Parametric and nonparametric Granger causality testing: Linkages between international stock markets

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Abstract

This study investigates long-term linear and nonlinear causal linkages among eleven stock markets, six industrialized markets and five emerging markets of South-East Asia. We cover the period 1987–2006, taking into account the on-set of the Asian financial crisis of 1997. We first apply a test for the presence of general nonlinearity in vector time series. Substantial differences exist between the pre- and post-crisis period in terms of the total number of significant nonlinear relationships. We then examine both periods, using a new nonparametric test for Granger noncausality and the conventional parametric Granger noncausality test. One major finding is that the Asian stock markets have become more internationally integrated after the Asian financial crisis. An exception is the Sri Lankan market with almost no significant long-term linear and nonlinear causal linkages with other markets. To ensure that any causality is strictly nonlinear in nature, we also examine the nonlinear causal relationships of VAR filtered residuals and VAR filtered squared residuals for the post-crisis sample. We find quite a few remaining significant bi- and unidirectional causal nonlinear relationships in these series. Finally, after filtering the VAR-residuals with GARCH-BEKK models, we show that the nonparametric test statistics are substantially smaller in both magnitude and statistical significance than those before filtering. This indicates that nonlinear causality can, to a large extent, be explained by simple volatility effects.

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1. Introduction

Since the late 1980s many national stock exchange markets in industrial countries have become aware of the increased competitiveness among these markets. This, in conjunction with a less restrictive climate toward capital movements has brought about the view among economists that the major financial markets of the world are systematically interrelated. This interrelationship may indicate a growing similarity in reactions toward external developments in macroeconomic policies and in the world financial environment. In addition, it may also reflect a temporary, or perhaps more lasting, causal relationship between various individual stock exchanges.

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Causal linkages among stock markets have important implications for security pricing, hedging and trading strategies, and financial market regulations. Also the presence of long-term linear and nonlinear relationships may be used to achieve financial gains from international portfolio diversification and to reduce systematic local risks. Consequently, there exists a large body of literature examining the presence of causal linkages between developed (less risky) markets. They typically find that the US market leads other developed markets (e.g. Ref. [31]). However, there is substantially less literature on stock market linkages between developed markets and emerging markets; see Section 2 for a selective overview. Moreover, quite a few studies relied on the restrictive assumption of a causal linear relationship between stock markets through the use of Granger’s [21], parametric, causality test. But, as noted by Hsieh [26,27] and many others, financial time series exhibit significant nonlinear features. Indeed, Hiemstra and Jones [25] argue that a nonlinear and nonparametric Granger causality test (hereafter HJ test), based on the work of Back and Brock [4], is more effective in uncovering certain nonlinear causal relationships in daily stock prices.

The HJ causality test seems to be the one most used in economics and finance. Examples include stock-price-volume relationships [25,43], futures and cash markets [15], stock price dividend relationships [29], fundamentals and exchange rates [35], equity volatility returns [7]. However, Diks and Panchenko [12,13] demonstrate that the HJ test can severely over-reject if the null hypothesis of noncausality is not true. In addition, with instantaneous dependence, the HJ test has serious size distortion problems. As an alternative the authors of Ref. [13] (hereafter DP) develop a new test statistic which does not suffer from these limitations. Their empirical results suggest that some of the rejections of the Granger noncausality hypothesis, using the HJ causality test, may be spurious.

The objective of the current paper is two-fold. The first one is to explore the existence of linear and nonlinear causal relationships among eleven stock markets. Six of these (Germany, Hong Kong, Japan, Singapore, UK, and US) belong to the group of world’s major stock markets, while five markets (India, Malaysia, South Korea, Sri Lanka, and Taiwan) are emerging stock markets in South-East Asia. Clearly South-East Asia as a region has undergone rapid market liberalization in the past decade, resulting in increased investment flows. A possible consequence of this financial openness is an increase in the causal linkages between these emerging markets and the world’s major financial markets. In particular, the time period after the 1997 Asian financial crisis may have changed the direction and strength of the causal relationships among the markets under study. A second objective is to explore the ability of the DP test to detect nonlinear causal relationships.

The paper has five remaining sections. Section 2 presents a brief overview of the relevant literature. Also we point out some limitations of the reviewed studies. In Section 3 we present some selected stock market indicators jointly with a discussion of the eleven stock market indices. Section 4, entitled “Testing methodology”, introduces (i) a multivariate test of nonlinearity; and (ii) the nonparametric DP causality test. The empirical findings are reported in Section 5. The final section closes the paper by discussing some of the main implications of the results and providing directions for future research.

2. Literature review

There is a wealth of literature on stock market interdependence and integration. However, depending on the data, methodology, and theoretical models used there is no clear resolution of the issue yet. Some previous work has have found that international stock markets are integrated; see, e.g., Refs. [2,23]. Others have found that stock markets are not interlinked; see, e.g., Refs. [41,44].

Most of the studies on stock market interdependence in emerging markets have been done on geographical groups of markets, such as markets in Central and Eastern Europe [20,22], Latin America [10,11,9], and in Asian countries. Since stock markets in South-East Asia form a substantial part of the set of markets considered here, we summarize some of the most recent findings.

