Int. Fin. Markets, Inst. and Money 20 (2010) 590–605

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

Time-shift asymmetric correlation analysis of global stock markets

Sergey K. Aityan[a,*], Alexey K. Ivanov-Schitz[b,1], Sergey S. Izotov[b,1]

[a] Department of Business and Economics, Lincoln University, 401 15th Street, Oakland, CA 94612, USA
[b] School of International Economic Relations, MGIMO University, 76 Prospekt Vernadskogo, 119454 Moscow, Russia

ARTICLE INFO

Article history:
Received 16 March 2010
Accepted 27 July 2010
Available online 6 August 2010

Keywords:
Stock market
Correlation
Asymmetric
Time-shift
Globalization

JEL classification:
C01
F21
G11
G15

ABSTRACT

The time-shift asymmetric correlation analysis method is introduced for stock exchanges with different but non-overlapping trading hours to analyze the degree of global integration between stock markets of different countries and their influence on each other. Next-day correlation (NDC) and same-day correlation (SDC) coefficients are introduced. Correlations between major U.S. and Asia-Pacific stock market indices are analyzed. Most NDCs are statistically significant while most SDCs are insignificant. NDCs grow over time and the U.S. stock market plays a pacemaking role for the Asia-Pacific region. The correlation coefficients can be used as a measure of the degree of globalization for the corresponding countries.

1. Introduction

As globalization progresses, economies of all countries have become more economically interdependent. However, different countries are engaged in this process to different degrees, which results in different impacts on their financial and securities markets.

Correlations of stock market returns have been studied for decades (Atchinson et al., 1987; Bollerslev, 1990; Badrinath et al., 1995; Chan, 1993; Yu and Wu, 2001; Cohen et al., 1980; Conrad and

* Corresponding author. Tel.: +1 510 628 8016; fax: +1 501 628 8012.
E-mail addresses: aityan@lincolnuca.edu (S.K. Aityan), alexey.k.ivanov@gmail.com (A.K. Ivanov-Schitz).
[1] Tel.: +7 495 434 60 56.

1042-4431/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.intfin.2010.07.006

Kaul, 1988; Ilina and Daragan, 2001a; Kumar and Dhankar, 2009; and many others) in the attempt to learn the market behavior for predicting trends and identifying hints for trading decisions. Stock market correlations have been attributed to information propagation including news and a variety of other factors that may impact the interrelations in the stock market on local or global scales.

Delays in information propagation may cause a lead–lag relationship in different stock markets and in different segments of a single stock market. Autocorrelation and cross-correlation approaches were used to learn about such a relationship and its impact on trading behavior. Researchers have utilized a variety of models for analyzing the lead–lag relationship. Correlations between stock markets or within a given stock market have been analyzed utilizing model-free conventional statistics or special models to account for more complex relationships and effects like random information delays, noise, and others. Among the most popular models used in econometrics are Autoregressive Conditional Heteroskedasticity (ARCH) proposed by Engle (1982) and its modifications like Generalized Autoregressive Conditional Heteroskedasticity (GARCH) proposed by Bollerslev (1986) for analysis of market volatility. The GARCH model has led to a variety of modifications such as EGARCH – Exponential GARCH (Nelson, 1991), QGARCH – Quadratic GARCH (Sentana, 1995), GARCH-M – GARCH-in-mean (Hentschel, 1995), TGARCH – Threshold GARCH (Zakoian, 1994) and many others.

Bollerslev et al. (1988) proposed a measure for determining the conditional covariance based on VECH representation, which would effectively become an ARMA model for the product of the error terms. To capture the asymmetric answer of the volatility by the different sign of the stock market shocks, Engle et al. (1990) proposed the AGARCH model.

It is well known by now that cross-correlations of stock market returns vary over time (Makridakis and Wheelwright, 1974; Koch and Koch, 1991; Knif and Pynnonen, 1999). Correlations increase as economic integration intensifies (Erb et al., 1994; Longin and Solnik, 1995; Goetzmann et al., 2005), but the correlations most likely are higher in bull markets and lower in the bear markets. Longin and Solnik (1995), Ang and Bekaert (2002), and Longin and Solnik (2001) showed that correlations between markets were going up during the periods of high volatility and correlation coefficients were higher than average when diversification was profitable. It was noticed that such a behavior of correlations leads to a quite insignificant return with portfolio diversification in a bear market (Baele, 2005).

Multiple studies identified that correlations between international stock markets has a tendency to increase when returns decrease (King and Wadhwani, 1990; Lin et al., 1994; Solnik et al., 1996; Chesnay and Jondeau, 2001; Baele, 2005).

Richardson and Peterson (1999) have found that cross-correlation between large and small stocks takes place even after controlling for own-autocorrelation. The lead–lag phenomenon among returns of size-sorted portfolios may imply a complex information transmission between large and small firms and can be used as an important source for trading decisions. Chan (1993) suggested that own- and cross-autocorrelations among stock returns occur due to imperfection of market-to-market information that causes correlation pattern asymmetry. Lo and MacKinlay (1990a,b) documented asymmetric return caused by cross-correlations and nonsynchronous trading. Yu and Wu (2001) applied asymmetric cross-correlation analysis approach to identify "the differential quality of information between large and small firms." It was suggested that the asymmetric cross-correlation between large and small firms is mainly caused by differences in the sensitivity of stock prices to market-wide information and cash flow information between those firms.

Ilina and Daragan (2001a) noted that if any two indices are highly correlated, then diversification between them makes no sense because the diversification effect will be quite slim. They conducted correlation analysis for studying international stock market indices including S&P 500 (U.S.), DAX (Germany), FTSE (UK), TSE 300 (Canada), and Nikkei 225 (Japan) from 1990 to 2001 (Ilina and Daragan, 2001b). The study identified the highest correlation between S&P 500 and the Canadian TSE 300 indices. The lowest correlation was found between S&P 500 and Japanese Nikkei 225 indices.

A well-known gravity model frequently used for explanations of trade patterns can also be used for the explanation of stock market correlations (Flavin et al., 2002). Its essential conclusion is that geography does matter for goods markets while physical location and trading costs should be less of an issue in asset markets. It was found that geographical locations still matter when examining equity market linkages. In particular, the number of overlapping opening hours and sharing a common border tends to increase cross-country stock market correlation. Flavin et al. (2002) wrote "these results may stem from asymmetrical information and investor sentiment, lending some empirical support for these explanations of the international diversification puzzle." Martens and Poon (2001) brought up the issue that the use of day-by-day close-to-close returns underestimates the correlation of returns because international stock markets in different countries have different trading hours. Growing interconnection of international stock markets and time-varying relationship of the returns was analyzed by Hu et al. (2008). They noted a dynamic relationship between major world stock markets over time and indicated a clear short-term continental integration of the selected markets which were replaced by a more complex global hedging behavior in the long run. However in their analysis Hu et al. (2008) did not take into account the differences in trading hours of different stock markets.

Though the ARCH-family models have been successfully applied in the analysis of stock market correlations and volatility, many researchers prefer model-free statistical testing and correlation analysis (Ilina and Daragan, 2001a,b; Aityan, 2007; Hong et al., 2007; Ivanov-Schitz and Aityan, 2009).

Michayluk et al. (2006) analyzed returns behavior and asymmetric volatility spillover effects and exceedance correlations in the example of real estate markets of different countries. They compared the correlations calculated on a daily basis when synchronously priced data were utilized with the correlations calculated on close-to-close returns and found that they are significantly different due to intraday information flows between both the markets. Li and Kazemi (2007) analyzed correlation asymmetry of daily returns of various hedge fund indices. In their research, they understood asymmetry as the correlation between two indices when both random variables were simultaneously above or below their means by more than their standard deviations. Chiang et al. (2007) and Centeno and Salido (2009) examined stock market asymmetric returns caused by positive and negative news and shocks. They found that negative news has a much stronger impact on returns than positive news. Thus researchers use term "correlation asymmetry" differently for a variety of different non-symmetric analyses.

