

Stock Market Integration: Granger Causality Testing with Respect to Nonsynchronous Trading Effects*

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Abstract

In this paper, we perform Granger causality analysis on stock market indices from several Asian, European, and U.S. markets. Using daily data, we point out the potential problems caused by the presence of nonsynchronous trading effects. We deal with two kinds of nonsynchronicity – one induced by differing numbers of observations in the series being analyzed and the other related to the different time zones in which the markets operate. To address the first problem, we propose a data-matching process. To address the second problem, we modify the regressions used in the Granger causality testing. When comparing the empirical results obtained using the standard technique and our modified methodology, we find substantially different results. Most of the relationships that are subject to nonsynchronous trading are not significant in the general case. However, when we use the adjusted methodology, the null hypothesis of a Granger non-causal relationship is rejected in all cases.

1. Introduction

The problem of stock market integration has been studied for several decades from many different perspectives. Some of the early studies were closely linked to portfolio theory and effective international diversification (see, for example, Grubel, 1968; Ripley, 1973; Lessard 1974, 1976; Panton et al., 1976; Hilliard, 1979; and others). The problem of diversification was linked to market integration by the role of correlation in the classical mean-variance approach. International diversification was considered a suitable choice because the weak correlation of returns on international stock markets allowed for the diversification of risk.

Even though the specific methods used in these studies differed, the conclusions were generally very similar. The overview of results presented in this section focuses on two aspects that are important to our own treatment of the problem: first, we examine the empirical results of the cited studies, which can be compared to ours. Even more interesting is the methodology that was used to obtain these results. We later show that the choice of model and data used may have significant consequences when dealing with stock markets with nonsynchronous trading.

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1.1 Stock Market Integration

By using vector autoregression models (VAR) on daily returns of nine stock indices, Eun and Shim (1989) examine the information transmission from U.S. to other markets. Their results support the evidence for U.S. dominance in the international stock markets.

Since the 1990s, most of the research conducted in the field of stock markets analysis has focused on the increased integration, international dependencies, and efficiency of the markets. The presence of these effects has been extensively analyzed by Granger causality testing.¹

Many empirical studies conclude that there is no clear evidence of a causal relationship between international stock markets. Malliaris and Urrutia (1992) investigate the Granger causalities of six stock market indices before, during, and after the October 1987 crash to identify the origin of the crisis. No significant lead-lag relationship is found in the pre- or post-crash period. Kwan et al. (1995) employ a similar methodology and examine the efficient markets hypothesis in its weak form. Again, no dominant market is identified, so they reject their hypothesis.

Masih and Masih (2001) analyze the short- and long-run causal relationships between international stock markets using VAR and vector error-correction models (VECM). In their next paper (Masih and Masih, 2002), they examine the degree of globalization using the same approach.

More recently, a unique dataset covering two years of high frequency data is utilized by Černý and Koblas (2008). Their objective was to describe stock market integration and the speed of information transmission. Their paper is particularly interesting, not only for the data used, but also for the selection of stock market indices, where they compare Polish, Hungarian, and Czech stock market indices with those from developed markets.

The above papers present only a small fraction of the papers published in this wide area of research. Additional information can be found in D'Ecclesia and Costantini (2006), Drakos and Kutun (2005), Soydemir (2000), and others.

1.2 Nonsynchronous Trading Effects

Even though the research in this area is quite extensive, only a few studies have addressed the potentially serious “nonsynchronous trading effect” problem in the use of data from stock exchanges in various countries. The consequence of this effect is that the time series of stock returns, covering the same corresponding periods, usually have unequal numbers of observations (using daily closing prices). These differences arise naturally from the fact that trading days in different countries are subject to different national and religious holidays, unexpected events, and so forth. More importantly, this effect can induce spurious cross-correlations of returns calculated from daily closing prices (first mentioned by Fisher, 1966; for more information see Campbell et al., 1997). The majority of studies neither precisely examines nor accounts for this type of nonsynchronicity of daily returns in tests for Granger causality.²

¹ If not stated otherwise, all references to “causality” should be understood in the sense of Granger causality.

The second problem³ with the analysis of data from different international stock markets occurs when one examines relations between stock market indices coming from countries located in different time zones. As this effect is also sometimes called the “nonsynchronous trading effect”, for the purposes of clarity, we distinguish between these two problems and refer to the latter as “nonsynchronous trading effect II”. The literature examining this issue is much more detailed.