Masih and Masih [33,34] found cointegration in the pre-financial crisis period of October 1987 among the stock markets of Thailand, Malaysia, the US, the UK, Japan, Hong Kong and Singapore. But there were no long-run relationships between these markets for the period after the global stock market crash of 1987. By contrast, Phylaktis and Ravazzolo [39] found no linkages and dynamic interactions amongst a group of Pacific-Basin stock markets (Hong Kong, South Korea, Malaysia, Singapore, Taiwan and Thailand) and the industrialized countries of Japan and US for the period 1980–1998. Further, Arshanapalli et al. [3] noted an increase in stock market interdependence after the 1987 crisis for the emerging markets of Malaysia, the Philippines, Thailand, and the developed markets of Hong Kong, Singapore, the US and Japan for the period 1986–1992. Likewise, when testing for causality-in-variance,
Caporale et al. [8] found some empirical evidence on the bi-directional causal relationships between stock prices and exchange rate volatility in the case of Indonesia and Thailand for the post-crisis period 1987–2000. Also, Najand [36], using linear state space models, detected stronger interactions among the stock markets of Japan, Hong Kong, and Singapore after the 1987 stock market crash.

Linkages among national stock markets before and during the period of the Asian financial crisis in 1997/98 were explored by Sheng and Tu [42]. In particular, adopting multivariate cointegration and error-correction tests, these authors focused on 11 major stock markets in the Asian-Pacific region (Australia, China, Hong Kong, Indonesia, Japan, Malaysia, Philippines, Singapore, South Korea, Taiwan and Thailand) and the US. Using daily closing prices, they found empirical evidence that cointegration relationships among the national stock indices has increased during, but not before, the period of the financial crises. More recently, Weber [46] revealed various causality-in-variance effects between the volatilities in the national financial markets in the Asian-Pacific region (Australia, Hong Kong, Indonesia, India, Japan, South Korea, New Zealand, Philippines, Singapore, Taiwan and Thailand) for the post-crisis period 1999–2006. Also, allowing for structural breaks such as the Asian financial crisis, Narayan et al. [37] found that stock prices in Bangladesh, India and Sri Lanka Granger-cause stock prices in Pakistan for the period 1995–2001.

All the above studies rely on the restrictive assumption of linearity either through the use of linear causality tests or via linear time series methodology. Moreover, some of these studies fail to notice that parametric linear Granger causality tests have low power against nonlinear alternatives; see Ref. [4]. Recognition of the nonlinear property of stock prices, and subsequently exploring for possible long-run nonlinear relations among national stock markets, came after publication of the study by Hiemstra and Jones [25]. For instance, using the HJ causality test, Hunter [28] focuses on the emerging markets of Argentina, Chile, and Mexico. Similarly, Ozdemir and Cakan [38] examine the dynamic relationships between the stock market indices of the US, Japan, France, and the UK. This latter study reports that there is a strong bi-directional nonlinear causal relationship between the US and the other countries, which has also been documented in the literature using linear causality tests. But, as explained in Section 1, the HJ test may lead to false inference. Clearly the causality and nonlinearity tests to be introduced in Section 4 provide a useful way to extend and update much of the above empirical knowledge on causal (non)linear relationships.

3. Data

Data consists of eleven time series of daily closing (5 days) stock market price indices, measured in domestic currencies. The data covers two periods: P1, from November 2, 1987 June 30, 1997, denoting the pre-Asian financial crisis period (2521 observations), and P2, the post-Asian financial crisis period, with data from June 1, 1998 December 1, 2006 (2220 observations). Recall that the on-set of the Asian financial crisis started with a 15%–20% devaluation of Thailand’s Baht which took place on July 2, 1997. This was subsequently followed by devaluations of the Philippine Peso, the Malaysian Ringgit, the Indonesian Rupiah, and the Singaporean Dollar. In addition, the currencies of South Korea and Taiwan suffered. Further in October, 1997 the Hong Kong stock market collapsed with a 40% loss. In January 1998, the currencies of most South-East Asian countries regained parts of the earlier losses. The data are taken from ‘DataStream’.

Table 1 presents some basic information about the eleven stock markets. Among the five emerging markets, the Taiwan (TAW) stock market is the largest in terms of market capitalization, followed by Malaysia (MAL) and India (IND). By contrast Sri Lanka (SL) is a relatively small market. Also, in terms of listed companies, the Sri Lankan market is the smallest. As can be seen from the listed trading values, the Asian financial crisis is clearly visible with a drop in the 1998 figures.

The six developed stock markets have been deregulated and liberalized for quite a very significant period of time. For the emerging markets, Bekker et al. [6] dates India’s integration into the world equity market as 1992. Malaysia, Taiwan and South Korea, however, are still deregulating and liberalizing their markets, a process which began in the late 1980s. Sri Lanka’s stock market (Colombo Stock Exchange (CSE)), on the other hand, underwent a rapid increase in foreign investment following liberalization in 1989. According to Ariff and Khalid [1] and Elyasiani et al. [16] the CSE was one of the best performing markets in the 1989–1994 period, with a 15-fold increase in annual turnover and an eight-fold increase in market capitalization.