Some empirical studies suggested that monetary variables can also be used in the analysis of the dynamic interrelationship between securities markets. Sasaki et al. (1999) identified the significant impact of monetary and credit policies on the interrelationship between the securities markets. Black and Fraser (1995), Bracker et al. (1999), Bekaert and Harvey (2000), Bekaert et al. (2001), Wu (2001), Pretorius (2002), Liu et al. (2006), and Mukherjee and Mishra (2007) showed that the dynamics of stock markets integration depends on monetary parameters such as interest rates, foreign investment, trade, and inflation.

Studies of correlations between stock markets have not been limited only to major markets. Da Costa et al. (2005) studied the correlations between developed and emerging markets. The scope of their analysis included emerging countries in Latin America such as Argentina, Brazil, Chile, Mexico, Asian countries such as South Korea, India, and Thailand, as well as developed countries such as the USA, Japan, and Great Britain. This study detected a growth of cross-correlations between the stock market indices in the 1980s and 1990s with a distinctive increase of the correlations in the 1990s as compared to the 1980s. The results suggested that efficiency of diversification in foreign markets decreases due to global integration. On the other hand, Kumar and Dhankar (2009) analyzed correlations between South Asian stock markets (India, Sri Lanka, Pakistan, and Bangladesh) and reported weak interdependency between these markets and global stock markets. The question arises: what did cause these studies to result in contradicting conclusions?

Hamao et al. (1990) and Balaban et al. (2001) used the two-step GARCH model for studying stock markets interdependencies for intraday and overnight returns. They identified the intraday market shocks on the first step and used them for overnight returns on the second step.

Different trading hours of different stock markets have been traditionally considered a disadvantage for correlation analysis (Martens and Poon, 2001) and major models like ARCH, GARCH, and others have been dealing with lead–lag relationships caused by real-time information delays mostly for overlapping trading hours. Martens and Poon (2001) showed that the use of close-to-close returns can underestimate return correlations for markets that trade at different times. Moreover, previous studies such as by Hamao et al. (1990) and Koutmos and Booth (1995), who utilized only opening and closing prices, have found it difficult to differentiate between contemporaneous and lagged spillover pricing effects from one market to another. They suggested that to avoid such a problem in correlation analysis, data must be synchronized by time, i.e. for every correlation pair the data must be observed at the same time.

In this paper, we propose a model-free time-shift asymmetric correlation analysis for studying correlations and the interdependency of international stock markets that have no overlap of trading hours. We analyze close-to-close stock market returns for the markets with non-overlapping trading hours taking into account that each market operates with the information available by the market close of the other stock market. For this reason, we need neither the detailed information about delays of intraday information propagation nor the detailed information about any specifically accurate intraday time-lags for autocorrelations. We are not using explicit time-lags and explicit cross-autocorrelations because the time difference between the close of one market and the open of another market may vary due to occasionally shortened operating time on some markets, weekends, and holidays. In our approach, we only use the fact that one market works with the information of another previously closed market. The time between the close of one market and the open of another market for markets with non-overlapping trading hours is sufficient for the information from one market to reach another market. This fact allows us to use a simple model-free approach rather than a more complicated approach with ARCH/GARCH family models to identify a lead–lag relationship between the markets.

The proposed approach helps overcome the disadvantage of using non-overlapping trading hours and turns it into a source of valuable information. This approach also helps identify which stock market is setting the pace and which ones are following the trend in the global environment. Though traditional correlation analysis does not identify the cause-and-effect relationship, the proposed time-shift asymmetric correlation analysis is able to solve this challenge utilizing the fact that stock exchanges in different countries operate at different times and with recent information about other stock markets with earlier trading hours (Aityan, 2007). Particularly, such an approach is quite efficient for cross-analysis of the U.S. and Asia-Pacific stock markets, where the U.S. stock markets are already closed at the time of trading on the Asia-Pacific stock markets, and vice versa.

We suggest that correlation coefficients calculated between daily rates of return for stock market indices of different countries adequately reflect the degree of integration of the appropriate economies and can be used as a measure of globalization.

2. Time-shift asymmetric correlation method (NDC-SDC)

The correlation coefficients are usually used to show the degree of the simultaneousness of changes but not to identify which market is setting up the pace and which one is following the pace. In order to identify the leading market, we take into account the fact that stock exchanges have different operation hours in different regions. For instance, when the NYSE and NASDAQ operate in the U.S. (9:30 AM to 4:00 PM EST), the Japanese Tokyo and Osaka stock exchanges are closed (they operate from 8:00 PM to 10:00 PM and 11:30 PM to 2:00 AM EST). Trading hours of major U.S. and Asia-Pacific stock exchanges are shown in Table 1.

The time-shift asymmetric correlation analysis (Aityan, 2007) is based on the fact that different markets operate at different hours and therefore one of them operates with recent information on another market. For example, on any given trading day the U.S. stock exchanges operate with known results of Japanese stock exchanges for the same calendar trading day. On the other hand, on the next trading day, Japanese stock exchanges operate with information available about the results of U.S. stock exchanges from the previous trading day as shown in Fig. 1.

In order to proceed with this analysis we need to introduce the following terms:

- *Same-day correlation* (SDC) is the correlation coefficient between two indices (or individual stock prices) at market close on the same calendar day.
- *Next-day correlation* (NDC) is the correlation coefficient between two indices (or individual stock prices) at market close on different days: for the first component on the given trading day and for the other one on the following trading day.

Table 1
Trading hours of stock exchanges.[a]

Country and stock exchange	Trading hours	
	(US EST)	(Local time)
U.S. (NYSE and Nasdaq)	9:30 AM to 4:00 PM	9:30 AM to 4:00 PM
Japan (Tokyo and Osaka stock exchange)	8:00 PM to 10:00 PM	9:00 AM to 11:00 AM
	12:00 PM to 2:00 AM	1:00 PM to 3:00 PM
Hong Kong (Hong Kong stock exchange)	10:00 PM to 12:30 PM	10:00 AM to 12:30 AM
	2:30 AM to 4:00 AM	2:30 PM to 4:00 PM
China (Shanghai stock exchange)	9:30 PM to 11:30 PM	9:30 AM to 11:30 AM
	1:00 AM to 3:00 AM	1:00 PM to 3:00 PM
Taiwan (Taiwan stock exchange)	9:00 PM to 1:30 AM	9:00 AM to 1:30 PM
South Korea (Korea exchange)	8:00 PM to 2:00 AM	9:00 AM to 3:00 PM
Singapore (Singapore exchange)	9:00 PM to 12:30 AM	9:00 AM to 12:30 PM
	2:00 AM to 5:00 AM	2:00 PM to 5:00 PM
Indonesia (Indonesia stock exchange)	10:30 PM to 1:00 AM	9:30 AM to 12:00 PM
	2:30 AM to 5:00 AM	1:30 PM to 4:00 PM
Malaysia (Bursa Malaysia)	9:00 PM to 12:30 PM	9:00 AM to 12:30 AM
	2:30 AM to 5:00 AM	2:30 PM to 5:00 PM

[a] The sources for international stock exchanges operating hours are provided in Appendix A.

To calculate SDC let us start with the following:

$$R_X(i) = \frac{V_X(i) - V_X(i-1)}{V_X(i-1)} \tag{1}$$

where $R_X(i)$ is the daily rate of return, $V_X(i)$ and $V_X(i-1)$ are the values of index (or an individual stock) X at the market close on day i, and on the previous trading day, respectively:

$$\mu_X(N) = \frac{1}{N}\sum_{i=1}^{N} R_X(i) \tag{2}$$

where μX is the mean of the rates of return of index (or individual stock) X within the period of N trading days:

$$\sigma_X^2(N) = \frac{1}{N-1}\sum_{i=1}^{N}[R_X(i) - \mu_X(N)]^2 \tag{3}$$

where $\sigma_X(N)$ is the variance of the rate of return of index (or individual stock) X for N trading days:

$$\rho_{AB}^{SD}(N) = \frac{\frac{1}{N-1}\sum_{i=1}^{N}\{[R_A(i) - \mu_A(N)][R_B(i) - \mu_B(N)]\}}{\sigma_A(N)\sigma_B(N)} \tag{4}$$

where $\rho_{AB}^{SD}(N)$ is the SDC for the pair of indices (or individual stocks) A and B for N trading days.