Eun and Shim (1989) recognize that national stock markets operate in various time zones with different opening and closing hours (local time), making the observed returns nonsynchronous. That is, when markets close on the same day on the various international exchanges, it does not happen at the same time (measured, for example, by coordinated universal time, UTC). The authors examine the problem of such nonsynchronicity with the conventional VAR methodology, where they inspect the impulse response functions of nine time series of daily stock market returns. Their conclusions emphasize the dominant position of U.S. markets in Granger-causing the returns of other world stock markets.

Many papers that perform correlation analyses use weekly or monthly data to avoid the nonsynchronicity problem (e.g., Longin and Solnik, 1995; Theodossiou et al., 1997; Ramchand and Susmel, 1998). A similar strategy can be found in papers that test for Granger causality (Kwan et al., 1995; Masih and Masih, 2001; Masih and Masih, 2002). Such solutions, however, may lead to small sample sizes and cannot capture the information transmission in shorter (daily) timeframes.

In general, the following approaches have been suggested to deal with nonsynchronous trading effects:

1. the use of weekly or monthly data,
2. the disaggregation of daily returns and/or the use of open-to-close or close-to-open methods in computing returns (Hamao et al., 1990),
3. rolling-average returns, sometimes adjusted for weekends and holidays (Forbes and Rigobon, 2002),
4. “synchronous closing prices”, also called a “common window” (Martens and Poon, 2001; Égert and Kočenda, 2007, 2011).

2. Data and Methodology

For our analysis of Granger causal relationships, we use the daily closing prices for the following indices: U.S. – Standard and Poor’s 500 (SP500); European markets – the UK’s FTSE 100 (FTSE) and the German DAX 30 (DAX); Asian – the Chinese Hang Seng (HSI) and the Japanese Nikkei 225 (N225). It has been shown in many empirical studies that closing prices are not stationary at their levels. Computing continuous returns makes the first differences of price logarithms of all time series stationary (the Phillips-Perron, ADF-GLS, KPSS, and Zivot-Andrews tests were applied). The entire causality analysis is therefore conducted using daily returns;

² Most of the papers use equal numbers of daily observations in their analyses, even though in most cases it is not clear how this is established. The problem of nonsynchronicity is potentially influential and therefore methodologically significant (as ignoring this effect might lead to different conclusions).

³ There is a third source of nonsynchronous trading effects that we do not consider – the last trades of the individual stocks in the index occur at different times.

Table 1 Descriptive Statistics and Normality Tests (Daily Returns)

<i>Index</i>	<i>Observations</i>	<i>Mean</i>	<i>Std. dev.</i>	<i>Min</i>	<i>Max</i>
SP500	2702	-0.0001	0.0139	-0.0947	0.1096
FTSE	2714	-0.0001	0.0133	-0.0926	0.0938
DAX	2735	0.0000	0.0165	-0.0743	0.1080
HSI	2676	0.0001	0.0167	-0.1358	0.1341
N225	2637	-0.0003	0.0162	-0.1211	0.1323
<i>Index</i>	<i>Median</i>	<i>Skewness</i>	<i>Kurtosis</i>	<i>Jarque-Bera</i>	<i>p-value</i>
SP500	0.0005	-0.1084	10.4035	6176.24	0.0000
FTSE	0.0003	-0.0970	8.9692	4033.63	0.0000
DAX	0.0007	0.0696	7.1385	1954.01	0.0000
HSI	0.0003	-0.0435	10.7089	6626.95	0.0000
N225	0.0000	-0.2919	9.0197	4018.99	0.0000

otherwise it would be subject to the obvious spurious causality stemming from the co-integration relationships.

We use publicly available data (Yahoo Finance) so that our research remains easy to replicate (all analyses are conducted using the open-source software R). Closing prices are denominated in local currencies. The indices therefore reflect information from national stock markets without swings in exchange rates. This procedure is consistent with Eun and Shim (1989) and others. We also do not control for dually listed stocks (for further information see, for example, Lieberman et al., 1999). The descriptive statistics and the tests for normality of all daily returns covering the period from January 2000 to September 2010 are presented in *Table 1*.

