< 0.0001
Iran	67.164	< 0.0001
Japan	55.676	< 0.0001
Kazakhstan	36.524	< 0.0001
Malaysia	46.217	< 0.0001
Philippines	138.723	< 0.0001
Russia	19.021	< 0.0001
Singapore	705.312	< 0.0001
Thailand	44.707	< 0.0001
Turkey	24.992	< 0.0001

Notes: Neural network test results are approximated from in-sample and jackknife out-of-sample forecasts from linear and neural network models.

The results for tests of linearity in the conditional mean for Indonesia, Japan, Malaysia, and Philippines show strong evidence of asymmetries in business cycle fluctuations. However, results for Iran, Kazakhstan, and Russia are largely linear. In contrast, Armenia, Thailand, and Singapore show weak evidence of business cycle asymmetries in real GDP growth rates. All statistical inferences for these tests are drawn at the 5% significance level without adjustment for multiple comparisons.

Linearity test results based on in-sample approximations from neural networks show evidence of nonlinearities in real GDP growth rates for Armenia, Indonesia, Iran, Japan, Kazakhstan, Malaysia, Philippines, Russia, Singapore, Thailand, and Turkey. Similarly, neural network nonlinearity test results based on jackknife out-of-sample approximations from ANNs support these results. All statistical inferences are drawn at the 5% significance level without adjustment for multiple comparisons.

3.4 Results of Selected Parameter Estimates

Following Kiani and Bidarkota (2004), our objective is to test for business cycle asymmetries in the selected 11 Asian economies. The sample includes highly developed, fast growing, transition, and developing economies, enabling us to test for business cycle asymmetries in many types of economies.

Selected parameters estimated from the most general switching models for each country are shown in Table 6. In this table, column 2 shows parameter estimates for nonlinearity term w_1 from the CDR-augmented models, whereas columns 4 and 6 show parameter estimates for the characteristic exponent α and switching parameter γ from the SETAR-switching models.

Table 6. Selected Parameter Estimates for Most General Models

	CDR-Augmented		SETAR-Switching			
Countries	ω_1	**SE**	α	**SE**	γ	**SE**
Armenia	−0.000021	0.011	1.560	0.277	3.019	1.604
Indonesia	−0.035	0.999	1.999	0.000	1.669	0.311
Iran	0.810	0.000	1.999	0.005	1.279	0.283
Japan	−0.295	0.334	1.999	0.000	0.964	0.154
Kazakhstan	0.294	0.023	1.999	0.000	1.244	0.385
Malaysia	0.843	0.954	1.718	0.093	1.718	0.143
Philippines	−0.004	0.013	1.400	0.000	1.246	0.197
Russia	0.001	0.012	1.999	0.000	0.730	0.150
Singapore	1.090	0.374	1.718	0.092	1.074	0.166
Thailand	0.028	0.208	1.652	0.203	2.383	1.074
Turkey	0.082	0.090	1.882	0.099	1.531	0.086

3.5 Nature of Asymmetries

The study results show that the parameter estimates for the characteristic exponent (α) are close to values that indicate the normal behavior in Indonesia, Iran, Japan, Kazakhstan, and Russia. However, values for Armenia, Malaysia, Philippines, Singapore, Thailand, and Turkey show fat tails. The values of the switching parameter (γ) are different across different countries, reflecting different volatility patterns in certain groups of countries. For example, high values of the switching parameter (γ) for Armenia, Indonesia, Iran, Kazakhstan, Malaysia, Philippines, Singapore, Thailand, and Turkey show that the volatility in high regimes in these countries is lower than those of the low regimes. The results for Japan and Russia, though, in sharp contrast, reveal that, compared to developing countries, developed countries have different volatility patterns during various phases of business cycles. Developing country volatilities have similar patterns irrespective of their geographical location. The values of ω_1 for Armenia, Indonesia, Japan, and Philippines are positive, implying that negative shocks are less persistent in these economies. In contrast, the values of ω_1 for Iran, Kazakhstan, Malaysia, Singapore, Thailand, and Turkey are negative, revealing that positive shocks are less persistent in these economies. This information can help policymakers to focus on policies for stabilizing their economies.

3.6 Discussion of Results

The results on nonlinearity tests based on time series models provide evidence of business cycle nonlinearities in real GDP growth rates for Indonesia, Iran, Japan, Malaysia, Philippines, Singapore, and Turkey. The results based on neural network linearity tests, which represent an improvement over the linearity tests from the nonlinear time series models, show evidence of nonlinearities in Armenia, Indonesia, Iran, Japan, Kazakhstan, Malaysia, Philippines, Russia, Singapore, Thailand, and Turkey. These results show that neural networks linearity tests outperform the nonlinear and switching time series models for detecting nonlinearities. These results are in line with previous studies, including Lee et al. (1993), Terasvirta et al. (1993), and Kiani et al. (2005). Additionally, volatility patterns in developed countries are in sharp contrast with developing countries when switching from one regime of a business cycle to the other. The characteristic exponent α which governs the tail behavior in these countries did not show any pattern like the other parameters did. Similarly, the results based on estimated value of the parameter ω_1 suggest that negative shocks are less persistent for Iran, Kazakhstan, Malaysia, Singapore, Thailand, and Turkey, whereas positive shocks are less persistent for Armenia, Indonesia, Japan, and the Philippines.

The results of nonlinearity in the conditional mean for Japan are in line with Bidarkota (2000), Andreano and Savio (2002), and Kiani and Bidarkota (2004). The evidence against linearity in conditional mean for Japan demonstrates that this finding is robust to changes in the sample period.

Blanchard and Simon (2001) showed a possible structural change in US time series in the early 1980s, whereas Koop and Potter (2001) investigated whether nonlinearities could arise from structural instability. We do not account for this possibility in the present work. Diebold and Inoue (2001) showed that a series that undergoes occasional structural change may show spurious evidence of long memory or spurious evidence of unit roots (Perron, 1989). This limitation applies in the present study.

4. Conclusion

We employ nonlinear time series models to test for business cycle asymmetries in real GDP growth rates for Armenia, Indonesia, Iran, Japan, Kazakhstan, Malaysia, Philippines, Russia, Singapore, Thailand, and Turkey. The time series models employed are fully parametric and are capable of accounting for any time-varying volatility, long memory, and outliers that might be present in the series. In addition, ANNs are also employed to construct neural network linearity tests.

Our results from nonlinear time series models reveal strong evidence of business cycle asymmetries in real GDP growth rates for Indonesia, Japan, Malaysia, and Philippines, weak evidence of business cycle asymmetries in Armenia, Singapore, Thailand, and Turkey, and no evidence of business cycle asymmetries in real GDP growth rates for Iran, Kazakhstan, and Russia.

The results from neural network linearity tests, which are based on in-sample approximations from neural networks and forecasts obtained from the relevant linear models, show evidence of business cycle asymmetries in real GDP growth rates for Armenia, Indonesia, Iran, Japan, Kazakhstan, Malaysia, Philippines, Russia, Singapore, Thailand, and Turkey. Similarly, results from neural network linearity tests, which are constructed from jackknife out-of-sample neural network approximations together with predictions from related linear models, also show evidence of business cycle asymmetries in all series.

Finally, the study results suggest that forecasts from linear models as well as those derived from vector autoregressions cannot be employed to anticipate the impact of monetary policy or other shocks to output in these economies. Therefore, policymakers in these countries should employ appropriate nonlinear models to anticipate the impact of monetary policy or other shocks to output.

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