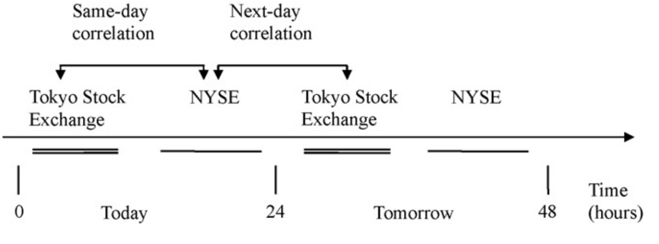

Fig. 1. SDC and NDC coefficients for Dow Jones and Nikkei.

Similarly, we calculate the NDC:

$$\mu_A(N) = \frac{1}{N}\sum_{i=1}^{N} R_A(i) \quad \mu_B^+(N) = \frac{1}{N}\sum_{i=1}^{N} R_B(i+1) \tag{5}$$

$$\sigma_A(N) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}[R_A(i)-\mu_A(N)]^2} \quad \sigma_B^+(N) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}[R_B(i+1)-\mu_B^+(N)]^2} \tag{6}$$

$$\rho_{AB}^{ND}(N) = \frac{\frac{1}{N-1}\sum_{i=1}^{N}\{[R_A(i)-\mu_A(N)][R_B(i+1)-\mu_B^+(N)]\}}{\sigma_A(N)\sigma_B^+(N)} \tag{7}$$

where superscript '+' in μ^+ and σ^+ indicates the appropriate values for next trading day and $\rho_{AB}^{ND}(N)$ is the NDC for the pair of indices (or individual stocks) A and B for N trading days.

Thus the SDC and the NDC correlation coefficients differ from each other only by values associated with stock index B, which are shifted by one trading day ahead in the NDC relative to one in the SDC.

By comparing the SDC and NDC one can make a conclusion about the level of correlation between the indices or individual stocks as well as on the market (or the individual stock) that plays a leading role in the pair of markets or stocks.

To make a decision on whether the calculated SDC or NDC coefficients are statistically significant, one has to conduct a test for acceptance or rejection of the null-hypothesis that states "no correlation."

The correlation coefficients are random numbers with an unknown distribution that makes it unclear how to test the null-hypothesis. To conduct the hypothesis test one has to convert the correlation coefficients to some other form that shows a known distribution or at least is close to a known distribution.

We use Fisher's z-transformation (Cramér, 1999):

$$z = \frac{1}{2}\ln\frac{1+\rho}{1-\rho} \tag{8}$$

to convert correlation coefficients into z-numbers that show a distribution close enough to the normal distribution:

$$f_{\mu,\sigma}(z) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{(z-\mu)^2}{2\sigma^2}\right) \tag{9}$$

It is convenient to transform normally distributed random numbers, z, to random numbers, ω, with standard normal distribution, i.e. with ($\mu = 0$ and $\sigma = 1$):

$$f(\omega) = \frac{1}{\sqrt{2\pi}}\exp\left(-\frac{\omega^2}{2}\right) \tag{10}$$

by applying the following transformation:

$$\omega = z\sqrt{N-3} = \frac{\sqrt{N-3}}{2}\ln\frac{1+\rho}{1-\rho} \tag{11}$$

As soon as ω-numbers are distributed very close to standard normal distribution, the null-hypothesis can be easily tested.

3. Data collection and processing

The date-matching procedure for the SDC was quite simple. Correlation pairs were taken only on the days when both markets were open. On the other hand, the date-matching procedure for the NDC was a bit more complex to properly handle weekends, holidays, and any other situations when the next trading day for the second market is different from the next calendar day for the first market. Actually, the "next day" was considered the next trading day rather than next calendar day. Some

Table 2
Date matching example for same-day and next-day correlations.

Day	Daily rate of return on market A	Daily rate of return on market B	Pair for same-day correlation	Pair for next-day correlation
D_1	$R_A\,(D_1)$	Market closed	–	$R_A\,(D_1) \times R_B\,(D_5)$
D_2	Market closed	Market closed	–	–
D_3	Market closed	Market closed	–	–
D_5	$R_A\,(D_5)$	$R_B\,(D_5)$	$R_A\,(D_5) \times R_B\,(D_5)$	$R_A\,(D_5) \times R_B\,(D_6)$
D_6	$R_A\,(D_6)$	$R_B\,(D_6)$	$R_A\,(D_6) \times R_B\,(D_6)$	–
D_7	$R_A\,(D_7)$	Market closed	–	–
D_8	$R_A\,(D_8)$	Market closed	–	$R_A\,(D_8) \times R_B\,(D_9)$
D_9	$R_A\,(D_9)$	$R_B\,(D_9)$	$R_A\,(D_9) \times R_B\,(D_9)$	$R_A\,(D9) \times R_B\,(D1_2)$
D_{10}	Market closed	Market closed	–	–
D_{11}	Market closed	Market closed	–	–
D_{12}	Market closed	$R_B\,(D_{12})$	–	–
D_{13}	$R_A\,(D_{13})$	$R_B\,(D_{13})$	$R_A\,(D_{13}) \times R_B\,(D_{13})$	Subj. to future date

examples to clarify the date matching procedures for the same-day and next-day correlations are shown in Table 2.

The SDC, Eq. (4) and NDC, Eq. (7), coefficients were calculated for every year, i.e. for 12-month periods, where N was equal to the number of the appropriate date-matching pairs in each particular year. As mentioned above, the days on which at least one of the markets of an analyzed pair of markets was closed were removed from the SDC data set for consistency. Similarly, for the NDC coefficients calculations the pairs were matched by the appropriate dates with the closest next-day data. In case of multiple-day holidays on one of the stock exchanges, the data were matched without duplication.

4. Correlations between Dow Jones and Nasdaq indices

Fig. 2 shows the correlation coefficients between Dow Jones Industrial Average (DJI) and Nasdaq Composite (IXIC) from 1998 through 2009. The SDC for these two indices is quite high, above 0.8, with a tendency for growth except for 3 years (1999–2001) during the Internet bubble. All SDC are statistically significant with the probability of results with null-hypothesis lower than 0.00001%, i.e. the null-hypothesis can be rejected with a significance factor much higher than 99%.

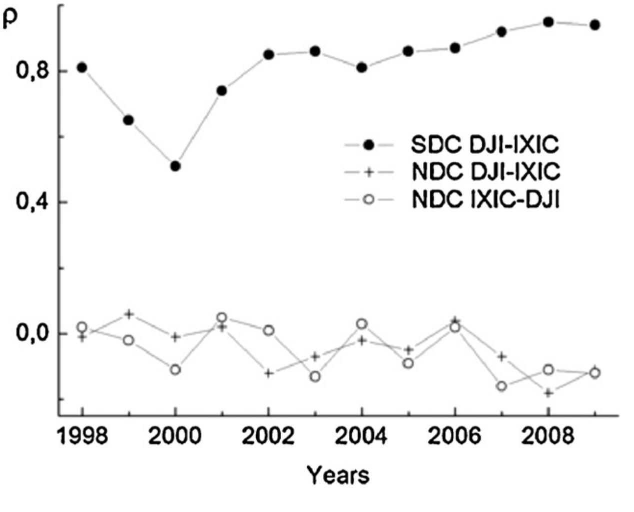

Fig. 2. SDC between Dow Jones (DJI) and Nasdaq (IXIC) indices.

Table 3
SDC between Dow Jones (DJI) and Nasdaq (IXIC) indices.

DJI-IXIC			
Year	SDC	N	Probability with null-hypothesis
2009	0.94	252	$<10^{-7}$
2008	0.95	253	$<10^{-7}$
2007	0.92	251	$<10^{-7}$
2006	0.87	251	$<10^{-7}$
2005	0.86	252	$<10^{-7}$
2004	0.81	252	$<10^{-7}$
2003	0.87	252	$<10^{-7}$
2002	0.85	252	$<10^{-7}$
2001	0.73	248	$<10^{-7}$
2000	0.5	252	$<10^{-7}$
1999	0.65	252	$<10^{-7}$
1998	0.81	252	$<10^{-7}$

The values of SDC for Dow Jones (DJI) and Nasdaq (IXIC) indices by year, the number of trading days per year, and the probability of such a result with null-hypothesis are shown in Table 3.