2.1 The Matching Process

Note that the number of observations in *Table 1* is different for all series. By acknowledging the effect of nonsynchronous trading, we have to account for national holidays and other cases where there are data missing from one or more indices. One way to get a corresponding sample is to omit all of the observations with missing information and keep only the days with records of all indices. However, such an easy and natural procedure may also have less obvious consequences.

It is quite common to analyze and model data not only on the levels of given variables, but also on their differences. When calculating continuous returns, we use price information from two consecutive days to calculate daily returns. Hence, by lagging the analyzed variables (or taking the difference in logarithms of prices), we combine the values of variables on two different days.

This “chaining” (i.e., the use of consecutive variable values) becomes a problem in situations where we have missing data. Omitting given observations from all indices makes the days before and after holidays in one market seem consecutive in other markets when in fact they are not. If we continued by taking the log difference, this would result in the calculation of returns over a longer time period, which clearly carries the risk of distorting the estimated statistics, such as by inflating the variance of the return time series, in cases where data are frequently missing (by mixing daily returns with returns calculated over other periods).

Table 2 An Example of the Synchronization Process

Date	Index A			Index B		
	Value	Lag 1	Lag 2	Value	Lag 1	Lag 2
t	a_t			b_t		
$t+1$	a_{t+1}	a_t		b_{t+1}	b_t	
$t+2$	a_{t+2}	a_{t+1}	a_t	b_{t+2}	b_{t+1}	b_t
$t+3$	a_{t+3}	a_{t+2}	a_{t+1}	b_{t+3}	b_{t+2}	b_{t+1}
$t+4$		a_{t+3}	a_{t+2}	b_{t+4}	b_{t+3}	b_{t+2}
$t+5$	a_{t+5}		a_{t+3}	b_{t+5}	b_{t+4}	b_{t+3}
$t+6$	a_{t+6}	a_{t+5}		b_{t+6}	b_{t+5}	b_{t+4}
$t+7$	a_{t+7}	a_{t+6}	a_{t+5}	b_{t+7}	b_{t+6}	b_{t+5}

Notes: Time series for two indices being synchronized, requiring data calculated from three consecutive trading days (e.g., the current and two lagged values). The dataset starts at time t and ends at $t+7$. Notice that for index A, we have a missing observation at $t+4$. Using the procedure described above, we have three usable observations – at times $t+2$, $t+3$, and $t+7$. We see how the missing lagged value for index A at time t makes the data at time t and $t+1$ unusable. Similarly, the missing value at time $t+4$ makes the data at time $t+4$, $t+5$, and $t+6$ unusable. Note that in cases where we have usable observations ($t+2$, $t+3$, and $t+7$), we have full information on both indices for all required lags. It is also clear that the lagged values are precisely one active trading day apart.

To overcome this problem, we synchronize our data using the following procedure. First, we define the units of our analysis as “active trading days,” which basically gives us a list of all dates with at least one exchange open.

Next, we determine the number of consecutive trading days needed for our analysis. We obtain this from the equations that we are about to estimate (call this number k). For example, an equation involving log differences and their one lagged value requires three active trading days (we need p_{t+1} , p_t , p_{t-1} to calculate the required returns, hence, $k=3$).

For each equation (or system of equations), we create a subset of the dataset, using the condition that for every observation to be included, we have to have k consecutive active trading days for all variables in our equation (or system of equations). This rule ensures that every observation in every regression uses only truly consecutive daily data. For a better understanding of the matching process, see *Table 2*.

This procedure has another advantage in that it does not influence the characteristics of the time series. For example, the autoregressive structure of the data and all statistical properties are not distorted by calculating returns over uneven periods as long as we include all relevant lags in our requirements for the appropriate k . The omission of data reduces the number of observations, but we consider this to be a minor issue in our case. The number of days in our dataset is in the thousands, which makes the omission tolerable.

The proposed procedure is clearly not perfect. It reduces the number of observations quite significantly, as the number of indices and lags in the equations rises. Specific national holidays on different days in different countries decrease the length of the usable data. An increase in the lag order of the estimated equations causes the omissions to propagate to a number of consecutive observations, making them unusable to a further extent. As our analysis is not very demanding on the choice of k , we consider this data selection process appropriate for our purposes.