The trading hours of the eleven stock exchanges are not perfectly synchronized, though there are several overlapping hours in each trading day for the developed markets. But, within the group of emerging markets, the trading activity is to a large extent concurrent. Nevertheless, the differences in closing times could cause sequential
Table 1
Some selected stock market indicators

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Number of listed companies

Market capitalization as a % of GDP

Trading value ($USm)

Source: Standard & Poors [45].

a From 2002 figures include data from both the Tokyo Stock Exchange and JASDAQ.
b Figures include data from the Tokyo Stock Exchange and Osaka Stock Exchange. From 2002, JASDAQ figures are included.
c Indicates a break in the series.

price responses to common information that could be mistaken for causal linkages. Intra-day market data may be used to disentangle these sequential responses from causal transmissions within a particular day. Regrettably these data are not available for the emerging markets under study.

In the first part of the study, we analyze daily returns $R_t = \ln P_t - \ln P_{t-1}$, where $P_t$ is the closing price of an index on day $t$. In the second part, we focus on the squared and unsquared residuals from linear VAR models fitted to $\{R_t\}$. The squared residuals may be considered as a useful proxy of volatility. Application of three augmented Dickey–Fuller tests (no trend and no intercept, intercept, and trend plus intercept) indicated that the series $\{R_t\}$ are integrated of order zero, i.e. stationary, with $p$-values less than 0.01. The appropriate lag lengths for the tests were selected by minimizing AIC. The Jarque–Bera test for normality indicated that the returns are not normally distributed.

Initial exploratory analysis of the sample cross-correlation matrix at lag 0 (contemporaneous correlation) indicated that almost all series are positively correlated, and significantly different from zero at the 1% level, for the series $\{R_t\}$, and for both time periods. Very low (insignificant) cross-correlations at lag 0 were obtained for the pairs SL–JAP,
SL–TAW, SL–UK, and SL–US. Significant sample cross-correlations at lag 1 were noted for the UK and US stock markets having uni-directional links with almost all other stock markets. However, it is well-known that correlations cannot fully capture the long-term dynamic linkages between the markets. Hence, these results should be interpreted with caution. Consequently, they are not included in the paper. Indeed, what is needed is a long-term causality analysis between the markets.

Empirical experience indicates that it is rather hard to absorb simultaneously large tables with numbers. To overcome this difficulty, and to save space, we use the following simplifying notation: “∗∗” means that the corresponding p-value of a particular test (causality and nonlinearity) is smaller than 1%; “∗” means that the corresponding p-value of a test is in the range 1%–5%; and “−” denotes that the corresponding p-value of a test is larger than 5%. Bi- and uni-directional causalities will be denoted by the functional representations ↔ and →, respectively.

4. Testing methodology

4.1. A multivariate test of nonlinearity

Let \( Y_t = (Y_{1,t}, \ldots, Y_{k,t}) (t = 1, \ldots, n) \) denote a stationary \( k \)-variate time series of length \( n \). A multivariate nonlinear model can be expressed as

\[
Y_{i,t} = \mu_i + f_i(\varepsilon_{1,t-1}, \varepsilon_{2,t-1}, \ldots) + \varepsilon_{i,t},
\]

where \( \{\varepsilon_{i,t}\} \) are serially uncorrelated, but may be cross-correlated at lag zero, and identically distributed random variables, and \( f_i(\cdot) \) are measurable real-valued functions. In general, \( f_i(\cdot) (i = 1, \ldots, k) \) can be represented by a discrete-time Volterra series of the form

\[
f_i(\varepsilon_{1,t-1}, \varepsilon_{2,t-1}, \ldots) = \sum_{s=1}^{k} \sum_{l=1}^{\infty} b_{i,s,l}\varepsilon_{s,t-l} + \sum_{s,u=1}^{k} \sum_{l,m=1}^{\infty} b_{i,s,u,l,m}\varepsilon_{s,t-l}\varepsilon_{u,t-m} + \sum_{s,a,v=1}^{k} \sum_{l,m,r=1}^{\infty} b_{i,s,u,v,l,m,r}\varepsilon_{s,t-l}\varepsilon_{u,t-m}\varepsilon_{v,t-r} + \cdots. \tag{1}
\]

This is a generalization of the Volterra representation of a nonlinear stationary univariate time series. A \( k \)-variate linear process results if all the coefficients of the second and higher-order terms in (1) equal zero. In practice the upper and lower limits in the summations are replaced by finite numbers.

For convenience, assume that each component of \( Y_t \) has mean zero. Then the idea for the test is that if a vector time series process is nonlinear, this structure will be reflected in the residuals of a fitted linear \( p \)th-order VAR model. The test procedure consists of the following steps.

1. Fit a VAR(\( p \)) model to \( Y_t \) by regressing \( Y_t \) on the \( pk \times 1 \) vector \( Z_t = (Y_{1,t-1}, \ldots, Y_{k,t-1}, \ldots, Y_{1,t-p}, \ldots, Y_{k,t-p}) \).

   Compute the \( k \times 1 \) vector of fitted values \( \hat{Y}_t, (t = p + 1, \ldots, n) \), the \( k \times 1 \) vector of residuals \( e_t = Y_t - \hat{Y}_t \), and the corresponding \( k \times k \) matrix \( SSR_1 \) of sum of squared and cross-product terms for the regression.