These results were expected because both indices, Dow Jones Industrial Average (DJI) and Nasdaq Composite (IXIC), are related to the U.S. stock market which is quite mature and for this reason highly correlated.

Both groups of NDC, for DJI-IXIC and IXIC-DJI, are around zero, which indicates no impact of the current-day returns on the next-day returns.

All correlation coefficients were calculated on an annual basis, i.e. for all appropriate matching pairs of trading days within the entire calendar year for each correlation coefficient.

5. Correlations between U.S. and Asia-Pacific stock markets

There are many geographic areas in the world which have their stock markets operating with non-overlapping trading hours. Among them are the Americas vs. Asia-Pacific, the Americas vs. Indo-Asia, the Americas vs. Oceania, the Americas vs. Eastern Europe, Western Europe vs. Asia-Pacific, Europe vs. Oceania, and others. We chose the U.S. vs. Asia-Pacific region for the current study as the most illustrative region that has both developed and emerging countries. We have studied the correlations between stock market indices of the U.S.—Dow Jones Industrial Average (DJI) and Nasdaq Composite (IXIC)—and various countries in the Asia-Pacific region, including: Japan–Nikkei (N225), South Korea–KOSPI Composite Index (KS11), Singapore–Straits Times Index (STI), Hong Kong (China)–Hang Seng (HSI), Taiwan–Taiwan Weighted (TWII), China–Shanghai Composite (SSEC), Malaysia–FTSE Bursa Malaysia KLCI (KLSE), and Indonesia–Jakarta Composite Index (JKSE). For this purpose, we calculated and analyzed NDC and SDC coefficients between the following pairs of U.S. and Asia-Pacific indices (DJI-N225, DJI-KS11, DJI-STI, DJI-HSI, DJI-TWII, DJI-SSEC, DJI-KLSE, and DJI-JKSE) as shown in Fig. 3 as well as IXIC-N225, IXIC-KS11, IXIC-STI, IXIC-HSI, IXIC-TWII, IXIC-SSEC, IXIC-KLSE, and IXIC-JKSE from 1998 through 2009 as shown in Fig. 4.

Tables 4 and 5 show the calculated SDC and NDC for the U.S. (DJI and IXIC) and Asia-Pacific indices from 1998 through 2009 along with the calculated probabilities of such results if the null-hypothesis is true. As it becomes evident from Tables 4 and 5, the SDC for all considered U.S. and Asia-Pacific pairs of indices are statistically insignificant with a significance level of 90% (i.e. there are no reasons to reject the null-hypothesis) with some exceptions for DJI-STI and DJI-HSI for which SDC is statistically significant for some years, particularly during global financial and economic instability. On the other hand, NDC for all considered U.S. and Asia-Pacific pairs of indices are statistically significant, i.e. the null-hypothesis can be rejected with a 90% significance level except for DJI-SSEC for which NDC is statistically insignificant.

It is also interesting to point out that the NDC is statistically significant with a 99% significance level for the entire period from 1998 through 2009 for all the industrially developed Asia-Pacific

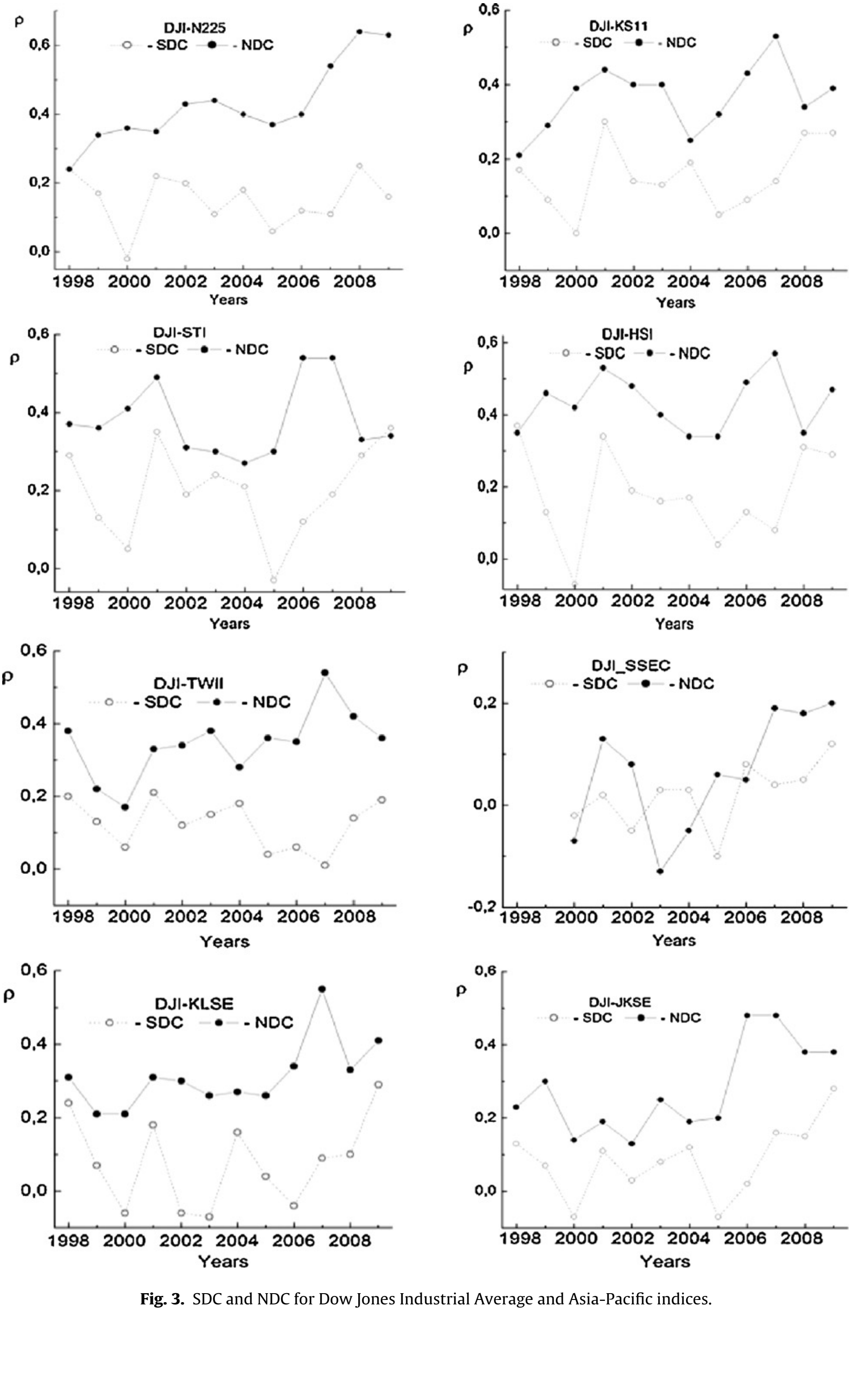

Fig. 3. SDC and NDC for Dow Jones Industrial Average and Asia-Pacific indices.