There is also one last concern about the proposed matching process. It could be argued that by omitting the missing periods from all indices the procedure could introduce bias into the analysis. As the existence of holiday effects is well known (see, for example, Kim and Park, 1994) the omission of such data could potentially have an impact on the dataset. This concern may be well justified, but there is no clear solution on how to include such days. Specifically, it is hard to see how a missing value could be sensibly used in the framework of Granger causality testing.

By omitting the days with missing values, we model the behavior of the indices under common circumstances. This should be sufficient for deciding on the nature and existence of a general relationship between different markets. What our proposed matching process prevents us to do is to draw conclusions about the relationships of indices on “special” occasions when some markets are not trading. An analysis focusing on these particular cases would require a different approach, which is beyond the scope and the objective of this paper.

2.2 Model Adjustments

The so-called nonsynchronous trading effect II is related to the fact that the various stock markets around the world do not all trade at the same time of day. As all the exchanges have trading hours based on local time, Asian markets are always the first to open and close on a given day. By the time trading starts in the U.S., the closing prices of the Asian markets are already known.

This raises the question of whether it is appropriate to consider the values obtained from the same calendar date to be corresponding. In particular, when trying to perform Granger causality tests, it might be necessary to review this assumption.

It is possible to see the problem more clearly by utilizing the concept of information sets, in the sense that they are used by Fama (1970) and others in testing the efficient markets theory. An information set can be seen in broad terms as the set of all information relevant for pricing an asset at a given time. Thus, all information at time t with the potential to influence the price of some asset is considered to be included in the information set Ω_t .

It is clear that information on trading in one market may be significant for trading in another (e.g., when a market opens). The problem is whether it is meaningful to assume that the values from two distinct indices – although from the same day, but trading at different, non-overlapping times – should be considered as belonging to the same Ω_t .⁴

In some cases, there is no difficulty and the data may be used chronologically based on the date, as in the case of the two U.S. indices. However, one should be more careful in the case of indices from different countries. If we consider an Asian and a U.S. index, the closing values of the Asian index are already known at the opening of the U.S. markets. In the other direction, the information set relevant for the close

⁴ Hanousek et al. (2009) and Hanousek and Kocenda (2011) show that there are significant intra-day spillover effects between the U.S. and European stock markets. Hence, trading on one market is relevant and should be considered to contribute to the corresponding information set when considering a different market. This is true in cases where there is a “common trading window,” as described in Hanousek et al. (2009). However, we are primarily interested in cases where there is no common window – or more generally when using daily data and closing values are not obtained simultaneously on all markets.

Table 3 Corresponding Lags in the Adjusted Granger Model

Dependent Variable	Independent variable		
	A	EU	US
A ($I_{t,A}$)	$I_{t-1,A}$	$I_{t-1,EU}$	$I_{t-1,US}$
EU ($I_{t,EU}$)	$I_{t,A}$	$I_{t-1,EU}$	$I_{t-1,US}$
US ($I_{t,US}$)	$I_{t,A}$	$I_{t,EU}$	$I_{t-1,US}$

Note: The superscripts distinguish between stock market indices from Asia (A), Europe (EU), and the United States (US)

of Asian markets certainly does not include information on U.S. trading on the same day, as it still lies in the future (again – when Asian markets close, the U.S. ones have not even opened). Thus, if the t in Ω_t designates a time variable expressing calendar dates, the information on the closing values of the Asian and the U.S. indices do not belong to the same information set.

In many analyses, the proper definition of information sets may not be critical. However, in the case of Granger causality tests, we find it to be of crucial importance. Ignoring the notion of information sets may lead to a model that is difficult, if not impossible, to interpret.

If we take into account nonsynchronous trading effect II, the generally used autoregressive distributed lag model formulation holds only for the Asian market (see Table 3). Formally, if we denote the first analyzed index (its daily returns) as I_{1t} , and the second index (its daily returns) as I_{2t} , the Granger causality model takes the following general form:

$$I_{1,t} = \alpha_0 + \sum_{i=1}^p \alpha_i I_{1,t-i} + \sum_{j=1}^q \beta_j I_{2,t-j} + \varepsilon_t \quad (1)$$

$$I_{2,t} = \alpha'_0 + \sum_{i=1}^p \alpha'_i I_{2,t-i} + \sum_{j=1}^q \beta'_j I_{1,t-j} + \varepsilon'_t \quad (2)$$