2. Compute a \( k \times 1 \) vector of squares of fitted values, say \( X_t \), from the \( k \)-variate AR(\( p \)) regressions in step (1). Remove the linear dependence of \( X_t \) on \( Z_t \) by a second \( k \)-variate AR(\( p \)) regression of \( X_t \) on \( Z_t \). Obtain the \( k \times 1 \) vector of fitted values \( \hat{X}_t \), and the \( k \times 1 \) vector of residuals \( u_t = X_t - \hat{X}_t \).

3. Regress the vector of residuals \( e_t \) from step (1) on the vector of residuals \( u_t \) from step (2).

4. Compute the corresponding \( k \times k \) sum of squared regressions matrix, \( SSR_2 \), and sum of squared errors matrix, \( SSE_2 \). Let \( SSR_{2|1} = SSR_2 - SSR_1 \) i.e. \( SSR_{2|1} \) is the extra sum of squares due to the addition of the second-order term to the model.

5. Compute the \( F \)-statistic \( \hat{F} \):

\[
\hat{F} = \left( \frac{n - p - pk - k}{k} \right) \left( \frac{1 - A^{1/2}}{A^{1/2}} \right), \tag{2}
\]
where $A = |SSR_2|/|SSR_2| + SSE_2|$ is Wilks' lambda statistic. Under the assumption that $Y_t$ follows a zero-mean Gaussian $\text{VAR}(p)$ process, and if the sample size $n$ is large, $\hat{F}$ follows approximately an $F_{v_1, v_2}$ distribution with degrees of freedom $v_1 = k$ and $v_2 = (n - p) - pk - k$. Simulation results of Harvill and Ray [24] indicate that, in general, the multivariate version of Keenan's [30] test is more powerful than the univariate tests for at least one of the component series, in particular when the nonlinearity in one series of the vector process is due solely to terms from the other series.

4.2. The nonparametric DP causality test

The general setting for a causality test is as follows. Assume $\{X_t, Y_t; t \geq 1\}$ are two scalar-valued strictly stationary time series. Then $\{X_t\}$ is a strictly Granger-cause of $\{Y_t\}$ if past and current values of $X_t$ contain additional information on future values of $Y_t$ that is not contained in the past and current $Y_t$-values alone. More formally, let $\mathcal{F}_{X,t}$ and $\mathcal{F}_{Y,t}$ denote the information sets consisting of past observations of $X_t$ and $Y_t$ up to and including time $t$, and let $\sim$ denote equivalence in distribution. Then $\{X_t\}$ is a Granger-cause of $\{Y_t\}$ if, for some $k \geq 1,$

$$(Y_{t+1}, \ldots, Y_{t+k})|(\mathcal{F}_{X,t}, \mathcal{F}_{Y,t}) \neq \sim (Y_{t+1}, \ldots, Y_{t+k})|\mathcal{F}_{Y,t}.$$  

(3)

This definition is general and does not involve model assumptions. In practice one often assumes $k = 1$, i.e. testing for Granger noncausality comes down to comparing the one-step-ahead conditional distribution of $\{Y_t\}$ with and without past and current observed values of $\{X_t\}$, which will also be the case considered here.

Note the testing framework introduced above concerns conditional distributions given an infinite number of past observations. In practice, however, tests are usually confined to finite orders in $\{X_t\}$ and $\{Y_t\}$. To this end, define the delay vectors $X_t^{\ell_x} = (X_{t-\ell_x+1}, \ldots, X_t)$, and $Y_t^{\ell_y} = (Y_{t-\ell_y+1}, \ldots, Y_t)$, ($\ell_x, \ell_y \geq 1$). If past observations of $X_t^{\ell_x}$ contain no information about future values, it follows from (3) that the null hypothesis of interest is given by

$$H_0 : Y_{t+1}|(X_t^{\ell_x}, Y_t^{\ell_y}) \sim Y_{t+1}|Y_t^{\ell_y}.$$  

(4)

For a strictly stationary bivariate time series, (4) comes down to a statement about the invariant distribution of the $\ell_x + \ell_y + 1$-dimensional vector $(X_t^{\ell_x}, Y_t^{\ell_y}, Z_t)$ where $Z_t = Y_{t+1}$. To simplify notation we drop the time index $t$. Further, it is assumed that $\ell_x = \ell_y = 1$. Hence, under the null, the conditional distribution of $Z$ given $(X, Y) = (x, y)$ is the same as that of $Z$ given $Y = y$. Then (4) can be restated in terms of ratios of joint distributions. Specifically, the joint probability density function $f_{X,Y,Z}(x, y, z)$ and its marginals must satisfy the relationship $f_{X,Y,Z}(x, y, z)/f_Y(y) = (f_{X,Y}(x, y)/f_Y(y))(f_{Y,Z}(y, z)/f_Y(y))$. Thus $X$ and $Z$ are independent conditionally on $Y = y$, for each fixed value of $y$. DP [13] show that this reformulated $H_0$ implies