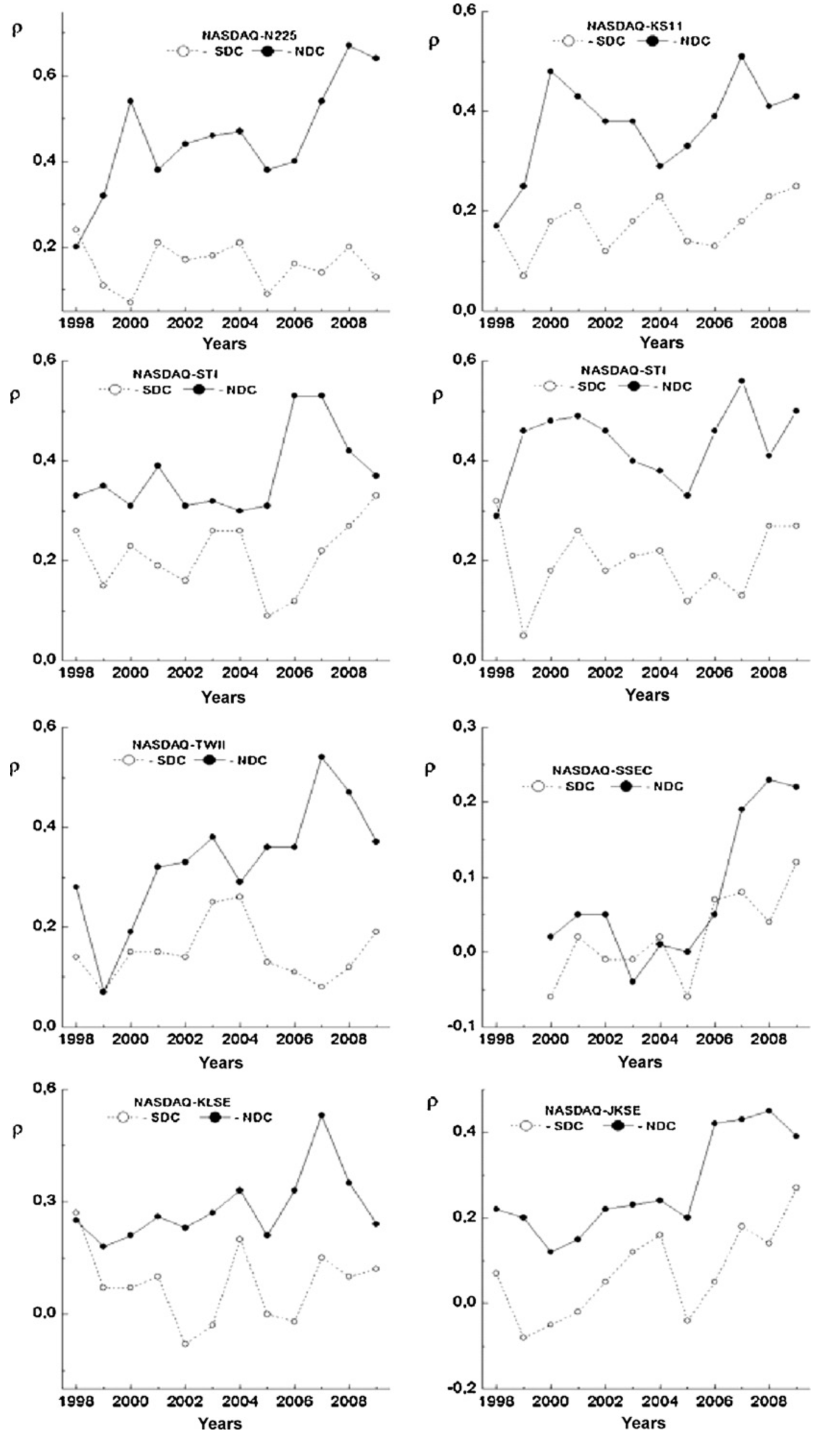

Fig. 4. SDC and NDC for Nasdaq Composite and Asia-Pacific indices.

Table 4
SDC, NDC, and the null-hypothesis testing results for Dow Jones Industrial Average and Asia-Pacific indices: DJI-N225, DJI-KS11, DJI-STI, and DJI-HSI, DJI-TWII, DJISSEC, DJI-KLSE, and DJI-JKSE.

Year	DJI-N225				DJI-KS11			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.16	1.84E−01	0.63	3.69E−14	0.27	1.44E−02	0.39	1.25E−04
2008	0.25	2.78E−02	0.64	5.55E−15	0.27	1.52E−02	0.34	1.35E−03
2007	0.11	3.73E−01	0.54	2.65E−09	0.14	2.47E−01	0.53	6.65E−09
2006	0.12	3.24E−01	0.4	8.14E−05	0.09	4.69E−01	0.43	1.58E−05
2005	0.06	6.36E−01	0.37	4.09E−04	0.05	6.92E−01	0.32	2.93E−03
2004	0.18	1.29E−01	0.40	9.34E−05	0.19	1.05E−01	0.25	2.68E−02
2003	0.11	3.73E−01	0.44	9.22E−06	0.13	2.84E−01	0.40	8.42E−05
2002	0.20	8.72E−02	0.43	1.64E−05	0.14	2.50E−01	0.40	9.67E−05
2001	0.22	5.96E−02	0.35	1.06E−03	0.30	6.60E−03	0.44	1.01E−05
2000	−0.02	8.79E−01	0.36	5.76E−04	0.00	1.00E+00	0.39	1.84E−04
1999	0.17	1.54E−01	0.34	1.52E−03	0.09	4.66E−01	0.29	8.11E−03
1998	0.24	3.50E−02	0.24	3.46E−02	0.17	1.52E−01	0.21	6.96E−02

Year	DJI-STI				DJI-HSI			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.36	4.53E−04	0.34	1.12E−03	0.29	3.10E−06	0.47	7.48E−07
2008	0.29	8.38E−03	0.33	2.05E−03	0.31	5.83E−07	0.35	7.86E−04
2007	0.19	1.01E−01	0.54	1.54E−09	0.08	2.11E−01	0.57	4.35E−11
2006	0.12	3.19E−01	0.54	1.43E−09	0.13	4.24E−02	0.49	1.73E−07
2005	−0.03	8.18E−01	0.30	5.44E−03	0.04	5.37E−01	0.34	1.35E−03
2004	0.21	6.62E−02	0.27	1.42E−02	0.17	8.09E−03	0.34	1.32E−03
2003	0.24	3.24E−02	0.30	5.44E−03	0.16	1.26E−02	0.40	7.86E−05
2002	0.19	1.01E−01	0.31	3.83E−03	0.19	3.00E−03	0.48	4.56E−07
2001	0.35	9.13E−04	0.49	2.18E−07	0.34	7.38E−08	0.53	9.60E−09
2000	0.05	6.90E−01	0.41	4.06E−05	−0.07	2.79E−01	0.42	2.65E−05
1999	0.13	2.79E−01	0.36	4.91E−04	0.13	4.41E−02	0.46	1.91E−06
1998	0.29	7.85E−03	0.37	3.35E−04	0.37	1.91E−09	0.35	8.69E−04

Year	DJI-TWII				DJI-SSEC			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.19	1.05E−01	0.36	5.92E−04	0.12	3.34E−01	0.2	9.20E−02
2008	0.14	2.45E−01	0.42	2.75E−05	0.05	6.91E−01	0.18	1.24E−01
2007	0.01	9.39E−01	0.54	3.09E−09	0.04	7.48E−01	0.19	9.71E−02
2006	0.06	6.35E−01	0.35	9.60E−04	0.08	5.11E−01	0.05	6.86E−01
2005	0.04	7.54E−01	0.36	6.08E−04	−0.1	4.52E−01	0.06	6.25E−01
2004	0.18	1.25E−01	0.28	1.11E−02	0.03	8.10E−01	−0.05	7.00E−01
2003	0.15	2.10E−01	0.38	2.27E−04	0.03	8.10E−01	−0.13	3.35E−01
2002	0.12	3.26E−01	0.34	1.41E−03	−0.05	7.00E−01	0.08	5.11E−01
2001	0.21	7.32E−02	0.33	2.29E−03	0.02	8.74E−01	0.13	2.76E−01
2000	0.06	6.37E−01	0.17	1.55E−01	−0.02	8.76E−01	−0.07	5.94E−01
1999	0.13	2.90E−01	0.22	5.85E−02				
1998	0.2	8.65E−02	0.38	2.41E−04				

Year	DJI-KLSE				DJI-JKSE			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.13	2.81E−01	0.25	2.59E−02	0.28	1.20E−02	0.38	2.48E−04
2008	0.1	4.15E−01	0.33	1.96E−03	0.15	2.14E−01	0.38	2.64E−04
2007	0.09	4.65E−01	0.55	6.20E−10	0.16	1.77E−01	0.48	4.08E−07
2006	−0.04	7.63E−01	0.34	1.38E−03	0.02	8.77E−01	0.48	5.38E−07
2005	0.04	7.53E−01	0.26	2.05E−02	−0.07	6.05E−01	0.2	8.79E−02
2004	0.16	1.81E−01	0.27	1.59E−02	0.12	3.27E−01	0.19	1.06E−01