where $\alpha_0, \alpha_i, \beta_j$ ($\alpha'_0, \alpha'_i, \beta'_j$) are the regression parameters and ε_t (ε'_t) denotes the regression residuals. Wald's F -test for joint significance of the parameters $\beta_{j,j} = 1, 2 \dots q$ is performed to evaluate the null hypothesis that I_{1t} does not Granger-cause I_{2t} (and vice versa). As usual, we use the term “Granger-cause” when the historical values for one time series contain additional information that is useful in explaining and predicting another time series (denoted as $I_{1,t} \Rightarrow I_{2,t}$). We propose a simple adjustment to the Granger causality model where the lag of the independent variable is chosen with respect to nonsynchronous trading effect II. The basic principle of the proposed adjustments is demonstrated in Table 3.

To determine the number of lags (and to control for serial correlations) in a model, the Akaike, Schwarz or Hannan-Quinn information criteria are generally applied; in our sample, a lag of 1 is selected according to these criteria for all cases. Most econometric software tools provide this option in a simple manner. However, according to the above discussion, these tools should not be used directly. The model selection phase usually encompasses the estimation of models of different order and comparison of the information criteria. Because all these alternatives are based on lagging the independent variables by at least one period, this generally accepted ap-

proach automatically discards models where, in some cases, it is necessary to use the values of independent variables which are not lagged at all. As the lags are determined based on information sets specific to given time series, the careless use of readily available software implementations may lead to dubious model specifications.

It is apparent from this discussion that the use of the VAR and VECM methodology in its general software implementations is not compatible with our approach. These general approaches should not be used directly when nonsynchronous trading effect II is a concern, as they only allow for lagging all the independent variables in the same manner. That is, they disregard the notion of information sets.

3. Results

The results from our models proposed above are shown in *Tables 4* and *5*. Each table contains Wald's F -statistics after omitting the independent (explanatory) variable from the Granger model.

Table 4 shows the results from the classic form of the Granger model without any adjustments, i.e., the direct use of daily data. These results would correspond to the models that do not take into account the effect of nonsynchronous trading effect II.

The results show evidence for a dominant position of the SP500, which Granger-causes all other indices on a one-day lag.⁵ These relationships are unidirectional for all cases. Because we are dealing with multiple comparisons, these relationships should be interpreted carefully. It could be argued that after applying general methods of alpha adjustment for multiple comparisons (e.g., Bonferroni's correction), the results might be different. However, this claim is only relevant for relationships in which the p -value is close to the chosen significance level.

In the group of Asian stock indices, we observe that both the HSI and the N225 are Granger-caused by all other indices. The opposite effect is not present, i.e., the Asian stock market indices do not Granger-cause any other indices in our sample at the 1% significance level. The significance of the daily lag in the case of strong influence on the HSI and N225 would imply that the transfer of information to Asian markets happens within a few hours, because, for example, U.S. markets close at 10:00 p.m., whereas Asian markets open at approximately 2:00 a.m. CET (Central European Time).

The above results are all based on a model quantified without accounting for nonsynchronous trading effect II and have been presented for comparison in *Table 5*, which shows the results of the same models with our proposed adjustments.

When comparing indices from the same time zone, the functional forms of the estimated models remain the same. It follows that we expect no significant changes in the results for such pairs of indices. The differences arise primarily when comparing indices from different zones, e.g., a European and an Asian index (these results are highlighted).

The results in *Table 5* show that in contrast to the findings of the unadjusted model, the Asian indices Granger-cause all the other indices. We believe that these findings are more reasonable.

⁵ Models with higher lags have also been fitted, producing very similar results. We therefore report the most parsimonious models, using only the first lags.

Table 4 Results from the Non-Adjusted Granger Causality Model H_0 : Does not Granger cause

	SP500	FTSE	DAX	HSI	N225
SP500	-	1.2485 (0.2640)	0.2734 (0.6011)	2.4229 (0.1197)	0.6705 (0.4130)
FTSE	398.9163*** (3.02E-82)	-	25.4223*** (4.93E-07)	0.1558 (0.6931)	3.0343* (0.0817)
DAX	177.1118*** (4.54E-39)	3.3996* (0.0653)	-	0.1100 (0.7402)	1.4852 (0.2231)
HSI	553.7597*** (7.27E-110)	246.2076*** (7.08E-53)	270.4710*** (9.89E-58)	-	0.0004 (0.9839)
N225	804.4480*** (1.37E-150)	380.4779*** (2.19E-78)	477.6895*** (2.22E-96)	15.4547*** (8.72E-05)	-