$$q \equiv E[f_{X,Y,Z}(X, Y, Z)f_Y(Y) - f_{X,Y}(X, Y)f_{Y,Z}(Y, Z)] = 0.$$  

Let $\hat{f}_W(W_t)$ denote a local density estimator of a $d_W$-variate random vector $W$ at $W_t$ defined by $\hat{f}_W(W_t) = (2\epsilon_n)^{-d_W}(n - 1)^{-1}\sum_{j, j \neq i} I_{ij}^W$, where $I_{ij}^W = I(||W_t - W_j|| < \epsilon_n)$ with $I(\cdot)$ the indicator function and $\epsilon_n$ the bandwidth, depending on the sample size $n$. Given this estimator, the test statistic of interest is given by

$$T_n(\epsilon_n) = \frac{n - 1}{n(n - 2)} \sum_{i} \bar{J}_{ij}^2(Y_t)(\hat{f}_{X,Z|Y}(X_i, Z_i|Y_t) - \hat{f}_{X|Y}(X_i|Y_t)\hat{f}_{Z|Y}(Z_i|Y_t)).$$  

(5)

Suppose that $\epsilon_n = Cn^{-\beta}$ ($C > 0$, $\frac{1}{4} < \beta < \frac{1}{3}$). Then DP [13] prove that (5) satisfies

$$\sqrt{n}(T_n(\epsilon_n) - q) \overset{D}{\to} N(0, 1),$$  

(6)

where $\overset{D}{\to}$ denotes convergence in distribution, and $S_n$ is an estimator of the asymptotic variance of $T_n(\cdot)$ as discussed in detail by DP [13, Appendix A].

\footnote{\textsc{fortran} code for computing $\hat{F}$ can be obtained from the first author.}

\footnote{C-code for computing the $T_n(\cdot)$ test statistic can be downloaded from: http://www1.fee.uva.nl/cendef/upload/15/GCTest.zip.}
Table 2
Multivariate nonlinearity test results (above diagonal) and orders of fitted VAR(\(p\)) models (below diagonal): Periods P1 (pre-Asian financial crisis) and P2 (post-Asian financial crisis)

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5. Empirical results

5.1. Multivariate nonlinearity test

Before investigating specific linear and nonlinear causal relationships between pairs of bivariate time series, it is desirable to test for the general vector nonlinear structure. Using linear VAR(\(p\)) models having \(p = 0, 1, \ldots, 10\), the AIC model selection criterion was used to select the “best” model fitted to pairs of time series. The optimal orders \(p\) are listed in Table 2 below the main diagonal. Applying the multivariate Keenan test of Section 4, a summary of information about the results of the nonlinearity test statistic is presented above the main diagonal. Some observations are in order.

The Asian financial crisis has an obvious impact on the orders of the selected VAR(\(p\)) models. The total number of pairs of series having the same VAR orders in both periods is 8 (14.5%) while in 47 cases (85.5%) there has been a change between the orders \(p\) selected for period P1 and period P2. Within the set of developed (emerging) markets these percentages are 6% (10%) and 94% (90%), respectively.

Nonlinearity, at the 1% level, is detected for 35 (64%) pairs of indices in period P1, and for 23 (42%) pairs in period P2. No evidence of general nonlinear structure, at the 1% level, in the data is indicated for 12 (22%) pairs in period P1, and for 29 (53%) pairs in period P2. Clearly, this is an overall view of the data. But these percentages suggest that there is weak evidence that the number of paired nonlinearities have changed between both periods.

At a more detailed level, however, there appear to be more differences between both time periods. In particular, we see that for 17 pairs (31%) the simplifying notation for the significance of the multivariate nonlinearity test changed from “**” to “–”, and for only 3 (5%) pairs it changed from “–” to “**”.

Among the whole set of nonlinearity test results, those presented for Malaysia are interestingly different. Indeed, there is evidence that this market has significant (***) nonlinear relationships with almost all other markets. Moreover, these relationships remain fairly persistent across both time periods.

Broadly, the significant nonlinearity test results reported in Table 2 motivate the search for causal and persistent nonlinear linkages between pairs of stock indices by a nonparametric test. Nevertheless these results should be interpreted with caution since high kurtosis in the returns may affect the null distribution of the test.

5.2. Parametric and nonparametric causality tests: No pre-filtering

For each of the eleven series \(\{R_t\}\) pairwise causality testing was carried out using the Wald variant of Granger’s test. Simulation results provided by Geweke et al. [19] show that this type of Granger causality test has a number of advantages over eight alternative tests of causality. In each case, the optimal lag orders reported in Table 2 are used for the unrestricted VAR model. It is well-known that the results of the Granger causality test are sensitive to the choice of the lag length, even when a sophisticated search routine for the lag length has been implemented in the process of finding the best VAR specification. Therefore it is safe to restrict the discussion below to causality results obtained at
suggest that there are significant and persistent linear and nonlinear causal linkages between the stock markets. However, the results obtained for the DP test may be blurred by the presence of the combined effect. In other words, even though we found nonlinear causality, the DP test should be reapplied to filtered