Table 4 (*Continued*)

Year	DJI-KLSE				DJI-JKSE			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2003	−0.07	6.03E−01	0.26	2.05E−02	0.08	5.23E−01	0.25	2.75E−02
2002	−0.06	6.52E−01	0.3	5.83E−03	0.03	8.15E−01	0.13	2.86E−01
2001	0.18	1.32E−01	0.31	4.80E−03	0.11	4.04E−01	0.19	1.31E−01
2000	−0.06	6.59E−01	0.21	7.39E−02	−0.07	6.08E−01	0.14	2.52E−01
1999	0.07	5.74E−01	0.21	6.79E−02	0.07	5.74E−01	0.3	5.83E−03
1998	0.24	3.46E−02	0.31	4.21E−03	0.13	2.81E−01	0.23	4.25E−02

countries such as Japan (DJI-N225 and IXIC-N225), Singapore (DJI-STI and IXIC-STI), Hong Kong (DJI-HSI and IXIC-HSI), South Korea (DJI-KS11, and IXIC-KS11), and Taiwan (DJI-TWII, and IXIC-TWII) while for the developing countries such as Malaysia (DJI-KLSE) and Indonesia (DJI-JKSE) the NDC becomes more statistically significant—i.e. the null-hypothesis can be rejected with the significance level of 99%—only in the most recent years. Both NDC and SDC for mainland China (DJI-SSEC and IXIC-SSEC) stay statistically insignificant.

All correlation coefficients were calculated on the annual basis, i.e. for all appropriate matching pairs of trading days within the entire calendar year for each correlation coefficient, SDC and NDC, according to the day matching algorithm described above and illustrated in Table 2. The number of days, N, was varying from year to year from 435 to 452 for each U.S.—Asia-Pacific correlation coefficients.

It also becomes evident from Figs. 3 and 4 and Tables 4 and 5 that for both U.S. indices, Dow Jones Industrial Average (DJI) and Nasdaq Composite (IXIC), most NDC with Asia-Pacific indices show a tendency for growth over time. For the most developed countries, like Japan, the NDC has reached levels above 0.6, which is quite high, particularly taking into account that the SDC between Dow Jones and Nasdaq is about 0.8 as shown in Fig. 2. The other indices, except SSEC, fall in the range of 0.4–0.6.

The NDC for the U.S. and the Asia-Pacific indices combined are shown in Fig. 5. It is interesting to note that NDC were pitching up during the periods of economic growth and pitching down in the times of recession and other economic instabilities.

The trends of different NDC for the U.S. and the Asia-Pacific indices with linear regression shown in Fig. 6 clearly indicate a general tendency for the correlations to grow over time.

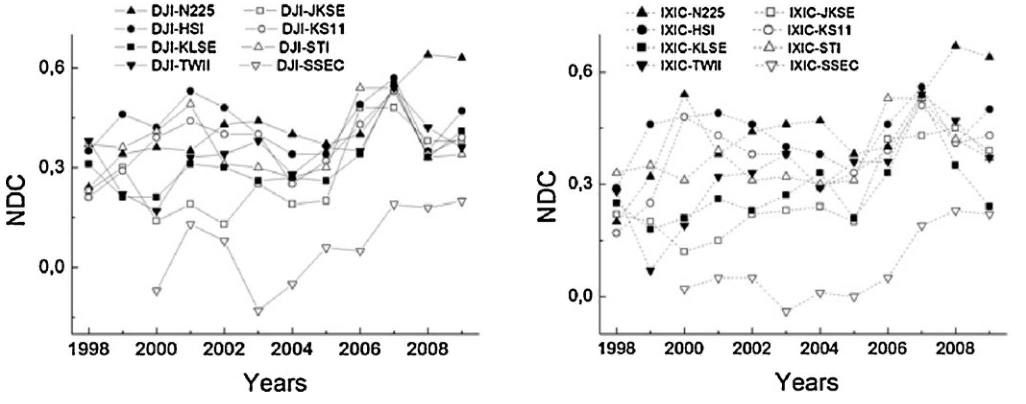

Fig. 5. NDC for the U.S. and the Asia-Pacific indices.

Table 5
SDC, NDC, and the null-hypothesis testing results for Nasdaq Composite and Asia-Pacific indices: IXIC-N225, IXIC-KS11, IXIC-STI, and IXIC-HSI, IXIC-TWII, IXIC-SSEC, IXIC-KLSE, and IXIC-JKSE.

Year	IXIC-N225				IXIC-KS11			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.16	2.89E−01	0.63	7.11E−15	0.27	2.52E−02	0.39	1.28E−05
2008	0.25	8.79E−02	0.64	0.00E+00	0.27	4.38E−02	0.34	4.70E−05
2007	0.11	2.49E−01	0.54	2.65E−09	0.14	1.27E−01	0.53	4.27E−08
2006	0.12	1.79E−01	0.4	8.14E−05	0.09	2.85E−01	0.43	1.47E−04
2005	0.06	4.71E−01	0.37	2.56E−04	0.05	2.45E−01	0.32	2.01E−03
2004	0.18	7.14E−02	0.40	1.20E−06	0.19	4.42E−02	0.25	8.38E−03
2003	0.11	1.29E−01	0.44	2.44E−06	0.13	1.27E−01	0.40	2.34E−04
2002	0.20	1.53E−01	0.43	8.82E−06	0.14	3.29E−01	0.40	2.64E−04
2001	0.22	7.39E−02	0.35	2.80E−04	0.30	7.26E−02	0.44	1.86E−05
2000	−0.02	5.76E−01	0.36	2.10E−09	0.00	1.34E−01	0.39	7.50E−07
1999	0.17	3.73E−01	0.34	3.25E−03	0.09	5.75E−01	0.29	2.62E−02
1998	0.24	3.50E−02	0.24	8.59E−02	0.17	1.52E−01	0.21	1.51E−01
Year	IXIC-STI				IXIC-HSI			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null−hypothesis
2009	0.36	1.65E−03	0.34	2.91E−04	0.29	1.40E−02	0.47	6.57E−08
2008	0.29	1.54E−02	0.33	2.75E−05	0.31	1.42E−02	0.35	3.91E−05
2007	0.19	5.33E−02	0.54	4.29E−09	0.08	2.78E−01	0.57	1.44E−10
2006	0.12	3.19E−01	0.54	3.98E−09	0.13	1.48E−01	0.49	1.73E−06
2005	−0.03	4.62E−01	0.30	3.83E−03	0.04	3.24E−01	0.34	2.01E−03
2004	0.21	1.89E−02	0.27	5.44E−03	0.17	5.53E−02	0.34	2.20E−04
2003	0.24	1.89E−02	0.30	2.65E−03	0.16	6.84E−02	0.40	7.86E−05
2002	0.19	1.74E−01	0.31	3.83E−03	0.19	1.26E−01	0.48	2.00E−06
2001	0.35	1.05E−01	0.49	1.42E−04	0.34	2.21E−02	0.53	3.10E−07
2000	0.05	4.21E−02	0.41	3.90E−03	−0.07	1.26E−01	0.42	4.56E−07
1999	0.13	2.06E−01	0.36	7.67E−04	0.13	6.93E−01	0.46	1.91E−06
1998	0.29	1.94E−02	0.37	1.88E−03	0.37	2.87E−03	0.35	8.11E−03
Year	IXIC-TWII				IXIC-SSEC			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.19	1.05E−01	0.36	3.76E−04	0.12	3.34E−01	0.2	6.07E−02
2008	0.14	3.24E−01	0.42	1.02E−06	0.05	7.51E−01	0.18	4.29E−02
2007	0.01	5.25E−01	0.54	3.09E−09	0.04	5.11E−01	0.19	9.71E−02
2006	0.06	3.72E−01	0.35	6.25E−04	0.08	5.68E−01	0.05	6.86E−01
2005	0.04	2.85E−01	0.36	6.08E−04	−0.1	6.46E−01	0.06	1.00E+00
2004	0.18	1.99E−02	0.28	8.11E−03	0.03	8.73E−01	−0.05	9.37E−01
2003	0.15	2.65E−02	0.38	2.27E−04	0.03	9.37E−01	−0.13	7.57E−01
2002	0.12	2.47E−01	0.34	2.10E−03	−0.05	9.37E−01	0.08	6.86E−01
2001	0.21	2.17E−01	0.33	3.31E−03	0.02	8.74E−01	0.13	6.88E−01
2000	0.06	2.16E−01	0.17	1.08E−01	−0.02	6.47E−01	−0.07	8.74E−01
1999	0.13	5.81E−01	0.22	5.80E−01				
1998	0.2	2.47E−01	0.38	1.16E−02				
Year	IXIC-KLSE				IXIC-JKSE			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2009	0.13	3.22E−01	0.25	3.35E−02	0.28	1.61E−02	0.38	1.51E−04
2008	0.1	4.15E−01	0.33	8.69E−04	0.15	2.49E−01	0.38	5.05E−06
2007	0.09	2.08E−01	0.55	4.96E−09	0.16	1.24E−01	0.48	1.34E−05
2006	−0.04	8.79E−01	0.34	2.05E−03	0.02	6.94E−01	0.48	2.98E−05
2005	0.04	1.00E+00	0.26	6.96E−02	−0.07	7.64E−01	0.2	8.79E−02
2004	0.16	8.72E−02	0.27	2.14E−03	0.12	1.81E−01	0.19	3.54E−02