Table 5 Results from the Adjusted Granger Causality Model H_0 : Does not Granger cause

	SP500	FTSE	DAX	HSI	N225
SP500	-	1183.3185*** (2.76E-211)	1634.8362*** (2.64E-274)	181.7863*** (6.28E-40)	91.1088*** (3.55E-21)
FTSE	407.8146*** (7.44E-84)	-	25.4223*** (4.93E-07)	487.7321*** (1.78E-98)	356.7544*** (5.97E-74)
DAX	183.3190*** (2.54E-40)	3.3996* (0.0653)	-	348.0917*** (9.54E-73)	246.6034*** (7.17E-53)
HSI	533.6257*** (2.98E-106)	247.8093*** (3.70E-53)	260.7462*** (8.54E-56)	-	0.0004 (0.9839)
N225	774.5497*** (1.08E-145)	372.5688*** (6.88E-77)	479.6349*** (1.04E-96)	15.4547*** (8.72E-05)	-

Notes: a) The tables contain Wald's F -statistics and p -values in parentheses. Significance levels are presented as 0.05*; 0.01**; 0.001***.

b) The tables should be read from right to left, i.e., stating that the variable in a given column "does not Granger-cause" the variable in a given row – e.g. the SP500 does not Granger-cause the FTSE, with p -value 7.44E-84.

c) The highlighted blocks represent results where adjustments for nonsynchronous trading effect II are necessary.

Similar findings are observed for the U.S. indices. The non-adjusted Granger models suggest that none of the examined indices has an impact on the U.S. indices. When we estimate the adjusted model to reflect nonsynchronous trading effect II, all of the analyzed indices significantly Granger-cause the SP500 (even when applying multiple comparison corrections).

The major difference in the findings of the two approaches is therefore in the character of the relationships found within each analysis. In the model according to *Table 4*, it was only possible to report unidirectional relationships with the U.S. market, whereas the relationships based on the adjusted model are bidirectional.

This therefore confirms that taking into account nonsynchronous trading effect II plays a crucial role in examining the lead-lag relationships among world stock

markets. Even taking into account long-run equilibrium relationships (cointegration of variables), by estimating the error correction model, still leads to the same conclusions.⁶

4. Conclusion

Analysis of the correlation of stock market indices has been an interesting topic for research over the past few decades. We focused on the estimation of Granger causalities between several world stock markets, including U.S., developed European, and Asian indices. However, our main objective was not primarily focused on the quantification of these effects. Our goal was to find an appropriate methodology for estimating some of the basic models used in such scenarios, taking into account nonsynchronous trading effects when dealing with daily data.

First of all, we described in detail the data-matching process we proposed. Despite the fact that many papers lack a thorough discussion on how the data was synchronized for their analysis, we feel that this issue is a serious one, as it may influence the outcome. Then we estimated simple models for Granger causality and suggested some suitable model adjustments. The results showed that our proposed modifications led to substantially different conclusions. This can be seen as a sign of the importance of choosing the right methodology when confronted with nonsynchronous trading effects. The main difference – bidirectional Granger causality between indices from Europe, Asia, and the U.S. – was identified only in our modified approach. Such empirical evidence also confirms the strengthening integration between international stock markets.

Even though we quantified only simple models, the general idea presented remains the same in more general situations. This can be easily seen with respect to the proposed model adjustments. In modeling Granger causalities and market dependence, it is important to select a model that does not “see into the future” in explaining dependent variables by as yet unobserved independent ones. This kind of problem may be described by using the classical concept of information sets.

Our findings raise a question on the use of a wide range of time-series models in the presence of nonsynchronous trading effects. Not only the general VAR, but also the multivariate GARCH models commonly used on daily data could be considered questionable if non-synchronicities are not accounted for. The error is particularly easy to make in these models, because their current implementations in most econometric software inherently assume synchronous data.

⁶ To determine whether or not the variables are cointegrated, we applied the basic methodology of Engle and Granger (1987) and followed the same logic of proposed adjustments to deal with nonsynchronous trading effect II. The detailed results and the equations used are available upon request.

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