### 5.3. Nonparametric causality testing: VAR-filtering

The results in Tables 2 and 3 suggest that there are significant and persistent linear and nonlinear causal linkages between the stock markets. However, the results obtained for the DP test may be blurred by the presence of the combined effect. In other words, even though we found nonlinear causality, the DP test should be reapplied to filtered
Table 4
Nonparametric causality testing for periods P1 (pre-Asian financial crisis) and P2 (post-Asian financial crisis) using unfiltered returns \( \{ R_t \} \)

<table>
<thead>
<tr>
<th></th>
<th>GER</th>
<th>HNG</th>
<th>JAP</th>
<th>SNG</th>
<th>UK</th>
<th>US</th>
<th>IND</th>
<th>MAL</th>
<th>SK</th>
<th>SL</th>
<th>TAW</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1 -</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>P2 -</td>
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</tbody>
</table>

Significant (**) or * entries indicate that stock market \( X \) (top row) has a causal nonlinear relationship with stock market \( Y \) (left column), i.e. \( X \rightarrow Y \).

Table 5
Nonparametric causality testing for period P2 (post-Asian financial crisis): Residuals \( \{ \hat{e}_t \} \) and squared residuals \( \{ \hat{e}_t^2 \} \) are obtained after filtering with linear bivariate VAR models

<table>
<thead>
<tr>
<th></th>
<th>GER</th>
<th>HNG</th>
<th>JAP</th>
<th>SNG</th>
<th>UK</th>
<th>US</th>
<th>IND</th>
<th>MAL</th>
<th>SK</th>
<th>SL</th>
<th>TAW</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \hat{e}_t )</td>
<td>**</td>
<td>**</td>
<td>*</td>
<td>**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{e}_t^2 )</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
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</tbody>
</table>

Significant (**) or * entries indicate that stock market \( X \) (top row) has a causal nonlinear relationship with stock market \( Y \) (left column), i.e. \( X \rightarrow Y \).

VAR-residuals to ensure that any causality found is strictly nonlinear in nature. Table 5 presents the DP nonparametric causality test for period P2, using residuals \( \{ \hat{e}_t \} \) and squared residuals \( \{ \hat{e}_t^2 \} \) obtained from the linear VAR models reported in Table 2.

Comparing the summary results for \( \{ \hat{e}_t \} \) in Table 5 with the results reported in Table 4 for the returns \( \{ R_t \} \) in period P2 it is interesting to see that both tables show identical pairwise significant (**) causal nonlinear relationships, except for the following cases:

- The causal nonlinear relationships from JAP \( \rightarrow \) UK, JAP \( \rightarrow \) SK, UK \( \rightarrow \) IND, SNG \( \rightarrow \) IND, SL \( \rightarrow \) TAW have changed from “**” in Table 4 to “-” in Table 5. Given the results presented in Table 2, it suggests the absence of nonlinear causality for the first three pairs above, while the last two pairs have no significant causal linear or nonlinear relationships. This is also the case for the significance of the relationship HNG \( \rightarrow \) US which changed from “*” in Table 4 to “-” in Table 5.

- On the other hand, the significance of the causal nonlinear relationship JAP \( \rightarrow \) IND changed from “*” in Table 4 to “**” in Table 5. Similarly, no significant (–) causal nonlinear relationship could be detected from MAL \( \rightarrow \) JAP in Table 4. But the result “**” in Table 5 clearly indicates: MAL \( \rightarrow \) JAP. These reverse changes in relationships are hard to interpret. In particular, since according to Table 2 no significant causal linear relationship could be detected between these two specific pairs (JAP–IND and MAL–JAP) at the 1% level.

When we exclusively focus on the results in Table 5, the following additional observations emerge.
The total number of significant (**) bi-directional causal nonlinear relationships is 33 (60\%) for \( \hat{\varepsilon}_t \), and 17 (31\%) for \( \hat{\varepsilon}_t^2 \). Only 16 pairs have significant common causal nonlinear relationships for both squared and unsquared residuals.

Again, there is almost no significant interdependence between the Sri Lankan market and the other markets. Only, in terms of squared residuals, significant (**) causal nonlinear relationships can be seen from MAL \( \rightarrow \) SL and from SK \( \rightarrow \) SL.

The nature and source(s) of the detected nonlinearities may be different from that of the linear Granger causality test. For instance, exchange rate volatility might induce nonlinear causality in the emerging markets. Caporale et al. \[\text{[8]}\] provide empirical evidence for this proposition using daily exchange rates (in local currencies) and stock price indices for Indonesia, Japan, South Korea, and Thailand. Also, persistent nonlinear causality can be induced by relatively high transaction costs. Research by Domowitz et al. \[\text{[14]}\] shows that trading costs in the emerging markets are significantly higher than those in more developed markets, with South Korea being one of the most expensive markets. This result still holds after correcting for factors affecting costs such as market capitalization and volatility. Consequently, investors in these markets pool their information until it is profitable to trade. Needless to say, there may be other sources of the observed nonlinearities.