Table 5 (*Continued*)

Year	IXIC-KLSE				IXIC-JKSE			
	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis	SDC	Probability with null-hypothesis	NDC	Probability with null-hypothesis
2003	−0.07	8.20E−01	0.26	1.54E−02	0.08	3.27E−01	0.25	4.51E−02
2002	−0.06	5.52E−01	0.3	4.34E−02	0.03	6.94E−01	0.13	5.69E−02
2001	0.18	4.23E−01	0.31	2.21E−02	0.11	8.87E−01	0.19	2.45E−01
2000	−0.06	5.82E−01	0.21	7.39E−02	−0.07	7.11E−01	0.14	3.31E−01
1999	0.07	5.74E−01	0.21	1.24E−01	0.07	5.51E−01	0.3	8.46E−02
1998	0.24	1.54E−02	0.31	2.65E−02	0.13	5.74E−01	0.23	5.38E−02

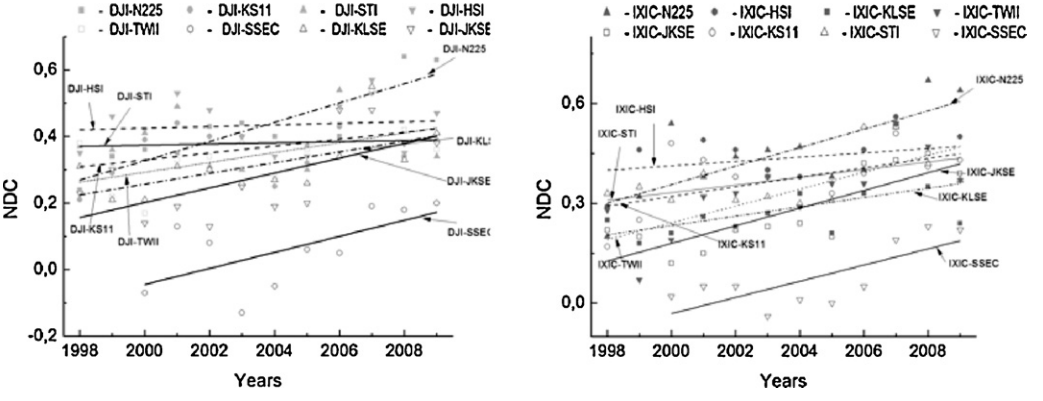

Fig. 6. NDC trends for the U.S. and Asia-Pacific indices with linear regression.

6. Conclusions

The analysis of SDC and NDC coefficients between U.S. stock indices—including Dow Jones Industrial Average (DJI) and Nasdaq Composite (IXIC)—and Asia-Pacific stock indices—including N225, KS11, STI. HSI, TWII, SSEC, KLSE, and JKSE—shows that NDC are statistically significant for all Asia-Pacific indices considered with the exception of SSEC. In contrast, analysis shows that most SDC are typically statistically insignificant, with a few exceptions for KLSE and LKSE in the years of recession and economic instability. The values of SDC are lower than the values of the corresponding NDC. The values of NDC were between 0.4 and 0.6 in 2007 for all indices except SSEC. In the last 2 years the NDC for DJI-N225 rose above 0.6, but the NDC for other indices decreased to 0.3–04. Such a drop can be explained by the typical reduction of correlations during global financial instability. Both SDC and NDC for DJI-SSEC are statistically insignificant and below 0.4 in value.

The fact that the NDC are statistically significant and are higher than the corresponding SDC—which are mostly insignificant—allows us to conclude that the U.S. stock market plays a pacesetting role at least on the scale of the U.S. and Asia-Pacific region, with the exception of the stock market of mainland China (SSEC). The introduction of SDC and NDC made such a conclusion possible, while the traditional correlation analysis does not identify cause-and-effect relationship. The analysis of NDC and SDC coefficients suggests that Asian stock markets are more likely following the U.S. market while the U.S. market behaves more independently of the Asian stock markets.

As it becomes evident from the results of this paper, the time-shift asymmetric correlation method with SDC and NDC helps better identify pairs of data for corellation analysis of the markets with different non-overlapping trading hours. Traditionally, researchers used only SDC matching pairs for close-to-close correlation analysis that, as was shown in this paper, leads to statistically insignificant results and underestimated correlation coefficients (Hamao et al., 1990; Koutmos and Booth, 1995; Martens and Poon, 2001; Michayluk et al., 2006; and others), while NDC coefficients show stronger correlations with very high statistical significance.

As we have suggested in this paper, correlation coefficients between stock market indices can be used as a measure of global integration for the corresponding countries. Low correlations between Chinese Shanghai Composite (SSEC) and U.S. Dow Jones (DJI) and Nasdaq Composite (IXIC) indicate that China, though it plays one of the leading roles in the global economy, has an even bigger internal market that offsets its complete integration in the global economy and its dependence on the global financial and economic instabilities.

Acknowledgements

The authors would like to thank Professor Robert Pisani (University of California, Berkeley) for his interest in this research and his very helpful discussions and suggestions.

The authors are very grateful to Ms. Nicole Marsh (Lincoln University, Oakland, California) for her valuable help in the preparation of this paper and to the administration of Lincoln University for a very stimulating and motivating interest to this research.

Appendix A. Sources on international exchanges trading hours

http://bourse.trader-finance.fr/horaire+ouverture+bourse/, http://www.idx.co.id/MainMenu/Trading/JamPerdagangan/tabid/214/lang/en-US/language/en-US/Default.aspx

http://www.klse.com.my/

http://www.londonstockexchange.com/

http://www.tse.or.jp/english/

http://www.kgieworld.com/Markets/Global/TradingHours.aspx?sc_lang=en

http://www.sgx.com/wps/portal/marketplace/mp-en/trading_on_sgx/securities_market/securities_trading_and_settlement

http://www.twse.com.tw/en/products/trading_rules/trading_hours.php.

References

Aityan, S.K., 2007. Asymmetric time-shift stock markets correlations, Paper presented at the Lincoln University Multidisciplinary Series, Oakland, CA.

Ang, A., Bekaert, G., 2002. International asset allocation with regime shifts. Review of Financial Studies 15, 1137–1187.

Atchinson, M., Butler, K., Simonds, R., 1987. Nonsynchronous security trading and market autocorrelation. Journal of Finance 42, 111–118.

Badrinath, S., Kale, J., Noe, N.H., 1995. Of shepherds, sheep, and the cross-autocorrelations in equity returns. Review of Financial Studies 8, 401–430.