### 5.4. Nonparametric causality testing: GARCH-BEKK filtered VAR-residuals

Given the causality results for \( \{\hat{\varepsilon}_t^2\} \) in Table 5, it is interesting to reinvestigate the hypothesis of nonlinear causality after controlling for conditional heteroskedasticity in the data. Many vector linear and vector nonlinear (asymmetric) time series models can be used for this purpose. As an illustration, we restrict our attention here to the bivariate GARCH-BEKK \[\text{[17]}\] processes of order \((p, q)\), in which \((\varepsilon_t) = (\varepsilon_{1,t}, \varepsilon_{2,t})'\) follows the equations

\[
\varepsilon_t = \mathbf{H}_t^{1/2} \nu_t, \quad \mathbf{H}_t = \mathbf{C}' \mathbf{C} + \sum_{i=1}^{p} \mathbf{A}_i \varepsilon_{t-i} \varepsilon_{t-i}', \mathbf{A}_i + \sum_{j=1}^{q} \mathbf{B}_j \mathbf{H}_{t-j} \mathbf{B}_j
\]

with parameter matrices

\[
\mathbf{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}, \quad \mathbf{A}_i = \begin{pmatrix} a_{11}^{(i)} & a_{12}^{(i)} \\ a_{21}^{(i)} & a_{22}^{(i)} \end{pmatrix}, \quad \mathbf{B}_j = \begin{pmatrix} b_{11}^{(j)} & b_{12}^{(j)} \\ b_{21}^{(j)} & b_{22}^{(j)} \end{pmatrix},
\]

and \(\{\nu_t\}\) is a sequence of i.i.d. random variables with mean zero and 2 \(\times\) 2 covariance matrix \(\mathbf{I}\). Note, \(\mathbf{H}_t\) is the conditional covariance matrix of \(\{\varepsilon_t\}\), i.e. \(\varepsilon_t|\mathcal{F}_{t-1} \sim (0, \mathbf{H}_t)\) with \(\mathcal{F}_{t-1}\) the information set at time \(t-1\). Through the matrices \(\mathbf{A}_i\) and \(\mathbf{B}_j\), (7) allows for own-market- and cross-market interactions. The residuals are obtained by the whitening matrix transformation \(\mathbf{H}_t^{-1/2} \varepsilon_t\). Weak restrictions on \(\mathbf{A}_i\) and \(\mathbf{B}_j\) guarantee that \(\mathbf{H}_t\) is always positive definite; see, e.g., Ref. \[\text{[5]}\] for a full account of the properties of multivariate GARCH models.\(^4\)

Using the results in Table 5, we initially selected 32 pairs of stock market indices showing significant (i.e. (**, **), (***, *), or (*, **)) causal nonlinear relationships in the squared and unsquared residuals. As a first step, we fitted GARCH-BEKK \((p, q)\) models to \((\hat{\varepsilon}_{1,t}, \hat{\varepsilon}_{2,t})'\) with values of the order \((p, q)\) in the range [1, 2]. At this point it is worth mentioning that fitted GARCH-BEKK models are only useful if the process under study is covariance stationary. This property can be verified by computing the eigenvalues of the expression \(\sum_{i=1}^{p} (\mathbf{A}_i \otimes \mathbf{A}_i) + \sum_{j=1}^{q} (\mathbf{B}_j \otimes \mathbf{B}_j)\) with \(\otimes\) the Kronecker product. If all the eigenvalues are less than one in modulus, the covariance-stationarity condition is satisfied. Only for eight pairs of residuals the maximum eigenvalue was less than one. Table 6 reports the “best” (in terms of minimal AIC values, and eigenvalues less than one) fitted models. Asymptotic standard errors are in parentheses. No efforts were made to improve the fitted models by setting insignificant parameters equal to 0. Table 6 also shows results of the nonparametric DP causality test statistic applied to the VAR-residuals before and after GARCH-BEKK-filtering.\(^5\)

\(^4\) Parameters of (7) will be estimated by the routine “mvBEKK.est” (default settings) contained in the R-package “mgarchBEKK”. The package can be downloaded from: http://www.vsthost.com.

\(^5\) As far as we know it is unclear how the asymptotic distribution of the nonparametric DP causality test statistic is affected by the use of estimated model (e.g. VAR, GARCH-BEKK, etc.) residuals.
Table 6
GARCH-BEKK estimation results applied to the VAR-residuals, and nonparametric causality test results applied to the VAR-residuals before and after GARCH-BEKK-filtering: Period P2 (post-Asian financial crisis)