Baele, L., 2005. Volatility spillover effects in european equity markets. Journal of Financial and Quantitative Analysis 40, 373–401.

Balaban, E., Bayar, A., Kan, O.B., 2001. Stock returns, seasonality and asymmetric conditional volatility in world equity markets. Applied Economic Letters 8 (4), 263–268.

Bekaert, G., Harvey, C.R., 2000. Foreign speculator and emerging equity markets. Journal of Finance 55 (2), 565–613.

Bekaert, G., Harvey, C.R., Lundblad, C.T., 2001. Emerging equity markets and economic development. Journal of Development Economics 66 (2), 465–504.

Black, A., Fraser, P., 1995. UK stock return: predictability and business conditions. The Mancherster School of Economic & Social Studies 63, 85–102.

Bracker, K., Docking, D.S., Koch, P.D., 1999. Economic determinates of evolution in international stock market integration. Journal of Empirical Finance 6 (1), 1–27.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307–327.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalised ARCH approach. Review of Economics and Statistics 72, 498–505.

Bollerslev, T., Engle, R., Wooldridge, J., 1988. A capital asset pricing model with time varying covariances. Journal of Political Economy 96, 116–131.

Centeno, M.C.G., Salido, R.M., 2009. Estimation of asymmetric stochastic volatility models for stock-exchange index returns. International Advances in Economic Research 15, 71–87.

Chan, K., 1993. Imperfect information and cross-autocorrelation among stock returns. Journal of Finance 48, 1211–1230.

Chesnay, F., Jondeau, E., 2001. Does correlation between stock returns really increase during turbulent periods? Economic Notes 30, 53–80.

Chiang, T.C., Chen, C.W.S., So, M.K.P., 2007. Asymmetrie return and volatility responses to composite news from stock markets. Muttinational Finance Journal 11 (3/4), 179–221.

Cohen, K., Hawawini, G., Mater, S., Schwartz, R., Whitcomb, D., 1980. Implications of microstructure theory for empirical research on stock price behavior. Journal of Finance 35, 249–257.

Conrad, J., Kaul, G., 1988. Time varying expected return. Journal of Business 61, 409–425.

Cramér, H., 1999. Mathematical Methods of Statistics. Princeton University Press.
Da Costa Jr., N., Nunes, S.C., 2005. Stock market comovements revisited. Economics Bulletin 7 (3), 1–9, http://www.economicsbulletin.com/2005/volume7/EB-05G10001A.pdf.
Engle, R.F., 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. Econometrica 50, 987–1008.
Engle, R.F., Ng, V., Rothschild, M., 1990. Asset pricing with factor ARCH covariance structure: empirical estimates for treasure bills. Journal of Econometrics 45, 213–238.
Erb, C.B., Harvey, C.R., Viskanta, T.E., 1994. Forecasting international equity correlations. Financial Analysts Journal 50, 32–45.
Flavin, T.J., Hurley, M.J., Rousseau, F., 2002. Explaining stock market correlation: a gravity model approach. The Manchester School 70, 87–106.
Goetzmann, W., Li, L., Rouwenhorst, G., 2005. Long-term global market correlations. The Journal of Business 78, 1–38.
Hamao, Y., Masulis, R.W., Ng, V., 1990. Correlations in price changes and volatility across international stock markets. Review of Financial Studies 3 (2), 281–308.
Hentschel, L., 1995. All in the family: nesting symmetric and asymmetric garch models. Journal of Financial Economics 39, 71–104.
Hong, Y., Tu, J., Zhou, G., 2007. Asymmetries in stock returns: statistical tests and economic evaluation. Review of Financial Studies 20 (Issue 5), 1547–1581.
Hu, Y.-P., Linb, L., Kaoa, J.-W., 2008. Time-varying inter-market linkage of international stock markets. Applied Economics 40, 2501–2507.
Ilina, E., Daragan, V., 2001a. Correlation of the stock indices. New Trading Ideas, Internet Journal, 01–02, http://www.basicsoftrading.com/journal/2-investment-strategies/2-002/index.shtml.
Ilina, E., Daragan, V., 2001b. Correlation of the stock indices. Part 2. International indices. New Trading Ideas Internet Journal, 01–02, http://www.basicsoftrading.com/journal/2-investment-strategies/2-003/index.shtml.
Ivanov-Schitz, A.K., Aityan, S.K., 2009. Integration of Russia into the world economy and globalization of stock markets. Vestnik MGIMO, 154–162.
King, M., Wadhwani, S., 1990. Transmission of volatility between stock markets. The Review of Financial Studies 3, 5–33.
Knif, J., Pynnonen, S., 1999. Local and global price memory of international stock markets. Journal of International Financial Markets, Institutions and Money 9, 129–147.
Koch, P.D., Koch, T.W., 1991. Evolution of dynamic linkages across daily national stock indices. Journal of International Money and Finance 10, 231–251.
Koutmos, G., Booth, G.G., 1995. Asymmetric volatility transmission in international stock markets. J.International Money and Finance 14 (6), 747–762.
Kumar, R., Dhankar, R.S., 2009. Asymmetric volatility and cross-correlations in stock returns under risk and uncertainty. Vikalpa 34 (4), 25–36.
Li, Y., Kazemi, H., 2007. Conditional properties of hedge funds: evidence from daily returns. European Financial Management 13 (2), 211–238.
Lin, W.L., Engle, R.F., Ito, T., 1994. Do bulls and bears move across borders? International transmission of stock returns and volatility. Review of Financial Studies 7, 507–538.
Liu, S.Z.K.C., Lin, S.M., Lai, 2006. Stock market interdependence and trade relations: a correlation test for the US and its trading partners. Economics Bulletin 7 (5), 1–15.
Lo, A., MacKinlay, A.C., 1990a. When are contrarian profits due to stock market overreaction? Review of Financial Studies 3, 175–205.
Lo, A., MacKinlay, A.C., 1990b. An econometric analysis of nonsynchronous trading. Journal of Econometrics 45, 181–211.
Longin, F., Solnik, B., 1995. Is the correlation in international equity returns constant? Journal of International Money and Finance 14, 3–26.
Longin, P., Solnik, B., 2001. Extreme correlation and international equity markets. Journal of Finance 56, 649–676.
Makridakis, S.G., Wheelwright, S.C., 1974. An analysis of the interrelationships among the major world stock exchanges. Journal of Business Finance and Accounting 1, 195–216.
Martens, M., Poon, S.H., 2001. Returns synchronization and daily correlation dynamics between international stock markets. Journal of Banking and Finance 25 (10), 1805–1827.
Michayluk, D., Wilson, P.J., Zurbruegg, R., 2006. Asymmetric volatility, correlation and returns dynamics between the U.S. and U.K. securitized real estate markets. Real Estate Economic 34 (1), 109–131.
Mukherjee, K., Mishra, R.K., 2007. International stock market integration and its economic determinates: a study of indian and world equity markets. Vikalpa 32 (4), 29–44.
Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica 59, 347–370.
Pretorius, E., 2002. Economic determinates of emerging stock market interdependence. Emerging Markets Review 3 (1), 84–105.
Richardson, T., Peterson, D.R., 1999. The cross-autocorrelation of size-based portfolio returns is not an artifact of portfolio autocorrelation. Journal of Finance Research (22), 1–13.
Sasaki, H., Yamagushi, S., Takamasa, H., 1999. The Globalization of Financial Markets and Monetary Policy, Paper presented in the Bank for International Settlements, Annual Autumn Meeting, 25–26 October.
Sentana, E., 1995. Quadratic arch models. Review of Economic Studies 62, 639–661.
Solnik, B., Boucrelle, C., Fur, Y.L., 1996. International market correlation and volatility. Financial Analysts Journal 52, 17–34.
Wu, G., 2001. The determinates of asymmetric volatility. The Review of Financial Studies 14 (3), 837–859.
Yu, C.-H., Wu, C., 2001. Economic sources of asymmetric cross-correlation among stock returns. International Review of Economics and Finance 10, 19–40.
Zakoian, J.M., 1994. Threshold heteroskedastic models. Journal of Economic Dynamics and Control 18, 931–955.