<table>
<thead>
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<tbody>
<tr>
<td><strong>Estimation results</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C)</td>
<td>0.0004</td>
<td>0.0065</td>
<td>0.0119</td>
<td>0.0049</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0006)</td>
<td>(0.0003)</td>
<td>(0.0005)</td>
</tr>
<tr>
<td>(A_1)</td>
<td>0.3449</td>
<td>0.4627</td>
<td>–0.2029</td>
<td>–0.2616</td>
</tr>
<tr>
<td></td>
<td>(0.0334)</td>
<td>(0.0397)</td>
<td>(0.0453)</td>
<td>(0.0369)</td>
</tr>
<tr>
<td>(A_2)</td>
<td>0.1065</td>
<td>–0.0457</td>
<td>0.2593</td>
<td>–0.0579</td>
</tr>
<tr>
<td></td>
<td>(0.0509)</td>
<td>(0.0382)</td>
<td>(0.0704)</td>
<td>(0.0375)</td>
</tr>
<tr>
<td><strong>Nonparametric causality test results: Before and after GARCH-BEKK-filtering</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C)</td>
<td>0.0064</td>
<td>0.0115</td>
<td>–0.0031</td>
<td>0.0053</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0006)</td>
<td>(0.0003)</td>
<td>(0.0004)</td>
</tr>
<tr>
<td>(A_1)</td>
<td>–0.5058</td>
<td>–0.0744</td>
<td>0.3433</td>
<td>0.1616</td>
</tr>
<tr>
<td></td>
<td>(0.0341)</td>
<td>(0.0631)</td>
<td>(0.0277)</td>
<td>(0.0401)</td>
</tr>
<tr>
<td>(B_1)</td>
<td>–0.1470</td>
<td>0.6005</td>
<td>–0.1981</td>
<td>–0.8368</td>
</tr>
<tr>
<td></td>
<td>(0.0722)</td>
<td>(0.0882)</td>
<td>(0.0279)</td>
<td>(0.0566)</td>
</tr>
<tr>
<td>(B_2)</td>
<td>–0.7191</td>
<td>0.0993</td>
<td>–0.1394</td>
<td>–0.0344</td>
</tr>
<tr>
<td></td>
<td>(0.0623)</td>
<td>(0.0779)</td>
<td>(0.0202)</td>
<td>(0.0036)</td>
</tr>
</tbody>
</table>

Note that the GARCH-BEKK-filtering yields substantially smaller values of the nonparametric causality test statistic. In all cases the statistical significance, as denoted by the short-hand notations **, *, and –, is much weaker after filtering than before. These differences in statistical significance indicate that the nonlinear causality is largely due to simple volatility effects. The GARCH-BEKK estimates are for the most part significantly different from zero. Significant bi-directional cross-market dependence can be noted, through checking the significance of the off-diagonal
elements in the matrices $A_i$ and $B_j (i, j = 1, 2)$, in the case of GER–HNG, HNG–UK, UK–US, IND–TAW, and SNG–US.

6. Summary and concluding remarks

Several interesting conclusions with respect to the internationalization of the stock exchanges have already emerged from this study. In particular, it was shown that almost all stock markets considered here have become more internationally integrated after the Asian financial crisis. But no significant long-term causal linkages were found between Sri Lanka and any of the other countries during both the pre- and post-Asian financial crisis period. Although this finding is in line with Elyasiani et al. [16] it is hard to explain this phenomenon. It may be due to the relatively small size of the CSE. Testing for linear and nonlinear causality in the stock-price–volume relation for Sri Lanka may provide some information on this matter. In addition, in their 1998 paper Elyasiani et al. noted that the Sri Lankan market suffers from a lack of market liquidity and from high concentration in blue chip stocks. As a consequence, local traders hold on to their stocks, especially blue chips, for longer time periods. Whether this phenomenon is still the case is worth investigating. However, given the fact that the Sri Lankan market is found to be relatively isolated from other markets in this study, it provides profit opportunities and diversification benefits to global investors.

The leading role of the US market in the world stock market is clearly visible throughout all causality tests and in both time periods. This is consistent with earlier findings by Eun and Shim [18]. In the post-Asian period the US market was influenced by Germany, Japan, Singapore, the UK, India, Malaysia, South Korea, and Taiwan; see Tables 4 and 5. This confirms the increased financial links between the US and the world economy. On the other hand, the Japanese market has relatively little influence on the stock price movements in other markets once linear effects have been removed through VAR-filtering; see Table 5. This finding gives further support to an earlier study by Malliaris and Urrutia [32] who concluded that the Japanese market plays a passive role in transmitting information to other stock markets.

Another finding is that no major differences exist between the persistence and strength of the bi-directional causal linkages among the industrialized markets and the emerging markets in the post-Asian financial crisis period. These results, apart from offering a much better understanding of the dynamic linear and nonlinear relationships underlying the movements of emerging Asian stock markets than that has been noted until now, have many implications for market efficiency. For instance, they may be useful in future research to quantify the process of financial integration of emerging markets. Also, the presence of causal nonlinear relationships may influence the greater predictability of these markets. This may, for instance, be investigated through a trading strategy using multivariate (non)parametric methodology.

Another topic for future research concerns the source(s) or cause(s) of the nonlinear causal linkages. Previously we conjectured that volatility effects might induce nonlinear causality. The fitted GARCH-BEKK models provide some guidance on this matter, but only in some special cases. Alternative specific parametrized structural models may be employed. Related to this, is a need for determining the economic factors driving the interdependence of emerging stock markets. Pretorius [40] studies this topic empirically by using cross-section and linear time series regression models. But more research is needed.

Finally, the empirical finding of nonlinear causal relationships between emerging stock markets may be analyzed in terms of their implications for the efficiency of these markets. The fact that there are long-term links between various markets may imply that excess (risk- and transactions cost-adjusted) returns exist. Given such inefficiency, authorities in emerging markets may then reconsider their policies regarding, for instance, brokerage fees, stock exchange charges, and other equity trading costs.

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6 There was no civil war in Sri Lanka during the period 2002–2006.
References


